TOPIC 1
TRANSPORT AND
LAND USE (SIG)

AN INTEGRATED APPROACH TO MODELLING THE IMPACT ON URBAN TRAVEL BEHAVIOUR OF STRATEGIES TO REDUCE GREENHOUSE GAS EMISSIONS

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Abstract

This paper presents an integrated urban passenger transport model system to evaluate the impact of policy instruments on urban travel behaviour and greenhouse gas emissions. A demand model system is combined with equilibrating criteria in location, automobile and commuting markets to predict travel demand by socio-economic segments, automobile classes and geographic locations.

INTRODUCTION

There is a renewed interest in Australia in strategic level transport model systems which not only emphasise travel decisions but also the interrelated decisions on location of activities and automobile purchases. The combined set of travel, location and vehicle decisions of individuals and households reflect the growing interest in the need to evaluate policies from an environmental perspective. This paper presents a new urban passenger transport model system with a strategic focus, and a capability of evaluating a large number of policy instruments. A software package has been developed to implement the model system.

This paper is organised as follows. We commence with an overview of the structure of the model system as a series of interlinked decision blocks; we then discuss the equilibration process within the travel, location and vehicle markets. The data requirements for model estimation and system application are then set out, with details of how the synthetic households used in applications are constructed and aged, followed by an illustration of how the model system operates in the presence of an exogenous policy shock. The simulator is capable of evaluating many policies.

THE DECISION BLOCKS AND DECISION LINKAGES IN THE STRATEGY SIMULATOR

Urban passenger transport demand is multi dimensional. It encompasses the location of activities, the alternative travel opportunities available, and the availability of types of motorised and non-motorised transport. A potential user of the transport system faces choice opportunities with varying degrees of availability. In the long run, individuals have increasing opportunities to review all key transport-related choices—where to live, where to work, the number and types of automobiles in the household, the choice of means of transport and time of departure for the journey to work, and even negotiation of the temporal and spatial nature of working hours (ie. flexitime, a compressed work week and telecommuting). In the short run, some of these choices are not available, and hence condition the choices which can be evaluated and changed.

The behavioural models in the ITS/BTCE simulator are presented in sub-modules representing the four natural divisions of:

(i) *commuter choice:* spatial and temporal choice of working hours, departure time choice, mode choice, and workplace location choice

(ii) *automobile choice:* vehicle type choice and household fleet size choice

(iii) *residential choice:* location and dwelling type choice, and

(iv) *automobile use:* total annual vehicle and household kilometres and the spatial composition of kilometres.

The decision blocks for location decisions, vehicle decisions, and travel decisions and their major linkages are summarised in Figure 1. Each of the blocks has a set of internal linkages; the blocks are themselves linked by a set of external linkages. Three instruments (land rents, used vehicle prices and commuting travel times) are used to equilibrate within three of the decision blocks. The non-commuting car use decision block does not have a market clearing facility in the current specification. The estimated models are detailed in Hensher et al. (1995, Report 5).

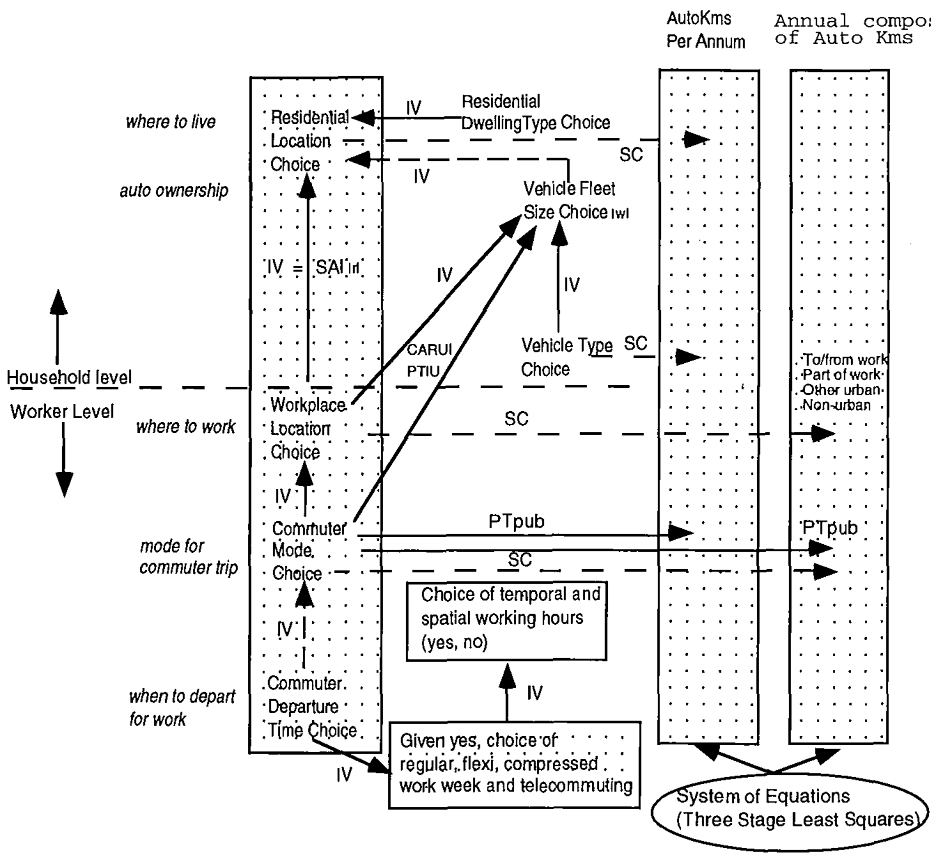
There is an assumed decision hierarchy in which residential location is the uppermost decision of a household, and as we move down the decision tree we condition each of the worker-related choices on the higher order decisions. The choice of workplace location for each worker in a household is conditional on the household's choice of residential location. Likewise the choice of commuter mode is conditional on the choice of residential and workplace location. The presence of more than one worker in a household is allowed for by having a separate choice for each worker, together with additional exogenous variables to account for the influence of the number of workers on each workers choice of mode, workplace and household residential location. In any future development an endogeneity link should be evaluated. The modal opportunities include the set of available alternatives and possible future investments in 'new' modes in specific spatial contexts such as light rail and bus priority systems. Stated choice experiments are combined with revealed preference data in the estimation of the departure time choice and commuter mode choice models (eg. Louviere et al. 1994 (Report 3), Hensher and Bradley 1993, Bradley and Daly 1993, Morikawa 1991). A summary of the strengths of revealed preference and stated preference data paradigms is given in Hensher et al (1995, Report 5).

