Travel Behaviour and Demand Analysis and Prediction

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Article Outline

Glossary

Activity-based approach A modeling method that accounts for the interdependent relationships among activities and persons to derive travel demand equations.

Dynamic planning The incorporation of trends, cycles, and feedback mechanisms into a process of actively shaping our future. Desired futures are first defined in terms of performance measures and a combination of forecasting and backcasting methods are used to identify the right paths to follow in achieving these futures.

Microsimulation A method to represent the movement in space and time of the most elementary units of a phenomenon. When applied in traffic engineering the units are vehicles. When applied in travel behavior the units are persons and households. Multi-agent microsimulation allows to also represent human interaction with each person modeled as an agent.

Travel demand The amount of travel within a time interval such as number of trips in a day, total amount of distance and total amount of travel time, the locations (destinations) visited, the means used to reach these locations, departure time and arrival time of trips, routes followed in reaching these locations, the sequencing and assembly of trips in groups, and the purpose or activity engaged in at the end of each trip.

Definition of the Subject

Transportation modeling and simulation aims at the design of an efficient infrastructure and service to meet our needs for accessibility and mobility. At its heart is good understanding of human behavior that includes the identification of the determinants of behavior and the change in human behavior when circumstances change either due to control (e. g., policy actions), trends (e. g., demographic change), or unexpectedly (e. g., disasters). This is the key ingredient that drives most decisions in transportation planning and traffic operations. Since transportation systems are the backbone connecting the vital parts of a city (a region, a state or an entire country), in-depth understanding of transportation-related human behavior is essential to the planning, design, and operational analysis of all the systems that make a city function.

Understanding human nature requires us to analyze and develop synthetic models of human agency in its most important dimensions and the most elemental constituent parts. This includes, and it is not limited to, understanding of individual evolution along a life cycle path (from birth to entry in the labor force to retirement to death) and the complex interaction between an individual and the anthropogenic environment, natural environment, and the social environment. Travel behavior research is one aspect of analyzing human nature and aims at understanding how traveler values, norms, attitudes, perception and constraints lead to observed behavior. Traveler values and attitudes refer to motivational, cognitive, situational, and disposition factors determining human behavior. Travel behavior refers primarily to the modeling and analysis of travel demand, based on theories and analytical methods from a variety of scientific fields. These include, but are not limited to, the use of time and its allocation to travel and activities, methods to study this in a variety of time contexts and stages in the life of people, and the arrangement or artifacts and use of space at any level of social organization such as the individual, the household, the community, and other formal or informal groups This includes the movement of goods and the provision of services having strong interfaces and relationships with the engagement in activities and the movement of persons.

Travel behavior analysis and synthesis can be examined from both objective (observed by an analyst) and subjective (perceived by the human) perspectives in an integrated manner among four dimensions of time, geographic space, social space, and institutional context. In a few occasions the models reviewed here include and integrate time and space as conceived in science with perceptions of time and space by humans in their everyday life. For this reason research includes theory formation, data collection, modeling, inference, and simulation methods to produce decision support systems for policy assessment and evaluation that combine different views of time and space. Another objective of understanding human behavior is conceptual integration. Explanation of facts from different perspectives can be considered jointly to form a comprehensive understanding of people and their groups and their interactions with the natural and built environment. In this way, we may see explanations of human behavior fusing into the same universal principles. These principles eventually will lead to testable hypotheses from different perspectives offering Wilson's, 1998, famous consilience among, for example, psychology, anthropology, economics, the natural sciences, geography, and engineering. Unavoidably this is a daunting task with many model propositions in the research domain and very few ideas finding fertile ground in applications. The analysis-synthesis path in travel behavior gave us methods that help us understand and predict human (travel) behavior only partially leaving many gaps [163]. However, policy questions are becoming increasingly impossible to address with old tools, a large pool of researchers is actively working on new methods, and many public agencies commenced a variety of tool development projects to fill the travel behavior analysis gaps. To capture these trends, we see modeling examples with ideas from a transdisciplinary viewpoint and contributors to modeling and simulation from a variety of merged backgrounds (e. g., see the evolution of ideas in a sequence of the International Association for Travel Behavior Research conferences – www.public.asu.edu/~rpendyal/iatbr/iatbr_index.htm).

In the next sections the evolving paradigm of modeling and simulation is reviewed in detail and three of its fundamental sources are presented. Through the lens of contemporary planning practice the analytical requirements for modeling and simulation are discussed. Then, these same requirements are refined by examining contemporary visions about the world surrounding us and the theories and technologies we can use to build policy analysis models. This article ends with a section describing the emerging modeling and simulation paradigm, a brief section of mathematical models and closes with a summary.

Introduction

The impressive movement forward of transportation modeling and simulation emerges from three related but distinct sources. The first source is a fundamental change in planning practice that one could name *dynamic planning practice* to indicate the existence of bi-directional time (from the past to the future and from the future to today), as well as, assessment cycles and adjustments taking place within the short term, medium term, and long term horizons. These cycles are also bidirectional in time. This source contains three fundamental directions of practice that are *inventory creation and maintenance*, *strategy measurement and evaluation*, *forecasting and backcasting*. The second source is a vision that generates the substantive problems that we need to solve and the specific policies we need to examine. It is named *sustainable and green visions*. Problems and solutions in this general area motivate and inspire contemporary substance and content of policies throughout the world. One can identify three complementary and mutually strengthening directions in the *economy*, *environment*, and *society* that are the three fundamental pillars of sustainability. The third source is the never ending research for improved understanding of the world surrounding us. This source is named *new research and technology* to capture the most important elements of new discovery and new techniques enabling new discovery but also modeling and simulation. Key directions of inquiry within research and technology are *theory building*, *modeling and simulation*, and *enabling technologies*.

Dynamic Planning Practice

Dynamic thinking means that time and change are intrinsic in the thought processes underlying planning activities. In the past, assumptions about the existence of a tenable and general equilibrium and our ability to build the infrastructure needed to meet demand did not require careful orchestration of actions. This was radically changed in the industrialized world to meet specific goals using available finite resources to maximize benefits. Together with our inability to build at will and a tendency to the preservation of non-renewable resources (e. g., land and open space, fossil fuels, time) we are much more motivated to think strategically and to consider in a more careful way the performance of the overall anthropogenic system as we plan, design, operate, and manage transportation systems. Any action of this type, however, requires that we have a detailed and accurate picture of our facilities, their interconnectedness, their status within the hierarchy of movements, their conditions, and their evolving role. An accurate and more complete picture like this is called an *inventory* herein.

Many planning activities at all geographical levels are preceded by data gathering steps of identifying all the sources of data and information about the specific study area's transportation system and its relationship with the rest of the world. These inventories include the typical information about the resident population – demographics and employment, land available and land uses, economic development and growth, and so forth. It is worth pointing out the inventory contains data and relationships within the geographic area of interest (region) but also the region's relationship with other areas with which substantial flow of people, goods, and communication takes place. Inventories may also include data and information about cultural and historical factors. For example, statewide plans identify a variety of corridors as buffers of land and communities around major routes of the movement of people and goods. Some of these routes were created centuries ago when pioneers were still exploring uncharted lands. These routes experienced a major change when waterways were the main links among economic and military centers, and they are still evolving. Today these same routes contain as backbones railways, freeways, rivers, and often they surround major distribution locations such as ports and airports. Their nature is heavily influenced by their historical and cultural context.

Travel behavior analysts are familiar with inventories created for the regional long range plans, which subdivide the study area in traffic analysis zones with data from the Decennial Census suitably reformatted and packaged for use in a specific application (i. e., the long range regional plan). Then, additional data are assigned to these same subdivisions to build a richer context for modeling and simulation. Thus, the inventory for a typical long range plan is an electronic map of where people live and work, the network(s) that connect different locations, availability of different modes on each segment of the network, as well as information about travel network performance (e. g., link capacities, speeds on links, congestion, and connectivity). Today the tool of choice for data storage and visualization is a Geographic Information System (GIS).

One of the thorniest problems within this context is maintaining an up to date inventory (e. g., characteristics of the population in each zone, presence of certain types of businesses, location and characteristics of intermodal facilities). This is a particularly important issue for periods in between decennial censuses. Year to year updates are very often required to provide "fresh" data. Many of these updates are becoming widely available and much less expensive than in the past. For example, the inventory of the highway network, with suitable additions and improvements, is available from the same private providers of in-vehicle navigation systems. In a similar way, inventories of businesses and residences can also be purchased from vendors. Census data, however, are required even when one uses data from private providers because they contain complementary data (e. g., the age distribution of the resident population) and they tend to provide wider coverage of a country. Although the need for inventories is undoubtedly extremely important many important issues are yet to be resolved. This is the core issue of two Transportation Research Board (TRB) conference proceedings on the National Household Travel Survey http://www.trb.org/Conferences/NHTS/Program.pdf and the US Census and the Census American Community Survey http://www.trb.org/conferences/censusdata/). Examples of unresolved issues include levels of detail we should use in updating the data we have, treatment of errors in the data and model sensitivity to these errors, frequency of data updates and treatment of missing data, and questions about merging different databases. Obviously, the answers to these questions are in the form of "it depends". It depends on the budget (time and money) available, consequences of errors in the data, and the use of models in decision making. In fact, one particular type of data collection is strategy measurement where some of these questions become even more important. We turn now to the second dimension in the dynamic planning practice which is about strategy and performance.

Strategic planning and performance-based planning changed the way we plan for the future. This has been a 20 year long process in the United States as its transportation policy at the Federal, State, and Metropolitan levels is shaped by three consecutive legislative initiatives (ISTEA, TEA-21, and SAFETEA-LU). Under all three legislative frameworks and independently of role, location and perceived need for investment, the overall goal of funding allocation has been to maximize the performance of the transportation system in its entirety and avoid major new infrastructure building initiatives. As a result, planning practice at the Federal, State, and local levels is becoming heavily performance based and designed in a way that motivates the measurement of policy and program outcomes and judging these outcomes for funding allocation. Two examples of performance-based planning are the Program Assessment Rating Tool (PART) at the federal level and performance-based transportation planning at the state level. PART is used to assess the management and performance of individual programs from homeland security to education, employment, and training. This is a tool that offers assessments about programs based on 25 questions divided into sections. For each program a tailored analysis yields summaries that receive a rating from 0 to 100 ranging from ineffective to effective [172]). In a different way but in the same spirit many states have created long range plans that are strategic and they measure transportation performance. Yearly evaluative updates are also used for a state's strategic transportation plan. After a comprehensive public involvement campaign a few themes capturing the desires of the resident population are first identified. To these themes technical requirements based on planners and agency inputs are added, a large number of objectives are created and then a variety of measures of performance are developed. These measures are given target levels that evolve over time to a desired future performance for the entire state and for a finite number of corridors of statewide significance. Yearly evaluations contain measures of target achievement and they should be used to guide an agency in its investments. The interface with regions is also included in this performance-based framework. Many infrastructure improvement projects in the US are selected from lists of projects that regions (called Metropolitan Planning Organizations) submit to their state to be included in a list of projects in the Transportation Improvement Program (TIP) and become candidates for funding. Under statewide performance-based planning, these projects are evaluated with respect to their contribution in meeting the statewide performance measures and in some states the performance measures of the relevant corridor [122]. Although these examples are far ranging in time and space, they contain operations components and yearly evaluations that: a) require data collection, modeling, and simulation at finer spatial and temporal scales than their counterpart planning feedbacks used in the long range transportation planning practice, and b) need a method that is able to coordinate the short, medium, and long term impacts. Emerging from these considerations are questions about the types of consistency we need among geographic scales for planning and operations actions to perform evaluations, policy requirements for coordination among planning activities to ensure consistency, need for suitable methods to coordinate smaller projects in broader contexts (either of policy assessment or geographical area), development of tools required to perform measurement of impacts and program evaluation at the newly defined assessment cycles, and optimal planning activity with evaluation methods. Only a few solutions to the issues above are offered by contemporary projects such as the TRANSLAND project [70]. Within the context of integration between land use and transportation planning and the context of the European Union some of the conclusions include a call to strengthen regional plans, a stronger emphasis on public transport, strategic planning involving all actors, and the packaging of policies aiming at the same objectives. These themes are very similar to statewide and US Federal and European Union levels of planning. Very little, however, is said about the assessment methods and the choices we make in impact estimation. Performance assessment and evaluation of program effectiveness require the use of the inventory discussed before and a battery of models to forecast future expectations as well as to identify the actions required today to achieve desired futures.

