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Land use–transport interaction modeling: A review of the literature and future research directions

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Abstract: The aim of this review paper is to provide comprehensive and up-to-date material for both researchers and practitioners interested in land-use-transport interaction (LUTI) modeling. The paper brings together some 60 years of published research on the subject. The review discusses the dominant theoretical and conceptual propositions underpinning research in the field and the existing operational LUTI modeling frameworks as well as the modeling methodologies that have been applied over the years. On the basis of these, the paper discusses the challenges, on-going progress and future research directions around the following thematic areas: 1) the challenges imposed by disaggregation—data availability, computation time, stochastic variation and output uncertainty; 2) the challenges of and progress in integrating activity-based travel demand models into LUTI models; 3) the quest for a satisfactory measure of accessibility; and 4) progress and challenges toward integrating the environment into LUTI models.
Keywords: Land-use, transportation, four-step model, activity-based approach, micro-simulation, stochasticity, uncertainty

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1 Introduction

Following the pioneering work of Hansen (1959) in Washington, DC, that established that trip and location decisions co-determine each other, the notion that land use and transportation interact with each other has been widely recognized and extensively studied. Over the past 60 years, considerable amount of cross-disciplinary research and professional collaborations have focused on understanding, integrating and predicting households' residential and job location choice, the associated daily activity-travel patterns as well as transport mode and route choice. These research efforts have culminated in the development of state-of-the-art operational LUTI models as decision support systems for assessing the

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impacts of land-use decisions on transportation and vice versa, as well as evaluating large-scale transportation investments.

The aim of this paper is to provide a comprehensive review of progress in LUTI research to date. Before proceeding, it is worth mentioning that a number of review papers have been published on the subject over the last decade (e.g., Badoe and Miller 2000, Timmermans 2003, Wegener 2004, Hunt, Kriger and Miller 2005, Chang 2006, Iacono, Levinson and El-Geneidy 2008, Silva and Wu 2012). These review papers focused on existing operational modeling frameworks, the challenges at the time, and the steps that were being taken to address them. This paper builds on the existing reviews. It begins with a discussion of the dominant theories that are being applied in LUTI research. This is followed with a discussion of the nature of the link between land use and transportation, both conceptually and from existing empirical research. Under section three, the two main travel-demand modeling approaches (i.e., the four-step approach and activity-based approach) are discussed highlighting their fundamental differences and similarities as well as their relative strengths and limitations. The penultimate section provides an overview of the state-of-the-art operational LUTI modeling frameworks, focusing on their structure, the modeling methodologies, and the geography of application of these models. On the basis of these, the current challenges, on-going progress, and areas needing further research are outlined and discussed.

2 The theoretical context

The field of LUTI research is eclectic, drawing on theoretical and conceptual propositions from a wide range of disciplines including economics, geography, psychology, and complexity science. On a more aggregate level of analysis, classical urban micro-economic theories of Alonso (1964), Ricardo (1821), Von Thunen (1826) and Wingo (1961), among others, provide the standard reference point to understanding the relationship between land use and transportation. Adopting a deterministic analytical approach and simplifying assumptions including monocentricity, spatial homogeneity and rationality, urban economic theory posits that transport cost, a function of travel distance, has profound impact on the location of activities and the overall optimum emergent structure of cities. Grounded in microeconomic theory, they enjoy sound theoretical basis and offer a robust framework for qualitative analysis of the relationship between location and transport (de la Barra 1989, Waddell 1997). However, as de la Barra (1989) notes, the applied fields of transportation and urban modeling have remained largely apart from urban economic theory due partly to the restrictions imposed by tradition of econometrics and the inability of such models to capture the richness of urban and regional geography.

Out of the quest for a practical approach to modeling LUTI emerged the gravity/spatial interaction (SI) approach in the 1960s. Popularized by Lowry (1964) in his model of the metropolis developed for the city of Pittsburgh, the SI approach came from the theory of social physics, grounded in the Newtonian concept of gravity and empirical analysis of human spatial interaction behavior. The basic Lowry gravity model states that the interaction between any two zones is proportional to the number of activities in each zone and inversely proportional to the friction impeding movement between them. Despite the simplicity and tractability of Lowry's gravity approach, it lacked any solid theoretical foundation (Berechman and Small 1988, Waddell 1997). Wilson (1970) drew on the concept of entropy maximization to provide a general theoretical framework for the SI approach. Entropy refers to the degree of disorder in a system, which in the context of LUTI modeling results from the relative location of workers, jobs and housing in the city (de la Barra 1989). Within the framework of entropy maximization, the amount of interaction between activity zones can be worked out as a doubly constrained, origin-constrained, destination-constrained, or an unconstrained matrix model.

From the 1970s onward, McFadden's (1973) Random Utility Theory (RUT) gained prominence in LUTI modeling. At the time, there was the need for a robust framework that could capture the complex choice behavior dynamics involved in land-use and transport decisions at the individual level while overcoming the weak assumptions and misspecification errors inherent in aggregate spatial interaction and urban economic models. This led to the development of utility-based models in which choices between alternatives are predicted as a function of attributes of the alternatives, subject to probabilistic variations in the knowledge, perceptions, taste, preferences, and socio-economic characteristics inter alia of decision makers. The adoption of utility theory allowed for the development of new generation of models based on the study of disaggregate behavior (Iacono, Levinson and El-Geneidy 2008). Contrary to gravity-based models, utility-based models are able to effectively address locational characteristics using a bundle of locational attributes, with each element in the bundle reflecting a distinct feature of the location, and a random component representing the unobserved characteristics of a location (Chang 2006). Despite enjoying sound theoretical foundation, utility-based LUTI models have been criticized for their inability to explicitly capture the underlying decision processes and behavioral mechanisms that result in observed location-travel decisions (Ettema 1996, Fox 1995, Pinjari and Bhat 2011).

Classical utility theory also assumes rationality and perfect information in choice decisions. However, within the transportation and activity system, decision makers face conditions of uncertainty, for example, in choosing departure times, activities, destinations, transport modes and routes (Rasouli and Timmermans 2014a). On the basis of these limitations imposed by utility theory, current research has begun to draw on a number of theories focusing on decision making under uncertainty. Decision making under uncertainty is viewed as a choice between gambles or lotteries (Tversky 1975). Thus, in contrast to classic utility models, in decision making under uncertainty, the characterization of the choice alternatives is captured in terms of probability distributions; individuals therefore are not sure about the exact state of the choice alternative or about the outcome of their decisions (Rasouli and Timmermans 2014a). A survey through the literature shows three standard theories of decision making under conditions of uncertainty being applied to transportation research. These are expected utility theory (Bernoulli 1738, von Neumann and Morgenstern 1944, Savage 1954), prospect theory (Kahneman and Tversky 1979) and regret theory (Bell 1982, Fishburn 1989, Loomes and Sugden1987).