Equilibration within the commuter car travel market is necessary. Given a predetermined volume of non-commuting passenger travel (expressed in vehicle units) and commercial vehicles, the commuter market is equilibrated on each origin-destination pair by using a relationship between travel time, volume and capacity for the *synthetic* road system. The presence of a departure time choice model suggests that equilibration should be determined for each time of day. This requires a separate travel time matrix for each time period and the ability to have travel substitution between times of day; that is a dynamic traffic assignment. In the current model system we have imposed a simplification (to be relaxed in ongoing development)—that equilibration is undertaken as if all travel occurs in the one time period (however defined). The resulting traffic however is allocated to the choice set of departure times in accordance with the choice probabilities, to give a *temporal* profile of the traffic "in equilibrium".

The two lowest decisions in the hierarchy endogenise spatial and temporal work practices defined by compressed work week choice and telecommuting choice. They are qualitative enhancements, which have important roles to play in influencing the mix of commuting and non-commuting kilometres and in changing the nature of the commuting peak (Hensher 1995 (Report 1)). Given the complexity of the overall model system we have assumed initially that the choices of telecommuting and compressed work week behaviour are not spatially dependent. The primary influences are assumed to be socio-economic and employment related.

Two important household-based decisions are meshed into the core hierarchy by selective linking. These are the choice of dwelling type which links into the residential location choice, and the choice of automobile number and composition which is linked with the residential and workplace location choice models. Fleet size (and commuter mode choice) varies according to residential and workplace location. The dwelling type choice model provides the interface with the notion of living density—each spatial location (ie. zone) contains a mix of three dwelling types (detached houses, town houses and flats). Within each zone, each dwelling type is given a plot size or density index which can vary between zones for the same dwelling type. Changes in residential density are triggered by an exogenous shock to the number of dwellings by type in each zone. Given that the current version of the behavioural model system is static, a number of exogenously determined impact conditions (or temporal allocation rules—see below) have to be imposed to ensure that impacts on each endogenous choice of change associated with a strategy are not instantaneous and hence misleading. Equilibration in the residential location market is achieved by the use of dwelling prices as the market clearing agent. The possibility of disequilibrium in the dwelling market is allowed for when a new stock of dwellings is injected into the system; since the possibility exists for excess supply when the number of households is not sufficient in a particular year to take up the total available stock of dwellings. To fully equilibrate would result in artificially reducing dwelling prices and would require the 'scrapping' of dwellings.

The automobile market at the household level is represented by a fleet size choice model and a vehicle type choice model system. Given the interest in environmental impact, the estimation of the vehicle type choice (and vehicle use) models for multi-vehicle households is undertaken at the vehicle level, with suitable procedures implemented to condition the choice of each vehicle type and their use on the set of vehicle types in the mix. The fleet size choice and type choice models are embedded within a nested logit framework, with a further nesting within type choice for multi-vehicle households. Automobiles in the vehicle type choice set are defined by size class, vintage and fuel type. The size classes for conventional fuelled automobiles are given below in Table 1. There are an additional 6 electric and alternative fuel vehicle types (small, medium and large). See Hensher et al. (1994, Report 4) for further details.



— — — — — ► = linkages evaluated but rejected as statistically non-significant

(IV = inclusive value index, SC = selectivity correction)

Figure 1 The Linked Model System

Table 1 Automobile size classes for conventional-fuelled automobiles

C1.	Micro (≤ 4 cylinders, < 1400 cc)
C2.	Small (4 cylinders, 1400—1900 cc)
C3.	Medium (4 cylinders, > 1900 cc)
C4.	Upper Medium 1 (6 cylinders, < 3000 cc)
C5.	Upper Medium 2 (6 cylinders, ≥ 3000 cc)
C6.	Large (≥ 8 cylinders)
C7.	Luxury (specific makes and engine capacities). All of: Mercedes, BMW, Rolls Royce, Jaguar, Audi, Bentley, Lexus, Daimler and Eunos Plus: Honda Legend / NSX (> 3000 cc), Volvo ≥ 2300 cc, Saab > 2100 cc
C8.	Light Commercial (ABS body types 30-39)
C9.	Four Wheel Drive (treated separately outside of ABS registrations)
C10.	Light Trucks (≤ 3.5 tonne, ABS body types 40-49)

The multiple-vehicle branches of the vehicle type choice system are represented hierarchically according to the chronological entry of each vehicle into the household. For example, if a household has two vehicles and one was acquired in 1989 and the other (through replacement or addition) in 1992, then the 1989 acquisition would be in the upper level (level 1) of the tree; the choice of the vehicle obtained in 1992 is conditional on the vehicle already held and which is not to be transacted at that time. The vehicle type choice models allow for the introduction of electric and alternative fuel vehicles (principally cng), with parameter estimates derived from both revealed preference and stated preference data (see Hensher et al. 1995, Report 5).