As illustrated later in this article a new approach emerges in which models of discrete choice are applied to individual decision makers that are then used to (micro)simulate most of the possible combinations of choices in a day. The result is in essence a synthetic generation of traveling for the entire population. When the microsimulation also includes activities and duration at activity locations it becomes a synthetic schedule. In parallel, for forecasting purposes a synthetic population is first created for each land subdivision with all the relevant characteristics and then models are applied to the residents of each subdivision to represent areawide behavior. Changes are then imposed on each individual as a response to policies and predictive scenarios of policy impacts are thus developed. The evolution of individuals, their groups, and the entire study area can be used for trend analysis that includes details at the level of decision makers (either for passenger travel and/or for freight). In addition, progression in time happens from the present to the future and one could identify paths of change by individuals and groups if the application has been designed in the proper way (e. g., keeping detailed accounting of individuals as they move in time, using models that are designed for transitions over time and so forth). In a forecasting setting progression in time follows calendar time, temporal resolution is most often a year, and the treatment of dynamics is an one-way causal stream to the future.

Within the broader study of futures, forecasting is the method we use to develop *projective scenarios*. Performance-based planning, however, requires tools that can extrapolate from future performance targets the actions required today to reach them. In essence we also need *prospective studies* that start from a desirable future and move backwards to identify specific actions that will lead us to that prospect. *Backcasting* was invented in a study of future energy options by [141], to do exactly this through a participatory process. Scenarios in backcasting are the "images" of the future and the possible paths that will take us to that future. A typical application includes the stages shown in Table 1. An open question, however, remains with respect to scenario construction and assessment. This is particularly important when one considers the serious issues we face with inadequate design of experiments/trials in the forecasting setting. Forecasting and backcasting have some important differences in their objectives. On one hand forecasting is employed to identify likely futures and to develop methods to help us identify small changes in our policies. It is also a method to extrapolate past trends into the future and possibly identify paths of changes that are heavily influenced by habit and inertia. Backcasting, on the other hand is designed to discover new ways to build desirable futures. It is perfectly aligned with strategic planning and it is a better suited method for developing a program of conditions to meet targets. Many of the models developed to date are designed for forecasting applications (either to inform the design of forecasting model systems or to create necessary components in the model systems). Yet, planning practice is moving towards strategy development and therefore needs model components that fit within a backcasting scenario building (see the reversed four-step model in Miller and Demetsky [120], and its neural network implementation in Sadek et al. [143] and the participatory tools in California (http://www.sacregionblueprint.org/ – accessed May 2007).

Sustainable and Green Visions

Policy actions also view the world surrounding us as an integral ecosystem placing more emphasis on its overall survival by examining direct and indirect effects of individual policy actions and entire policy packages or programs (see the examples in [116]). This trend is not limited to transportation. Lomborg [104], shows that a sustainable and green vision encompasses the entire range of human activity and the entirety of the ecosystem we live in. Although these are good news, because the approach enables analyzes and policies that are consistent in their vision about futures, comprehensive views also reveal that the pace of economic growth and development is in clear conflict with the biological pace of evolution with unknown consequences [162] strengthening the view that more comprehensive analytical frameworks are required.

In fact, one of the most recent studies on research needs, which addresses the transportation and environment relationship by the Transportation Research Board of the National Academies [167,168], expands the envelope to incorporate ecology and natural systems and addresses human health in a more comprehensive way than in the past reiterating the urgency to address unresolved issues about environmental damage. As a result, we also experience a clear shift to policy analysis approaches that have an expanded scope and domain and they are characterized by explicit recognition of transportation system complexity and uncertainty.

Reflecting all this, *sustainable transportation* is now often used to indicate a shift in the mentality of the community of transportation analysts to represent a vision of a transportation system that attempts to provide services that minimize harm to the environment. In fact, in one of the most comprehensive reviews of policies in North America, Meyer and Miller [116], contrast the nonsustainable to the sustainable approaches. They provide a compelling argument about the change in these policies and pathways toward a more sustainable path. In the US during the past twenty years, the need, to examine these new and more complex policy initiatives, has also become increasingly pressing due to the passage of a series of legislative initiatives (Acts) and associated Federal and State regulations on transportation policy, planning, and programming. The multi-modal character of the new legislation, its congestion management systems and the taxing air quality requirements for selected US regions have motivated many new forecasting applications that in the early years were predominantly based on the Urban Transportation Planning System and related processes but during the last five years motivated a shift to richer conceptual frameworks. In point of fact, air quality mandates motivated impact assessments of the so called transportation control measures and the creation of statewide mobile source air pollution inventories [65,107,154] that require different analytical forecasting tools than in any pre-1990 legislative initiatives [124]. An added motivation is also lack of substantial funding for transportation improvement projects and a shift to charge the firms that benefit the most from transportation system improvements creating a need for impact fee-assessment for individual private developers. These assessments create the need for higher resolution in the three dimensions of geography (space), time (time of day), and social space (groups of people with common interests and missions, households, individuals) used in typical regional forecasting models but also the domain of jurisdictions where major decisions are made. They also create a pressing need for interfaces with traffic engineering simulation tools that are approved and/or endorsed in legislation (for examples see Paaswell et al. [126]). Another push for new tools is the assessment of technologies under the general name of Intelligent Transportation Systems (i. e., bundles of technological solutions in the form of user services attempting to solve chronic problems such as congestion, safety, and air pollution). Natural and anthropogenic tragic recent events are adding requirements for modeling and simulation and urgency in their development and implementation as well as more detail in time and space [75].

As Garrett and Wachs [46], discuss in the context of a lawsuit against a regional planning agency in the Bay Area, traditional four-step regional simulation models [30,80,125] are outpaced by the same legislative stream

Travel Behaviour and Demand Analysis and Prediction, Table 1
Backcasting schema

Content	Method
Determine objectives, purpose of the analysis, temporal, spatial and substantive scope of the analysis, decide the number and type of scenarios. Identify endogenous and exogenous variables	Problem orientation with technical representatives and stakeholders
Specify goals, constraints and targets for each scenario analysis and exogenous variables	Stakeholder creativity workshop and brainstorming sessions
Describe present system (building and updating of inventories), patterns and trends. Define processes, their actors, and determinants of outcomes. Identify exogenous variables and inputs to scenario analysis.	Scenario development by technical experts
Scenario analysis. Select suitable approach, analyze system evolution at end time points and intermediate time points, develop scenarios, iterate to make sure all components are consistent/coherent	Scenario assessment by technical experts and stakeholders
Undertake impact analysis. Consolidate scenario results. Analyze social, economic and environmental impacts. Compare results of the last with targets, iterate analysis with any other step as required to ensure consistency between goals and results	Backcasting workshops and stakeholder consultation (repeat to follow the iterations)
Implement Policy Actions	

of the past 20 years that defined many of the policies described above. Unlike the "energy crisis" of the 1970s, the urgency and timeliness of modeling and simulation is becoming more urgent, more complex, and requires an "integrated" approach. Under these initiatives, forecasting models, in addition to long-term land use trends and air quality impacts, need to also address issues related to technology use and information provision to travelers in the short and medium terms. Similarly, the European Union focuses on issues such as: increasing citizen participation, intra-European integration, decentralization, deregulation, privatization, environmental concerns, mobility costs, congestion management by population segments, and private infrastructure finance (see van der Hoorn [174]). Table 2 provide an overview of policy tools that are loosely ordered from the longer term of land use and governance to medium and shorter term operational improvements depending on the lag time required for their impacts to be realized.

These policy initiatives place more complex issues in the domain of regional policy analysis and forecasting and amplify the need for methods that produce forecasts at the individual traveler and her/his household levels instead of the traffic analysis zone level. In addition to the long range planning activities and the typical traffic operations management activities, analysts and researchers in planning need to also evaluate the following: a) traveler and transportation system manager information provision and use (e. g., location based services, smart environments providing real time information to travelers, vehicles, and operators); b) combinations of transportation management actions and their impacts (e. g., parking fee structures and city center restrictions, congestion pricing), and c) assessment of combinations of environmental policy actions (e. g., carbon taxes and information campaigns about health effects of ozone).

To perform all this we need tool that also have forecasting and backcasting capabilities that are more accurate and detailed in space and time. In fact, planning initiatives are moving toward parcel by parcel analysis and yearly assessments. It is also conceivable that we need separate analyzes for different seasons of a year and days of the week to capture seasonal and within a week variations of travel. Echoing all this and in the context of the Dutch reality Borgers, Hofman, and Timmermans [21] have identified five information need domains that the new envisioned policy analysis models will need to address and they are (in a modified format from the original list):

1. social and demographic trends that may produce a structural shift in the relationship between places and time allocation by individuals invalidating existing travel behavior model systems;
2. increasing scheduling and location flexibility and degrees of freedom for individuals in conducting their every day business leading to the need to consider additional choices (e. g., departure time from home, work at home, shopping by the internet, shifting activities to the weekend) in modeling travel behavior;
3. changing quality and price of transport modes based on market dynamics and not on external to the travel behavior policies (e. g., the effect of deregulation in public transport);

Travel Behaviour and Demand Analysis and Prediction, Table 2
Examples of Policy Tools

Type of policy tool	Brief description	Source of information*
Land use growth and management programs	Legislation that controls for the growth of cities in sustainable paths	www.smartgrowth.org, www.awcnet.org www.fhwa.dot.gov/planning/ppasg.htm www.compassblueprint.org
Land use design and attention to neighborhood design for non-motorized travel	Similar to the previous but with attention paid to individual neighborhoods	www.sustainable.doe.gov/landuse/luothtoc.shtml www.planning.dot.gov/Documents/DomesticScan/domscan2.htm
City annexations and spheres of influence	City boundaries are divided into incorporated, within the sphree of influence, and external to manage growth	http://countypolicy.co.la.ca.us/BOSPolicyFrame.htm www.ite.org/activeliving/files/Jeff_Summary.pdf
Accelerated retirement of vehicles programs	Programs to eliminate high emitting and older technology vehicles	ntl.bts.gov/DOCS/SCRAP.html
Public involvement and education programs	Programs aiming at defining goals based on the public's desires	www.fhwa.dot.gov/reports/pittd/contents.htm
Health promoting programs	Programs that promote physical activity in travel to benefit health	www.activelivingbydesign.org
Safety measures	A process to incorporate safety considerations in transportation planning	tmip.fhwa.dot.gov/clearinghouse/docs/safety/ www.fhwa.dot.gov/planning/scp/ www.safetyanalyst.org/
Emission control, vehicle miles traveled, and other fee programs (including carbon taxes and trading)	Programs that shift taxation from traditional sources towards pollutant emissions and natural- resource depletion agents	www.fresh-energy.org/ www.fhwa.dot.gov/environment/ www.fightglobalwarming.com/
Congestion pricing and toll collection programs	A premium is charged to travelers that wish to travel during the most congested periods	www.vtpi.org/london.pdf
Parking fee management	Parking pricing used as a tool to restrict access by space and time	www.gmu.edu/depts/spp/programs/parkingTaxes.pdf
Non-motorized systems	Programs to support walking and biking	www.vtpi.org/tdm/tdm25.htm www.psrc.org/projects/nonmotorized
Telecommuting and Teleshopping	The employment of telecommunications to substitute-complement-enhance travel	www.telework-mirti.org www.vtpi.org/tdm/tdm43.htm
Flexible and staggered work programs	Programs that change the workweek of individuals and firms	www.its.dot.gov/JPODOCS/REPTS_PR/13669/section05.htm
Goods movements (freight) programs to improve operations	A variety of programs to facilitate and minimize the damage for freight movement	ntl.bts.gov/DOCS/harvey.html
Highway system improvements in traffic operations and flow	Improved data collection, monitoring, and traffic management	www.transportation.org ite.org/mega/default.asp
Intelligent Transportation Systems (ITS)	Use of telecommunications and information technology to manage and control travel	www.itsa.org/ www.ertico.com/ www.its.dot.gov/index.htm/
Special event planning and associated traffic management	Enhanced procedures to handle the demands of a special event	tmcpfs.ops.fhwa.dot.gov/cfprojects/new_detail.cfm?id=32xxxnew=0
Security preparedness through metropolitan planning processes	A process to incorporate safety considerations in transportation planning	www.planning.dot.gov/Documents/Securitypaper.htm
Individualized marketing techniques with improved information and communication with the "customer"	Public programs to provide personal help in changing travel behavior in favor of environmentally friendly modes	www.local-transport.dft.gov.uk/travelplans/index.htm http://www.travelsmart.gov.au/

*accessed May 2007

4. shifting of attitudes and potential cycles in the population outlook about travel options; and
5. changing scales/jurisdictions (scale is the original term used to signify the different jurisdictions) – different

policy actions in different sectors have direct and indirect effects on transportation and different policy actions in transportation have direct and indirect effects in the other sectors (typical example in the US is the welfare to work program).

