16
Transportation models and their applications

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16.1 INTRODUCTION

Transport models have been defined in many ways and there are various kinds of models. In this chapter, a model is defined as a simplified representation of part of reality. The main goal of transport models is to estimate the behaviour of the real system in different scenarios (see Chapter 14) in a specific forecasting year. Possible outputs of these models may be, for example, the number of passenger kilometres in a country, region or city, in a certain year or, often combining transport models and impact models, societally relevant outcomes in the area of accessibility, safety or the environment, and increasingly health. Models are often used to get an insight into the behaviour of the system in a do-nothing scenario and/or to gain an insight into the effects of proposed measures/policies on transport and other system-related components such as land use. Usually, not one but several futures are predicted whereby the effects of transport are computed for several scenarios concerning the socio-economic development and policy variants (see Chapters 14 and 15).

This chapter provides readers with an introduction to how transport models work and shows what they can be used for. This knowledge should enable the reader to form an opinion as to whether a specific model can be used to answer certain questions. This chapter is focused on what are often called 'strategic models'. These are models that aggregate volumes of travellers for a faster representation of mobility patterns in a city, region or country. In contrast, models for reproducing traffic flows on highways, intended for real-time traffic management, require modelling each vehicle. They are presented in Chapter 7 and are not dealt with in this chapter. At specific places in the text, we may refer to other modelling levels for the sake of distinction and clarification. For further insights into transport modelling, the authors recommend the book by Ortúzar and Willumsen (2011).

Section 16.2 provides an overview of strategic models. Section 16.3 introduces the concept of elasticity which is used in many strategic models. Section 16.4 discusses the traditional strategic aggregated models, while disaggregated models are discussed in Section 16.5. Section 16.6 deals with model validation. Section 16.7 presents some examples of models currently used in The Netherlands. Section 16.8 addresses the question of what can and cannot be done using transport models. The main conclusions of the chapter are presented in Section 16.9.

16.2 TYPES OF TRANSPORT MODELS

Models can be classified in various ways. Some of these classifications are presented in this section, but we do not claim to have covered them all. Before discussing the model categories, it is useful to remember what all models have in common, as indicated in the introduction: they are a simplified representation of part of reality.

A transport model describes human behaviour based on a theory of how humans behave in their daily mobility choices. This theory describes the connections between the variables in the model. Exogenous (independent) variables are variables that are determined externally, outside of the model. From these, we can distinguish variables the modeller will not change, for example, the GDP growth estimations coming from economics experts, and the experimental factors which will be changed to form scenarios such as the capacity of several road links or the public transport price. Endogenous variables are variables whose value depends on the model behaviour over time. For example, in a model where one wants to determine car ownership as a function of (among other things) economic growth, economic growth is exogenous and car ownership is endogenous. For a causal relationship at least three main criteria should be met: (1) empirical association, (2) temporal priority of the independent variable, (3) non-spuriousness, and preferably two more: (4) identifying a causal mechanism, and (5) specifying the context in which the effect occurs (Chambliss and Schutt, 2019).

The mathematical formulas in a model often contain so-called coefficients, which quantitatively indicate how the value of an exogenous variable affects the value of an endogenous one. A fictional example of a model based on elasticities (see Section 16.3, and Chapters 3 and 6) is a 1% increase in the income level leading to a 0.4% increase in car ownership. The value of 0.4 is the coefficient here. Determining the coefficients in a model is known as the model estimation. The aim is to make the model results as similar as possible to the collected empirical data that is kept for validation purposes. It is often the case that part of the data is used for the estimation of coefficients (calibration) and the other part for validation purposes. Statistical methods are often used to achieve this in a so-called statistical estimation method. Maximum likelihood estimation is an example of such methods, a method whereby one aims at maximizing the probability that the empirical data can be obtained by the mathematical structure that has been chosen to explain the phenomenon. Statistical estimation packages such as SPSS, Statistica or the R language allow you to apply this and other statistical methods.

