MODELLING TRANSPORT:
A Synthesis of Transport Modelling Methodologies

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1. INTRODUCTION AND BACKGROUND

The transport sector contributes to a significant proportion of the energy consumed in an urban area (Figure 1, for instance, depicts energy consumption in London, by sector, for the year 2001). In order to quantify the energy consumed by the transport sector, it is necessary to develop travel demand models that can predict the travel needs of the population by mode, time of day, duration and location. Such travel demand models must consider the travel needs not only of individuals but also of businesses and other organizations.

![Figure 1. Total energy consumption, by sector, in primary energy equivalents, 2001](source: Department of Trade and Industry (DTI, 2002))
1.1. A Brief History of Land-use and Travel Demand Modelling

The need for travel demand models was recognized by urban and transport planners and researchers as far back as the mid-nineteenth century with the macroeconomic modelling of the spatial flows of people and commodities (see, for example, Carey, 1859). For nearly a century transport planners relied on various aggregate approaches of estimating spatial movements and flows, such as entropy- and gravity-based models. The mid-twentieth century saw the development of a sequential process of estimating travel demand, based on aggregate approaches, that was known as the four-step model. A relatively disaggregate version of the 4-step model is used to this day by several metropolitan planning organisations worldwide.

Parallel to the development of the four-step model of travel demand, urban planners also recognised the intricate interactions between the transport network and the rest of the urban system. Figure 2 presents a conceptual representation of the interactions between the various players in an urban system (Southworth, 1995). At the core of this figure is the transport system, which is influenced by the land-use configuration and the travel needs of people and businesses, and regulated by government plans and controls. Changes in the transport supply, in turn, influence the residential and work location choices of the population as well as business location decisions, thus influencing the land-use configuration. Further, there are demographic and firmographic processes independent of the transport system that influence the land-use configuration and thus indirectly influence the demand for transport. The final piece of this puzzle is the environment, in the form of emissions and energy-consumption resulting from transport and other activities undertaken by people and businesses. The environmental link has long been considered as being external to the land use-transport system, and it is only in recent times that the importance of internalising environmental impacts has been acknowledged.
In recognition of the complex dynamics of an urban system, urban planners in the 1950s and ’60s initiated the development of integrated land use-transport (LU-T) models. The first of these models to gain popular notice was Lowry’s model of Metropolis in 1964. Since then there have been several integrated LU-T models developed worldwide such as ITLUP (Putman, 1983), MEPLAN (Echenique, 1985), MUSSA (Martínez, 1992), and UrbanSim (Waddell, 2002). While the land-use components of these LU-T models have been rapidly evolving from simple aggregate representations to complex economic and econometric models of the market processes, the 4-step model continues to represent the transport modelling component.

Meanwhile, however, the travel demand model has evolved greatly from the simple 4-step models of the 1960s. On the one hand, advances in econometric modelling led to the adoption of disaggregate choice models within the 4-step modelling framework. Further enhancements were due to conceptual advances such as the recognition of the linkages between trips, which resulted in tour-based 4-step models. A paradigm shift occurred with the development of the activity-based approach to travel demand modelling (see Axhausen and Gärling, 1992, for a description). This approach, a direct result of the growth in travel behaviour research, recognises that the travel needs of an individual (or firm) are driven by the desire (or
need) to participate in activities at different geographical locations. Activity-based models thus shift the focus from a descriptive analysis of flows to an intricate understanding of decision-making by various entities. Although there exists a vast body of literature on activity-based modelling and the state-of-the-art of activity-based models is fairly advanced, there are few fully operational activity-based travel demand models.

With the development of state-of-the-art activity-based modelling systems, the 21st century is also witness to the development of ‘next-generation’ integrated LU-T models such as ILUTE (Salvini and Miller, 2003) and RAMBLAS (Veldhuisen et al., 2000), as well as the evolution of existing models such as UrbanSim. These ‘next-generation’ LU-T models are disaggregate, activity-based and strive for greater integration between the various components of the land use-transport system.

1.2. Structure of the Report

The rest of this report is structured as follows.

Section 2 describes in detail the land-use transport models in existence today. This section also identifies the many modelling methodologies applied within the land-use and travel demand modelling systems.

In recent years, the development of disaggregate, agent-based models of land-use and travel demand has been accompanied by the development of micro-simulation based methods of implementation. Section 3 discusses the micro-simulation approach in brief and describes the key components of such an implementation model.

Section 4 presents a relatively recent body of literature that examines the links between transport provision and economic productivity. Although the link between transport and productivity has been long acknowledged, transport planners and policy-makers have not, until recently, attempted to clearly understand this link. Understanding this link, and further internalising this within the LU-T model, is key to accurate estimation of the effects of changes to the transport system.