The first substantive implication of all these considerations is an expanded envelope of modeling and simulation. Many processes that were left outside the realm of transportation modeling and simulation need to be included as stages of the travel model system. One notable example is the inclusion of *residential location choice, work location choice, and school location choice* to capture the spatial distribution and relative location of important anchor points on travel behavior and to also capture the impact of transportation system availability and level of service on these choices. In this way when implemented policies lead to improved level of service and the relative attractiveness of locations change, shifts in residential location, work location, and possibly school location can be incorporated as impacts of transportation. A similar treatment is needed for *car ownership and car type choices* of households or *fleet sizes and composition* for firms. These car-related choices are expressed as functions of parking availability, energy and other costs and level of service offered by the transportation system (highway and transit). To account for other resources and facilities available for household travel we also need to consider processes for *driver's licensing*, acquiring of *public transportation subscription* (*passes*), and participation in *car sharing programs*. In this way, variables of car availability and public transportation availability in households can be used as determinants of travel behavior. Similar treatment is required for policies that change attitudes, perceptions and knowledge about travel options.

To address some of the policies of Table 2, we need to transition to a domain that contains a variety of outputs that include shares of program participation, sensitivity to accessibility and prices, and the usual indicators of travel on networks using input variables from the processes and behaviors discussed up to this point. Although the number of vehicles per hour per lane is the typical input of traffic operations software, a variety of other variables such as speeds on network links and types of vehicles are also needed for other models such as emissions estimation.

Ideally longer term social, economic, demographic, resource/facilities, and circumstances of people should be converted into yearly schedules identifying periods of vacation, workdays, special occasions, and so forth. These in turn should lead to weekly schedules separating days during which people stay at home from days during which people go to work and days during which they run errands and/or engage in other non-work and non-school related activities. In this way patterns of working days versus not working days can be derived in a natural (con)sequence. As we will see in a later section, a fundamental leap of faith intervenes in practice and converts all this background information into a representative day that is used to create a more or less complete sequence of activities and trips with their destinations and modes used.

In this way decisions and choices people make are organized along the time scale in terms of the time it takes for these events to occur and their implications. For example, decisions about education, careers and occupation, and residential and job location are considered first and they condition everything that happens next. These should be formulated in terms of one or more life course long projects and not represented by a cross-sectional choice model. Similarly, decisions about yearly school and work schedules that determine work days and vacation days in a year should also be modeled as a stream of interrelated choices. Conditional on all this are the daily schedules of individuals and the myriad of decisions determining a daily schedule, which are modeled in much more detail and paying closer attention to the mutual dependency among the different facets of a within a day schedule. The next section explores this further in the context of research and enabling technology. A section on mathematical models later in this article shows the beginning of a new way in modeling a simulation that emphasizes human interaction.

New Research and Technology

The planning and policy analysis discussion identified many requirements for modeling and simulation. Planning and policy expanded the context of travel behavior models to entire life paths of individuals and for this reason a more general modeling framework is emerging. In fact, modeling made tremendous progress toward a comprehensive approach to, in essence, build simulated worlds on computer enabling the study of complex policy scenarios. Although, passenger travel received the bulk of the attention, similar contributions to new research and technology are found in modeling the movement of goods [151,153]. The emerging framework, although incomplete, is rich in the directions taken and potential for scientific discovery, policy analysis, and more comprehensive approaches in dealing with sustainability issues.

There are four dimensions that one can identify in building taxonomies of simulation models. The first is the *geographic space* and its conditional continuity, the second is the *temporal scale* and calendar continuity, the third is interconnectedness of *jurisdictions*, and the fourth and most important is the set of relationships in *social space* for individuals and their communities. The first dimension, *geographic space* here is intended as the physical space in which human action occurs. This dimension has played important roles in transportation planning and modeling because the first preoccupation of the transportation system designers has been to move persons from one location to another (i. e., overcoming spatial separation). Initial applications considered the territory divided into large areas (traffic analysis zones), represented by a virtual center (centroid), and connected by facilities (higher level highways). The centroids were connected to the higher level facilities using a virtual connector summarizing the characteristics of all the local roads within the zone. As computational power increased and the types of policies/strategies required increased resolution, the zone became smaller and smaller. Today, is not unreasonable to expect software to handle zones that are as small as a parcel of land and transportation facilities that are as low in the hierarchy as a local road (the centroid becomes the building on a parcel and the centroid connector is the driveway of the unit and they are no longer virtual).

In modeling and simulation we are interested in understanding human action. For this reason in some applications geographic space needs to consider more than just physical features (p. 387 in [49]) moving us into the notion of place and social space (see also below). The second dimension is *time* that is intended here as continuity of time, irreversibility of the temporal path, and the associated artificiality of the time period considered in many models. For example, models used in long range planning applications use typical days (e. g., a summer day for air pollution). In many regional long-range models the unspoken assumption is that we target a typical work weekday in developing models to assess policies. Households and their members, however, may not always (if at all) obey this strict definition of a typical weekday to schedule their activities and they may follow very different decision making horizons in allocating time to activities within a day, spreading activities among many days including weekends, substituting out of home with in home activities in some days but doing exactly the opposite on others, and using telecommunications only selectively (e. g., on Fridays and Mondays more often than on other days). Obviously, taking into account these scheduling activities is by far more complex than what is allowed in existing transportation planning models. The third dimension is *jurisdictions* and their interconnectedness. The actions of each person are "regulated" by jurisdictions with different and overlapping domains such as federal agencies, state agencies, regional authorities, municipal governments, neighborhood associations, trade associations and societies, religious groups, and formal and informal networks of families and friends. In fact, the federal government defines many rules and regulations on environmental protection. These may end up being enforced by a local jurisdiction (e. g., a regional office of an agency within a city). On the one hand, we have an organized way of governance that clearly defines jurisdictions and policy domains (e. g., tax collection in the US). On the other hand, however, the relationships among jurisdictions and decision making about allocation of resources does not follow always this orderly governance principle of hierarchy. A somewhat different and more "bottom up" relationship is found in the social network and for this reason requires a different dimension that is the fourth and final dimension named *social space* and the relationships among persons within this space. For example, individuals from the same household living in a neighborhood may change their daily time allocation patterns and location visits to accommodate and/or take advantage of changes in the neighborhood such as elimination of traffic and the creation of pedestrian zones. Depending on the effects of these changes on the pedestrian network we may also see a shift in the within the neighborhood social behavior. In contrast, increase in traffic to surrounding places may create an outcry by other surrounding neighborhoods, thus, complicating the relationships among the residents.

One important domain and entity within this social space is the household. This has been a very popular unit of analysis in transportation planning recognizing that strong relationships within a household can be used to capture behavioral variation (e. g., the simplest method is to use a household's characteristics as explanatory variables in a regression model of travel behavior). In this way any changes in the household's characteristics (e. g., change in the composition due to birth, death, or children leaving the nest or adults moving into the household) can be used to predict changes in travel behavior. New model systems are created to study this interaction within a household looking at the patterns of using time in a day and the changes across days and years. It is therefore very important in modeling and simulation to incorporate in the models used for policy analysis interactions among these four fundamental dimensions, which bring us to the next major issue that of scale.

The typical long range planning analysis is usually defined for larger geographical areas (region, states, and countries) and addresses issues with horizons from 10 to 50 years. In many instances we may find that large geographic scale means also longer time frames applied to wider mosaics of social entities and including more diverse jurisdictions. On the other side of the spectrum issues that are relevant to smaller geographic scales are most likely to be accompanied by shorter term time frames applied to a few social entities that are relatively homogeneous and subject to the rule of very few jurisdictions. This is one important organizing principle but also an indicator of the complex relationships we attempt to recreate in our computerized models for decision support. In developing the blueprints of these models one can choose from a variety of theories (e. g., neoclassical microeconomics) and conceptual representations of the real world that help us develop these models. At the heart of our understanding of how the world (as an organization, a household, a formal or informal group, or an individual human being) works are models of decision making and conceptual representations of relationships among entities making up this world.

Transportation planning applications are about judgment and decision making of individuals and their organizations. There are different settings of decision making that we want to understand. Three of these settings are the travelers and their social units from which motivations for and constraints to their behavior emerge; the transportation managers and their organizations that serve the travelers and their social units, and the decision makers surrounding goods movement and service provision that contain a few additional actors, Southworth [151]. These include land use markets (see www.urbansim.org). Travelers received considerable attention in transportation planning and the majority of the models in practice aim at capturing their decision making process. The remaining settings received much less attention and they are poorly understood and modeled.

Conceptual models of this process are transformed into computerized models of a city, a region, or even a state in which we utilize components that are in turn models of human judgment and decision making (e. g., travelers moving around the transportation network and visiting locations where they can participate in activities). Models of this behavior are simplified versions of strategies used by travelers when they select among options that are directly related to their desired activities. In some of these models we also make assumptions about hierarchies of motivations, actions, and consequences. Some of these assumptions are explicit (e. g., when deriving the functional forms of models as in the typical disaggregate choice models or the rules in a production system) and in other models these assumptions are implicit.

When designing transportation planning model interfaces for transportation planners and managers we also implicitly make assumptions about the managers' ability to understand the input, agent representation, internal functioning, and output of these computerized models. Our objective is therefore not only to understand travel behavior and build models that describe and predict human behavior but also to devise tools that allow transportation managers to understand the assumed behavior in the models, study scenarios of policy actions, and define and explain policy implications to others. This, in essence, implies that we, the model system designers, create a platform for a relationship between planners and travelers. A similar but more direct relationship also exists between travelers and transportation managers when we design the observation methods that provide the data for modeling but also the data used to measure attitudes and opinions such as travel surveys. In fact, this relationship is studied in much more detail in the survey design context and linked directly to the image of the agency conducting the survey and the positive or negative impression of the travelers about the sponsoring agency [33]. Most transportation research for modeling and simulation, however, has emphasized traveler behavior when building surveys and their models neglecting the interface with the planners. The summary of theories below, however, applies to individuals traveling in a network but also to organizations and planners in the sense used by H.A. Simon in his Administrative Behavior [150].

Rational decision making is a label associated with human behavior that follows a strategy in identifying the best course of action. In summary, a decision maker solves an optimization problem and identifies the best existing solution to this problem. Within this more general strategy when an operational model is needed and this operational model provides quantitative predictions about human behavior some kind of mathematical apparatus is needed to produce the predictions. One such machinery is the subjective expected utility [146] formulation of human behavior. In developing alternative models to SEU Simon [149] defines four theoretical components:

- A person's decision is based on a utility function assigning a numerical value to each option – *existence and consideration of a cardinal utility function*;
- The person defines an exhaustive set of alternative strategies among which just one will be selected – *ability to enumerate all strategies and their consequences*;
- The person can build a probability distribution of all possible events and outcome for each alternate option – *infinite computational ability*; and
- The person selects the alternative that has the maximum utility – *maximizing utility behavior*.