Expected utility theory (EUT) was formulated in the 18th century by Bernoulli (1738) and further developed by von Neumann and Morgenstern (1944) and Savage (1954) as a descriptive model of economic behavior. The foundational contribution of Bernoulli is linked to the so-called St. Petersburg paradox—the puzzle surrounding what price a reasonable person should be prepared to pay to enter a gamble, a game of infinite mathematical expectation, consisting of flipping a coin as many times as is necessary to obtain 'heads' for the first time. EUT states that the decision maker chooses between risky or uncertain prospects by comparing his or her expected utility values—the weighted sums obtained by adding the utility values of outcomes multiplied by their respective probabilities (Mongin 1997). Critical evaluation of the limitations of EUT and efforts devoted toward developing alternatives to EUT can be found in Starmer (2000) and Kahneman and Tversky (1979).

On the basis of several classes of choice problems associated with EUT as a valid descriptive theory of human choice behavior, Kahneman and Tversky (1979) formulated the prospect theory (PT). The key principle underpinning the theory is that decisions are made based on the potential value of loss and gains rather than the final outcomes. These losses and gains are evaluated using heuristics. Proponents posit a two-stage decision-making process. The first stage involves the use of various decisions to frame possible outcomes in terms of gains and losses, relative to some neutral reference point, while the second stage involves evaluation of the outcomes of each alternative according to some value function and transforms objective probabilities into subjective probabilities (Rasouli and Timmermans 2014a).

An extension to PT is heuristic decision/bounded rationality theory (Simon 1957, 2000, Tversky 1969). Taking their roots from social psychology and behavioral economics, proponents argue that decisions are made on subsets of factors, affected by perpetual cognitive biases, uncertainty and information asymmetry, and do not necessarily result in optimal choices (Payne, Bettman and Johnson 1993, Innocenti, Lattarulo and Pazienza 2013, Zhu and Timmermans 2010). Leong and Hensher (2012) in their review, identified four types of heuristics strategies employed by individuals in their choice behavior: satisficing, lexicography, elimination-by-aspects, and majority of confirming dimensions. Few research studies in the area of transportation and location choice have, however, applied these heuristic strategies in understanding choice behavior (e.g., Arentze et al. 2000, Foerster 1979, Innocenti, Lattarulo and Pzienza 2013, Recker and Golob 1979, Young 1984, Zhu and Timmermans 2010). This perhaps, is due to the difficulty in operationalizing the principles of heuristics compared to utility maximization theory.

Regret theory (RT) is attributed to seminal works of Bell (1982), Fishburn (1989) and Loomes and Sugden (1982, 1987). The theory is grounded in "the notion that individuals' utility of choosing an alternative is not only based on the anticipated payoff of each individual choice alternative across different states of the world, but also on anticipated payoff of the other alternative" (Rasouli and Timmermans 2014a, p8). Thus, RT focuses on the opportunity loss in decision making—the difference between actual payoff and the payoff that would have been obtained if a different course of action had been chosen.

Another relevant behaviorally focused theory from the psychology literature is theory of planned behavior (TPB) proposed by Ajzen (1985, 1987). The central claim of TPB is that intentions are the motivational factors that influence behavior and that behavior in turn can be predicted with high accuracy from attitudes toward the behavior, subjective norms, and perceived behavioral control (Ajzen 1991). Proponents further posit that these components of behavior are determined by behavioral beliefs, normative beliefs and control beliefs, and that changes in these beliefs should lead to behavior change (Heath and Gifford 2002). The most recent land-use and transport-related research that has adopted TBP includes the works of Bamberg, Ajzen, and Schmidt (2003), De Bruijn et al. (2009), Haustein and Hunecke (2007) and Heath and Gifford (2002).

An equally important theoretical tradition relevant for LUTI modeling is the time-geography paradigm attributed to the original work of Hagerstrand (1970) and Chapin (1974). The time-geography paradigm posits that spatial interaction occurs within a framework of spatio-temporal constraints, which necessitates trading of time for space (Miller and Bridwell 2009 Peters, Kloppenburg, and Wyatt 2010). Conceptually, time-geography theory uses a space-time prism to analyze the envelope of possibilities open to an individual, subject to a number of spatio-temporal constraints. Crease and Reichenbacher (2013) and Miller (2005) identified three main spatio-temporal constraints of spatial interaction namely: capability constraints, the ability or otherwise of an individual to overcome space in time; coupling constraints, arising from the need to undertake certain activities with other people for given durations; and authority constraints, resulting from common social, political, cultural and legal rules as well as exclusionary mechanisms that restricts an individual's physical presence at a location. Although Hagerstrand's time-geography paradigm is conceptually simple, modeling activity-travel behavior using the framework in practice is difficult and complex (Ben-Akiva and Bowman 1998, McNally 2000).

Complexity theory and general systems theory (von Bertalanffy 1950, Boulding 1956, Forrester 1993) have also gained recognition in the field of urban and regional planning in general and LUTI modeling in particular. As a contemporary embodiment of general systems theory (Batty 2007), complexity theory provides the framework to think about cities as complex adaptive systems with several interacting components that manifest perpetual disequilibrium (Albeverio 2008, Batty 2007, Christensen 1999). Applied in the context of LUTI modeling, complexity theory can provide a robust framework to study the path-dependent and emergent behavioral outcomes of urban actors as well as the dynamic feedback relationship between the land-use and transportation systems. On-going efforts to develop computer simulation models, including agent-based approaches to capture complex interactions of linked responses that lead to a co-evolution of urban structure with transportation infrastructure are grounded in systems and complexity theory (Albeverio, 2008, Batty 2007, Samet 2013).

In sum, research over the past six decades has drawn on a number of theories that can be applied either at an aggregate or disaggregate level of understanding decision-making behavior. Figure 1 provides a summary of the link between the levels of (dis)aggregation at which these theories are meant to be applied, and the varying degrees of complexity involved in operationalizing them. Urban economics theory and entropy-based gravity models allow for macro-level analysis using simple and tractable mathematical models and therefore impose relatively low and moderate levels of complexity in operational modeling respectively.

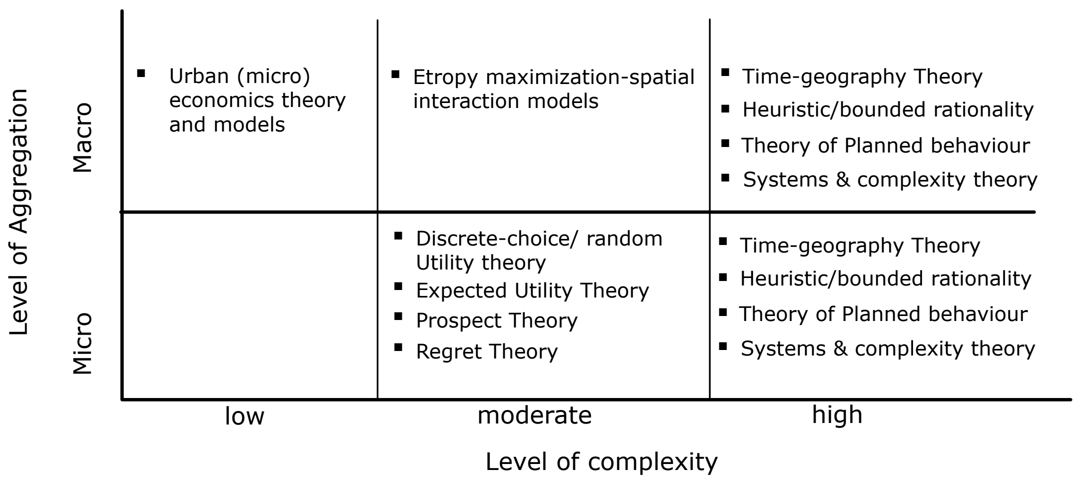

Figure 1: Level of aggregation and degree of complexity involved in operationalizing theories