16.2.1 Descriptive Versus Explanatory Models

Descriptive models represent the correlations between variables without explicitly considering causality, whereas explanatory models will map out causes as well as consequences.

In general, statistical data and their analyses provide only limited indications as to what the theory should be like. It is possible to develop a perfect statistical (descriptive) model about the relationship between the number of storks and the number of births (most storks are to be found in developing countries, where the number of births is high). But the statistical correlation between variables does not provide an insight into the causality and its direction. In other words, that model is not an explanatory model. An explanatory model could reveal, for example, if the presence of an airport in a region causes extra economic growth or if airports are typically situated in regions with a strongly developing economy.

Although models should ideally be based on an explicit theory of cause and effect, descriptive models can nonetheless often be useful. For example, by using data mining techniques a file containing many variables can be searched systematically for the existence of correlations which are a good start to building explanatory models. A concrete example in traffic safety is relating accident frequencies to road characteristics, regional characteristics, time of day and period, and so on (Wang et al., 2013). Afterwards, it can be studied whether the relationships that have been found can be explained in any useful way. In other words, are the relationships theoretically underpinned? In general, in any research project, it is advisable to start with descriptive analysis (e.g. by frequency and cross-tabulations) before developing models. The current trend in modelling based on machine learning and artificial intelligence ('big data') often departs from descriptive models, that, in later stages, can be further developed into explanatory models.

16.2.2 Spatial Versus Non-Spatial Models

Models can be divided into spatial and non-spatial models. In the latter, physical space does not play a role whilst in the former, the location of activities in space is an explicit component in the model.

An example of a non-spatial model is a model to explain car use in a country, estimated based on a time series using as explanatory variables (exogenous) the population age groups, the gross domestic product (GDP), fuel prices, road capacity and the price per kilometre for road transport.

In the case of spatial models, the research area is often divided into zones/regions/areas. Furthermore, there are networks for cars and other transport modes, often with many thousands of nodes and links (intersections and road segments). Each zone has its centroid, which is connected to the networks for cars and public transport through so-called connector links. One of the objectives of such spatial models is to estimate the origin-destination (OD) matrices, which indicate for each transport mode the number of trips between every pair of zones in the study area. But they can be used just for the statistical analysis of the relation between car usage and public transport accessibility using statistical regression.

Between the spatial and non-spatial models, one can have spatial statistical explanatory models. These are models that aim to explain a certain dependent variable that is expressed at the level of a zoning system but recognize the influence that zones have on each other. For example, the usage of metro in a city does not only affect the zone in which a metro station exists but also the zones around. This is known as spatial autocorrelation (Ibraeva et al., 2021).

16.2.3 Aggregated Versus Disaggregated Models

In the traditional aggregated models such as the 4-step model (see Section 16.4), the zone is the unit of generation and attraction of trips, and the trips are aggregated per time interval. In disaggregated models (see Section 16.5) travellers are modelled individually often with very specific descriptions for their origin and destination locations.

The aggregated models date back to the 1950s in the USA. They have been developed at a period where the 'predict-and-provide' approach was the mainstream transport planning policy, especially in the USA. Owing to prosperity, car ownership and car use strongly increased, which required extra road infrastructure. Forecasts were being produced for car usage in the next decade(s) ('predict') and, based on those forecasts, the roads and/or the extra number of lanes to be built were being determined ('provide'). During the 1970s in many Organisation for Economic Cooperation and Development (OECD) cities and regions, this line of thought shifted in favour of the idea that it would be impossible to meet the demand for car mobility indefinitely and therefore it was decided to opt for a different approach: a combination of containing measures, regulations, promoting alternatives for the car, optimal use of existing infrastructure and limited building of new infrastructure. Such a combination of measures, which can generally be called "transport demand management", arguably requires a different type of models, models that are disaggregated.

Owing to the progress achieved in statistical estimation techniques from the 1970s onwards, disaggregated models can nowadays be estimated much more efficiently by focusing on individual mobility rather than zone averages. Note though that the models thus developed need to be aggregated to make them workable for forecasting. After all, it is not the mobility of one specific individual that transport policy-makers are interested in, their interest is in the aggregated passenger flows on the roads and in public transport.