This behavioral paradigm served as the basis for a rich production of models in transportation that include the mode of travel, destinations to visit as well as the household residence (see the examples in the seminal textbook by Ben-Akiva and Lerman [9]. It served also as the theoretical framework for consumer choice models and for attempts to develop models for hypothetical situations (see the comprehensive book by Louviere, Hensher, and Swait [108]. It has also replaced the aggregate modeling approaches to travel demand analysis as the orthodoxy against which many old and new theories and applications are compared and compete with. SEU can be considered to be a model from within a somewhat larger family of models under the label of weighted additive rule (WADD) models [127]. Real humans, however, may never behave according to SEU or related maximizing and infinitely computational capability models (Simon labels this the Olympian model, [149]). Based on exactly this argument different researchers in psychology have proposed a variety of decision making strategies (or heuristics). For example, Simon created alternate model paradigms under the label of *bounded rationality – the limited extent to which rational calculation can direct human behavior* [149,150] to depict a sequence of a person's actions when searching for a suitable alternative. The modeled human is allowed to make mistakes in this search giving a more realistic description of observed behavior (see also Rubinstein [142]). Tversky is credited with another stream of decision making models starting with the *lexicographic approach* [169, in which *a person first identifies the most important attribute, compares all alternatives on the value of this attribute, and chooses the alternative with the best value on this most important attribute*. Ties are resolved in a hierarchical system of attributes. Another Tversky model [170 assumes *a person selects an attribute in a probabilistic way and influenced by the importance of the attribute, all alternatives that do not meet a minimum criterion value (cutoff point) are eliminated*. The process proceeds with all other attributes until just one alternative is left and that one is the chosen. This has been named the *elimination by aspects strategies* (EBA) model. Later, Kahneman and Tversky [86] developed *prospect theory* and its subsequent version of *cumulative prospect theory* in Tversky and Kahneman [171] in which a simplification step is first undertaken by the decision maker editing the alternatives. Then, a value is assigned to each outcome and *a decision is made based on the sum of values multiplying each by a decision weight*. Losses and gains are treated differently. All these alternatives to SEU paradigms did not go unnoticed in transportation research with early significant applications appearing in the late 1980s. In fact, a conference was organized attracting a few of the most notable research contributors to summarize the state of the art in behavior paradigms and documented in Garling, Laitila, and Westin [45]. One of the earlier examples using another of Simon's inventions, the *satisficing behavior – acceptance of viable choices that may not be optimal* – is a series of transportation-specific applications described in Mahmassani and Herman [110]. Subsequent contributions continue along the path of more realistic models and the most recent example, discussing a few models, by Avineri and Prashker [7], uses cumulative prospect theory giving a preview of a movement toward more realistic travel behavior models. As Garling et al. [45] and Avineri and Prashker [7] point out, these paradigms are not ready for practical applications, contrary to the Mahmassani and colleagues efforts that have been applied, and additional work is required to use them in a simulation framework for applications. Another aspect is contextual *adaptation*. Payne, Bettman, and Johnson [127] provide an excellent review of decision making models and their differentiating aspects. They also provide evidence that decision makers *adapt* by switching between decision making paradigms *to the task and the context of their choices*. They also make mistakes and they may also fail to switch strategies. As Vause [175] discusses to some length transportation applications are possible using multiple decision making heuristics within the same general framework and employing a production system approach [123]. A key consideration, however, that has received little attention in transportation is the definition of context within which decision making takes place. Recent production systems [5] are significant improvements over past simulation techniques. However, travelers are still assumed to be passive in shaping the environment within which they decide to act (action space). This action space is viewed as largely made by constraints and not by their active shaping of their context. Goulias [58,60] reviews another framework from human development that is designed to treat decision makers in their active and passive roles and explicitly accounts for mutual influence between an agent (active autonomous decision maker) and her environment.

Transportation modeling and simulation experienced a few tremendously innovative and progressive steps forward. Interestingly these key innovations are from non-engineering fields but very often transferred and applied to transportation systems analysis and simulation by engineers. These are listed here in a somewhat sequential chronological order merging technological innovations and theoretical innovations. At exactly the time that the Bay Area Rapid Transit system was studied and evaluated in the 1960s, Dan McFadden (the Year 2000 Nobel Laureate in Economics) and a team of researchers produced practical mode choice regression models at the level of an individual decision maker (see http://emlab.berkeley.edu/users/mcfadden/ – accessed June 2007). The models are based on random utility maximization (of the SEU family) and their work opened up the possibility to predict mode choice rates more accurately than ever before. These models were initially named *behavioral travel-demand models* [155] and later the more appropriate term of *discrete choice models* [9] prevailed. Although restrictive in their assumptions, these models are still under continuous improvement and they have become the standard tool in evaluating discrete choices. Some of the most notable and recent developments advancing the state of the art and practice are:

- Better understanding of the theoretical and particularly behavioral limitations of these models [45,50,115];
- more flexible functional forms that resolve some of the problems raised in Williams and Ortuzar [184] allowing for different choices to be correlated when using the most popular discrete choice regression models [14,16,95];
- combination of revealed preference, stated choices by travelers, with stated preferences and intentions, answers to hypothetical questions by travelers, availability of data in the same choice framework to extract in a more informative way travelers willingness to use a mode and willingness to pay for a mode option [10,108]. This latter "improvement" enables us to assess situations that are impossible to build in the real world;
- computer-based interviewing and laboratory experimentation to study more complex choice situations and the transfer of the findings to the real world [111]TS2. This direction, however, is also accompanied by a wide variety of research studies aiming at more realistic behavioral models that go beyond mode choice and travel behavior [50]; and
- expansion of the discrete choice framework using ideas from *latent class models* with covariates that were first developed by Lazarsfeld in the 1950s and their estimation finalized by Goodman in the 1970s (see the review in [56], and discrete choice applications in [20]). This family of models was used in Goulias [57] to study the dynamics of activity and travel behavior and in the study of choice in travel behavior [12].

As mentioned earlier the rational economic assumption of the maximum utility model framework (that underlies many but not all of the disaggregate models) is very restrictive and does not appear to be a descriptive behavioral model except for a few special circumstances when the framing of decisions is carefully designed (something we cannot expect to happen every time a person travels on the network). Its replacement, however, requires conceptual models that can provide the types of outputs needed in regional planning applications. A few additional research paths, labeled as *studies of constraints*, are also functioning as gateways into alternate approaches to replace or complement the more restrictive utility-based models. A few of these models also consider knowledge and information provision to travelers. The first aspect we consider is about the choice set in discrete choice models. Choice set is the set of alternatives from which the decision maker selects one. These alternatives need to be mutually exclusive, exhaustive, and finite in number [166]. Identification, counting, and issues related to the alternatives considered have motivated considerable research in choice set formation [77,78,140,158,159]. Key threat to misspecification of the choice set is the potential for incorrect predictions [161]. When this is an issue of considerable threat as in destination choice models where the alternatives are numerous, a model of choice set formation appears to be the additional burden [71]. Other methods, however, also exist and they may provide additional information about the decision making processes. Models of the processes can be designed to match the study of specific policies in specific contexts. One such example and a more comprehensive approach defining the choice sets is the situational approach [25]. The method uses in depth information from survey respondents to derive sets of reasons for which alternatives are not considered for specific choice settings (individual trips). This allows separation of analyst observed system availability from user perceived system availability (e. g., due to misinformation and willingness to consider information). This brings us to the duality between "objective choice attributes" and "subjective choice attributes". Most transportation applications, independently of the decision making paradigm adopted, assume the analysts (modelers) and the travelers (modeled) measured attributes to be the same. Modeling the process of perceived constraints may be far more complex when one considers the influence of the context within which decisions are made. Golledge and Stimpson (pp. 33–34 in [49]) describe this within a conceptual model of decision making that has a cognitive feel to it. They also link the situational approach to the activity-based framework of travel extending the framework further (pp. 315–328 in [49]).

Chapin's research [28], providing one of the first comprehensive studies about time allocated to activity in space and time, is also credited for motivating the foundations of

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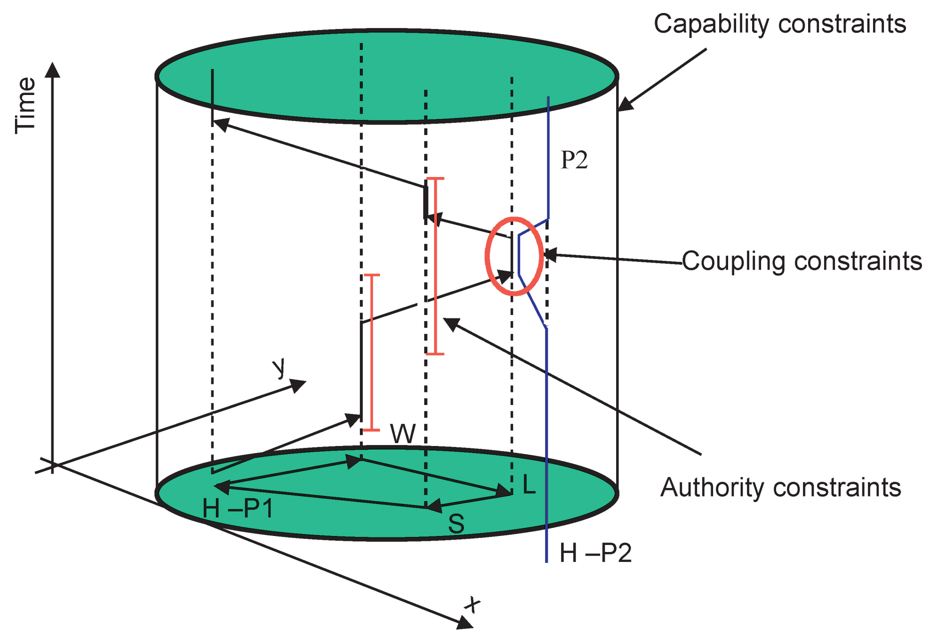
activity-based approaches to travel demand analysis. His focus has been on the propensity of individuals to participate in activities and travel linking their patterns to urban planning. In about the same period Becker also developed his theory of time allocation from a household production viewpoint [8] applying economic theory in a non-market sector and demonstrating the possibility of formulating time allocation models using economics reasoning (i. e., activity choice). In parallel another approach was developing in geography and Hagerstrand's seminal publication on time geography [72] presents the foundations of the approach. The idea of constraints in the movement of persons was taken a step further by this time-geography school in Lund. In that framework, the movement of persons among locations can be viewed as their movement in space and time under external constraints. Movement in time is viewed as the one way (irreversible) movement in the path while space is viewed as a three dimensional domain. It provides the third base about *constraints* in human paths in time and space for a variety of planning horizons. These are *capability constraints* (e. g., physical limitations such as speed); *coupling constraints* (e. g., requirements to be with other persons at the same time and place); and *authority constraints* (e. g., restrictions due to institutional and regulatory contexts such as the opening and closing hours of stores). Figure 1 provides a pictorial representation in space and time of a typical activity-travel pattern of two persons (P1 and P2) and the three types of constraints. H indicates home, W indicates work, L indicates leisure, and S indicates shopping.

Cullen and Godson [31] also reviewed by Arentze and Timmermans [5] and Golledge and Stimpson [49] appear to be the first researchers attempting to bridge the gap between the motivational (Chapin) approach to activity participation and the constraints (Hagerstrand) approach by creating a model that depicts a routine and deliberated approach to activity analysis. The Cullen and Dobson study also defined many terms often used today in activity-based approaches. For example, each activity (stay-home, work, leisure, and shopping) is an episode characterized by start time, duration, and end time. Activities are also classified into fixed and flexible and they can be engaged alone or with others. Moreover, they also analyzed sequencing of activities as well as pre-planned, routine, and on the spur of the moment activities. Within this overall theoretical framework is the idea of a project which according to Golledge and Stimpson [49], *is a set of linked tasks that are undertaken somewhere at some time within a constraining environment* (pp. 268–269). This idea of the project underlies one of the most exciting developments in activity-based approaches to travel demand analysis and forecasting because seemingly unrelated activity and trip episodes can be viewed as parts of a "big-picture" and given meaning and purpose completing in this way models of human agency and explaining resistance to change behavior.