Section 5 concludes this report and discusses the approach to modelling an urban system in its entirety, with specific focus on the issue of energy consumption. This section also presents a framework of land use and transport related policies that a LU-T model should ideally be able to address.
2. INTEGRATED LAND-USE TRANSPORT MODELS

As described in the previous section, the development of land-use and travel demand models can be presented in three distinct strands. One strand follows the development of travel demand models from the early 4-step models to the advanced activity-based travel demand models. The second strand follows the development of operational integrated land use-transport models with the 4-step model predominantly forming the transport component. And the third strand follows the development of advanced ‘next-generation’ LU-T models that are disaggregate and use the activity-based approach within the transport component. Each of these three strands is discussed in greater detail in the following sections (sections 2.1–2.3). This is followed by a discussion of the key modelling methodologies applied in current LU-T modelling systems (section 2.4).

2.1. Development of Travel Demand Models

2.1.1. Aggregate Models

The earliest travel demand models were simple mathematical models, such as a gravity model or an entropy model that quantified travel as a function of the size of a zone. These were essentially aggregate level trip-based models. The number of trips generated from a zone was considered to be proportional to the population in the zone, while the number of trips attracted to a zone was considered to be proportional to the number of sources of attraction in the zone. Moreover, the travel between zones was considered to be inversely proportional to the distance between the zones (also referred to as ‘impedance’).

2.1.2. Disaggregate Trip-based Models

Advances in modelling techniques resulted in a shift away from these aggregate models and led to the development of disaggregate trip-based models. These models use disaggregate level data on the trips made by individuals between the zones in the study area, and apply modelling methodologies such as constrained optimization and random utility maximisation. The fundamental difference between aggregate and disaggregate models is that the disaggregate models view the individual (or household or firm) as the decision-making unit. In other words, the disaggregate models take into account the effects of individual socio-demographics (or firm characteristics) on travel-related choices. However, in practice, due to data limitations
and modelling constraints, disaggregate trip-based models are sometimes (even to this day) implemented in an aggregate manner with aggregate zonal socio-demographic data.

Despite the move to a disaggregate approach, trip-based models continued to exhibit several critical limitations. The most criticised of these limitations was the fact that trip-based models do not consider the linkages between trips. For instance, a commute trip from home to work in a trip-based model is treated independently of the return commute from work to home, and both trips are classified as home-based work trips. As a result, these early models could potentially assign different modes of travel to the home-work and the work-home trips. Tour-based models were developed to address this limitation.

2.1.3. Tour-based Models

Most travel demand models currently in operation use a tour-based 4-step modelling approach. This approach divides all individual travel into tours based at home and trips not based at home. For instance, a home-based work tour involves travel from home to work and back to home. Operational tour-based models typically consider the following home-based tour purposes – work, education, shopping, personal business, employers’ business and other. All the remaining non-home based trips, such as a trip from the work place to lunch, or a trip from one shopping location to another, or a business trip from work, are classified under two purposes – non-home based employer’s business and non-home based other. Within the 4-step modelling framework, the frequency of these tours and trips is first predicted (known as the tour generation step). This is typically followed by mode-destination choice models or mode-destination-time period choice models in more advanced model systems (combined tour distribution and mode choice step). And finally, the network assignment procedure allocates the tours to the transport network.

Tour-based models, although popular in practice, are still rather limited. They suffer from a lack of behavioural realism on several counts, many of which they share in common with the trip-based approach. First, tour-based models continue to neglect linkages between trips. For instance, if a person drives from home to work and then stops at the grocery store on the way back home, this would be viewed by tour-based models as one home-based work trip and one non-home based ‘other’ trip. Second,
tour-based models often neglect trips made specifically to serve passengers (example, pick-up or drop-off children at school). Third, tour-based models do not consider potential trade-offs across travel purposes. For instance, an individual with limited time on her hands may decide against shopping for the day and choose to eat out instead. Fourth, tour-based models do not consider the effects of household interactions on travel. Fifth, tour-based models do not consider the effects of in-home activities on travel. Clearly, the key shortcoming of tour-based models is that they are not behaviourally realistic.

2.1.4. Activity-based Models

The solution to the limitations of the trip and tour-based approaches is the activity-based paradigm (see Bhat et al., 2003, for a detailed discussion of the differences between trip/tour-based and activity-based models). Activity-based models acknowledge the fact that the travel needs of the population are determined by their need to participate in activities spread out over time and space. Consequently, an individual’s activity patterns, both in-home and out-of-home, influence the individual’s travel patterns. For instance, if a person participates in e-shopping over the internet at home, the in-home activity may satisfy her shopping needs and she may, as a result, not make a trip to the local mall. In order to accurately quantify the travel needs of the population, it is therefore important to model the activity-travel patterns of the population (the activity-travel pattern of an individual is defined as a complete string of activities undertaken by the person over the course of a day characterised by location, time of day, and mode of travel between locations). Further, it is important to acknowledge that human beings are not islands and that they interact with each other extensively. Therefore an individual’s activity-travel patterns are influenced by those of other individuals within the population, and particularly by the activity-travel patterns of other household members.