Classical utility theory and theories of decision making under uncertainty both focus on the micro/individual level of analysis. These theories are operationalized using mathematical formulations of mainly logistic regression models that vary in their complexity but are reasonably parsimonious and tractable. The last family of theories—the time geography paradigm, the social psychological theories, and complexity theory—is applied at both the macro and micro levels of analysis, but requires relatively highly complex formulations in operationalization. The time-geography paradigm for example, imposes a high level of complexity and combinatorial challenges. Heuristic/bounded rationality theory and the theory of planned behavior are social cognitive models that can be operationalized but with very abstract and subjective psychological constructs using complex statistical methods such as structural equation modeling.

3 The land-use-transport nexus: A complex two-way dynamic process

A number of conceptual propositions have contributed to understanding the nature of the link between land-use and transportation. The 'land-use transport feedback cycle' (Wegener 2004) offers one of the simple, yet insightful, frameworks for conceptualizing the complex two-way dynamic link between the land-use system and transportation system. According to this framework, the distribution of land use determines the location of activities. The need for interaction arises as a consequence of the spatial separation between land-use activities. The transport system creates opportunities for interaction or mobility, which can be measured as accessibility. The distribution of accessibility in space, over time, co-determines location decisions and so results in changes in the land-use system.

In addition to the land-use transport feedback cycle, the 'Brotchie triangle' (Brotchie 1984) has been useful in conceptualizing the land-use-transport symbioses. The framework shows the relationship between spatial structure/dispersal (e.g., degree of decentralization of working places) and spatial interaction as some measure of total travel (e.g. average trip length or travel time). Thus, the 'Brotchie triangle' represents the universe of possible constellations of spatial interaction and spatial structure (Lundqvist 2003). It allows various hypothetical combinations of spatial structure and their mobility implications, starting from a monocentric structure in which there is zero dispersion of jobs, to highly decentralized urban structures in which all jobs are as dispersed as population.

Despite the recognition that land use interacts with transportation, at least at the conceptual level, the mechanisms through which the systems impact each other have been difficult to isolate and measure empirically. This is because of the complex interaction among several forces of physical, socio-demographic, economic and policy changes underlying the observed structure of the land-use and transport systems (Lundqvist 2003, Wegener 2004). The term land use, for example, encapsulates a variety of subsystems such as residence, workplace, and physical infrastructure as well as the outcome of complex urban market process (Mackett 1993). Consequently, the underlying processes of change in the overall urban environment is difficult to track and much more complex to disentangle in both space and time.

Furthermore, there appears to be little consensus in the literature on the causal mechanisms by which urban form influences travel and vice versa. Some studies have concluded that urban structural variables (i.e., density, diversity, design, destination accessibility, and distance to transit) have statistically significant influence on travel behavior (e.g., Aditjandra, Mulley and Nelson 2013, Grunfelder and Nielsen 2012, Gim 2013, Handy, Cao and Mokhtarian 2005, Meurs and Haaijer 2001, Næss 2013). Other studies have, however, reported a marginal or weak causal link between commuting behavior and urban form (e.g. Cevero and Landis 1997, Chowdhury, Scott and Kanaroglou 2013, Nelson and Sanchez 1997). Despite the on-going intellectual debate, the fundamental principle that land use impacts transport and vice versa is acknowledged by many scholars and supported by empirical findings from different contexts.

The rest of this section discusses the key components that have constituted the focus of LUTI research and operational model development based on a conceptual framework shown in Figure 2. This is followed by a brief discussion of the pertinent issues under each of the components.

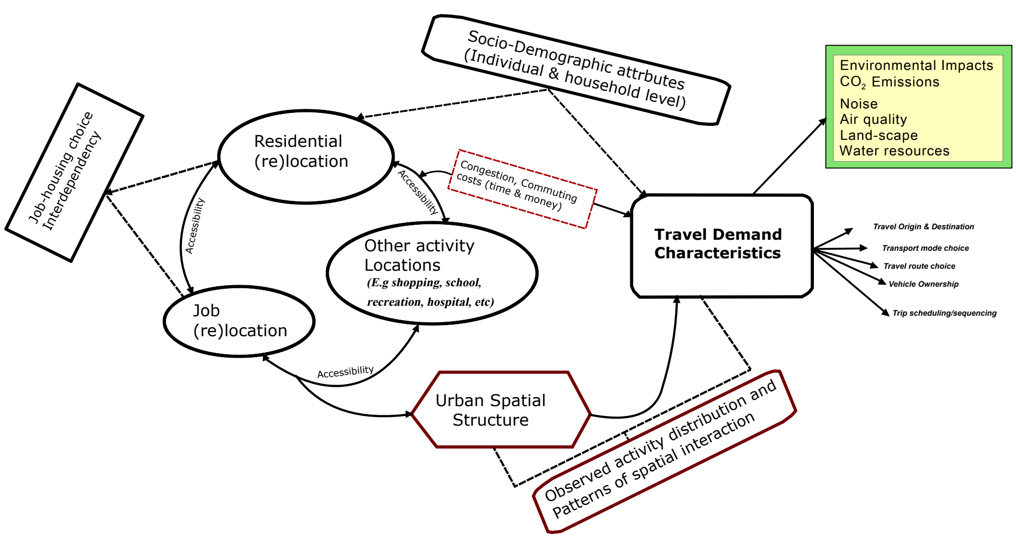

Figure 2: A conceptual model showing the components the land-use-transport system

3.1 The land-use component: Residential–job location choice interdependencies

The land-use component comprises all activity locations—residential, employment, and ancillary activities such as shopping, schools, and recreation. A key focus area of LUTI research has been to understand long-term choice behavior of households with regard to housing (re)location and job (re)location and the interdependency between them. Residential location is considered a long-term choice that directly impacts spatial structure and defines the set of activity-travel environment attributes available to a household or individual (Pinjari and Bhat 2011). Combined with employment location, the two location choice sets provide the spatial anchor to understanding commuting possibilities as well as the commuting implications of urban spatial structure over time (Yang and Ferreira 2008).

According to classical utility maximization theory, people will select the most accessible residential locations to their workplaces to minimize commute costs, all things being equal. Grounded in monocentric urban economic models, access-space-trade-off models assume that workplace choice is predetermined or exogenous to residential location choice (Waddell 1993, Waddell et. al 2007). The residential location component of a number of operational LUTI models is based on the classical exogenous workplace assumption (e.g., DRAM/EMPAL, CATLAS METROSIM, TRANUS, MEPLAN, and UrbanSim). These models, with the exception of UrbanSim, also assume only one-worker households in their analysis (Waddell et al. 2007).