The final module is automobile use. The emphasis is on both the total annual use of each automobile in the household's fleet and its composition. The latter is disaggregated into commuting travel, travel as part of work, other urban travel and non-urban kilometres. From a greenhouse gas emissions perspective, changes in vehicle kilometres is the most useful measure of changes in emissions, given the fuel efficiency of the vehicle fleet and the equivalent change in greenhouse gas emissions per litre of fuel consumed. There are four equations in the model system, one for total annual vehicle kilometres, and three for the proportion of kilometres associated with each use class, with one class defined as the base (see below). The system of equations is estimated by the method of two stage least squares. This accounts for the correlation between the unobserved effects associated with each left-hand side endogenous variable.

Annual vehicle use is a function of the location of residence, the cost of operating an automobile, automobile age, physical and performance attributes of an automobile and socioeconomic characteristics of a household. Changes in the operating costs of automobiles have a direct impact on a number of travel choices such as commuter mode choice, automobile type choice and automobile use. The structure of the strategy simulator allows for the multiple impacts, which filter through the entire model system.

The determination of the influences on the composition of vehicle kilometres involves a method called linear logit, based on grouped or proportions data. With 4 alternatives we have 3 equations, where the right-hand side endogenous variable for each model is the natural logarithm of the ratio of the proportion of kilometres associated with a particular class of travel to the proportion of kilometres associated with a base class of travel. We have selected non-urban kilometres as the base class. Full details of the method is given in Hensher and Johnson (1981, pages 172-177). The forms of the 3 *estimation* equations and the 4 *application* equations are given below:

$$\ln\left(\frac{P_i}{P_b}\right) = \sum_{k=1}^{K} \beta_{ki} X_k \text{ (3 estimated equations)} \quad (1)$$

$$\hat{P}_{og} = \exp\hat{L}_{0g}/(1 + \exp\hat{L}_{0g} + \exp\hat{L}_{1g} + \exp\hat{L}_{2g}) \text{ (Propn of vkm predicted for use class 0)} \quad (2)$$

$$\hat{P}_{1g} = \exp\hat{L}_{1g}/(1 + \exp\hat{L}_{0g} + \exp\hat{L}_{1g} + \exp\hat{L}_{2g}) \text{ (Propn of vkm predicted for use class 1)} \quad (3)$$

$$\hat{P}_{2g} = \exp\hat{L}_{2g}/(1 + \exp\hat{L}_{0g} + \exp\hat{L}_{1g} + \exp\hat{L}_{2g}) \text{ (Propn of vkm predicted for use class 2)} \quad (4)$$

$$\hat{P}_{bg} = 1/(1 + \exp\hat{L}_{0g} + \exp\hat{L}_{1g} + \exp\hat{L}_{2g}) \text{ (Propn of vkm predicted for use base class b)} \quad (5)$$

where $\hat{L}_{ig} = \sum_{k=1}^{K} \beta_{ki} X_k$ and X_k are a set of right-hand side variables

Separate model systems are estimated for 1, 2 and 3 vehicle households for each of the vehicles in the household. In recognition of the possibility that some unobserved influences on vehicle use may be correlated with the unobserved influences of various travel, location and vehicle choices, we have undertaken tests to determine if each of the choices—commuter mode choice, residential location choice, workplace location choice and vehicle type choice—have unobserved effects correlated with the unobserved effects in the vehicle use models. If this were true then we would correct for such bias by the inclusion of a set of selectivity correction (SC_i) indices. Selectivity variables (SC_i) from all four choice models were not statistically significant in the current application context. This suggests that there are no correlated disturbance terms due to the possible correlation of some unobserved influences on each of the choices and the unobserved influences of automobile use. Experience suggests that we might expect non-significant selectivity variables if the vehicle use model is well specified, since the key correlates have already been identified by explicit exogenous variables of instrumented 'endogenous' variables. The concept of selectivity is set out in Hensher et al. (1993, Report 2); how they might be implemented is summarised in Appendix B.

