Land Use-Transport Interaction Modelling: A Review of the Literature and Future Research Directions

Abstract

The aim of this review paper is to provide a comprehensive and up-to-date material for both researchers and professionals interested in Land-use-Transport Interaction (LUTI) modelling. 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, the existing operational LUTI modelling frameworks as well as the modelling 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 towards integrating the environment into LUTI Models.

***Key Words**: Land-use, Transportation, Four-step Model, Activity-based Approach, Micro-Simulation, Stochasticity, Uncertainty*

1. Introduction

Following the pioneering work of Hansen (1959) in Washington DC which established that trip and location decisions co-determine each other, the notion that land-use and transportation interact with each other has been widely recognised 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 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 *et al*., 2005; Chang, 2006; Iacono *et al*., 2008; Silva and Wu, 2012). These review papers focused on existing operational modelling frameworks, the challenges as of the time and the steps that were being taken to address them. The current paper builds on the existing reviews. It begins with a discussion of the dominants 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 modelling 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 modelling frameworks, focusing on their structure, the modelling methodologies, and the geography of application of these models. On the basis of these, the current challenges, on-going progress and the 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 micro-economic theory, they enjoy sound theoretical basis and offer a robust framework for qualitative analysis of the relationship between location and transport (~~Barra~~de la Barra, 1989; Waddell, 1997). However, as ~~Barra~~de la Barra (1989) notes, the applied fields of transportation and urban modelling 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 modelling LUTI emerged the Gravity/Spatial Interaction (SI) approach in the 1960s. Popularised 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 behaviour. 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 modelling results from the relative location of workers, jobs and housing in the city (~~Barra~~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 onwards, McFadden's (1973) Random Utility Theory (RUT) gained prominence in LUTI modelling. At the time, there was the need for a robust framework that could capture the complex choice behaviour dynamics involved in land-use and transport decisions at the individual level, whilst 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 behaviour (Iacono *et al*., 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 behavioural mechanisms that result in observed location-travel decisions (Ettema 1996; Fox, 1995; Pinjari and Bhat, 2011).

Classical u~~U~~tility theory ~~is also grounded in unrealistic assumptions of~~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 have begun to draw on a number of theories focusing on decision making under uncertainty. Decision making under uncertainty is viewed as 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 are therefore 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 (Daniel Bernoulli, 1738; von Neumann and Morgenstern, 1944; Savage, 1954), Prospect theory (Kahneman and Tversky, 1979) and Regret theory (~~David~~Bell, 1982; Fishburn, 1982; Loomes and Sugden, 1982, 1987).

Expected Utility theory (EUT) was formulated in the 18th century by Daniel Bernoulli (1738) and further developed by von Neumann and Morgenstern (1944) and Savage (1954) as a descriptive model of economic behaviour. 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 their 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 towards 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 behaviour, 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 whilst 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, 1955, 1957, 2000; Tversky, 1969). Taking their roots from social psychology and behavioural 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 *et al.,* 1993; Innocenti *et al.,* 2013; Zhu and Timmermans, 2010). Leong and Hensher (2012) in their review, identified four types of heuristics strategies employed by individuals in their choice behaviour namely; satisficing, lexicography; elimination-by-aspects and majority of confirming dimensions. Few research in the area of transportation and location choice have however, applied these heuristic strategies in understanding choice behaviour (e.g. Arentze, *et al.,* 2000; Foerster, 1979; Innocenti *et al.,* 2013; Recker and Golob, 1979; Young, 1984; Zhu and Timmermans, 2010). This perhaps, is due to the difficulty in operationalising the principles of heuristics compared to utility maximization theory.

Regret theory (RT) is attributed to seminal works of ~~David~~Bell (1982), Fishburn (1982) 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 behaviourally focused theory, from the psychology literature is Theory of Planned Behaviour (TPB) proposed by Ajzen (1985, 1987). The central claim of TPB is that intentions are the motivational factors that influence behaviour and that behaviour in turn, can be predicted with high accuracy from attitudes toward the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991). Proponents further posit that these components of behaviour are determined by behavioural beliefs, normative beliefs and control beliefs; and that changes in these beliefs should lead to behaviour change (Heath and Gifford, 2003). The most recent land-use and transport related research that have adopted TBP include the works of Bamberg and colleagues (2003), De Bruijn *et al.* (2009) , Haustein and Hunecke (2007), Heath and Gifford (2000) and Wu and Silva (2014).