Residential (re)location choice is influenced by several factors. These include housing type, traffic noise levels, municipal taxes or rent levels (Hunt 2010), transport times and costs, density of development, access to high-quality schools and developments in small towns/rural areas (Pagliara, Preston and Kim 2010). Other factors identified in the literature are the degree of commercial or mixed land uses in an area, incomes, neighborhood composition (Pinjari and Bhat 2011), social networks (Tilahun and Levinson 2013) and the evolution of household membership and family structures over time (Habib, Miller, and Mans 2011, Lee and Waddell 2010).

More recent empirical works (e.g., Boschmann 2011, Habib, Miller, and Mans 2001, Kim, Pagliara and Preston 2005, Pinjari and Bhat 2011, Tilahun and Levinson 2013, Waddell et al. 2007, Yang, Zheng and Zhu, 2013) have, however, established that initial residential and job location choices as well as subsequent housing and job mobility decisions are jointly determined. Existing and new operational models will need to incorporate this newly emerging empirical evidence to realistically model housing and job location choice and for improved travel demand forecasting. Adopting a joint approach, however, presents the challenge of multi-dimensionality—a difficult analytical problem of modeling interdependence due to the many possible choice sets (Waddell et al. 2007). Besides using joint logit or sequential ordering methods, a novel latent structure approach has been adopted by Waddell and colleagues (2007) to address the dimensionality problem associated with modeling job-housing location choice interdependency without imposing a structure on the decision process a priori.

Further research is also needed in different contexts to better understand the effects of life-course events and changes in individual and household circumstances on job-housing location choice, the influence of households' most recent residence on evaluating future location choice as well as the job-housing location choice interdependence among multiple worker households (Lee and Waddell 2010, Waddell et al. 2007).

3.2 The transport component: Modeling approaches and limitations

The transport component of LUTI models, as shown in Figure 2, focuses on understanding travel behavior as a basis for predicting and managing travel demand. The key issues of concern, therefore, include trip origin and destination, transport mode choice, vehicle ownership, and trip scheduling/

sequencing behavior. As shown in the conceptual framework, these attributes of travel demand are influenced by spatial structure as well as socio-demographic factors. Travel behavior and the associated transport infrastructure in turn poses environmental impacts through greenhouse gas emission, noise generation, and effects on air quality, landscape, and water resources.

Two main approaches to modeling travel demand can be found in the literature. These are the four-step, trip-based travel demand modeling approach and the activity-based modeling approach. The key features, strengths and limitations of these two approaches are discussed in the sections that follow.

3.2.1 The four-step transport demand model

Gaining prominence from the 1950s, the four-step travel demand model (FSM) has become the traditional tool for forecasting demand and evaluating performance of transportation systems and large-scale transport infrastructure projects (McNally 2000). The typical FSM consists of four distinct steps of trip generation, trip distribution, modal split, and route assignment. Each step is intended to capture intuitively reasonable questions relating to: how many travel movements are made, where they will go, by what mode the travel will be carried out, and what route will be taken based on aggregate cross-sectional data (Bates 2000). Travel is modeled using trips as the unit of analysis based on origin-destination (O-D) survey. The spatial unit within which trips occur is represented as a number of aggregate traffic analysis zones (TAZ) defined based on socio-economic, demographic, and land-use characteristics (Bhat and Koppelman 1999, Fox 1995, Martinez, Viegas and Silva 2007).

Trip generation measures the frequency of trips based on trip ends of production and attraction to estimate the propensity and magnitude of travel. At the trip distribution stage, trip productions are distributed to match the trip attractions and to reflect underlying travel impedance (i.e. time/cost), yielding trip tables of person-trip demands. The relative proportions of trips made by alternative modes are factored into the model at the stage of modal split. At the final stage, assignment/route choice, modal trip tables are assigned to mode-specific networks. Generally, three different trip purposes: home-based work trips, home-based non-work trips, and non-home-based trips are defined in the model (McNally 2000).

The dominance of the conventional FSM in producing aggregate forecasts as part of the transport planning process to date derives from its logical appeal simplicity and tractability (Bates 2000, Davidson et al. 2007). A fundamental conceptual problem with this approach, however, is its reliance on trips as the unit of analysis. As a trip-based approach, the FSM ignores the fact that travel is a derived demand; the motivation for the trips are, therefore, not explicitly modeled (Pinjari and Bhat 2011, Malayath and Verma 2013, McNally 2000). Given that different trip purposes are modeled separately, the scheduling and spatio-temporal interrelationships between all trips and activities comprising the individual's activity-travel pattern are not considered by the FSM (Dong et al. 2006, McNally 2000). Aggregate zonal analysis also implies that the effects of socio-demographic attributes of households and individuals as well as the behavioral complexities in travel captured in the FSM is limited (Martinez, Viegas and Silva 2007, Silva 2009). This limits the ability of the approach to evaluate demand management policies and travel impacts of long-term socio-demographic shifts (Bhat and Koppelman 1999, Fox 1995, Pinjari and Bhat 2011).

3.2.2 Activity-based modeling approach

The activity-based approach (ABA) gained momentum around the 1990s with the promise of delivering a behaviorally-oriented alternative to the FSM. The conceptual underpinnings of this approach integrate aspects of the time-geography paradigm and human activity system analysis, as well as economic theory of consumer choice (i.e. utility maximization).

The fundamental tenet of ABA is that travel is a derived demand; the need to travel is derived from people's desire to pursue in various activities, which are interrelated (McNally and Rindt 2007). The key areas of investigation in this approach, therefore, include the demand for activity participation, the spatio-temporal constraints within which activity-travel behavior occurs, the complex interpersonal dynamics resulting from the interaction among household members and social networks, and activity scheduling and trip-chaining behavior in time and space (Ettema 1996, Bhat and Koppelman 1999, Kitamura 1988, Pinjari and Bhat 2011).

Early activity-based models adopt a "tour-based" representation of trips. This refers to a closed chain of trips starting and ending at a base location to capture the interdependency of choice attributes (i.e., time, destination, and mode) among trips of the same tour (Davidson et al. 2007). More recently, emphasis has shifted to activity scheduling and trip chaining behavior of households. Activity scheduling attempts to capture the processes by which individuals implement an interrelated set of activity decisions interactively with others during a defined time cycle (Axhausen and Gärling 1992, Ettema 1996). Whereas a trip-based approach is satisfied with models that generate trips, ABA focuses on what generated the activities that in turn generated the trips through analysis of observed daily or multi-day patterns of behavior (McNally 2000, Dong et al. 2006, Lin, Lo and Chen 2009).

Contrary to the FSM, few activity-based models include route choice; activity-based models generate time-dependent O-D matrices, and if predictions of traffic flows are needed, these matrices serve as input to conventional route assignment algorithms (Rasouli and Timmermans 2014a). The data requirements, model outputs, and fundamental principles of modeling travel demand using the FMS and/or ABA are not entirely different (Recker 2001). However, the distinguishing feature of ABA relates to the "integrity, allowance for complex dependencies, higher resolution and time as a coherent framework" (Rasouli and Timmermans 2014b, p34).