There are a few operational activity-based models in use today, such as the BB System (Bowman and Ben-Akiva, 2000) and the Albatross model (Arentze and Timmermans, 2004). On the other hand, there are several state-of-the-art (prototype) activity-based modelling systems that approach behavioural realism in their representation of travel-related choices but are not yet ready to become operational (see, for example, PCATS by Kitamura and Fuji, 1998, AMOS by Pendyala et al., 1998, SIMAP by Kulkarni and McNally, 2001, CEMDAP by Bhat et al., 2004). Most
activity-based modelling systems are either based on a system of econometric models (e.g., BB System), or are computational process models based on a system of rules and heuristics (e.g., Albatross). See Algers et al. (2005) for a brief over-view of activity-based models and a discussion on their potential to become operational.

2.1.5. Modelling Freight Demand

Most operational travel demand models treat freight demand in an aggregate and often ad-hoc manner. Although there have been several studies aimed at understanding the various aspects of freight demand (for instance, Sivakumar and Bhat, 2002, develop a destination choice model for freight unloaded at Texas ports) there have not been too many attempts at developing behaviourally realistic model systems of freight demand that can be integrated into the LU-T models. The reasons for this lag in freight demand modelling is a combination of factors including the lack of awareness of the importance of freight transportation, the lack of data sources that support a behavioural understanding, and the inherent and staggering complexity of freight movements into, out of, and within an urban area.

However, there have been several analytical advances that can contribute to improved state-of-the-practice in freight modelling; for example, input-output models and spatial interaction models of trip distribution (Sorratini and Smith, 2000), and discrete-continuous models of shipment selection and mode choice (Abdelwahab, 1998). See Holguín-Veras et al.(2001) for a description of the analytical advances in freight modelling and a detailed assessment of different freight transport modelling methodologies.

2.2. Operational Integrated LU-T models

Travel is derived from the need of households and businesses to interact with their environment. Specifically, it is a result of a firm’s logistical needs and an individual’s desire to participate in activities such as work, education, shopping and leisure, at locations that are distributed over space. Clearly, the spatial configuration of an urban system (also known as the land-use pattern) influences the travel-related decisions that individuals make. For instance, if an urban area offers shopping opportunities only within a well-defined shopping neighbourhood, then households will necessarily need to travel to this location for their shopping needs. A household located far away from the shopping district will then have greater incentive to own
private vehicles, and such a household is likelier to exhibit auto-centric activity-travel patterns. Or, to take another example, businesses may choose to locate (or relocate) themselves in less congested parts of an urban area so as to minimize productivity losses through congestion in the transport system.

2.2.1. Static Models

The earliest LU-T models that attempted to capture the interactions between the land-use and transport systems were essentially static models, driven typically by gravity formulations or input-output formulations (see, for example, Lowry, 1964). These early models are not very responsive to policy analyses.

Operational static LU-T models are typically entropy-based models and are linked directly to a four-stage transport model (see, for instance, LILT, the Leeds Integrated Transport package, Mackett, 1983, and DRAM/EMPAL by Putman, 1995). Market processes are not modelled by these systems. Other static models, such as IMREL (Anderstig and Mattson, 1991) and MUSSA (Martinez, 1996) estimate equilibrium patterns of land-use corresponding to the accessibilities output by a transport model, usually through iteration with the transport model.

The static models, by their very nature, cannot realistically capture urban spatial processes and their effects on the transport system. In fact, all static models treat land-use and transport systems as being exogenous to each other. Nevertheless, some static models continue to be used to this day, either as a means of adding a land-use dimension to existing transport models without undertaking the extra work needed to create a dynamic model, or because the static model represents an equilibrium state which is of interest in itself.

2.2.2. Dynamic Models

The development of improved modelling methodologies such as entropy-based interaction, random utility theory, bifurcation theory and non-linear optimization, together with significant computational advances has paved the way to the development of several dynamic land use-transport model systems. These dynamic land use-transport model systems can be broadly classified, based on the unit of analysis and the operational theory, into General Spatial Equilibrium models (example MEPLAN, see Hunt and Simmonds, 1993) and Agent-based Micro-simulation models (example UrbanSim, see Waddell, 2002).
Figure 1 (Waddell, 2005) presents the relationships between each of the categories of static, spatial equilibrium and micro-simulation LU-T models and their evolution over time.

2.2.2.1. General Spatial Equilibrium Models

Spatial equilibrium models such as MEPLAN (Hunt and Simmonds, 1993) and TRANUS (de la Barra, 1989) are typically spatially aggregate models with fully integrated land-use and transport elements. The interactions between these elements are determined by input-output analysis or discrete choice models, and these interactions are used to derive the demand for transport. General spatial equilibrium model systems are, therefore, based on random utility theory and theories of competitive markets.