Important policy variables are included in the final set of vehicle use models (Hensher et al. 1995, Report 5). The major influences on vehicle use are vehicle operating cost, the propensity of commuters to use public transport, distance of residence from central city, vehicle attributes (weight, age) and life cycle characteristics (adults with no children, single parent family, number of children in the household, number of workers). Operating cost (opcost) fully decomposed contains information on fuel efficiency, fuel prices and excise duties, and is the link into price-related applications such as a carbon tax and a congestion charge, and the introduction of electric vehicles and/or alternative fuelled vehicles:

opcost = [{cityFuel*propCityF + hwyFuel*(1-propCityF)}*0.01] * [tPricePetrol*(1-propnDiesel) + tPriceDiesel*propnDiesel + carbonTax * {carbLitD*propnDiesel+ carbLitP*(1-propnDiesel)}] + (cTank + carbonTax*carbTAlt) / rangealf + (cCharge + carbonTax* carbTElc) / rangeelc

where:

cityFuel	= city cycle fuel efficiency (litres/100 km)
hwyFuel	= highway cycle fuel efficiency (litres/100 km)
propCityF	= proportion of use which is in the city fuel cycle (default = 0.7)
propnDiesel	= proportion of conventional-fuelled vehicles using diesel
tPricePetrol	= wpricepetrol + expricepetrol (cents per litre)
wpricepetrol	= wholesale price of petrol (cents per litre)
expricepetrol	= excise component of price of petrol (cents per litre)
tpricediesel	= wpricediesel + expricediesel (cents per litre)
wpricediesel	= wholesale price of diesel (cents per litre)
expricediesel	= excise component of price of diesel (cents per litre)
carbonTax	= carbon tax (cents per kg)
carbLitD	= carbon per litre of diesel (kg/litre)
carbLitP	= carbon per litre of petrol (kg/litre)
carbTElc	= carbon per full electric recharge (kg)
carbTAlt	= carbon per tank of alternative fuel (kg)
cTank	= wctank + extank (cents)
wctank	= wholesale cost of a tank of alternative fuel (cents)
extank	= excise component of cost of a tank of alternative fuel (cents)
cCharge	= wccharge + excharge (cents)
wccharge	= wholesale cost of a full electric recharge (cents)
excharge	= excise component of cost of a full electric recharge (cents)
rangeelc	= range of electric vehicle on a fully charged battery (km)
rangealf	= range of alternative fuelled vehicle on a full tank (km)

The electric and alternative-fuelled vehicles can be introduced onto the market and have an impact on operating cost via the equation above. In the absence of these fuel-types the operating cost component of the formula relating to such fuels is not operative in the strategy simulator.

Throughout the model system a large number of choice probabilities are generated per worker and per household. The summation of these probabilities, after base year calibration, in various dimensions such as socioeconomic segment (income by life cycle), vehicle class (vintage by size class), and residential location enables the model system to produce a rich set of useful planning and policy outputs. Within each of these presentation summations we can identify distributions of emissions, energy consumed, annual vehicle kilometres, total end-user cost (decomposed into money and time costs), consumer surplus, government revenue, and relevant absolute numbers and market shares of automobile types owned by households and commuter modal shares.

EQUILIBRATION IN THE TRAVEL, LOCATION AND VEHICLE MARKETS

The travel market

Handling equilibration in the commuter trip market requires special comment in the absence of a detailed micro spatial—network model. At the strategic level the interest is not on travel times and congestion of particular links in the highway network, but on the overall adjustment in commuting travel times consequent on particular strategies. It is necessary, however, to identify the way that a behavioural response to a strategy is traced through the spatial *"network"* to establish any impact on travel times. Changes in travel times will operate iteratively through feedback from the trip to the market to the trip etc. until a convergence limit is reached, as exogenously defined by a change which is less than a fixed percentage change. As an *alternative* to a network-based approach, we use an empirical equation calibrated on the sample of commuting trips to represent the travel time profile of commuters (*by time of day*). The exogenous variables must be capable of predicting changes in travel time due to the accumulated behavioural responses throughout the model system.

A travel time model for each time of day would have the following exogenous variables for each origin-destination pair: the number of trips, the road capacity, and base free flow conditions represented by distance/speed. This equation is *calibrated* on observed travel times and thus represents the base equilibrium conditions. If desired, this linking equation can be replaced with a full-blown network for users who wish to link the model system to a traffic assignment package such as TRANSTEP or EMME/2. This is not part of the initial specification of the simulator, although the integration is feasible. The possibility of time of day commuter switching is very real in our model system. To provide a reliable mapping between travel times and the three major exogenous variables, we use a network model to generate average travel times under a large number of mixtures of trip volumes, road capacities and distances. Details of the estimation procedures are given in Hensher et al. (1995, Report 5).

The resulting data base is used to obtain parameter estimates to represent the role of the volume capacity ratio in determination of predicted travel times. This enables us to impose an endogeneity condition on travel time at the aggregate level. That is, whereas each individual commuter cannot influence their own travel time once a time of day is chosen, the aggregation of individual choices (ie. total trips) within a given network defined by capacity and the spatial network will influence average travel times. This gives an empirical relationship to revise travel times within the location-to-location matrix in arriving at revisions in the probabilities of household commuters choosing particular modes between particular residential and workplace locations, which get aggregated iteratively to adjust total trips and hence travel times, given distance and capacity. This procedure also provides a capability for evaluating the impact of changes in location-specific road infrastructure (eg. a new toll road, a bus priority system). The introduction of rail infrastructure is handled via the commuter mode choice model where we can exogenously adjust the attribute levels of existing rail public transport or add in a new rail alternative (the latter by the inclusion of the light rail utility expression). The manner in which new modes are introduced into an urban area, in particular where they are located, is discussed in detail in Hensher et al. (1995, Report 7).