Most subsequent contributions to the activity-based approach emerge in one way or another from these initial frameworks with important operational improvements (for reviews see [5,17,89,114]). The basic ingredients of an activity based approach for travel demand analysis [5,84] are:

a) explicit treatment of travel as derived demand [112], i. e., participation in activities such as work, shop, and leisure motivate travel but travel could also be an activity as well (e. g., taking a drive). These activities are viewed as episodes (i. e., they are characterized by starting time, duration, and ending time) and they are arranged in a sequence forming a pattern of behavior that can be distinguished from other patterns (i. e., a sequence of activities in a chain of episodes). In addition, these events are not independent and their interdependency is accounted for in the theoretical framework;
b) the household is considered to be the fundamental social unit (i. e., decision making unit) and the interactions among household members are explicitly modeled to capture task allocation and roles within the household, relationships at one time point and change in these relationships as households move along their life cycle stages and the individual's commitments and constraints change and these are depicted in the activity-based model; and
c) explicit consideration of constraints by the spatial, temporal, and social dimensions of the environment is given. These constraints can be explicit models of time-space prisms [130] or reflections of these constraints in the form of model parameters and/or rules in a production system format [5].

Input to these models are the typical regional model data of social, economic, and demographic information of potential travelers and land use information to create schedules followed by people in their everyday life. The output are detailed lists of activities pursued, times spent in each activity, and travel information from activity to activity (including travel time, mode used, and so forth). This output is very much like a "day-timer" for each person in a given region. Figure 2 provides an example of time allocation to different activities from an application that collected activity participation data [2,3]. It displays time allocation by one segment of the population showing the proportion of persons engaging in each activity by each hour of a day. Figure 3 shows the output from a model that

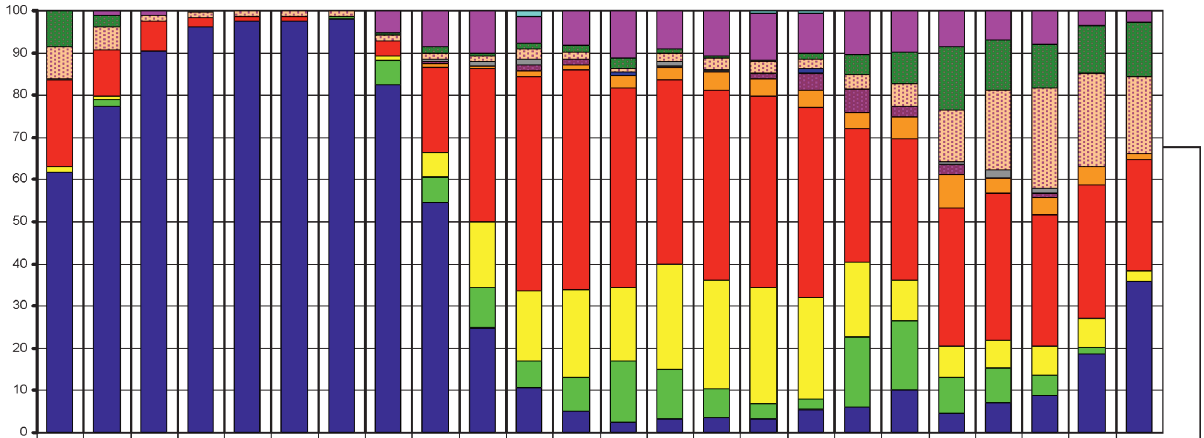


Travel Behaviour and Demand Analysis and Prediction, Figure 1
A two-person (P1 and P2) activity-travel pattern and the time and space limits imposed by constraints (source: Pribyl [132])

predicts the presence of persons in each building during each hour of a day engaging in each activity type. Combining an activity model with a typical travel demand model produces "volumes" of individuals at specific locations and on the network of a city as shown in Figure 4 (a more detailed description of this study can be found in [67,97,99].

Many planning and modeling applications, however, aim at forecasting. Inherent in forecasting are the time changes in the behavior of individuals and their households and their response to policy actions. At the heart of behavioral change are questions about the process followed in shifting from a given pattern of behavior to another. In addition to measuring change and the relationships among behavioral indicators that change in their values over time, we are also interested in the timing, sequencing, and staging of these changes. Moreover, we are interested in the triggers that may accelerate desirable or delay undesirable changes and the identification of social and demographic segments that may follow one time path versus another in systematic patterns. Knowledge about all this is required to design policies but it is also required to design better forecasting tools. Developments in exploring behavioral dynamics and advancing models for them have progressed in a few arenas. First, in the data collection arena with panel surveys, repeated observation of the same persons over time that are now giving us a considerable history in developing new ideas about data collection but also about data analysis [55,61] and interactive and laboratory data collection techniques [34] that allow a more in-depth examination of behavioral processes. The second arena is in the development of microeconomic dynamic formulations for travel behavior that challenge conventional assumptions and offer alternative formulations [91]. The third arena, is in the behavior from a developmental viewpoint as a single stochastic process, a staged development process [57], or as the outcome from multiple processes operating at different levels [59]. Experimentation with new theories from psychology emphasizing development dynamics is a potential fourth area that is just beginning to emerge [60]. Behavioral dynamics are also examined using more comprehensive analyzes [68] and models [136].

These models focus more on the paths of persons in space and time within a somewhat short time horizon such a day, a week, or maybe a month. The consideration of behavioral dynamics has expanded the temporal horizons to a few years. However, regional simulation models are very often designed for long range plans spanning 25 years or even longer time horizons. Within these longer horizons, changes in the spatial distribution of activity locations and residences (land use) are substantial, changes in the demographic composition and spatial distribution of demographic segments are also substantial, and changes in travel patterns, transport facilities, and quality of service offered can be extreme. Past approaches in modeling and simulating the relationship among land use, de-

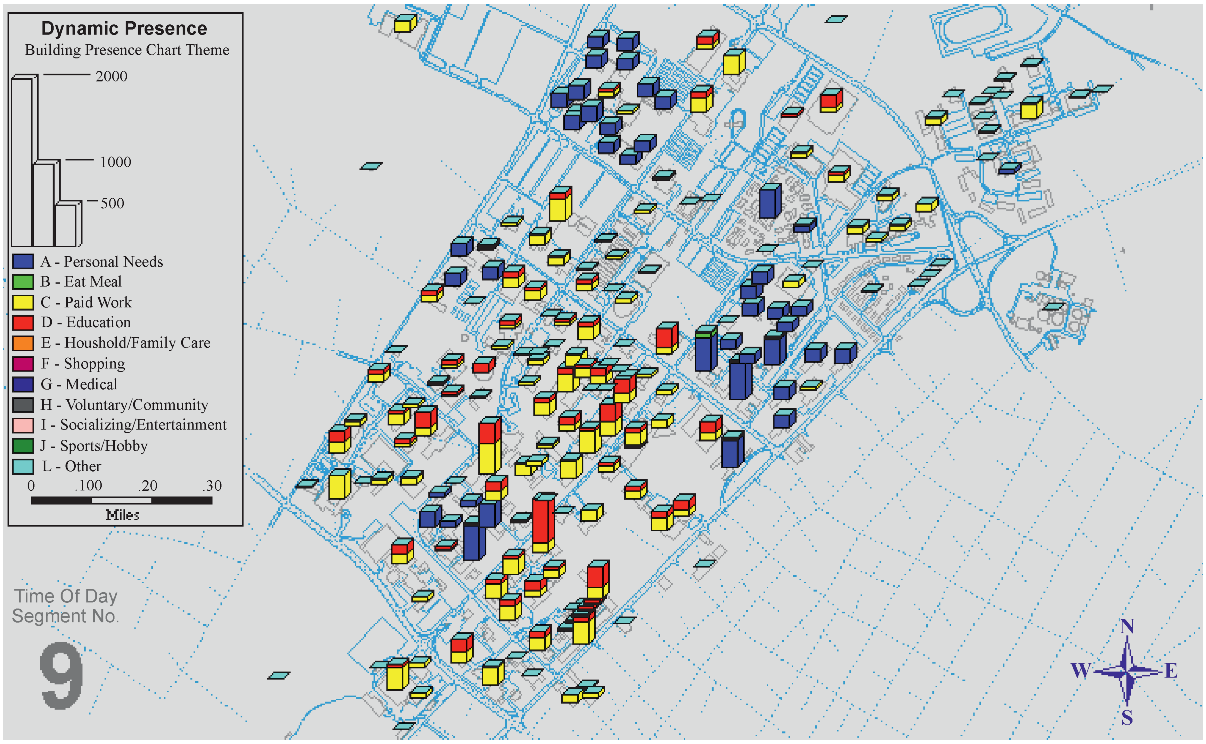


	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
L	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.3	0.0	0.0	0.0	0.0	0.6	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0
K	0.0	1.0	1.2	0.3	0.0	0.0	0.0	5.2	8.4	10.0	6.4	8.3	11.3	9.0	10.7	11.2	9.6	10.4	9.9	8.4	6.8	8.0	3.5	2.8
J	8.4	2.7	0.0	0.0	0.0	0.0	0.0	0.5	1.7	0.6	1.3	1.5	2.2	1.0	0.6	0.1	1.3	4.6	7.3	15.1	12.0	10.3	11.1	12.9
I	7.7	5.6	1.3	1.3	1.3	1.3	1.3	1.3	1.3	1.4	2.6	1.8	1.1	2.0	2.6	2.8	2.1	3.6	5.7	12.4	18.9	23.7	22.2	18.2
H	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	1.2	1.3	0.0	0.0	1.2	0.2	0.0	0.0	0.0	0.0	0.5	1.9	1.3	0.0	0.0
G	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.2	0.0	1.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0
F	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.0	1.4	1.3	0.0	0.2	0.2	1.3	4.0	5.4	2.4	2.4	0.0	1.0	0.0	0.0
E	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.1	1.0	0.5	1.3	1.2	3.0	2.9	4.3	4.1	4.2	3.7	5.2	7.9	3.5	4.2	4.3	1.3
D	20.5	10.9	7.1	2.2	1.3	1.3	0.0	3.7	20.2	36.3	51.0	52.1	47.3	44.0	45.1	45.5	45.1	31.8	33.4	32.9	35.2	31.2	31.9	26.6
C	1.3	1.0	0.0	0.0	0.0	0.0	0.0	1.0	5.7	15.6	16.6	20.8	17.5	24.9	25.6	27.7	24.0	17.6	9.7	7.5	6.5	6.8	6.6	2.6
B	0.0	1.6	0.0	0.0	0.0	0.0	0.6	5.8	6.0	9.6	6.2	7.9	14.4	11.6	6.9	3.4	2.5	16.9	16.5	8.3	8.2	4.7	1.7	0.0
A	61.9	77.2	90.4	96.2	97.4	97.4	98.1	82.5	54.7	24.8	10.8	5.1	2.5	3.3	3.5	3.3	5.6	5.9	10.0	4.7	7.1	8.9	18.6	35.7

Time Segment (Hour)

Travel Behaviour and Demand Analysis and Prediction, Figure 2
Time allocation to different activities in a day (source: Alam [2]) A: Personal Needs (includes sleep), B: Eat meal, C: Paid work, D: Education, E: Household and family care, F: shopping, G: medical, H: Volunteering/Community, I: Socializing, J: Sports and Hobbies, K: Travel, L: All other

mographics, and travel in a region attempted to disengage travel from the other two treating them as mutually exogenous. As interactions among them became more interesting and pressing, due to urban sprawl and suburban congestion, increasing attention was paid to their complex interdependencies. This led to a variety of attempts to develop "integrated model systems" that enable the study of scenarios of change and mutual influence between land use and travel. An earlier review of these models with heavy emphasis on discrete choice models can be found in Anas [4]. Miller [117] and Waddell and Ulfarsson [180] twenty years later provide two comprehensive reviews of models that have integrated many aspects in the interdependent triad of demographics-travel-land use models. Both reviews trace the history of some of the most notable developments and both link these models to the activity-based approach above. Both reviews also agree that a microeconomic and/or macroeconomic approach to modeling land and transportation interactions are not sufficient and more detailed simulation of the individuals and their organizations "acting" in an time-space domain need to be simulated in order to obtain the required output for informed decision making. They also introduce the idea of simulating interactive agents in a dynamic environment of other agents (multi-agent simulation). The vast literature is reviewed by Timmermans [163] and Miller [118], from different viewpoints about progress made until now. However, they both agree that progress is rapidly made and that integration of land use and transportation models needs to move forward. Creation of integrated systems is further complicated by the emergence of an entire infrastructural system as another layer of human activity – telecommunication. Today telecommunication and transportation relationships are mostly absent from regional simulation planning and modeling as well from the most advanced land use and transportation integrated models. Considerable research findings, however, have been accumulating since the 1970s [53,66,81,96,111,113,121,128,129,144,182]. Another type of technologies (named enabling herein) helped us move modeling and simulation further.