An equally important theoretical tradition relevant for LUTI modelling is the Time-Geography paradigm attributed to the original work of Hägerstrand (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, 2005; Peters *et al*., 2010). Conceptually, time-geography theory uses a space-time prism to analyse the envelope of possibilities open to an individual, subject to a number of spatio-temporal constraints. Crease and Reichenbacher (2013) and Miller (2004) 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; *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 Hagertrand's time-geography paradigm is conceptually simple, modelling activity-travel behaviour using the framework in practice, is difficult and complex (Ben-Akiva and Bowman, 1998; McNally, 2000).

Complexity theory and general systems theory (~~Bertalanffy~~ von Bertalanffy , 1950; Boulding, 1956; Forrester, 1993) have also gained recognition in the field of urban and regional planning in general and LUTI modelling 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 modelling, complexity theory can provide a robust framework to study the path-dependent and emergent behavioural 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 in order 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 have drawn on a number of theories that can be applied either at an aggregate or disaggregate levels of understanding decision-making behaviour. 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 modelling respectively.

Level of aggregation	Low	moderate	High
Macro	- Urban (micro) economics theory and models	- Entropy maximization-spatial Interaction models	- Time-geography theory - Heuristic/bounded rationality - Theory of Planned behaviour Systems & complexity theory
Micro		- Discrete-choice/ random Utility theory - Expected Utility Theory - Prospect Theory - Regret Theory	- Time-geography theory - Heuristic/bounded rationality - Theory of Planned behaviour - Systems &~~and~~ complexity theory

Level of complexity

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 ~~also focus on~~are applied at both the macro and micro~~-~~ levels of analysis, but require relatively highly complex formulations in their operationalization. The time-geography paradigm for example, imposes high level of complexity and combinatorial challenges. Heuristic/bounded rationality theory and the theory of planned behaviour are social cognitive models that can be operationalized but with very abstract and subjective psychological constructs using complex statistical methods such as Structural Equation Modelling~~s~~ ~~(SEM).~~

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 conceptualising 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 the 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 decentralisation 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 interact with transportation, at least at the conceptual level, the mechanisms through which the systems impact each other have been difficult to isolate and measured empirically. This is because of the complex interaction among the 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 encapsulate 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 behaviour (e.g. Aditjandra *et al.*, 2013; Grunfelder and Nielsen, 2012; Gim, 2013; Handy et al, 2005; Meurs and Haaijer, 2001; Næss, 2013). Other studies have however, reported marginal or weak causal link between commuting behaviour and urban form (e.g. Cevero and Landis, 1997; Chowdhury *et al.,* 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.

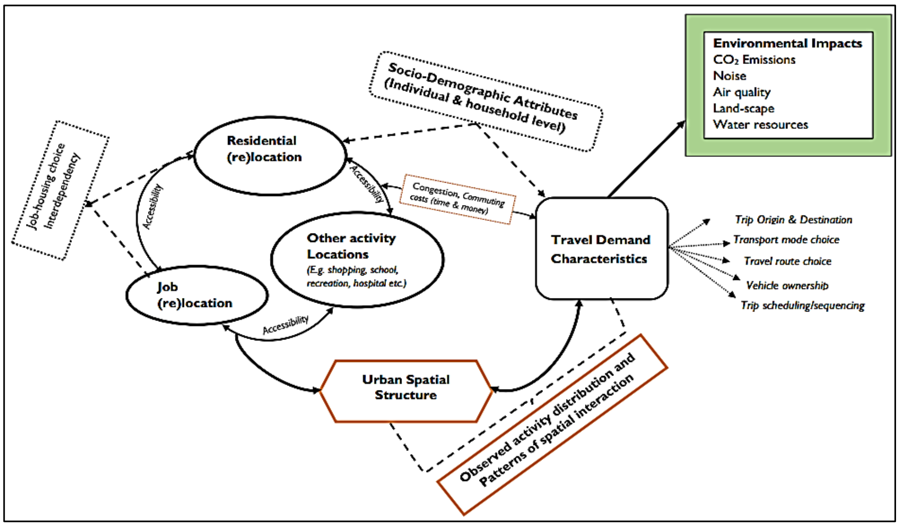

Figure 2: A conceptual model showing the components the land-use-transport system