Spatial equilibrium models treat land-use and transport systems endogenously and thus capture the interactions between these systems more accurately. However, these models, in being spatially aggregate, are not entirely behaviourally realistic.
2.2.2.2. Agent-based Micro-simulation Models

Agent-based micro-simulation models such as Delta (Simmonds, 1999), ILUTE (Miller et al, 2004) and UrbanSim (Waddell, 2002) are activity-based models of land-use with the individual (one person, household, firm, or any other agent in the urban system) as the unit of analysis. Hence, these models are intuitive in their formulation and capture the interactions between land-use and transport systems to the greatest extent possible. For instance, in DELTA, households follow a utility maximising formulation, the market adjusting prices within a time period. In UrbanSim, on the other hand, households maximise a consumer surplus measure and use a bid-choice function.

2.3. Next-Generation Integrated LU-T Models

Figure 4 presents a conceptual representation of a typical operational LU-T model. As shown in this figure, operational LU-T models, regardless of whether they are static or dynamic as described above, consist of a transport component and a land-use component. A few links between the two components attempt to capture the land use-transport interactions. The most common link is one of accessibility. Accessibility measures derived from the land-use configuration feed into the travel demand models, and a feedback system is built-in to update the accessibilities in response to the outputs from the travel demand models.
Another shortcoming of currently operational LU-T models is that, while they have advanced micro-simulation based land-use components, many of them still possess a simple 4-step travel demand component and have not kept up with the state-of-the-art in travel demand modelling.

To summarize (see Hunt et al., 2005), the primary shortcomings of currently operational LU-T models are as follows:

1. Excessive spatial aggregation
2. Excessive reliance on static equilibrium assumptions (with associated assumptions of large time steps and lack of path dependencies)
3. Overly aggregate representations of households and firms, and a lack of representation of individuals as decision-making units separable from their households
4. Lack of endogenous demographic processes
5. Lack of endogenous car-ownership processes, and further, the lack of more intricate links between the land-use and travel demand components
6. Reliance on four-stage travel demand modelling methods.
The next-generation integrated LU-T models attempt to address these shortcomings. Examples include ILUTE in Canada (Salvini and Miller, 2003), ILUMASS in Germany (Moeckel et al., 2003), TLUMIP work in Oregon, USA (1), and RAMBLAS in Netherlands (Veldhuisen et al., 2000). Moreover, existing models such as UrbanSim and MUSSA are continuing to evolve and address their shortcomings significantly.

These next-generation models build on the strengths and experience of currently operational models, which include generally strong microeconomic formulations of land and housing/floor-space market processes and coherent frameworks for dealing with land use-transport interactions. The key tool used in these models is the micro-simulation of market processes. However, of the several next-generation LU-T models currently in evolution, UrbanSim is the only model that we are aware of that attempts to build integrated activity-based micro-simulation models of land-use and transport.

2.4. Modelling Methodologies

The travel demand models and LU-T models presented in this section apply a variety of different modelling methodologies. The choice of modelling methodology is usually motivated by the conceptual model structure, advances in economic and econometric modelling, the data availability, and the computing capability. While early modelling methodologies supported macroeconomic theories, more recent methodologies support classical microeconomic and behavioural decision theories. The following sections present brief descriptions of some of the more commonly applied modelling techniques in LU-T models.

2.4.1. Gravity and Entropy Maximization

The first approach to address movements and flows across space was the macroeconomic gravity model based on Newton’s Theory of Gravity, dating back to the late 1800s. The first gravity model, as seen in equation 1, computes the number of trips between origin i and destination j \( (T_{ij}) \) as a simple function of the sizes of the origin and destination \( (P_i \text{ and } P_j) \), and the distance between them \( (d_{ij}) \) using a scaling factor \( k \).
This formulation then gave way to a more general one that recognizes that the relationships embedded in equation 1 may vary across trip types and with the socio-economic attributes of zones. The new formulation also recognizes that many origin and destination attributes, rather than just the two size variables, could potentially influence the flow patterns. This more general gravity formulation (Haynes and Fotheringham, 1984), used in current LU-T models, computes the number of trips between origin $i$ and destination $j$ ($T_{ij}$) as

$$T_{ij} = k \frac{P_i P_j}{d_{ij}^\beta},$$  \hspace{1cm} \text{Eq. 1}$$

where $T_{ij}$ is the number of trips between origin $i$ and destination $j$, $P_i$ is the population of origin $i$, $P_j$ is the population of destination $j$, and $d_{ij}$ is the distance between $i$ and $j$. The exponent $\beta$ represents the weight given to distance.