Travel Behaviour and Demand Analysis and Prediction, Figure 3
Persons and activities assigned to buildings (source: Alam [2])

A few of the most important technologies are *stochastic simulation*, *production systems*, *geographic information systems*, *interactive and technology-aided data collection approaches*, and more *flexible data analysis techniques*.

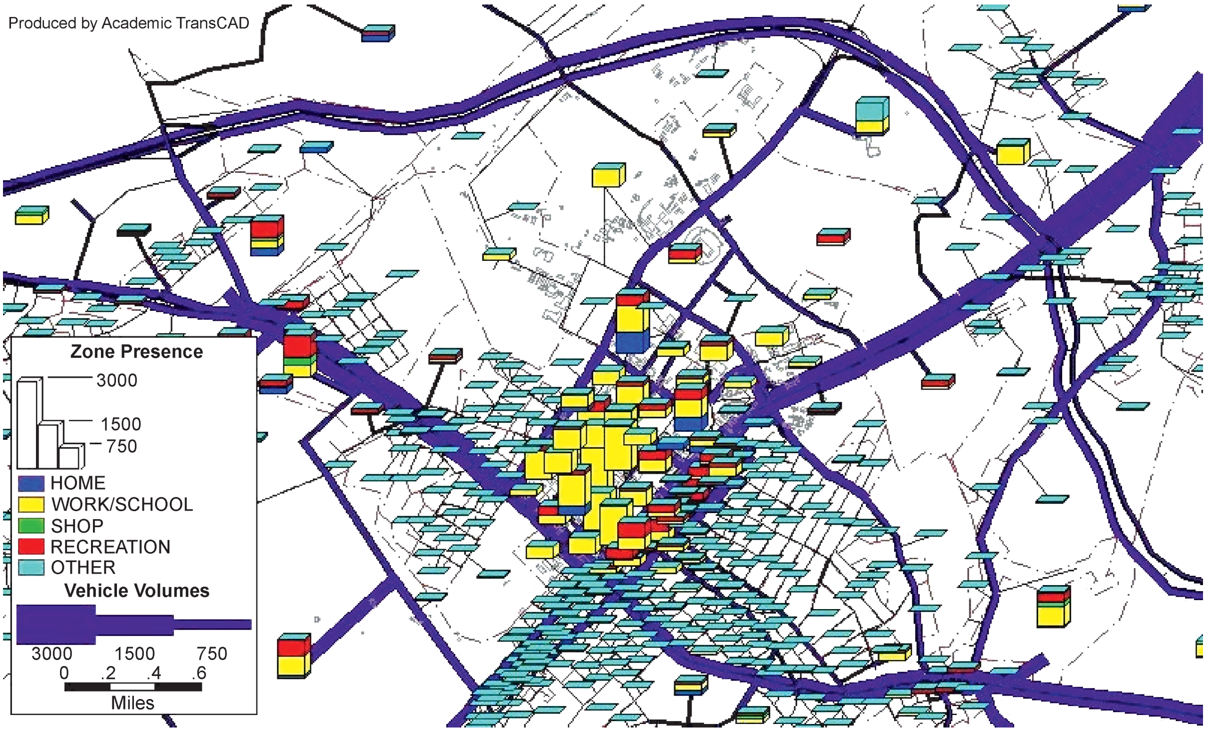
Stochastic microsimulation, as intended here, is an evolutionary engine software that is used to replicate the relationships among social, economic, and demographic factors with land use, time use, and travel by people. As discussed above the causal links among these groups of entities are extremely complex, non-linear, and in many instances unknown or incompletely specified. This is the reason that no closed form solution can be created for such a forecasting model system. An evolutionary engine, then, provides a realistic representation of person and household life histories (e. g., birth, death, marriages, divorces, birth of children, etc.), spatio-temporal activity opportunity evolution, and a variety of models that account for uncertainties in data, models, and behavioral variation (see [59,117], for overviews and [157] TS3 for an application).

Production systems were first developed by Newell and Simon [123] to explicitly depict the way humans go about solving problems. These are a series of condition-action (note the parallel with stimulus-response) statements in a sequence. From this viewpoint they are search processes that may never reach an absolute optimum and they replicate (or at least attempt to) human thought and action. Models of this kind are called *computational process models* (CPM) and through the use of IF …THEN… rules have made possible the creation of a variety of new models.

Geographic information systems are software systems that can be used to collect, store, analyze, modify, and display large amounts of geographic data. They include layers of data that are able to incorporate relations among the variables in each layer and allow to build relationships in data across layers. One can visualize a GIS as a live map that can display almost any kind of spatio-temporal information. Maps have been used by transportation planners and engineers for long time and they are a natural interface to use in modeling and simulation. GIS today is moving beyond this relational database definition and is transforming the entire field into GI Science, which is beyond the scope of this article.

Advanced data collection methods and devices that are technologies that merit a note, although, not strictly developed for modeling. The first is about data collection and particularly data collection using internet technologies to build complex interviews that are interactive and

TS3 Please check reference. There is an entry for Sundararajana and Goulias for the year 2002?



Travel Behaviour and Demand Analysis and Prediction, Figure 4
Persons and activities assigned to buildings and travel to the network (source: Goulias et al. [67])

dynamic [34]. In the same line of development we also see the use of geographic positioning systems (GPS) that allow one to develop a trace of individual paths in time and space [35,186]. Very important development is also the emergence of devices that can record the bulk of environmental data surrounding a person's movement, classify the environment in which the individual moves, and then ask simplified questions [74].

Soft computing and non-parametric data analysis is the last innovation mentioned here. In the data analysis we see greater strides in using data mining and artificial intelligence-born techniques to extract travel behavior patterns [134,160] and advanced and less restrictive statistical methods to discover relationships in travel behavior data (e. g., [88]). Soft computing is increasingly finding many applications in activity-based models (see www.imob.uhasselt.be). For a more recent and accessible review see Pribyl [133].

The Evolving Modeling Paradigm

Policies are dictating to create and test increasingly more sophisticated policy assessment instruments that account for direct and indirect effects of behavior, procedures for behavioral change, and to provide finer resolution in the four dimensions of geographic space, time, social space, and jurisdictions. Dynamic planning is also stressing the need to examine trends, cycles, and the inversion of time progression to develop paths from the future visions to today's actions. New model developments are also becoming increasingly urgent. Although, tremendous progress has been observed in the past 20 years, development requires a faster pace to create new policy tools. These policy tools need to disentangle the actions of persons under different policy actions and the impact of policy actions on aggregates to identify conflicts and resolutions. Supporting all this is a rich collection of decision paradigms that are already used and a few new ideas are starting to migrate to practice as illustrated below.

Early models incorporating activity-based behavioral processes into applications were published in the late 1970s and early 1980s as proof-of-concept and experimental applications. Following Hagerstrand's time-geography approach, PESASP [103] is one of the first models to operationally show the use of a time-space prism and to account for the relationship among activities. The Cullen and Godson [31] study was also the first comprehensive treatment of activities that brought different research findings together. In parallel, models were developed that were utility-maximizing models such as Adler and Ben-Akiva model [1] and much later the Kawakami and Isobe model [87]. Following these studies, BSP [79] and Computational Algorithms for Rescheduling Lists of Activities – CARLA [83] also use the activities within a time-space prism paradigm and define the foundations of data collection for activity-based approaches.

After this period of experimentation three streams in model development emerged. The first is in deriving representative activity patterns (RAPs) and then using regression techniques to correlate RAPs to person and household social and demographic data and then forecasting. The second development refines the methods used to simulate persons and adds to the forecasting repertoire other forecasting tasks via *microsimulation*. The third is a movement that expands the envelope to include cognition and explicit representation of mental processes through CPMs.

The Simulation of Travel/Activity Responses to Complex Household Interactive Logistic Decisions (STARCHILD – Recker and McNally [138,139] derived RAPs, employed a utility-based model and incorporated constraints. It is considered a fundamental transition development from research to practical application of an activity-based approach and it is still the foundation of models that first derive representative patterns and then forecast travel behavior. The more recent SIMAP [100] is a direct derivation of STARCHILD. In this line of development, Ma [109] created a model system that combined long term activity patterns (Long-term activity and travel planning – LATP) with a within-a-day activity scheduling and simulation (Daily Activity and Travel Scheduling – DATS) incorporating day-to-day variation and history dependence. Her model system produced very accurate forecasts. However it required panel survey data (the repeated observation of the same persons and households over time) that are rarely collected. In the LATP/DATS system longitudinal statistical models are extracted from longitudinal records and they capture important aspects of behavioral dynamics such as habit persistence, day-to-day switching behaviors, and account for observed and unobserved heterogeneity contributed by the person, the household, the area of residence, and the area of workplace.

One of the first models to include a microsimulation in its paradigm is ORIENT [152]. This methodology suitably refined was demonstrated in a countrywide model for the Netherlands developed between 1989 and 1991 and named the Microanalytic Integrated Demographic Accounting System (MIDAS – Goulias and Kitamura [63,64]). MIDAS integrates demographic microsimulation, with dynamic car ownership models and a comprehensive suite of travel behavior equations. A cross-sectional version of MIDAS using data from the United States was also developed by Chung and Goulias [29]. MIDAS-USA simulates the evolution of households along with car ownership and travel behavior for Centre County, PA, and it is linked to a model to assign fees for development using GIS. A more ambitious development is the Activity Mobility Simulator – AMOS – by Kitamura et al. [93], which defines a few RAPs as templates. Then, uses a neural network to identify choices and a satisficing rule to simulate schedule changes due to policies. While MIDAS is a strictly longitudinal process econometric model progressing one year at a time, AMOS is constraint-based model designed for much finer temporal resolution. DEMOS, developed by Sundararajan and Goulias [157] TS3, is another MIDAS derivative. DEMOS is an object-oriented environment designed to simulate the evolution of people and their households using a variety of external data with the core models based on the Puget Sound Transportation Panel. It also simulates activity participation, travel, and telecommunication market penetration using a few representative patterns that were derived in Ma's LATP/DATS supplemented by telecommunications and travel behavior models.

SCHEDULER (Gärling et al. [43] is the first CPM that adds a psychometric cognitive implementation based on the Hayes-Roth and Hayes-Roth [73] planning model. In SCHEDULER, activities, selected from the long term calendar that represents a person's long term memory, comprise a schedule that is "mentally executed". Models start to combine CPM, microsimulation, and data derived behavioral patterns with random utility models to fill different modeling needs. The Simulation Model of Activity Scheduling Heuristics (SMASH – Ettema et al. [38]) is a CPM and econometric utility-based hybrid model that focuses on the pre-trip planning process predicting sequences of activities. In parallel, COMRADE [37], uses competing risk hazard models for activity scheduling and incorporates duration models in the system. The Model of Action Space in Time Intervals and Clusters (MASTIC – Dijst and Vidakovic [32]), identifies clusters in the action space to perform and schedule activities. Time-space prisms are also the foundation of the Prism-Constrained Activity-Travel Simulator (PCATS – Kitamura [90], Kitamura and Fujii [92]), which is also a utility-based model. A direct operational derivative of SCHEDULER [44] was developed by Kwan, in her 1994 dissertation [101,102], and named GIS-Interfaced Computational-process modeling for Activity Scheduling (GISICAS). It is a simplified CPM, that uses time-space constraints and GIS to incorporate spatial information into a behavioral model to create individual schedules, starting with activities at higher levels of priority. Other models also attempt to recreate personal schedules such as Vause's model [175], a CPM that creates a restricted choice set for creating activity patterns, a model by Ettema [39], and VISEM [41], a data-driven model that is a part of PTV Vision, an urban and regional transportation planning system, that creates daily activity patterns for behaviorally homogeneous groups within the population. Stopher et al. [156] also proposed the Simulation Model for Activity Resources and Travel (SMART) using a time geography framework and a taxonomy of activities in a GIS environment. All these use observed patterns to derive behavioral models. In contrast, Recker [137], developed the Household Activity Pattern Problem (HAPP) as a normative model based on the pick up and delivery time window problem to be used as a yardstick model testing optimal behavioral hypotheses.