The activity-based paradigm has proven to pose serious impediment to the development of application models despite its conceptual clarity and purported unmatched potential for providing better understanding and prediction of travel behavior (Recker 2001). The approach is criticized for its lack of sound theoretical and rigorously structured methodological foundations (McNally and Rindt 2007). Given that activity-travel decision processes have infinite feasible outcomes of many dimensions, modelers are presented with a fundamental combinatorial challenge (Ben-Akiva and Bowman 1998, Rasouli and Timmermans 2014b) and several others problems related to the process of activity scheduling such as how utilities or priorities are assigned to activities and which heuristics and decision rules are used (Axhausen and Gärling 1992). Despite these challenges and limitations, several activity-based application models have been developed by the academic community and metropolitan planning organizations. A classification of existing application models based on modeling techniques adopted is presented in Table 1.

All activity-based models are disaggregate. As shown in Table 1, two main disaggregate modeling approaches, utility-based-econometric approach and micro-simulation, have been adopted in existing application models. Utility-based econometric models are systems of equations that capture relationships between individual-level socio-demographics and activity-travel environment to predict probabilities of decision outcomes (Ben-Akiva and Bowman 1988). Grounded in discrete choice and random utility theory, these models rely on multinomial logit and nested logit probability formulations. These systems achieve the needed simplification of the combinatorial problem by aggregating alternatives and subdividing the decision outcomes (Ben-Akiva and Bowman 1998).

Table 1: Activity-based travel modeling: Applications and modeling techniques

Utility Maximization-based models	Micro-Simulation models	Other
Atlanta ARC (PB, Bowman and Bradley 2006)	ALBATROSS (Arentze et al. 2000, Arentze and Timmermans 2004)	HAPP (Recker 1995)—based on operations research approach
CEMDAP (Bhat et al. 2004)	AMOS (Pendyala et al. 1997)	
CEMUS (Eluru et al. 2008)	CARLA (Clarke, 1986)	
Columbus MORPC (PB Consult 2005)	HATS (Jones et al. 1983)	
FAMOS (Pendyala et al. 2005)	LUTDMM (Xu, Taylor and Hamnett, 2005)	
New York NYMTC (Vovsha and Chiao 2008)	MATSIM (Balmer, Meister and Nagel, 2008)	
Portland METRO (Bowman 1998)	STARCHILD (Recker, Mcnally and Root 1986)	
SACSIM (Bradley, Bowman and Griesenbeck 2009)	SCHEDULER (Gärling et al. 1989)	
SFCTA (Outwater and Charlton 2008)	SMASH (Ettema, Borgers and Timmermans,1996)	
Sacramento SACOG- DaySim (Bowman and Bradley 2005)	TASHA (Miller & Roorda, 2003)	
	TRANSIMS (Smith et al. 1995, Nagel and Rickert 2001)	

The period after the mid-1980s witnessed a growing application of micro-simulation approaches in transportation and land-use research. The concept of micro-simulation is one in which the aggregate behavior of a system is explicitly simulated over time as the sum of the actions and interactions of the disaggregate behavioral units within the system (Iacono, Levinson and El-Geneidy 2008, Miller and Savini 1998). While both micro-simulation and utility-based methods tend to be disaggregate models, the main advantage of the former over the latter is that it allows one to model the increasing heterogeneity of the urban lifestyle, new tendencies in mobility behavior as well as environmental impacts of land-use and transport policies at the necessary spatial resolution (Hunt et al. 2008, Wagner and Wegener 2007). Micro-simulation models also derive their strength from their dynamic nature, which makes it possible to trace model components (e.g., individuals, households, jobs, and dwellings) over time to observe the modeled processes of change at a level of detail that is not possible in other types of models (Pagliara and Wilson 2010).

Most activity-based travel demand models including CARLA, STARCHILD, SCHEDULER, TASHA, AMOS and ALBATROSS are hybrid micro-simulation systems that combine a rule-based computational process approach with recent paradigms of agent-based modeling (ABM) to mimic how individuals build and execute activity-travel schedules. Rule-based computational process models are computer simulation programs that use a set of rules (e.g., choice heuristics) in the form of condition-action (if-then) pairs to specify how a task, such as household activity-travel sequencing is carried out (Ben-Akiva and Bowman 1998). AMOS, for example, simulates the scheduling and adaptation of schedules and resulting travel behavior of individuals and households using `satisficing' rule as a guiding principle.

ABM, another disaggregate approach, is a bottom-up computational method that allows for the creation, analysis and experimentation with models composed of autonomous agents that interact with each other and their environment locally (Gilbert 2008, Railsback and Grimm 2011, Railsback, Lytinin and Jackson 2006, Wu and Silva 2010). ABM as a modeling technique allows for a natural description of a complex system in a flexible and robust manner so as to capture emergent phenomenon (Batty 2001, Bonabeau 2002, Castle and Crooks 2006, Wu and Silva 2010, Silva 2011). While the use of behavioral rules is similar to other disaggregate simulation techniques, ABM approach allows the agents (e.g., household members) to learn, modify, and improve their interactions with their environment (Batty 2007, Pinjari and Bhat 2010, Jin and White 2012, Silva 2011). TRANSIMS, for example, uses agent-based modeling and cellular automata (CA) techniques. CA are objects associated with areal units or cells; they follow simple stimulus-response rules to change or not to change their state based on the state of neighboring cells (Batty 2007, Silva 2011). In the CA-based TRANSIMS model, the transportation network is divided into a finite number of cells, approximately the length of a vehicle. At each time step of the simulation, each cell is examined for a vehicle occupant; vehicles can only move to unoccupied cells according to a simple set of rules. The CA approach in TRANSIMS allows one to simulate large numbers of vehicles and to maintain fast execution speed (Smith et al. 1995).

There are a number of constraints imposed by micro-simulation-based models. In addition to the large input data requirements, such models are slow to execute and require several running times, outputs between runs are also subject to significant stochastic variation and uncertainty (Krishnamurthy and Kockelman 2003, Nguyen-Luong 2008, Wagner and Wegener 2007). Stochasticity implies that model outputs after each run or iteration lack any predictable order. Micro-simulation often uses Monte Carlo simulation methods where random numbers are used in the process of deciding which of the available alternatives the decision maker will choose, given the calculated probabilities; model results are thus different if the model is rerun with different random numbers (Feldman et al. 2010). Over the years, innovative methodologies have been developed and applied to handle these challenges in existing operational models. These are discussed later under section 5.

As shown in table 1, the household activity pattern problem (HAPP) adopts a rather different modeling technique, which has had less application in transport and land-use research. The mathematical programming approach adopted draws inspiration from operations research, which involves the application of advanced analytical methods to arrive at optimal or near-optimal solutions to complex decision-making problems. The HAPP model is constructed as a mixed integer mathematical program to address the optimization of the interrelated paths through the time/space continuum of a series of household members with a prescribed activity agenda and a stable of vehicles and ridesharing options available (Recker 1995).