The residential location and dwelling type market

Households adjust their residential location in response to changes in the transport system and for other reasons. Consequently any one of a number of strategies can influence the probability of a household both living in a particular location and the type of dwelling they choose to occupy. At any point in time there will be a total demand for dwelling types in each residential location. Excess demand will result in an increase in location rents and dwelling prices; excess supply will result in a reduction in the respective rents and prices. In the simulator, dwelling prices are used to clear both the market for dwelling types and location, in the absence of data on location rents. The market clearing mechanism is linked into a set of impact indices which 'allocate' heuristically the impact of a strategy on the choice of residential location and dwelling type across time so that, in the absence of a dynamically specified adjustment process within the behavioural model set, the temporal response profile is 'realistic'. Equilibration is secured for both the dwelling type market and the residential location market. Disequilibrium is allowed for when an injection of new dwellings creates excess supply given the number of households. Under this strategy the simulator needs only to ensure that the demand for dwellings by type in a residential zone does not exceed supply for the zone. Any additional dwellings will be left vacant in the particular year as an indication that property developers may have created too much stock at that time. In future years as households grow the take up rate increases without creating increases in dwelling prices until the market is cleared.

It is important to observe the process of equilibration or disequilibration under a temporal allocation rule applied to a static model system as a proxy for a dynamic model specification. At the first iteration of equilibration, a set of choice probabilities are obtained and scaled according to the temporal allocation rule (see Table 2). The summed probabilities are used to identify the aggregate relationship between demand and supply for each type of dwelling in each residential location. A set of directional dwelling price adjustments are created as input into the second iteration prediction of dwelling prices; they reflect the partial adjustment of the market to the initial exogenous shock (ie. strategy). A resulting set of new probabilities based on the adjusted prices are obtained. These second-round choice probabilities are assumed to represent further adjustments in the probabilities associated with the one-period temporally adjusted annual impact probability outcomes; however since the choice model still has the property of instantaneous response, a further temporal adjustment is undertaken in each subsequent iteration in the annual equilibration. Another way of expressing this is that iterations after the first iteration *fine tune* the adjustments applicable to a year's choice response. Where the adjustment is complete in one year (ie. temporal allocation is 100% in one year), then the static model is essentially a dynamic model and the rules for each iteration are identical. This same logic applies to equilibration in all three markets—travel, location and automobiles.

The automobile market

Identification of automobile scrappage rates and expected future prices of used vehicles are important features of the simulator. In the base year (1993) we begin with an observed set of used and new vehicle registrations in each class (and vintage); for classes in subsequent application years we identify the number of vehicles on register in the existing and the new classes, the latter added over time at the annual rate of 10 conventional fuel classes (see Table 1) and 6 non-conventional fuel classes (if applicable—ie. two fuels and 3 vehicle sizes). New vehicles should be introduced ideally in accordance with manufacturers' release plans; however such information is not readily available. We have determined the total number of new vehicles to be released on the market each year as follows: given exogenously defined new vehicle prices (cost-based), total demand for vehicles by class is determined through the application of the vehicle type choice and fleet size models; scrappage of used vehicles is also calculated using cost-based prices. A percentage of used vehicles leave the market for various reasons, typically associated with age and value. Value is linked to both the decision to repair a vehicle in a crash and whether it is still worth injecting money into the vehicle to make it roadworthy. The difference between demand and scrappage gives the number of new vehicles *by class*. These new vehicles are then fed into the equilbration process for the base situation and for a policy application.

Used vehicle prices in the model are set as depreciated new vehicle prices and reset each year for each vintage of a class, so that if the prices of new cars in all classes (or just one) rose, then the used car market would rise in price also. The used car prices of each age within a class are set as a constant function of new car prices to give a price decay to establish the relativity of used to new prices each year. These prices are then used in all demand calculations in type choice and fleet size models, as well as in the scrappage functions.

The simulator requires an empirical scrappage model as well as a used price model which can be used to identify future stocks of passenger vehicles (by class) as at December 1995, December 2000, December 2005 and December 2010. A scrappage rate model of the following form is parameterised

$$\frac{NR_{p-1}^{91}-NR_{p}^{92}}{NR_{p-1}^{91}} = \beta_0 + \beta_1 Price_p^{92} + \sum_{a=1}^{A} \beta_{2a} age_{ap}^{92} \tag{6}$$

where

$\frac{NR_{p-1}^{91}-NR_{p}^{92}}{NR_{p-1}^{91}}$ is the scrappage rate (as a percentage) over a period p, NR_z^y is the number of vehicles on register in a class in year y and period z, $Price_z^y$ is the (expected future) price in year y and period p for a vehicle class, and the other exogenous variables are, for each class of vehicle, a series of dummy variables (1,0) representing ages of vehicles. In the current version of the simulator (Version 1.0), the scrappage rate model is estimated on annual data in 1991 and 1992, the latter based on a linear interpolation from registration data for 1991 and 1993.

The expected price equation was estimated as a lagged dependent variable model using two stage least squares, with allowance for serial correlation. The loss rate equation was estimated as an ordinary least squares model with correction for heteroskedasticity. The expected price in the loss rate model is a prediction from the expected price equation. The combination of the two equations enables us to predict vehicle loss rates for each forecast year and to equilibrate on vehicle prices taking into account the role that vehicle prices have on loss rates. We have built in a recognition that retailers have been prepared to discount new vehicle prices in a particular class where sales are sluggish.