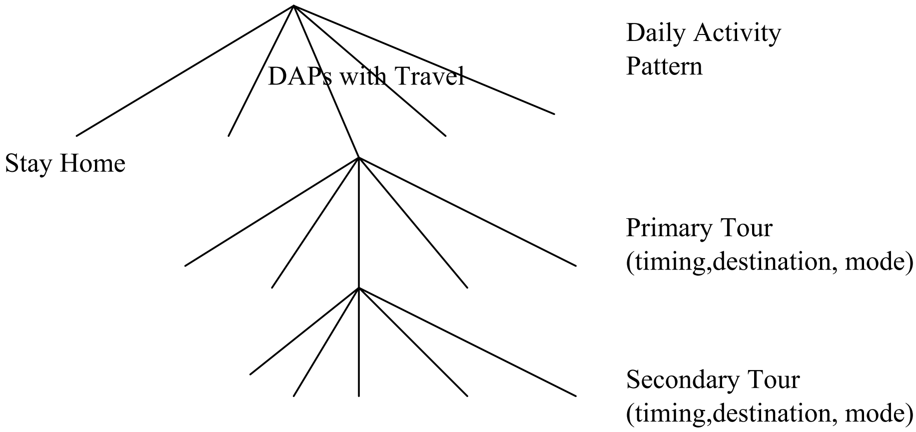
The model framework that impacted practice the most in the United States is the Daily Activity Schedule model by Ben-Akiva et al. in [11]. This model, was used to create the Portland Daily Activity Schedule Model [23], advocating modeling lifestyle and mobility decisions on a scale of years. These influence daily activity schedules, which are comprised of primary and secondary tours constrained in time and space. It contains two key elements that simplify activity-based model development and takes advantage of the research surge in developing more general discrete choice models. A similar simplification using conditional probabilities was also developed for Los Angeles by Kitamura et al. [94].

Figure 5 shows this hierarchy of decisions and the scheme used to convert the daily pattern into a system of discrete choices. This framework was used to design new models for the regions around San Francisco, New York, Columbus, Denver, Atlanta, and Sacramento [24].

Arentze and Timmermans [5] designed the most complete CPM named ALBATROSS, which is a multi-agent simulation and predicts the time, location, duration, activity companionship, and travel modes subjecting everything to spatio-temporal, institutional, and household constraints. The theoretical underpinnings of this model are by far wider and all encompassing than any other activity-based model. However, it does not simulate route choice and does not produce data suitable for traffic assignment algorithms. Development of the third version of ALBATROSS is currently underway [76]. This model is also representative of raising the ambitions of travel modelers. The Alam Penn State Emergency Management model (Alam-PSEM, Alam and Goulias [3]) is a building-by-building simulation of activity participation and presence at specific locations of a university campus for each hour of a typical day. In parallel Bhat and his co-workers [15,18] developed the Comprehensive Activity-Travel Generation System for Workers (CATGW), which is a series of econometric models that replicate a commuter's evening mode choices, number of evening commute stops, and the number of stops after arriving home. The models developed by Bhat and colleagues are characterized by the use of hazard/duration regression models that were specifically developed for activity-based approaches and are by far more flexible that other regression methods. Another econometric model, the Conjoint-Based Model to Predict Regional Activity Patterns (COBRA), developed by Wang and Timmermans in [181], generates general patterns of stops for specific activities using a conjoint-based model with stated preference data instead of travel or activity diary data. The Wen and Koppelman model [183] utilizes three layers of decisions that are influenced by exogenous variables to generate activity patterns.

All these models point to new directions such as spatial choice needs to be dealt in more detail [3], activity choice and duration need to be dealt in a way the recognizes satiation in activity participation (e. g., in the duration models of Bhat [15]), sooner of later we will need to account for unobserved patterns and lack of experimental data (e. g., using conjoint experiments Wang and Timmermans [181]), and relations within the household need to also receive attention and inserted in the model hierarchy [183].

Spatial aspects of model development were considered in the CentreSIM regional model [67,98,99] that uses time-of-day activity and travel data for different market segments to predict hour-by-hour presence at locations and travel among zones. In 2004, as a part of the Longitudinal Integrated Forecasting Environment (LIFE) framework [58], Pribyl and Goulias [135] developed CentreSIM (medoid simulation) to derive a few representative patterns and simulate daily schedules accounting explicitly for within-household interactions for entire daily patterns. In the Netherlands, PATRICIA (Predicting Activity-Travel Interdependencies with a Suite of Choice-Based, Interlinked Analyzes), was developed by Borgers et al. [22] to help assess the performance of ALBATROSS. PATRICIA is a suite of linked models that incorporates an expanded set of activity choices, based on 63 distinct patterns, and activity destinations and describes activity transport modes and sequences. AURORA [82,165], which is a complementary model to ALBATROSS, is a utility-based system that models the dynamics of activity scheduling and rescheduling decisions as a function of many choice facets. AURORA is for short-term adaptation and rescheduling using just a few critical pa-



Travel Behaviour and Demand Analysis and Prediction, Figure 5
The Bowman and Ben-Akiva daily activity model formulation

rameters. The model has since been expanded to include many new facets [76]. A much simpler model is PETRA [42] that allows the model to work with a small number of daily travel patterns with some statistical advantages (see also Henson et al. [76]). Microsimulation software experienced another push forward by the development of a multi-million investment in TRansportation ANalysis SIMulation System. This model system was developed in the decade 1995–2005 and one of its versions is now available via a NASA open source license from TMIP at http://tmip.fhwa.dot.gov/transims/download_transims/files/3_1_1/TS5. TRANSIMS is a survey data-driven cellular automata microsimulation and was developed by a team at Los Alamos National Laboratory [106]. It was one of the first simulation packages to contain models that create a synthetic population, generate activity plans for individuals using directly observed data in travel surveys, formulate routes on a network based on these, and execute activity plans. Microsimulation models also evolved in the interface between land use and travel behavior. The Integrated Land Use, Transportation and Environment (ILUTE) model [145] model is designed to simulate the evolution of people and their activity patterns, transportation networks, houses, commercial buildings, the economy, and the job market over time. Within this vision, Miller and Roorda [119], developed the Toronto Area Scheduling model for Household Agents (TASHA) that uses *projects* to organize activity episodes into schedules of persons. Schedules for members in a household are simultaneously generated to allow for joint activities. Both ILUTE and TASHA utilize CPMs and econometric utility-based paradigms.

Another microsimulation that uses econometric models to simulate daily activity travel patterns for an individual, is the Comprehensive Econometric Microsimulator for Daily Activity-travel Patterns (CEMDAP) model [19] that is based on land use, socio-demographic, activity system, and level-of-service (LOS) attributes. Key distinctive element of CEMDAP is its reliance on hazard-based regression models to account for the continuous nature time of activity duration. It includes population synthesis as well as the activity-pattern generation and scheduling of children, which is missing form many other simulators. Another model that utilizes constraints is the Florida Activity Mobility Simulator (FAMOS) [131]. FAMOS encompasses two modules, the Household Attributes Generation System (HAGS) and PCATS. Together, they comprise a system for modeling the activity patterns of individuals in Florida. The output is a series of activity-travel records. FAMOS is currently being further enhanced to include intra-household interactions and capture task allocation behavior among household members. Most recently, Ettema et al. [40] developed PUMA (Predicting Urbanization with Multi-Agents), a full-fledged multi-agent system of urban processes that represents land use changes in a behaviorally realistic way. These processes include the evolution of population, businesses, and land use as well as daily activity and travel patterns of people. To simulate activity-travel patterns, an updated version of AURORA by Arentze et al. [6] will be created and also in the model FEATHERS (Forecasting Evolutionary Activity-Travel of Household and their Environmental Repercussions) to simulate activity-level scheduling decisions, within-a-day rescheduling, and learning processes in high resolutions of time and space. Developed as a complement to ALBATROSS, FEATHERS is econometric utility-based microsimulation that utilizes constraints that focuses on the short-term dynamics of activity-travel patterns. Members from this same Dutch team also developed MERLIN [173] and RAMBLAS [176].

Microsimulations have continued to gain in popularity in the activity-based modeling universe as they move from research applications to practice. Besides the Portland Daily Activity Schedule Model mentioned previously, New York's "Best Practice" Model (2002) and the Mid-Ohio Regional Planning Commission (MORPC) Model [179] TS6, both developed by Vovsha et al., and the San Francisco model [85] are currently being utilized by their respective MPO. The San Francisco model is currently being updated to implement enhanced destination choice models and being recalibrated using more recent household and census data. Four other models for Atlanta, Sacramento, the San Francisco Bay Area, and Denver are currently in various stages of implementation [24].

Although many past activity-based models have undefined or large time resolutions, STARCHILD already in mid-1980s used 15-min temporal resolution. The most recent models, however, go even further to simulate activities at small time intervals such as 5 min (TASHA) and 10 min intervals (SIMAP), minute by minute (MASTIC, CentreSIM, MASTIC, GISICAS, and RAMBLAS), and second-by-second (TRANSIMS-LANL, ALBATROSS, AURORA, CATGW, CEMDAP, FAMOS, and FEATHERS). Many applications, however, operate with large resolutions of one hour and they are implemented with a target of 30 min to one hour [24]. Spatial resolution of the models is still dominated by the zonal level. ALBATROSS and MORPC both can operate at the subzone level. Alam-PSEM, AURORA, CEMDAP, FEATHERS, GISICAS, ILUTE, PUMA, SIMAP, SMASH, and TRANSIMS-LANL utilize data at essentially the building or point level. Only two applications have spatial resolutions below the zonal level (Denver model that contains a two-stage destination locator to predict the address within a zone and the Sacramento model that operates at the parcel level). Cognitive theories (models of knowledge and memory as well as behavioral process for planning activities) were used only in SCHEDULER and based on that in ALBATROSS and FEATHERS. Behavior is most often incorporated as intra-household interaction in ALBATROSS, CEMDAP, FAMOS, FEATHERS, ILUTE/TASHA, and CentreSIM as well as some of the applications in regions such as MORPC.

Examples of Mathematical Models

In this section additional details of two examples of mathematical models for activity and travel behavior analysis are offered. Both examples aim at incorporating human interaction in time allocation models and they are multilevel regression models (based on Goulias [59]) and group decision making utility maximization models (based on Zhang et al. [187]).

Multilevel Regression Models

These regression models are known by different names in different fields of research such as random coefficient models ([69] and p. 669 in [105]) TS7, multilevel models [48], mixed models [147], and hierarchical linear models [26]. They describe the contextual nature of the data and/or the way of accounting for dependent variable variation from multiple sources. Key advantages of these models are: explicit recognition in model formulation of the hierarchical, multiple level and nested structure of the data we analyze, and model specification using three groups of regression components in the same regression model. The first group assumes constant sensitivity to explanatory variables among the units of analysis representing the mean effect of an explanatory variable on the dependent variable. The second group assumes a random deviation around this mean and the third group is the usual random error term(s) of the regression equation. When compared to traditional regression models, which contain only one level, multilevel models do not underestimate the standard errors of coefficient estimates avoiding overstatements about the statistical significance of policy variables (e. g., we do not exaggerate the effect of taxation on car ownership or the effect of time and cost on route choice). A system of multilevel regression models can be written as follows. TS8

$$Y^q_{tij} = \alpha^q_{tij} + \beta^q_k X_{tij} + \gamma^q_m T_t ij \quad (1)$$

$$a^q_{tij} = \gamma^q_0 + v^q_j + u^q_{ij} + \varepsilon^q_{tij}\,, \quad \text{where } q = 1, \ldots, Q\,, \quad (2)$$

$$\beta^q_{k1} = \gamma^q_{k1} + u^q_{k1ij}\,, \quad \beta^q_{k2} = \gamma^q_{k2} + v^q_{k2j}\,. \quad (3)$$

Equation (1), represents Q equations that are one for each Y^q_{tij} variable that we want to explain and use in travel demand forecasting. They can be the amount of time dedicated to activities and travel or distances to specific destinations or even attributes of routes considered by trip makers. The index t represents the time at which an observation was made for a person i from within a household j

(with $t = 1, 2, 3, \ldots, T$, $i = 1, 2, \ldots$, number of people in household j, $j = 1, 2, \ldots$, number of households in sample). In this way we can identify change from one time point to another by an individual and study the relationships among individuals within social units (e. g., households, associations, neighborhoods and so forth).