Despite the growing number of activity-based travel demand models, their adoption and use in practice, either independently or as transportation sub-models in existing operational LUTI modeling frameworks, has rather been slow (Rasouli and Timmermans 2014b, Recker 2001). Instead, as will be discussed in the immediately following section on integrated land-use and transport models (Section 4), the transportation sub-models of most of the existing operational LUTI models adopt the four-step approach.

4 Overview of current operational LUTI models

Over the past six decades, several LUTI models have been developed, calibrated, and applied in policy analysis at different spatial scales. As shown in Figure 3, most operational LUTI models have three main sub-model components, namely land use, socio-demographic, and transportation. These sub-models are either fully integrated or loosely coupled with each other to provide input-output linkages during model execution.

The land-use sub-model often contains important information on the urban land market, including residential and employment space ratio, land values, dwelling and occupancy types, land-use mix, housing vacancy, demolition and redevelopment. Most of the existing models (e.g., IMREL, KIM, MEPLAN, TRESIS, METROSIM, MUSSA, PECAS, RURBAN, TLUMIP, TRANUS, DELTA and URBANSIM) have detailed urban land and housing market sub-models.

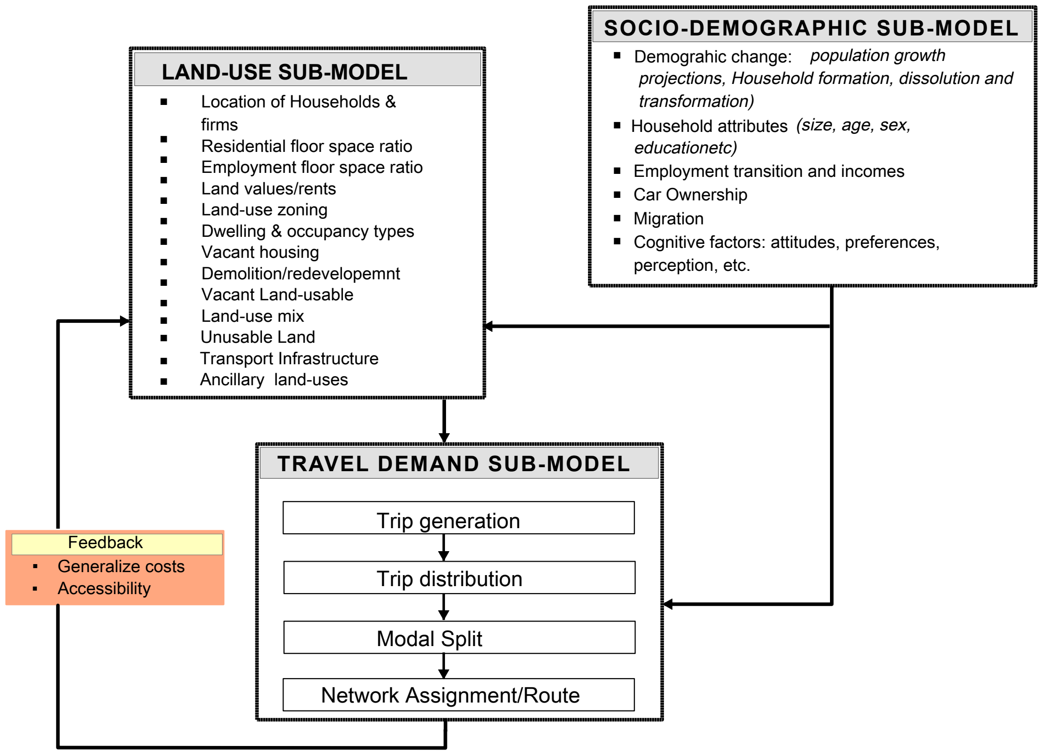

Figure 3: Generalized structure of an operational LUTI model

The socio-demographic sub-model contains important socioeconomic variables that mediate households' location choice and travel behavior. Different model platforms have varying levels of detail they capture in terms of socio-demographic factors and processes. DELTA-START (Simmonds and Still 1999 Simmonds 2001) and UrbanSim (Waddell 2000), for example, have detailed demographic transition sub-models that capture the dynamics of household formation, dissolutions, and transformations as well as an employment transition model that simulates the creation and removal of jobs. At the household level, the demographic sub-models of most LUTI modeling frameworks often divide households into segments of similar socioeconomic groups. LILT (Mackett 1983, 1990, 1991), MUSSA–ESTRAUS (Martinez 1992, 1996) and RAMBLAS (Veldhuisen, Timmermans, and Kapoen, 2000) are based on 3, 13, and 24 different population segments respectively. Some operational models—DELTA-START and IRPUD (Wegener 1982, 1996, 2004) capture migration processes as part of their socio-demographic sub-models.

There have been calls to combine revealed preference data with stated preference data in most utility-based LUTI models in order to avoid biases in selecting appropriate variables and generating choice sets associated with the former (Wardman 1988, Chang 2006). In TRESIS—the Transportation and Environment Strategy Impact Simulator—developed by Hensher and Ton (2002), for example, the behavioral system of choice models for individuals and households is based on a mixture of revealed and stated preference data.

The transportation sub-model of most of the existing operational LUTI models, particularly the spatial interaction-based and utility-based ones, adopt the four-step approach. As shown in Figure 3, the land-use sub-model is dynamically coupled with the transportation sub-model containing a network assignment component. The extent and capacity of networks in the transportation sub-models for most models is held fixed or treated as a policy variable and, therefore, does not allow for evolutionary dynamics in transport networks (Iacono, Levinson, and El-Geneidy 2008). Generalized transport costs, manifested by congested networks, travel times, and distance are fed into the calculation of accessibility indexes, which in turn provide a dynamic feedback input into the land-use system.

The development of operational LUTI models has undergone waves of modeling techniques. It is worth mentioning that the transition from one approach to the other does not necessarily result in a complete abonnement of the previous approaches. Rather, new modeling paradigms have combined lessons from the past with emerging theoretical and empirical insights, with the goal of overcoming the limitations of their predecessors. Table 2 shows a classification of exiting operational frameworks according to modeling techniques; each column reflects the dominant theoretical and methodological persuasion of the model developers.

As shown in Table 2, three main modeling methodologies have been applied in the development of existing operational models. Early LUTI models were aggregate spatial interaction-based, drawing on the gravity analogy with entropy maximization as the underlying theory. In nearly all spatial interaction-based models, space is treated as discrete systems of aggregate zones; the zone systems afford the advantage of linking models with available data more easily and developing more mathematically tractable models (Pagliara and Wilson 2010).