APPLICATION ISSUES

The suite of behavioural choice and vehicle use models together with the conditions for equilibration define one part of the simulator. The application of the model system to evaluate a wide range of strategies and to derive useful empirical outputs such as changes in consumer surplus, government revenue, greenhouse gas emissions, total end user costs, total annual automobile kilometres, and energy consumed, requires a specification of a number of contextual dimensions. In particular the simulator requires as inputs the following data:

- The population of households
- The population of automobiles (number by type)
- The population of dwelling stock by location
- The population of employment opportunities (ie. jobs) by location
- The attributes of automobiles
- The socio-economic characteristics of individuals and households
- The network characteristics of each form of transport
- The future time profile of exogenous variables in a status quo scenario (eg. fuel prices, income, population growth, dwelling prices, public transport fares and service levels, new vehicle releases, automobile prices, and attributes of new vehicles)

The sample of travellers and households used in model estimation are not used in model application. *Synthetic households* define the application units. Each synthetic household is defined by two core socioeconomic variables—household income and lifecycle stage (defined in terms of the number of adults by age and number of dependent children). A weight is attached to each synthetic household to indicate its incidence in the population. The set of socioeconomic characteristics which exist in the set of travel, vehicle and location models are broader than the two core socioeconomic variables.

To ensure that the richness of the fuller set of socioeconomic variables contributing to the explanation of each choice are captured in the definition of synthetic households, so that the diversity of household responses is captured throughout the model system, we draw additional samples off of each 'core' synthetic household. The approach involves taking a random sample of households from the 1% unit record sample of households from the 1991 census, conditional on each core synthetic household. Since each of these households is a random sample from a 1% random sample, we capture the distribution of household types within each core synthetic household type. The data associated with each of these sampled households is sufficiently rich in socioeconomic characteristics of the household and its members. The variables available at the household level from the 1% sample are: household income, dwelling type, number of vehicles; the variables available at the person level are: age, industry sector, hours worked, industry, occupation, labour force status, relationship in the household, income, sex, education qualifications and mode for the journey to work.

In application, each synthetic household is 'introduced' into an urban area, carrying only a bundle of socioeconomic descriptors for each household member and the household as a whole. Through the application of the behavioural model system and given the specification of an urban area's transport network, location attributes (eg. number of jobs, number and types of dwellings, dwelling prices), and automobile stock and attributes, the simulator calculates a full set of choice probabilities and vehicle use predictions associated with each of the alternatives in each of the models in Figure 1. The probabilities and predictions of use are expanded up for each synthetic household to represent the demand by all households in the population represented by a synthetic household. The calculations are repeated for each synthetic household and then equilibration in the three markets (travel, location and vehicle) is undertaken to arrive at a final set of demand estimates. The set of outputs are accumulated throughout the simulator calculations so that a comparison can be made for each application year of each output before and after the simulation of one or more policy instruments which define a strategy.

Complementing the synthetic households are data specifications for new and used automobiles by class and fuel type, the transport network for existing and new modes (eg. light rail, busways), spatial and dwelling attributes for residential locations, and employment attributes for workplace locations. Forecasting the set of exogenous factors through time (up to the year 2017 in the current application) relies on external benchmarks for population growth, household size growth, price changes for dwellings, fuel, vehicles, fares etc., and the release of new vehicles by type. In addition the simulator requires descriptions of electric and alternative fuel vehicles (in terms of the attributes driving the vehicle type choice model), new public transport modes, and tollroads. Full details of the matrix of location, person and vehicle attributes are given in Hensher et al. (1995, Report 7).

The simulator is calibrated for the current population profiles in December 1993, and then applied annually with summaries of outputs for each year over the range of specified years. Each of the behavioural models is calibrated to reproduce the base 1993 shares and total on each alternative. We have selected the following data items for calibration in 1993 (Table 2).

SPECIFYING THE CRITICAL PATHS AND COMPONENTS IN THE MODEL SYSTEM

To understand how the simulator can identify the impact of a strategy, we have selected one illustrative instrument—a fuel tax increase, which involves an initial exogenous shock imposed on the vehicle and travel choice blocks. The imposition of an increase in the tax on automobile fuel, via its impact on unit operating cost (c/vkm) has an immediate and direct influence on (i) the use of each vehicle for particular trips such as the commuter trip (ie. mode choice, which includes both a switch to public transport and vehicle-substitution from within the household's vehicle park), (ii) a change in the timing of the commuter journey to reduce the increased costs associated with traffic congestion, and hence (iii) a change in the overall and non-commuting use of each automobile available to a household. It also directly affects the household's choice of types of automobiles from the set of conventional fuel, electric and alternative-fuel vehicles (the last two vehicle fuel types introduced in any year, under a reasonable expectation of availability). The indirect impacts include a change in residential location via the change in modal and spatial accessibility to work opportunities, and a change in the number of vehicles in a household (given the increased operating costs). Changes in residential location may further affect the total use of each automobile, as well as the mix of urban (commuting and non-commuting) and non-urban kilometres. The adjustment in commuter travel may also affect non-commuting car use if a vehicle previously used for commuting is released for use by another non-working member of the household. Some adjustment in the loss rate of automobiles will also occur. The response paths are summarised in Figure 2.