3.1. The Land-use Component: Residential-Job Location 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 behaviour of households with regards 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 *et al*., 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 in order 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). Although in many urban models all employment is endogenous, the ~~The~~ residential location component of ~~a number of~~some operational LUTI models are 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 household 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 et al., 2010). Other factors identified in the literature are the degree of

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commercial or mixed land uses in an area, incomes, neighbourhood composition (Pinjari et al, 2011), social networks (Tilahun and Levinson, 2013) and the evolution of household membership and family structures over time (Habib et al., 2011; Lee and Waddell, 2010).

More recent empirical works (e.g. Boschmann, 2011; Habib *et al.,* 2001; Kim *et al.,* 2005; Pinjari *et al.,* 2011; Tilahun and Levinson, 2013; Waddell *et al.*, 2007) 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 these newly emerging empirical evidence in order 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 modelling 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 modelling 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~~).~~

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3.2. The Transport Component: Modelling Approaches and Limitations

The transport component of LUTI models, as shown in figure 2, focuses on understanding travel behaviour 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 behaviour. As shown in the conceptual framework, these attributes of travel demand are influenced by spatial structure as well as socio-demographic factors. Travel behaviour and the associated transport infrastructure in turn, poses environmental impacts through greenhouse gas emission, noise generation, effects on air quality, landscape and water resources.

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

3.2.1The 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 travels 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 modelled 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 *et al.,* 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., 2010). 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 modelled (Pinjari and Bhat, 2011; Malayath and Verma, 2013; McNally, 2000). Given that different trip purposes are modelled 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 behavioural complexities in travel captured in the FSM is limited (Martinez *et al.,* 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 Modelling Approach

The Activity-Based Approach (ABA) gained momentum around the 1990s with the promise of delivering a *behaviourally-oriented* alternative to the FSM. The conceptual underpinnings of this approach integrate aspects of the time-geography paradigm, 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 constrains within which activity-travel behaviour occurs; the complex interpersonal dynamics resulting from the interaction among household members and social networks; and activity scheduling and trip-chaining behaviour in time and space (Ettema, 1996; Bhat and Koppelman, 1999; Kitamura, 1988; Pinjari and Bhat, 2010;).

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, 2010). More recently, emphasis has shifted to activity scheduling and trip chaining behaviour of households. Activity scheduling attempts to capture the processes by which individuals implement interrelated set of activity decisions interactively with others during a defined time cycle (Axhausen and Gärling, 1992; Ettema, 1996). Whereas trip-based approach is satisfied with models that generate trips, ABA focuses on what generated the activities which in turn generated the trips through analysis of observed daily or multi-day patterns of behaviour (McNally, 2000; Dong *et al.,* 2006; Lin *et al.,* 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 modelling 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, 2014 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 behaviour (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 dimension, modellers are presented with a fundamental combinatorial challenge (Ben-Akiva and Bowman, 1998; Rasouli and Timmermans, 2014) 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 modelling techniques adopted is presented in Table 1.

All activity-based models are disaggregate. As shown in Table 1, two main disaggregate modelling approaches namely; 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 in order 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 Modelling: Applications and Modelling Techniques

Utility Maximization-based models	**Micro-Simulation models**	**Other**
Atlanta ARC (PB et al., 2006)	ALBATROSS (Arentze and Timmermans, 2000, 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 *et al.,* 2005)	
New York NYMTC (Vovsha, et al., 2002)	MATSIM (Balmer *et al.,* 2005)	
Portland METRO (Bowman, 1998)	STARCHILD (Recker *et al.,* 1986)	
SACSIM (Bradley et al., 2009)	SCHEDULER (Gärling *et al.,* 1994)	
SFCTA (Outwater and Charlton, 2006)	SMASH (Ettema *et al.,* 1993, Ettema et al., 1996)	
Sacramento SACOG- DaySim (Bowman and Bradley, 2005)	TASHA (Miller & Roorda 2003)	
	TRANSIMS (Smith et al., 1995; Nagel *et al.,*2001)	