The next major advance in the macroeconomic modelling of spatial flows was the development of the entropy maximization theory (Wilson, 1974), which give rise to a family of spatial interaction models including the gravity model, the production-constrained model (equation 3), the attraction-constrained model (equation 4), and the doubly-constrained model (equations 5, 6, 7).

$$T_{ij} = \frac{O_i P_j^\beta d_{ij}^\beta}{\sum_j P_j^\beta d_{ij}^\beta},$$  \hspace{1cm} \text{Eq. 3}$$

$$T_{ij} = \frac{D_j P_i^\alpha d_{ij}^\beta}{\sum_i P_i^\alpha d_{ij}^\beta}, \text{ and}$$

$$T_{ij} = A_i O_i B_j D_j d_{ij}^\beta,$$  \hspace{1cm} \text{Eq. 5}$$

where

$$A_i = \sum_j (B_j D_j d_{ij}^\beta)^{-1},$$  \hspace{1cm} \text{Eq. 6}$$

$$A_i = \sum_j (B_j D_j d_{ij}^\beta)^{-1},$$  \hspace{1cm} \text{Eq. 7}$$

$O_i$ is the known total flow from origin $i$, $P_j$ is the population of destination zone $j$, and $D_j$ is the known total inflow into destination $j$. The entropy procedure is
based on the enumeration approach of combinatorial analysis, and is derived from statistical mechanics. The basic premise of these models is to enumerate all the possible zone-to-zone flow interchanges and pick the one with the highest uncertainty subject to constraints. However, as with the gravity model, these models have also been criticized for lacking a behavioral perspective in explaining individual travel decisions (despite which the production-constrained spatial interaction model continues to be widely used in passenger and freight travel demand models).

2.4.2. Constrained Optimization

The evident need for spatial flow models that can describe an individual’s choice of location resulted in the adoption of classical microeconomic theory and with it the use of constrained optimization models. Constrained optimization models construct the utility of the decision-maker (individual, household, factory etc.) as a demand and supply function, wherein resources are consumed and utility is gained to varying degrees depending on the choice of the alternative and the decision-maker selects the alternative that maximizes utility subject to resource constraints (such as time or money). A general formulation of a constrained optimization model is presented in equation 8, where $U$, the utility of the decision-maker, is a function of the decision variables in vector $\mathbf{x}$; $\mathbf{c}$ is a vector of cost functions associated with the decision variables; and $C$ is total quantity of resources available to the decision-maker.

$$\text{max } U(\mathbf{x}), \text{ subject to } \mathbf{c} \mathbf{x} \leq C \quad \text{Eq. 8}$$

Constrained optimization models are primarily used as analytic tools for generating a better understanding of travel behaviour under time and budget constraints. Constrained optimization models have also been applied to represent firm or industrial location choice decisions.

2.4.3. Markov Chain

The use of markov chain models appeared in spatial choice modelling as one of the first attempts at incorporating behavioural realism within the micro-economic approach. Specifically, markov chain models of location choice for shopping were developed to investigate the adaptive or evolutionary learning behaviour of decision-makers. In general, if $D = \{D_1, \ldots, D_i, \ldots, D_k\}$ is a constant set of mutually exclusive and exhaustive location choice alternatives, then the set of probabilities
that an individual $i$ will choose spatial alternative $D_i$ \((i = 1, 2, \ldots k)\) on his or her next \((n+1)^{th}\) choice is given by the assumption of a steady-state Markov process. Under suitable assumptions of Markov processes the probabilities for any chain of location choices may be determined. Log-linear models (Cadwallader, 1995) are simply extensions of simple markov chain processes that allow the probabilities to vary by choice occasion (non-stationary markov processes).

### 2.4.4. Multi-attribute Preference

Multi-attribute preference models, with their roots in information integration theory (Louviere, 1984), are used to model the subjective element of individual choices. These models are typically based on stated-preference (SP) survey data, which are based on individual responses to experimentally designed questions. Individuals indicate their preference for various attributes, both subjective and objective, of the choice alternatives and their utilities are formulated as being an integration of the evaluation of all the attributes. In Louviere (1984), for instance, the utility of the alternatives is modelled as a weighted function of the various attributes. Multi-attribute preference models are also known in the literature as decompositional models or conjoint choice models, though the term ‘conjoint choice models’ is typically extended to all kinds of formulations that use SP data including multinomial logit formulations based on random utility maximization.

### 2.4.5. Random Utility Maximization

The derivation of the discrete choice model, based on the theory of random utility maximization (RUM), by McFadden in the late 1970s provided a big impetus toward the modelling of individual and firm choice behaviour. The discrete choice paradigm not only brings the problem of understanding choice behaviour down to the individual decision-maker but also acknowledges the discrete nature of many of these choices.

According to random utility theory, individuals associate a utility with each alternative and the alternative with the highest utility is chosen. The utility that individual $i$ attributes to alternative $j$ is given as

$$U_{ij} = V_{ij} + \varepsilon_{ij}$$

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where $V_{ij}$ represents the measurable component and $\varepsilon_{ij}$ represents the random error component, from the modeller’s perspective.