Table 2 Base year calibration criteria

Decision Block	Data Criteria
Location (per location)	. dwelling type share . total number of households . total number of workers . household fleet size distribution (0,1,2,3+)
Vehicle (per vehicle class)	. vehicle class shares . total registered passenger vehicles . total passenger vehicle kilometres . household fleet size composition
Travel	. commuter mode share . travel time (origin-destination) . commuter departure time profile . sample spatial and temporal work practice composition

The adjustments in vehicle, travel and location choices at the household level translate at the aggregate level into a new set of equilibrium levels for traffic congestion (broadly measured by the ratio of travel time to distance travelled), residential densities, total kilometres of travel by automobiles and various forms of public transport, fuel consumed and greenhouse gas emissions. To establish the equilibration in the market, we allow for a series of feedbacks between individual traveller and household responses, and what this means in terms of the key market clearing variables which lead, in an iterative manner, to further adjustments in behaviour as the market settles down to a steady state from which we can extract summaries of behavioural outcomes.

SELECTIVE APPLICATIONS OF THE ITS/BTCE STRATEGY SIMULATOR

The strategy simulator is a complex software package designed to evaluate the influence that one or more policy instruments will have on changes in greenhouse gas emissions and changes in total end user costs. Through the evaluation of each policy instrument, each varied to such an extent that an impact profile is identified in emissions-cost space, we are able to identify the minimum end-user cost solution over a predefined evaluation period, for a given percentage reduction of greenhouse gas emissions *in a target year*.

The ITS/BTCE simulator (Version 1.0) is written in C++ using Borland C++4.5. The source code for the simulation core is completely generic and can be compiled and executed on any computing platform with a C++ compiler which supports C++ templates and exceptions. The Simulator's interface is written using a Borland OWL 2.0 class library and is dependant on both the Borland C++ compiler and a Windows or Windows/NT computing platform.

In addition to establishing the financial and emission implications of alternative policy scenarios, the simulator generates outputs summarising changes in vehicle kilometres, vehicle type market share, commuter modal shares, end-use consumer surplus, end-use government revenue, and energy consumed by socioeconomic market, residential location and vehicle class.

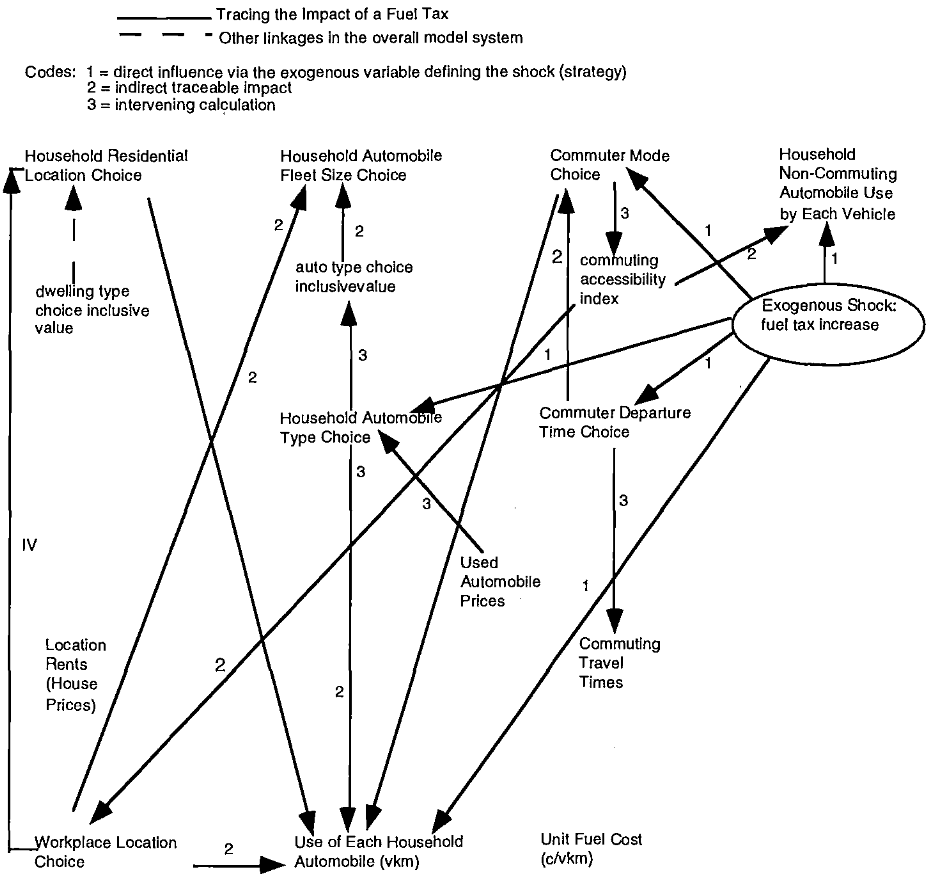


Figure 2 Tracing the impact of a fuel tax

Each policy instrument is varied in its level of implementation in order to trace out the change in the total end-user cost (TEUC) curve (in $93 present value terms) associated with percentage changes in greenhouse gas emissions. The minimum TEUC envelope traces the minimum end-user cost solution over the range of change in greenhouse gas emissions. Total end use cost includes *all* money cost dimensions plus time costs, the latter associated only with any changes in commuting travel time for all modes. Full details of the underlying assumptions and data specifications for the software are given in Hensher et al (1995, Report 7) together with an user-friendly manual to assist the analyst in operating the ITS/BTCE simulator.

The current version of the software (Version 1.0) is able to evaluate one or more policy instruments (ie a strategy) simultaneously; starting or terminatimg policy instruments in any year (eg introduce electric vehicles in year 2000). The level of an instrument can be varied through time. This flexibility enables the analyst to undertake very powerful investigations of the impact of instruments in combination or separately with any variation in the magnitude of the policy instrument.