16.2.4 Static Versus Dynamic Models

In dynamic models, as opposed to static models, time plays a crucial role in the status of the variables that measure the state of the system. Changes in behaviour are assumed not to occur instantly but over a certain period. More importantly, the area (often: region) of interest is assumed never to reach a final equilibrium, there are always factors (exogenous or endogenous) that lead to change in the system over time.

One example is a model for the effect of the price of fuel on car use. If the fuel price per litre were to rise from €1.35 to €2.70 tomorrow, the short-term effect would be limited. Many commuters go to work by car and would have to do so tomorrow as well, for lack of alternatives. Any effects would only become visible in the medium to the long run (see also Chapter 6). These effects may be choosing a different mode of transport, different destinations closer by (e.g. for shopping), fewer frequent trips, finding a job closer to home, moving to a place closer to work, keeping the currently owned car for a longer time (to keep down depreciation costs), switching to a more fuel-efficient car, cut back on expenditures other than those linked to the car, and so on. In this case, the effect of the variable (e.g. the fuel price) on other variables (e.g. the commuting distance) is 'lagged' with unexpected consequences in the long term that are difficult to predict with a static model, for example on the land use. For the reader's reference, System Dynamics is a good modelling approach for such systems that exhibit delays and multiple feedback loops. However, they do have the disadvantage of only rarely being used for studying spatial interactions given their very aggregated nature (Legêne et al., 2020).

In transport studies, static models are usually estimated based on what are called cross-section data. These data constitute a snapshot taken at one moment in time. Dynamic models require time-series data. Preferably, these data capture a constant group of individuals over time, the so-called panel data. An advantage of such data is that the development of the exogenous as well as the endogenous variables over time is known for each individual.

16.2.5 Models Based on Revealed Preference Versus Stated Preference Data

When collecting data on individual choice behaviour, regarding transport mode choice or house buying location, for example, two options are open: that of revealed preference (RP) and that of stated preference (SP). In the case of RP, the actual choices made by the individual are observed in a real situation whilst in the case of SP, the researcher confronts the individual with hypothetical selection situations.

In the case of RP, people are asked, for example, to keep a travel diary indicating data like origin, destination, travel mode, time of day and travel purpose for every trip. Or data are collected automatically by making use of information and communications technologies (ICT) ('big data'), for example via cellphones (Demissie et al., 2015). In the case of SP, respondents, for example, are shown five to ten choice sets each with two trip alternatives, from which they are currently asked to choose their preferred one. This kind of data has two major advantages. Firstly, it is often less expensive. Secondly, it can be used for making predictions regarding non-existent alternatives, like the demand for an automated vehicle for accessing a train station as first-mile transport (Yap et al., 2016). Of course, there are also drawbacks, the most important of which is that the models have to be adjusted for respondents' bias as many times social norms dictate an answer that is not what the respondent would opt for in reality. So-called social-desirability bias can be quite critical in evaluating new technologies such as electric vehicle adoption (Smith et al., 2017).

It's also possible to combine RP and SP data, and often advisable. RP data provides a scale of realistic preferences between the existing alternatives whilst SP is used to compare such alternatives with the new ones to be introduced, like in the example of introducing new vehicles to the market. A vehicle is still a vehicle with some common attributes like size and power, but new fuel/energy (electricity, hydrogen) can change some of the characteristics of the vehicle as well as of its usage (Brownstone et al., 2000).

16.2.6 Trip-Based Versus Activity-Based Models

Early transport models, and still most of the currently used models, consider travel behaviour in isolation, studying trip OD matrices as being generated in space by the land use of a region but with very little connection between the demand over different time periods. Later, so-called activity-based models made travel dependent on the activity patterns of the individuals and their households.