Based on the theory of utility maximization and conditional on assumptions placed on the random error component, several formulations such as the multinomial probit or logit models may be derived. The multinomial logit model, for instance, is based on the assumption of extreme value distribution of the error term and is given by

$$p_{ij} = \frac{e^{V_{ij}}}{\sum_{j \in C} e^{V_{ij}}}, \quad \text{Eq. 10}$$

where, $p_{ij}$, is the probability that individual $i$ selects location $j$, and $C$ is the choice set of locations available to the individual. Over the last few decades there have been several advances in discrete choice modelling that support the development of flexible and behaviourally realistic models of travel behaviour.

2.4.6. Heuristics

Another approach to describing and modelling travel-related choices that is seen in LU-T models is that of rule-based models (also known as computational process models). Some of the tools applied in rules-based models include decision trees, neural networks, informal map analysis and trend surface analysis. An example of a fully operational computational process model is the Albatross LU-T model (Arentze and Timmermans, 2004).

A computational process model (CPM) such as Albatross is basically a computer program implementation of a production system model, which is a set of rules in the form of condition-action (IF-THEN) pairs that specify how a task is solved. The modelling approach focuses on the process of decision-making and captures heuristics and short-cuts that are involved, as opposed to assuming overriding paradigms such as utility maximization.

Hence, the modelling approach offers more flexibility than econometric models in representing the complexity of travel decision making. A major drawback of CPM is that they lack a statistical error theory, which makes it more difficult to generalize their outcomes and apply them to policy evaluation. In addition, the models generally have very challenging data requirements for model estimation, application
and validation, and the assumptions they make about the search process have not been validated.

2.4.7. Bid-Rent Models

Bid-Rent models are commonly used to represent the market processes within a land-use system. Bid rent theory is a geographical theory that refers to how the price and demand on land changes as the distance towards the Central Business District increases. This theory is based upon the reasoning that the more accessible an area the more profitable it will be.

A bid-rent model can be specified in many different ways. A potential specification for a stochastic bid-rent model is a conditional probability approach that could predict the probability that a location having the hedonic bundle $z$ would be occupied by a consumer of type $h$, $\forall h \in h$. Bid-rent markets are therefore centred around land as a resource. While RUM predicts that a consumer chooses a certain type of location to live in, stochastic bid-rent models forecast that a dwelling unit is occupied by a certain type of consumer.

3. AGENT-BASED MICRO-SIMULATION

Underpinning all the models of land use transport interaction mentioned above are models describing the decision making behaviour of individual agents (e.g., travellers, developers, employers etc.). Developments in the technologies available for modelling these agent-level behaviours, such as agent-based computing and non-linear system theory, have been a strong driving and enabling force in the wider development of land-use transport modelling.

Computational advances in the last decade, in particular, have made agent-based micro-simulation an eminently suitable approach in implementing the state-of-the-art LU-T models as is evidenced by the multitude of micro-simulation based LU-T models in existence today. However, as discussed in section 2.3, although there are several micro-simulation based prototype models of travel demand on the one hand and operational LU-T models with micro-simulation land-use components on the other hand, there are currently no integrated LU-T models that are truly micro-simulation based. A notable exception is RAMBLAS, which is explicitly agent-based in both design and implementation. UrbanSim is also currently evolving to include a
micro-simulation based activity-travel demand component, although in its current form it is not truly agent-based.

Agent-based micro-simulation models are ones in which each individual actor in the system of interest is modelled as an autonomous ‘agent’. Each agent possesses an identity, attributes and the capability to ‘behave’, i.e. to make decisions and act within the system. Agent-based micro-simulation modelling is increasingly being recognized as the most computationally efficient and practical design paradigm across virtually the entire gamut of socio-economic modelling. Specifically, it is widely believed that agent-based micro-simulation modelling represents the best approach currently available to modelling large, complex, dynamic, agent-based socio-economic systems such as an entire urban region. There are two broad reasons for this belief. First, a more disaggregate approach to modelling socio-economic processes such as travel behaviour, residential location etc. is generally desirable in order to reduce model aggregation bias and enhance behavioural fidelity. Second, dynamic evolution of urban systems must be explicitly captured if future system states are to be properly estimated. Urban systems evolve in a path-dependent fashion that may not be well captured by conventional static equilibrium models. Agent-based micro-simulation on the other hand is inherently based on tracing the path of evolution of a system. The key strengths and weaknesses of the agent-based micro-simulation approach are summarized in Figure 5.