Temporal allocation rules are introduced as heuristic's given the absence of a dynamic process in the set of behavioural choice models. The simulator allows for the transition period in the adjustment period, simulating behavioural inertia, with the user defining the rate of adjustment between adjacent years. The 'temporal allocation' works as follows. The user specifies the proportion of the change in a choice probability associated with each and every choice model which occurs between period t and period t+1. This proportion can vary between each of the choice models but can be the same if the analyst wishes to treat it as a constant proportion. A set of default proportions are available (Table 3). The changes in vehicle use occur fully in the one year. This temporal allocation applies to both the base case and the application case.

Table 3 The rules for temporal allocation of policy impacts (defaults in column 2)

Behavioural Choice	Proportion changed annually
Residential location choice (slow adjustment)	0.5
Workplace location choice (slow adjustment)	0.5
Fleet size choice (slow adjustment)	0.5
Work practices choice (slow adjustment)	0.5
Commuter mode choice (medium adjustment)	0.6
Vehicle type choice (medium adjustment)	0.6
Commuter departure time (fast adjustment)	0.8

To illustrate how the ITS/BTCE simulator handles the temporal response heuristics, suppose we introduce a carbon tax in 1995. The simulator commences in 1993 with no change until 1995. The status quo or base ('business as usual') situation for total end use cost and GGE's in 1995 and each subsequent year over the forecast period is initially determined, with appropriate temporal adjustment proportions. The base results for each year are stored since they only need to be obtained once. Suppose the probability of choosing a particular mode in year t in the presence of a strategy is 0.5. and in year t+1 it is 0.6. Given the temporal adjustment constant of 0.5, the relevant choice probability in year t+1 is 0.5 + 0.5 *(0.6—0.5) = 0.55. A full set of adjusted probabilities are calculated for each alternative in each choice model for each synthetic household. The ITS/BTCE simulator using 0.55 and all the other adjusted probabilities, and then equilibrates in year t+1.

In year t+1 we have to adjust the 'with policy base' at the end of year t to allow for changes in items such as the stock of dwellings by type and by location, and the number of people using each commuter mode by O-D pair etc, which arise through equilibration under the policy. The simulator then sums the end user cost changes each year (and converts them into $93 present value terms) and calculates the greenhouse gas emission changes between the base year and the target year to obtain the total change in end use cost and GGE's. This produces one point on a graph in cost-emissions space. The same strategy can be repeated with different levels of the same policy instrument(s). Other strategies can also be evaluated in a sequence, each always relative to the do-nothing or business-as-usual situation, to obtain a trace of the impact of each policy or policy set. A minimum cost envelop can then be identified, as illustrated in Figure 3. The strategy can continue to have an influence up to the year 2017 if required. A comparison of the base and application results for each year is automatically provided in the outputs.

CONCLUSIONS

This paper presents the essential elements of a new micro simulation model of the urban passenger transport sector, which recognises and accommodates the important linkages between location decisions, travel decisions and automobile ownership and use decisions.

The ITS/BTCE simulator combines a set of behavioural choice models, equilibration conditions and a profile of the base transport system, base automobile market and base location market, into a unified architecture to give the user a powerful decision support system for investigating the implications of a large number of evaluative strategies. Output dimensions are extensive—they include consumer surplus, government revenue, total end user (generalised) cost, energy consumed, emissions of greenhouse gases, composition of the automobile fleet, commuter modal shares and automobile use. Each output can be summarised by geographical location within each city, socioeconomic class (income and life cycle) and vehicle type (by fuel class).

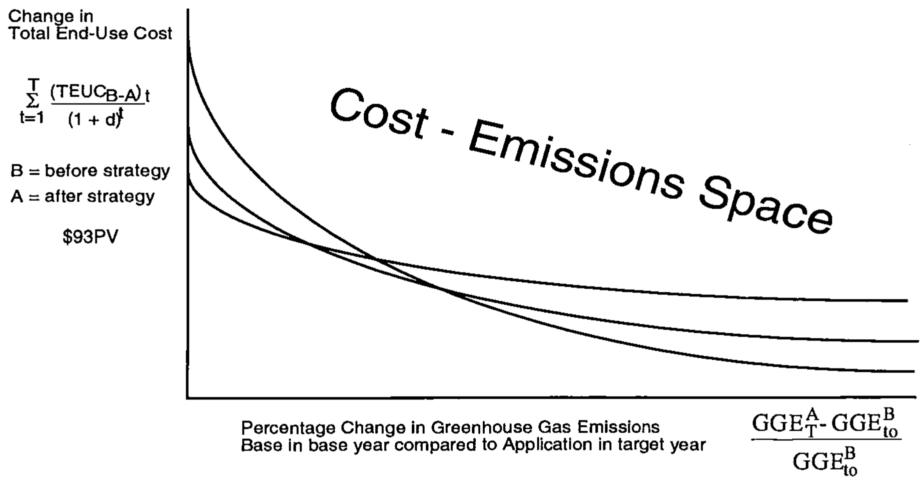


Figure 3 Illustrative minimum cost strategy given GGE target

The simulator emphasises end-use; additional costs such as those associated with automobile manufacture, energy generation and infrastructure provision (roads and public transport) have to be added into a final calculation of the full costs of the strategies evaluated by the ITS/BTCE simulator (necessary inputs into a calculation of producer surplus).

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