Table 2: Operational LUTI models and modeling techniques

Aggregate spatial interaction-based models	Aggregate utility-based models	Micro-simulation models	Other
ITLUP : DRAM, EMPAL, METROPILUS (Putman 198, 1991, 1998)	BASS / CUF Model (Landis 1994, Landis and Zhang 1998)	ABSOLUTE (Arentze Timmermans, 2000, 2004)	MARS (Pfaffenbichler 2011, Mayerthaler et al. 2009)— systems dynamics-based
KIM (Kim 1989, Rho and Kim 1989)	CATLAS, METROSIM (Anas 1983 1984 1994)	ILUTE (Miller and Savini, 1998, Miller et.al 2011)	
Leeds Integrated Land-Use model (Mackett 1983, 1990,1991)	DELTA-START (Simmonds and Still 1999, Simmonds 2001)	ILUMASS (Moeckel, Schürmann and Wegener 2002)	
Lowry-Garin model (Lowry 1964)	IMREL (Anderstig and Mattsson 1991 1998)	PECAS (Hunt et al. 2008)	
MEPLAN (Echenique, Crowther and Lindsay 1969, Echenique et al.1990)	IRPUD (Wegener1982, 1996, 2004)	RAMBLAS (Veldhuisen, Timmermans and Kapoen 2000)	
STASA (Haag 1990)	MUSSA -ESTRAUS (Martinez 1992 1996)	SIMPOP(Bura et al. 1996, Sanders et al. 1997)	
The Projective Land Use Model (Goldner, Rosenthall and Meredith1972)	RURBAN (Miyamoto and Udomsri 1996, Miyamoto et al 2007)	TRESIS (Hensher and Ton 2002)	
Time Oriented Metropolitan Model (Crecine1964)	Uplan(Johnston,Shabazian and Gao 2003)	UrbanSim (Waddell 2000, 2002, Waddell et al. 2003)	
TRANUS (de la Barra 1989, Donnelly and Upton 1998)			

The need to capture complex individual behavioral dynamics and to overcome the weak assumptions and misspecification errors inherent in aggregate spatial interaction models have culminated in the adoption of aggregate utility-based and micro-simulation methods—discussed under section 3.2.2—in LUTI modeling.

The metropolitan activity relocation simulator (MARS) adopts a somewhat different modeling approach. The model uses a systems dynamics approach in which a set of qualitative and quantitative tools are used to describe and analyze the dynamic feedback relationships between the land-use and transport systems and the underlying behavior (Pfaffenbichler 2011).

Besides modeling approaches, the geography of application of the existing models is worth discussing. That is the spatial contexts in which models have originated or which models have been calibrated with data. Out of the 28 models reviewed, nine have originated from the United States (i.e., BASS/CUF, CATLAS, METROSIM, UrbanSim, Uplan, Lowry-Garin model, TOMM, Irvine simulation models, and TLUMIP). To the knowledge of the authors, three of the models have been applied in the Asian context: LILT and RURBAN in Japan, and MARS in Chiang Mai, Hanoi, and Ubon Ratchathani. Moreover, three of the models (LILT, MEPLAN, and DELTA-START) have come from the United Kingdom. IRPUD, MEPLAN, and ILUMASS have been applied in the Dortmund region in Germany, while RAMBLAS and TRANUS have been applied in the Eindhoven region in the Netherlands and Curacao, La Victoria and Caracas in Venezuela, respectively. TRESIS has been used to investigate strategic-level policy initiatives for Sydney, Melbourne, Adelaide, Brisbane, Perth, and Canberra in Australia. Few of the existing models (i.e., LILT, ITLUP, MEPLAN, MARS and URBANSIM) have had large-scale international applications. ITLUP, a computer software for forecasting metropolitan spatial patterns of residential location and transportation, for example, has been calibrated for over 40 regions across the world. To the knowledge of the authors, not one of the existing LUTI models as of now has either been developed in or calibrated with data from any African city.

5 Discussion of the challenges, progress and future research directions

5.1 The challenges with disaggregation

A number of technical and practical challenges are imposed by disaggregate modeling approaches such as micro-simulation. First, micro-simulation-based disaggregate models increase considerably the demand for high-quality data, making model development and calibration very difficult tasks (Iacono, Levinson, and El-Geneidy 2008). Detailed data on activity participation and mobility patterns at the individual level, required in activity-based models, for example, are not readily available from national census, and are therefore expensive and time consuming to be conducted independently. Despite the unique opportunity presented by sensor technology such as GPS in mobile phones in allowing one to directly monitor travel, their use raises a number of privacy concerns and could meet opposition from civil society groups (Wegener 2011).

Another challenge emphasized in the literature is the long execution time involved in running disaggregate models as well as stochastic variation in model outputs for smaller samples and large numbers of choice alternatives (Harris 2001, Nguyen-Luong 2008, Veldhuisen et al. 2000, Waddell 2011, Wagner and Wegener 2007). This makes it difficult to examine a large number of scenarios required for the composition of integrated strategies or policy packages (Wegener 2011, Waddell 2011).

Besides the huge data requirement and stochastic variation, disaggregate models are fraught with uncertainties with respect to model outputs. Uncertainties about model outputs can result from model misspecification, imperfect input information, and innate randomness in events and behaviors that are being modeled (Krishnamurthy and Kockelman 2003, Poole and Raftery 2000). Krishnamurthy and Kockelman (2003) examined the propagation of uncertainty in outputs of DRAM-EMPAL in Austin, Texas. Their study found that over a 20-year prediction period, uncertainty levels due solely to input and parameter estimation errors were on the order of 38 percent for total regional peak-period vehicle miles travel, 45 percent for peak-period flows, and 50 percent and 37 percent for residential and employment densities, respectively. Such substantial variation in model results can be problematic especially when used to make a critical cost-benefit analysis of project alternatives that require huge investments.

There have been on-going efforts to develop state-of-the-art methodologies to address the problems of stochastic variation and associated uncertainty in predicted outputs of existing models. Under constraints of data collection, computing time, and stochastic variation, Wegener (2011) has advanced the need of modelers to work toward a theory of balanced multi-level urban models, which are as complex as necessary in scope, space, and time and yet parsimonious. Such a multi-level modeling approach has been applied to the IRPUD model developed for the Dortmund region; the model simulation takes place at three spatial scales (i.e. region, zones, and grid cells). ILUMASS adopts a similar three-tier scale of micro, meso- and macro-level modeling.

A handful of research studies in the field (e.g., Clay and Johnston 2006, Krishnamurthy and Kockleman 2003, Ševčíková, Raftery and Waddell 2011, 2007) have examined and applied methodologies for incorporating uncertainty to enhance the decision-making and evaluation capabilities of existing LUTI models. Monte Carlo simulation and multivariate regression analysis have been the main methods for assessing the distribution of outputs, which are functions of random inputs in LUTI models (see for example, Johnston and Clay 2006, Krishnamurthy and Kockelman 2003, Silva and Clarke 2002, 2005). Monte Carlo simulation, however, requires clear specification of outputs and single function inputs; these are extremely difficult for most integrated model outputs, and accuracy in approximation requires the use of high-order derivatives, further complicating the analyses (Krishnamurthy and Kockelman 2003). Ševčíková, Raftery and Waddell (2007, 2011) have modified and applied Bayesian melding, a method proposed by Raftery, Givens and Zeh (1995) and Poole and Raftery (2000), to assess uncertainty about quantities of policy interest in UrbanSim. Their results showed that simple repeated runs method produced distributions of quantities of interest that were too narrow, while Bayesian melding gave well calibrated uncertainty statements (Ševčíková, Raftery and Waddell 2007). Moreover, the application of emulators and ensembles—a statistical representation of the output of a more complex behavioral model to reduce computation times and to generate probabilistic forecasts—is being explored (e.g., Rasouli and Timmermans 2013). It is, however, early as far as research on the application of emulators to resolving uncertainty in transportation research is concerned (Rasouli and Timmermans 2014b).