The period after the mid-1980s has 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 behaviour of a system is explicitly simulated over time as the sum of the actions and interactions of the disaggregate behavioural units within the system (Iacono *et al.,* 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 to model the increasing heterogeneity of urban lifestyle, new tendencies in mobility behaviour 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 in order to observe the modelled 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 rule-based computational process approach with recent paradigms of agent-based modelling (ABM) to mimic how individuals build and execute activity-travel schedules. Rule-based computational process models are computer simulation programmes 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 behaviour 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 (~~Nigel~~Gilbert , 2008; Railback and Grimm, 2011; Railsback *et al.,* 2006; Wu an Silva, 2010). ABM as a modelling 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~~ Castle and crook~~*et al.*~~, 2006; Wu and Silva, 2010; Silva, 2011). While the use of behavioural 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 and Wu, 2010). TRANSIMS for examples uses agent-based modelling 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 neighbouring 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 simple set of rules. The CA approach in TRANSIMS allows to simulate large numbers of vehicles and to maintain fast execution speed (Smith *et al.,* 1995).

There are a number constraints imposed by micro-simulation-based models. In addition to the large input data requirements, such models are slow to execute and requires several running time; outputs between runs are also subject to significant stochastic ~~variation and~~variation and uncertainty (Krishnamurthy *et al.,* 2003; Nguyen-Luong, 2008; Wagner and Wegener, 2007). Stochasticity implies that model outputs after each run or iteration lacks any predictable ~~Over~~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.

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As shown in table 1, the Household Activity Pattern Problem (HAPP) adopts a rather different modelling 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 nearoptimal 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 activity-based travel demand models, their adoption and use in practice, either independently or as transportation sub-models in existing operational LUTI modelling 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-model 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.

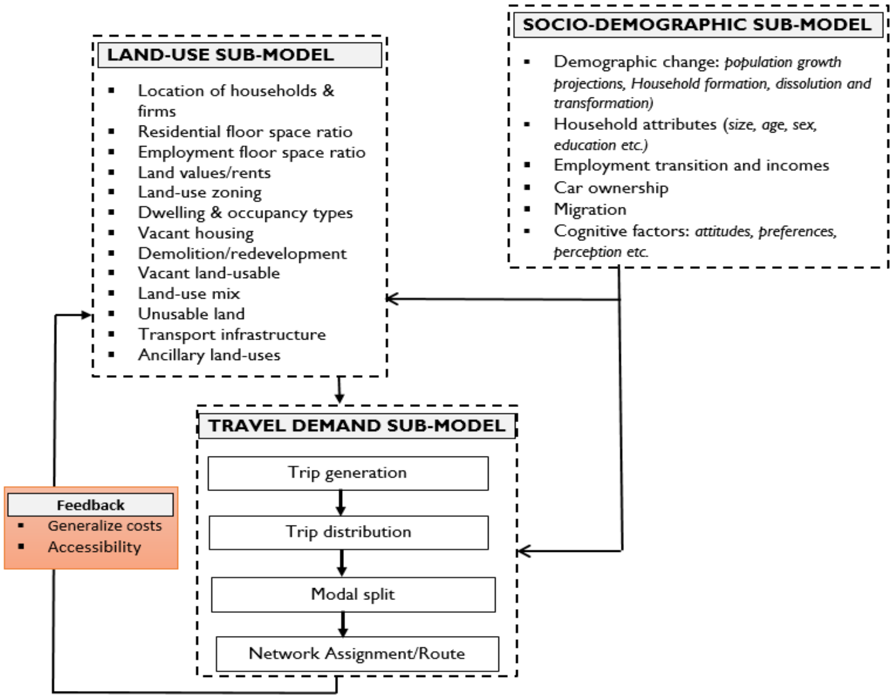

Figure 3: Generalized structure of an operational LUTI Model

The land-use sub-model often contains important information on 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.