In the early models, the interactions between successive trips of an individual or household were not considered; in fact, individuals and their families were not the units of analysis, as explained, the zone was. However, it is known that individual characteristics such as income and time-budget restrictions greatly affect travel behaviour. There are all kinds of constraints that are connected to the life-cycle stage in which the individual and the household find themselves that influence the trips that are taken during a day, a week, a month or a year. Synchronization of different activities within the family (for example meals or shopping activities) as recognized in time geography, (see Chapter 3) put extra time restrictions on the choice of behaviour concerning the activities and the travelling between those. These constraints ultimately determine the set of feasible alternatives (see Chapter 3). The advantages of these 'activity-based models' are (1) that they provide a better description of behaviour and, in connection with this, (2) that they produce better estimations of aggregate behaviour under a wider range of policies and measures. The major drawback is that this type of model rapidly gets very complex and it needs a larger number of resources to estimate and use.

16.2.7 Models That Consider Versus Do Not Consider Land-Use Changes

Traditional models describe transportation as a derivative of spatial planning. In practice, however, transport and land use mutually interact. The presence or absence of transport infrastructure affects the pattern of spatial activities, and land-use patterns influence the development of transport networks (see also Chapter 2 and Figure 2.1). The models that take the interaction between land use and transport into account are the so-called Land Use and Transportation Interaction (LUTI) models.

The spatial effects of the transport infrastructure can be considerable, especially in the long run (think of cities that came into being near natural harbours or river crossings). The building of a new road or railway, for example, may well lead to businesses settling in their vicinity, or businesses may leave an area because this is now under heavy congestion.

The first example of an operational LUTI static model is the Lowry model (Lowry, 1964), which became quite famous. Using road accessibility to explain where people live and work in a city, Lowry produces a static equilibrium between the different areas of an urban region in terms of population and jobs mediated by transport accessibility. This is what came to be called a spatial interaction type of model (Iacono et al., 2008).

A drawback of the use of these spatial interaction models is, however, that in reality the land-use effects only appear after a long time and need not be solely due to infrastructure changes. Therefore the possibility of validating these models remains difficult. In particular, the validation relies on data about the development of several system variables over time, such as population dynamics and house market supply and demand. This data may be difficult to access.

An example of a more modern and complete dynamic LUTI model is the Integrated Land Use, Transportation, Environment (ILUTE) model developed for the region of

Toronto-Hamilton by the University of Toronto (Farooq and Miller, 2012). This model will be explained in Section 15.7. More information about LUTI models can be found in Geurs and Ritsema van Eck, 2004, Iacono et al., 2008 and Lopes et al., 2019. The TIGRIS XL model should also be mentioned; this is a LUTI model that is used in The Netherlands by government agencies to assess long-term mobility and transport policies (Zondag et al., 2015).

16.2.8 Passenger Transport Versus Freight Transport Models

The majority of the transport modelling studies deal with passenger transport, not addressing, the freight component. In fact, on most roads, the share of freight transport is limited. Yet models for freight transport have gained importance in recent years (Tavasszy and de Jong, 2014). Freight transport has been growing and is expected to continue to grow more than passenger transport. Trucks are an increasingly important part of road transport modelling studies because the CO2 emissions per passenger car have been decreasing more rapidly than that of trucks. Besides, heavy trucks damage the road surface, and slow, heavy trucks can induce traffic jams.

One of the problems in developing freight transport models is the availability of data. Aggregated economic statistics often use a too coarse classification of economic sectors. Disaggregated data are hard to collect, because their collection is dependent on the voluntary cooperation of businesses and because one company encompasses many different actors (management, administration, production departments, logistics department, transportation department) (Thoen et al., 2020).

16.2.9 Agent-Based Models

The last generation of transport models is the so-called agent-based models (ABMs) (Iacono et al., 2008). This is a methodology for modelling any kind of complex system and it has been used in the transport domain for the past two decades. The agent-based principle is one of ‘emergence of behaviour’, a bottom-up approach that is grounded on modelling the system agents in their relationships with each other and also with the relevant environment. For example, a vehicle driver in traffic can be considered an agent that has to interact with other vehicles and make decisions on braking, steering and accelerating as well as more strategic decisions such as which route to choose based on traffic congestion (Wang et al., 2019). ABMs, therefore, are highly disaggregated, dynamic, spatial transport models that can incorporate a lot of the knowledge that has been built over the years in the previous modelling methodologies.