<table>
<thead>
<tr>
<th>STRENGTHS</th>
<th>WEAKNESSES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Can explicitly model interactions in time and space</td>
<td>Associated with ambitious scales of time, space and scope in coverage of human choices</td>
</tr>
<tr>
<td>Can handle complex non-linear decision rules</td>
<td>Require large amounts of computing time and file storage</td>
</tr>
<tr>
<td>Eminently suitable for non-equilibrium situations</td>
<td>Require consistent starting conditions for policy analyses</td>
</tr>
<tr>
<td>Produces clear descriptions of system evolution of time, i.e. traces path of system evolution</td>
<td>Need a means of removing the effects of random number seeds</td>
</tr>
</tbody>
</table>

Figure 5. Key strengths and weaknesses of agent-based micro-simulation models

An agent-based micro-simulation model of the LU-T system would potentially consist of three broad components: (a) the modelling framework that describes the sequence of land-use and travel demand models and the interactions between them, (b) the implementation platform that executes the micro-simulation model, and (c) the
synthetic population that forms the key input to micro-simulation model. Agent-based micro-simulation models thus generate the need for a synthetic population complete with socio-demographic attributes, household structure, and residence and work locations identified within the study area. Since the synthetic population of individuals (and firms) representing the study area forms the primary input to the micro-simulation model, the generation of synthetic populations has been another major area of research among transport planners and modellers in recent times.

4. TRANSPORT AND PRODUCTIVITY

The primary objective of next-generation LU-T models is the development of behaviourally realistic and accurate model systems that exploit the econometric and computational advances made over the last century. Specifically, they attempt to develop a model of individuals’ travel behaviour, firm behaviour, real estate markets and demographic processes that is as close to reality as possible. Stated simply, integrated LU-T models are evolving toward being comprehensive models of the entire urban system.

Comprehensive as they may be, current LU-T models do not truly internalise issues such as environmental impacts, energy consumption and economic productivity. With the advent of climate change, fuel shortage and globalization issues, transport planners and policy-makers are beginning to acknowledge the importance of these links. The relationship between transport and economic productivity is the most complex of these links and has been researched extensively in the last few decades by transport economists.

Several studies have indicated that in neglecting to account for the relationship between transport provision and economic productivity LU-T models present an incomplete picture of the costs and benefits of the transport system (see, for example, Lynde and Richmond, 1993, and Seitz, 1995). Consequently, policy analyses based on these LU-T models are likely to inaccurate.

The main economic basis for the existence of cities and urban areas is the existence of agglomeration economies, i.e., productivity benefits of clustering economic activity together into dense spatial units. Therefore, transport improvements within the urban area could potentially improve links between firms and relax constraints on access to the city centre thus increasing overall city employment and
consequently productivity. Conversely, increased congestion in the urban area not only affects economic welfare measures but also productivity and therefore GDP (Venables, 2004, Graham, 2006). Moreover, in order not to overestimate the costs and benefits of transport provision on productivity, models of the transport system must include agglomeration effects.

Figure 6. Links between transport and economic performance


Borrowing a schematic from the Eddington Transport Study (Eddington, 2006), Figure 5 presents the links between transport and economic performance. The direct impacts of transport interventions are in the form of travel time savings and/or increased comfort and safety. These direct impacts are typically captured by welfare measures. However, as users (commuters, non-work travellers, business travellers, freight) respond to these welfare measures, we perceive wider productivity impacts such as increased business efficiency, increased business investment and innovation, a healthy labour market, increased competition, and increased trade. Further these productivity benefits have a self-perpetuating effect as they increase clusters and agglomerations.
5. CONCLUSION

Local authorities have long been aware of the need for integrated land-use transport models to make accurate estimates of travel demand and to predict the effects of policies on travel demand. Underpinning all the models of land use transport interaction discussed in this report are models describing the decision making behaviour of individual agents (e.g., travellers, developers, employers etc.). Developments in the technologies available for modelling these agent-level behaviours have been a strong driving and enabling force in the wider development of land-use transport modelling. The earliest models of agent-level behaviour focussed principally on predicting the choice of specific facets (such as mode or route) of individual trips and tended to be deterministic in nature (typically assuming that behaviour was driven solely by considerations of cost or travel time minimisation). From the 1970s onwards these approaches were gradually replaced by models which at the conceptual level, consider travel decisions explicitly as part of the broader context of an individual’s programme of activity participation (Hägerstrand, 1970; Jones et al., 1983; Lenntorp, 1976) and at a methodological level, treat decision making as a stochastic (rather than deterministic) process (McFadden, 1978; Train, 2003). The current state-of-the-art is represented by techniques based on the random utility formalism, which can accommodate a wide variety of decision making contexts including both individual and group decisions, decision regarding both discrete and continuous outcomes, static and dynamic decisions, decisions with single or multiple expressed outcomes, decisions made under uncertainty and those influenced by qualitative as well as quantitative factors. These methods can also be used as a means of integrating data both from real market outcomes (so called “revealed preference data”) and data from hypothetical market studies (so called “stated preference data”).

In understanding energy consumption vis-à-vis transport, it is important to take into account not only the short-term decisions such as destination and mode choice, but also the medium to long-term decisions made by individuals and firms with respect to residential and workplace location, auto-ownership, labour force participation etc. Therefore, the proposed model of the urban system must contain an integrated land-use transport model along the lines discussed in this report. Moreover the model must internalise aspects of economic productivity and environmental
impacts. The synthesis of modelling methodologies suggests that micro-simulation is the ideal implementation framework for the proposed model.