The time points can be the same for all individuals or they may vary depending on the data collection procedures and willingness of respondents to provide information. Equation 1 is called the level 1 model because it is written at the level of the time point (observation occasion). The first term in the right hand side of Eq. (1) is a random intercept, α, given by Eq. (2). This component has specific meaning. For example, α^q_{tij} is the mean value of person i in household j at time t for variable q. The term ε^q_{tij} is a random temporal variation (also called within person variation) and it is the deviation of time expenditure around γ^q_0. The term u^q_{ij} is a random person to person variation (also called within household variation) and it is also a deviation of around γ^q_0. The term v^q_j is a random household to household variation and it is also a deviation around γ^q_0. These are also called random error components and they are usually assumed normally distributed with $E(\varepsilon) = E(u) = E(v) = 0$, with $\mathrm{Var}(\varepsilon) = \sigma^2_\varepsilon$, $\mathrm{Var}(u) = \sigma^2_u$, and $\mathrm{Var}(v) = \sigma^2_v$ to be estimated. It is worth noting that the system of equations represented by Eq. (1) contain a set of gamma coefficients (associated with a matrix Z representing explanatory variables) that are defined in a similar way as in typical regression models. The βs, however, that multiply the matrix X are defined as random with a mean and a variation around the means γs. This variation can be due to the temporal, personal, and/or household levels. In this way, we can define a variety of equations at each of these levels to represent heterogeneous behavior that is either due to temporal fluctuations, personal variation, or household variation. Equation (3) differentiates between βs that vary within individuals and those that vary within households. In this way, at each level we have a level-specific variance-covariance matrix of all the random terms (εs, us, vs). The significance of the elements in each of these three matrices can be tested using goodness-of-fit measures based on the deviance, which is the difference in the −2Log(likelihood) at convergence between two nested (in terms of specification) models. In addition, the γs can also be tested if they are significantly different than zero using a t-test. The γs in Eq. (1) are called the *fixed effects* and the remaining terms are called the *random effects* at each of the three levels in the hierarchy. Estimation of all the fixed and random parameters can be accomplished either by Full Information Maximum Likelihood, FIML, applied to Y directly or applied to the least-squares residuals, called Restricted Maximum Likelihood-REML that can be used in tandem with a generalized least squares approach. Longford [105], Bryk and Raudensbush [26] and [48] provide a comprehensive review of estimation techniques, their performance assessment, and detailed algorithms.

Household Utility Models

The second example is also representative of a movement toward more detailed consideration of within household decision making dynamics. Although the model was specified by Zhang et al. [187] for time allocation to shared (j) and non-shared activities (s), it is a potentially useful model for other trip making decisions. Each person in a household is assumed to form two utility functions. One utility is for the shared activities (i. e., engagement in activities with other household members) and non-shared activities. These utility functions are given by Eq. (4) (shared activity) and 5 (non-shared activity).

$$u_{is} = \exp\left(\left(\alpha_s + \sum_k \beta_{sk} x_{isk}\right)\right.$$
$$\left.\ln\left(\sum_m \kappa_{sm}\tau_{ism}\right) + \varepsilon_{is}\right)\ln(t_{is}) \quad (4)$$

$$u_{ij} = \exp\left(\left(\alpha_j + \sum_k \beta_{jk} x_{ijk}\right)\right.$$
$$\left.\ln\left(\sum_m \kappa_{jm}\tau_{ijm}\right) + \varepsilon_{ij}\right)\ln(t_{ij}) , \quad (5)$$

where:

α_s	is the constant term for each shared activity *s*.
α_s	is the constant term for each shared activity *s*.
x_{isk}	is the *k*th explanatory variable (and/or attribute) of household member *i* for shared activity *s*.
β_{sk}	is the parameter associated with the *k*th attribute of the shared activity.
τ_{ism}	is the travel time by mode m for each activity s by person *i*.
κ_{sm}	is the parameter associated with travel time by mode *m*.
ε_{is}	is a random error term of the shared activity *s* by person *i*.
t_{is}	is the amount of time dedicated to activity s by person *i*.
α_j	is the constant term for each non-shared activity.
x_{ijk}	is the *k*th explanatory variable (attribute) of household member *i* for non-shared activity *j*.

β_{jk} is the parameter associated with the kth attribute of non-shared activity.
τ_{ijm} is the travel time by mode m for each activity s by person i.
κ_{jm} is the parameter associated with travel time by mode m.
ε_{ij} is a random error term of the non-shared activity j by person i.
t_{ij} is the amount of time dedicated to activity j by person i.

The overall utility of activity participation and travel for each person i under the assumption of a multi-linear utility is given by Eq. (6).

$$u_i = \sum_{j=1}^{J+S} r_{ij} u_{ij} + \sum_{j=1}^{J+S} \sum_{j'>j} \delta_i r_{ij} r_{ij'} u_{ij} u_{ij'} \qquad (6)$$

where,

u_{ij} is the utility of activity j for person i.
r_{ij} is the relative interest of person i for activity j.
δ_i is parameter of activity dependency for member i.
$J+S$ is the number of non-shared and shared activities for a person within the unit of time under consideration.

In a similar way the household utility function is a multi-linear combination of the individual utilities in Eq. (7).

$$\mathrm{HUF} = \sum_{i=1}^{n} w_i u_i + \lambda \sum_{i=1}^{n} \sum_{i'>i} (w_i w_{i'} u_i u_{i'}) \qquad (7)$$

where,

HUF is the household utility combining the utilities of all household members n.
u_i is the utility of household member i.
w_i is the relative influence of each household member i.
λ is a parameter of within household interaction.

Under the assumption of maximizing HUF it is possible to create a Lagrangian function that accounts for constraints (i. e., total amount of time available, signs of parameters and so forth) and through a maximization solution derive equations that can be used to estimate the unknown parameters in Eqs. (4–7) (details are provided in Zhang et al. [187] for time allocation). It is worth noting that Zhang et al. [187], derived two alternate model systems by changing the utility functions to represent different intra-household bargaining models (for a detailed review see Bengstrom 1995 TS9). Then through a linearization process they developed a system of linear equations and estimated the parameters using a multiple equations econometric approach (the Seemingly Unrelated Regression Estimation, Greene, 1993 TS10) that is a simplifying alternative to the multilevel models described earlier in this section. A more general review of this type of model formulation is also provided by Timmermans [164].

Summary

Similarities and differences among the implemented modeling ideas are:

- A hierarchy of decisions by households is assumed that identifies longer term choices determining the shorter term choices. In this way different blocks of variables can be identified and their mutual correlation used to derive equations that are used in forecasting.
- Anchor points (Home location – work location – school location) are inserted in the first choice level and they define the overall spatial structure of activity scheduling.
- Out-of-home activity purposes include work, school, shopping, meals, personal business, recreation, and escort. These expand the original home-based and non-home based purposes in travel behavior and the three activity types in home economics (labor for pay, labor at home, and leisure).
- In-home activities are explicitly modeled or allowed to enter the model structure as a "stay-at-home" choice with some models allowing for activity choice at home (work, maintenance and discretionary). In this way limited substitution between at home and outside home can be reflected in the models.
- Stop frequencies and activities at stops are modeled at the day pattern and tour levels to distinguish between activities and trips that can be rescheduled with little additional efforts versus the activities and trips that cannot be rescheduled (e. g., school trips).
- Modes and destinations are modeled together. In this way the mutual influence – sequential and/or simultaneous relationships can be reflected in the model structure.
- Time is included in a few instances in activity-based models. For example departure time for trips and tour time of day choice are modeled explicitly. Model time periods are anywhere between 30 min and second-by-second and time windows are used to account for scheduling. This modeling component allows to incorporate time-of-day in the modeling suites. It also allows to identify windows of activity and travel opportunities.

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TS10 Please check Greene (1993). There is no entry in the bibliography.

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  The presence of departure time also enables models to trip matrices for any desired periods in a day. In fact, output of time periods depends on route choice and traffic assignment needs and can be adjusted almost at will.

- Human interaction, although limited for now to the within-household interaction, is incorporated by relating the day pattern of one person to the day patterns of other persons within a household, their joint activities and trip making are explicitly modeled (joint recreation, escort trips), and allocation of activity-roles are also modeled.
- Spatial aspects of a region are accounted for using methods that produce spatially distributed synthetic populations using as external control totals averages and relative frequencies of population characteristics.
- Accessibility measures are used to capture spatial interaction among activity locations and the level of service offered by the transportation systems. These are also the indicators used to account for feedback among the lower level in the hierarchy decisions (e. g., activity location choices, routes followed, congestion) and the higher level such as residence location choice.
- Spatial resolution is heavily dependent on data availability and it reached already the level of a parcel and/or building at its most disaggregate level. Outputs of models are then aggregated to whatever level is required by traffic assignment, mode specific studies (nonmotorized and/or transit) and reporting needs and requirements.

Overall, the plethora of advances includes: a) models and experiments to create computerized virtual worlds and synthetic schedules at the most elementary level of decision making using microsimulation and computational process models; b) data collection methods and new methods to collect extreme details about behavior and to estimate, validate, and verify models using advanced hardware, software, and data analysis techniques; and c) integration of models from different domains to reflect additional interdependencies such as land use and telecommunications.

Future Directions

Much more work remains to be done in order to develop models that can answer more complex questions in policy analysis and for this reason a few steps are outlined here. In policy and program evaluation, transportation analysis appears to be narrowly applied to only one method of assessment that does not follow the ideal of a randomized controlled trial and does not explicitly define what experimental setting we are using for our assessments. Unfortunately this weakens our findings about policy analysis and planning activities. Although we have many laboratory experiments that were done for intelligent transportation systems we lack studies and guidelines to develop experimental and quasi-experimental procedures to guide us in policy development and large scale data collection.

In addition, many issues remain unresolved in the areas of coordination among scale in time and space and related issues. In addition very little is known about model sensitivity and data error tolerance and their mapping to strategy evaluations. This is partially due to the lack of tools that are able to make these assessments but also due to lack of scrutiny of these issues and their implications on impact assessment.

Regarding strategic planning and evaluation, we also lack models designed to be used in scenario building exercises such as backcasting and related assessments. The models about change are usually defined for forecasting and simple time inversion may not work to make them usable in backcasting. This area does not have the long tradition of modeling and simulation to help us develop suitable models. Should more attention be paid to this aspect? Is there room for a combination of techniques including qualitative research methods? What is the interface between this aspect and the experimental methods questions in program evaluation?

In the new research and technology area, since we are dealing with the behavior of persons, it is unavoidable to consider perceptions of time and space. What role should perceptions of time and space [51] play in behavioral models and what is the most appropriate use of these perceptions? The multiple dimensions of time such as tempo, duration, and clock time Levine (1997) TS11 are neglected in behavioral models – is there a role for them in behavioral models?

Human interaction is considered important and is receiving attention in more recent research Golob and McNally [54], Chandrasekharan and Goulias [27], Simma and Axhausen [148], Gliebe and Koppelman [47], Goulias and Kim [62], Zhang et al. [187], but only partially accounted for in applications as illustrated by Vovsha and Petersen [177]. Future applications will increasingly pay attention to motivations for human interactions and the nature of these interactions within households and in a wider social network context.

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