The socio-demographic sub-model contains important socio-economic variables that mediate households' location choice and travel behaviour. Different model platforms have varying levels of detail they capture in terms of socio-demographic factors and processes. DELTA-START (Simmonds and Still, 1998; Simmonds, 2001) and UrbanSim (Waddell, 2000) for example, have detailed demographic transitions sub-models that capture the dynamics of household formation, dissolutions and transformation as well as employment transition model that simulates the creation and removal of jobs. At the household level, the demographic sub-model of most LUTI modelling frameworks often divide households into segments of similar socio-economic groups. LILT (Mackett, 1983, 1990, 1991), MUSSA–ESTRAUS (Martinez, 1992, 1996) and RAMBLAS (Veldhuisen, *et al*, 2000) are based on 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 (2001) for example, the behavioural 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 *et al.,* 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 modelling 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 modelling 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 modelling techniques; each column reflects the dominant theoretical and methodological persuasion of the model developers.

Table 2: Operational LUTI Models and Modelling Techniques

Aggregate Spatial Interaction-based Models	**~~Utility maximization~~Aggregate Utility-based Models**	**Micro-Simulation Models**	**Other**
ITLUP : DRAM, EMPAL, METROPILUS *(Putman,1983, 1991, 1998)*	BASS / CUF Model *(Landis, 1994; Landis & Zhang, 1998)*	ABSOLUTE *(Arentze et al., 2003)*	MARS *(Pfaffenbichler, 2011; Pfaffenbichler et al., 2010; 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 a.l, 2011)*	
Leeds Integrated Land-Use model (*Mackett, 1983, 1990, 1991)*	DELTA-START (*Simmonds and Still, 1998; Simmonds, 2001)*	Irvine simulation models *(McNally, 1997, 1998)*	
Lowry-Garin model *(Lowry, 1964; Garin 1966)*	IMREL *(Anderstig & Mattsson, 1991,1998)*	ILUMASS *(Moeckel, et al., 2002)*	
MEPLAN *(Echenique et al., 1969, 1990; Hunt & Echenique, 1993)*	IRPUD *(Wegener,1982;* 1996;2004*)*	PECAS *(Hunt et al., 2008)*	
STASA *(Haag, 1990)*	MUSSA -ESTRAUS *(Martinez, 1992, 1996)*	RAMBLAS *(Veldhuisen, et a.l, 2000)*	
The Projective Land Use Model *(Goldner, 1972)*	RURBAN *(Udomsri, 1996; Miyamoto et al., 2007)*	SIMPOP*(Bura, et al., 1996; Sanders, et al., 1997)*	
Time Oriented Metropolitan Model *(Crecine,1964)*	Uplan *(Johnston, et a.l, 2003)*	TRESIS (Hensher and Ton, 2001)	
TRANUS *(d~~D~~e la Barra 1989; Donnelly and Upton, 1998)*		UrbanSim *(Waddell 2000, 2002; Waddell et al., 2003)*	

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As shown in table 2, three main modelling 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 to develop more mathematically tractable models (Pagliara and Wilson, 2010). . The need to capture complex individual behavioural dynamics and to overcome the weak assumptions and misspecification errors inherent in aggregate spatial interaction models has culminated in the adoption of ~~dis~~aggregate utility-based and micro-simulation methods—, d~~D~~iscussed under section *3.2.2*– in LUTI modelling.

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The Metropolitan Activity Relocation Simulator (MARS) adopts a somewhat different modelling approach. The model uses a systems dynamics approach in which a set of qualitative and quantitative tools are used to describe and analyse the dynamic feedback relationships between the land-use and transport systems and the underlying behaviour (Pfaffenbichler, 2011).

Besides modelling 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, 9~~11~~ have originated from the USA (i.e. ~~MEPLAN,~~ BASS/CUF, ~~MUSSA ESTRAUS,~~ CATLAS, METROSIM, UrbanSim, Uplan, Lowry-Garin model TOMM, Irvine simulation models and TLUMIP). To the knowledge of the authors, 3 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, 3 of the models (LILT, MEPLAN and DELTA-START) have come from the UK. IRPUD, MEPLAN, and ILUMASS have been applied in the Dortmund region in Germany whilst 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, none of the existing LUTI models as of now, have 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 modelling 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 *et al.,* 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 to directly monitor travel, their use raises a number of privacy concerns and may meet opposition from civil society groups (Wegener, 2011).