Despite the growing innovation in methodologies for handling uncertainty, it is acknowledged in the literature that the outputs of different modeling frameworks are differently affected by variations in inputs and parameters. On the basis of this, it is essential that future research focuses on, among other things, understanding the growth in predicting uncertainties over time and across different model frameworks toward a principled way of addressing the problem of uncertainty (Waddell 2011).

5.2 Integrating activity-based models into LUTI models: Challenges and progress

Although there is increasing adoption of activity-based models by US metropolitan planning organizations, application of such models in Europe seems to have stagnated, while many Asian countries have demonstrated a complete lack of interest in these models (Rasouli and Timmermans 2014b). There are a number of reasons that explain the slow adoption of activity-based models. Practically, there is reluctance on the part of professionals to adopt this new approach as it requires a complete and massive substitution of their current models and associated practices (Wang, Waddell and Outwater 2011). Activity-based travel models are also fraught with the challenges of huge data requirement, stochastic variation, and output uncertainty associated with the micro-simulation methodology used. Notwithstanding the foregoing challenges, efforts are currently underway to integrate activity-based transport models with land-use models. There has been the attempt to incrementally integrate land-use models with activity-based travel models for operational use by Wang, Waddell and Outwater (2011). Other LUTI modeling frameworks including Ramblas, ILUMASS, UrbanSim, and TLUMIP also integrate the activity-based travel demand modeling paradigm.

Beyond the issue of integration, there are a number of areas needing further research in activity-based research. Experts have underscored the need for better understanding of the activity and vehicle allocation behavior among members of households; how negotiation and altruistic processes among individuals shape activity-travel patterns; the impacts of children and other mobility dependent individuals on adults activity-travel scheduling and implementation behavior; the appropriate time frame for different types of activities; and the complex interlacing of multiple time horizons that may be associated with the planning, scheduling, and execution of different activities and related travel over time

(Pinjari and Bhat 2011). Moreover, there is the growing need for a better understanding of the role of social networks in shaping activity-travel patterns in activity research beyond the descriptive and analytical narratives presented by existing empirical works (Axhausen 2005, Rasouli and Timmermans 2014b).

Future research in activity-based modeling and the integration of this research into existing LUTI modeling frameworks need to incorporate the principles of theories focusing on decision making under uncertainty to realistically capture the behavioral complexities underlying observed location and travel decisions of households. Furthermore, operational activity-based models of travel demand lack integrity across days of the week as existing models simulate activity-travel patterns of a typical day; future research needs to develop robust frameworks for conceptualizing and integrating the blurring boundaries between activity and travel episodes—resulting from the advent of smartphones, mobile computing and other information communication technology—into comprehensive activity-based LUTI modeling frameworks (Rasouli and Timmermans 2014b).

5.3 Measuring accessibility: Toward a satisfactory methodology

Accessibility impacts land values and shapes the location behavior of households and firms, which in turns impacts observed patterns of spatial interactions. Thus, to adequately assess and evaluate the long-term impacts of investment and policies affecting land use on transport and vice versa, more robust methodology is needed for deriving accessibility indices as the feedback mechanism of the land-use-transport link. However, accessibility, the key concept that links land-use with transportation is quite difficult and complex to theorize and operationalize in any meaningful and acceptable way (Geurs, De Bok, and Zondag 2012, Hanson and Giuliano 2004). Conventional approaches to accessibility measurement have included "person-based," "location-based," and "infrastructure-based" measures. A major drawback of location-based accessibility is that measures are aggregate as it treats all individuals in the reference zone as having the same level of accessibility to the destination (Hanson and Giuliano 2004). Also, Infrastructure-based accessibility measures exclude the land-use component and therefore do not correctly measure accessibility impacts of land-use strategies that affect the spatial distribution of activities (Geurs, De Bok and Zondag 2012). A "utility-based' accessibility measure (Geurs, De Bok and Zondag 2012), grounded in random utility maximization theory, and "space-time autonomy" approach have been proposed as more satisfying measures in the literature. The latter, however, is very difficult and complex to operationalize. It is also suggested that existing activity-based models be employed to develop activity-based measures of accessibility and be tested in modeling of various longer lifestyle decisions, as well as in more specific residential and workplace choices (Shiftan 2008).

5.4 Integrating the environment into LUTI models

Considerations for the environmental impacts of land use and transport in existing models are still very limited. Given that land use and transport activities impact the environment through greenhouse emissions, air pollution, and traffic-noise generation, there is the need for land-use transport models to be linked to advanced environmental sub-models (Wegener 2004). The ILUMASS project (Wagner and Wegener 2007) and TRESIS—the Transportation and Environment Strategy Impact Simulator (Hensher and Ton 2002)—constitute on-going efforts toward the integration of land use, transportation, and the environment. The UK Tyndall Centre for Climate Change Research Cities program is also developing a GIS-based integrated land-use transport model and climate change impact analysis tools to explore the implications of climate risks as a result of different spatial planning strategies that will enable urban planners to explore the trade-offs between these strategies (Ford et al. 2010).

Existing LUTI models are unable to forecast the impact of future urban-policy responses to climate change such as carbon taxes and emission trading, enforcement of anti-sprawl legislation, transport demand management through road pricing or parking fees, the redirection of transport investment to public transport, promotion of alternative vehicles or fuels, and the impacts of significant energy price increases among others (Wegener 2011). The potential impacts of these policy responses on urban location and mobility decisions, as opposed to the known impacts of individual lifestyles and preferences, and the implications for modeling techniques will be an interesting line of inquiry in future research.

6 Conclusion

This paper has provided a comprehensive overview of some 60 years of research in the field of LUTI modeling. The review has shown that the field has benefited from new possibilities accruing from advances in computing technologies including GIS and disaggregate modeling methodologies such as micro-simulation. Notwithstanding the on-going progress and innovation, there are a number of areas needing further research. Further research is needed to understand uncertainty propagation over time and across different model frameworks and to develop and apply innovative methodologies to handle the challenge of stochastic variation and associated uncertainties in disaggregate model outputs. Second, there is the need to bridge the gap between the proliferation of activity-based travel demand models and their integration with operational LUTI models in practice. Third, the capabilities of existing models need improvement with respect to integrating the environment and forecasting the impact of future urban policy responses on climate change and energy scarcity. The potential effects of increased energy prices on urban location and mobility choices of individuals and their implications for modeling methodologies are also worth exploring. Finally, robust methodologies for measuring accessibility, the key concept that links land-use and transportation, are needed to adequately evaluate the effects of land-use policies on transportation and vice versa.

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