During the course of this review a framework of land-use, transport and other policies was also identified (see Hunt et al., 2005) that have a direct or indirect effect on the activity-travel patterns of individuals and therefore their energy consumption. This framework of policies is presented in Figures 6-8.

<table>
<thead>
<tr>
<th>Policy Category</th>
<th>Specific Policy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pricing</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Taxation: property taxes</td>
</tr>
<tr>
<td></td>
<td>Subsidies: Business Redevelopment Zones</td>
</tr>
<tr>
<td></td>
<td>Development charges</td>
</tr>
<tr>
<td>Infrastructure and services</td>
<td>Public housing</td>
</tr>
<tr>
<td></td>
<td>Servicing land (excluding transportation, e.g. sewers, waters, wired city)</td>
</tr>
<tr>
<td></td>
<td>Government buildings/other not-for-profit institutions (i.e. location of these as 'seeds'/cores for development)</td>
</tr>
<tr>
<td>Regulatory</td>
<td>Zoning (uses, densities)</td>
</tr>
<tr>
<td></td>
<td>Micro-design building/neighbourhood issues ('shadowing', pedestrian-scale massing, neo-traditional design, etc.)</td>
</tr>
<tr>
<td>Education/marketing</td>
<td>Changing/how to change attitudes and sensitivities (e.g. traveller 'value of time' as opposed to deeply held values)</td>
</tr>
</tbody>
</table>

**Figure 7. Land Use Policies**

<table>
<thead>
<tr>
<th>Policy Category</th>
<th>Specific Policy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pricing</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Road tolls/congestion pricing</td>
</tr>
<tr>
<td></td>
<td>Gas taxes</td>
</tr>
<tr>
<td></td>
<td>Subsidies (capital, operating)</td>
</tr>
<tr>
<td></td>
<td>Transit fares</td>
</tr>
<tr>
<td></td>
<td>Parking pricing</td>
</tr>
<tr>
<td>Infrastructure and services</td>
<td>Build roads, high-occupancy vehicles</td>
</tr>
<tr>
<td></td>
<td>Build rail/dedicated transit ways</td>
</tr>
<tr>
<td></td>
<td>Operate transit services</td>
</tr>
<tr>
<td></td>
<td>ITS (i.e. infrastructure technology; system optimization, transportation system management (TSM), etc.)</td>
</tr>
<tr>
<td></td>
<td>Parking</td>
</tr>
<tr>
<td>Regulatory</td>
<td>Parking provision regulations (off-street)</td>
</tr>
<tr>
<td></td>
<td>Rules of the road (speed limits, on-street parking, high-occupancy vehicle lanes, traffic operations, etc.)</td>
</tr>
<tr>
<td></td>
<td>Non-pricing TDM (e.g. employer trip reduction programmes, etc.)</td>
</tr>
<tr>
<td></td>
<td>Vehicle/driver licensing (i.e. granting of access)</td>
</tr>
<tr>
<td>Education/marketing</td>
<td>Changing/how to change attitudes and sensitivities (e.g. traveller 'value of time' as opposed to deeply held values)</td>
</tr>
</tbody>
</table>

**Figure 8. Transportation Policies**
<table>
<thead>
<tr>
<th>Policy Category</th>
<th>Specific Policy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pricing</strong></td>
<td>• Car purchase tax</td>
</tr>
<tr>
<td></td>
<td>• Licence charges</td>
</tr>
<tr>
<td></td>
<td>• Income redistribution (e.g. progressive taxation, welfare, etc.)</td>
</tr>
<tr>
<td><strong>Infrastructure and services</strong></td>
<td>n/a</td>
</tr>
<tr>
<td><strong>Regulatory</strong></td>
<td>• Air quality standards (area wide)</td>
</tr>
<tr>
<td></td>
<td>• Emissions standards (vehicle-specific)</td>
</tr>
<tr>
<td></td>
<td>• Noise</td>
</tr>
<tr>
<td></td>
<td>• Safety (accidents)</td>
</tr>
<tr>
<td></td>
<td>• Vehicle technology standards (e.g. must have 10% electric vehicles in CA, etc.)</td>
</tr>
<tr>
<td><strong>Education/marketing</strong></td>
<td>• Changing/how to change attitudes and sensitivities (e.g. traveller 'value of time' as opposed to deeply held values)</td>
</tr>
</tbody>
</table>

Figure 9. Other Policies
REFERENCES


Bhat, C.R., J. Guo, S. Srinivasan, and A. Sivakumar, "Guidebook on Activity-Based Travel Demand Modeling for Planners," Product 4080-P3, prepared for the Texas Department of Transportation, October 2003.