Another challenge emphasised 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).

Beside 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 behaviours that are being modelled (Krishnamurthy *et al.,* 2003; Poole and Raftery, 2000). Krishnamurthy and colleagues (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 was on the order of 38% for total regional peak-period Vehicle Mile Travel, 45% for peak-period flows, and 50% and 37% for residential and employment densities, respectively. Such substantial variation in model results can be problematic especially when used to make 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 or modellers to work towards 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 modelling 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 adopt a similar three-tier scale of *micro*, *meso* and *macro level* modelling.

A handful of research in the field (e.g. Clay and Johnston, 2006; Kockleman, 2003, 2006; Ševcˇíková *et al.,* 2011; Ševcˇíková et al., 2007) have examined and applied methodologies for incorporating uncertainty in order 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, Clay and Johnston, 2006; Krishnamurthy *et al.,* 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 *et al.,* 2003). Ševcˇíková *et al.,* (2007, 2011) have modified and applied Bayesian melding, a method proposed by Raftery *et al.,* (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 (Ševcˇíková *et al.,* 2007). Moreover, the application of emulators and ensembles—a statistical representation of the output of a more complex behavioural model to reduce computation times and to generate probabilistic forecasts is being explored (e.g. Rasouli and Timmermans, 2013). It is however early days yet 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 modelling frameworks are differently affected by variations in inputs and parameters. On the basis of this, it is essential that future research focuses, among other things, on understanding the growth in predicting uncertainties over time and across different model frameworks, towards a principled way of addressing 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 seem to have stagnated whilst 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 *et al.,* 2011). Activity-based travel models are also fraught with the challenges of huge data requirement, stochastic variation and output uncertainty associated with micro-simulation methodology used. Notwithstanding the foregoing challenges, efforts are currently underway to integrating activity-based transport models with land-use models. There has been the ~~first~~ attempt to incrementally integrate land-use models with activity-based travel models for operational use by Wang and colleagues (2011). Other LUTI modelling frameworks including Ramblas, ILUMASS, UrbanSim and TLUMIP also integrate the activity-based travel demand modelling 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 behaviour 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 behaviour; 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, 2010). 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, 2006; Rasouli and Timmermans 2014b).

Future research in activity-based modelling and their integration into existing LUTI modelling frameworks need to incorporate the principles of theories focusing on decision making under uncertainty in order capture realistically, the behavioural 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 need to develop robust frameworks for conceptualizing and integrating the blurring boundaries between activity and travel episodes—resulting from the advent of smart phones, mobile computing and other ICT—into comprehensive activity-based LUTI modelling frameworks (Rasouli and Timmermans, 2014b).

5.3 Measuring Accessibility: Towards a Satisfactory Methodology

Accessibility impacts land values and shapes the location behaviour of households and firms which in turns impact observed patterns of spatial interactions. Thus, in order 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 theorise and operationalize in any meaningful and acceptable way (Geurs et al., 2012; Hanson, 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, 2004). Also, Infrastructure-based accessibility measure excludes the land-use component and therefore do not correctly measure accessibility impacts of land-use strategies that affect the spatial distribution of activities (Geurs et al., 2012). A “utility-based’ accessibility measure (Geurs et al., 2012), grounded in random utility maximisation 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 modelling 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 impacts 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 towards the integration of land-use, transportation and the environment. The UK Tyndall Centre for Climate Change Research Cities programme 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 modelling techniques will be an interesting line of enquiry in future research.

6. Conclusion

This paper has provided a comprehensive overview of some 60 years of research in the field of LUTI modelling. The review has shown that the field has benefited from new possibilities accruing from advances in computing technologies including GIS and disaggregate modelling methodologies such as micro-simulation. Notwithstanding the on-going progress and innovation, there are a number of areas needing further research. Further research in 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. Secondly, 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. Thirdly, 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 modelling methodologies are also worth exploring. Finally, robust methodologies for measuring accessibility, the key concept that links land-use and transportation, is needed in order to adequately evaluate the effects of land-use policies on transportation and vice versa.

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