In advanced transport models, especially those that have a LUTI component, the main agents are typically citizens in a region who choose between which activities to perform, what modes of transport to take and what paths to take to reach their daily destinations. The agents are representative of the real population, and it is possible today, with modern computers, to model one synthetic agent for each real citizen. There is a natural relationship between the ABM approach and the activity-based models explained before. A computer agent representing a citizen will require the generation of an activity plan for him/her and possibly for the household that it belongs to.

The level of detail of these models can vary considerably with the objectives of the model. Typically the modeller decides which agents are relevant for the problem, the level of detail of the agents' behaviour and the level of detail of the environment. The ILUTE model that was mentioned above is also an ABM that integrates an activity-based module; it considers what its agents need to do daily. Furthermore, it goes beyond the transport sector by aiming at forecasting how land use will evolve in a region (Farooq and Miller, 2012). Nevertheless, it lacks the details of how humans behave in the transport system itself, meaning, for example, how they drive and behave when they face traffic congestion. A popular ABM (and activity-based model) of the traffic component of a city is MATSim (Axhausen, 2016) which has been recently used for several purposes such as modelling the impacts of automated vehicles (Fagnant et al., 2016).

16.3 ELASTICITIES

Many models contain what are called 'elasticities'. This has already been briefly discussed in Chapters 3 and 6. In this section, the notion is further elaborated on.

Elasticities enable us to quickly get an insight into the following question: to what extent is a change in one variable associated with changes in other variables? An example is the elasticity of car use (in kilometres) as a function of the fuel price. If this elasticity is −0.4, car use will reduce by 4% if the fuel price rises by 10%. In general, elasticity E of a variable y because of a change in a variable x is defined as:

$$x - elasticity\ of\ y{:}E = \frac{\partial \mathrm{y}/\mathrm{y}}{\partial \mathrm{x}/\mathrm{x}} \tag{16.1}$$

Two kinds of elasticities are distinguished: direct elasticities and cross elasticities. The previous example is about direct elasticities: the effect of an attribute of cars on the car usage itself. If we look at the effect of fuel price changes on, for example, public transport, we are dealing with cross elasticity. If one focuses on price elasticities, direct elasticities are negative (an increase in price leads to lower demand) whereas cross elasticities are usually positive (the competing mode gets transferred demand). Cross elasticity of the use of public transport as a function of the car's fuel price might be, for example, 0.1. In that case, the use of public transport would increase by 1% if the fuel price rose by 10%. In this example, therefore, the cross elasticity is quite small or inelastic: this corresponds to the fact that substitution between the car and public transport is very limited (Cullinane and Cullinane, 2003; Lunke et al., 2021; Steg, 2003). If fully independent goods or services are at stake, the cross elasticity is 0.

Elasticities are especially popular because they are simple and understandable. However, the risk of misuse is considerable. Elasticities are usually not constant: a rise in fuel prices from €1.35 to €2.70 (double the cost) may have a different effect than what a fuel price rise from €2 to €4 would (also double). Therefore elasticities are point specific and direction-specific (increase or decrease). For mode choice instead of making simple approximations with elasticities, one may have to consider the demand curve as a function of price. To obtain such a demand curve, one would have to estimate a statistical model. Based on such a model, it is possible to calculate the elasticity at any point as another indicator of the behaviour of the curve. Nevertheless using elasticities as a single method is a too simplistic approach, even if derived from a statistical model that explains demand as a function of price, and that is because the transport system is a complex system with multiple feedbacks connecting different components. Take the example of induced demand in an urban road network, once the fuel prices increase there will be a reduction of demand, however with that reduction of demand there is a reduction in the travel time which in the medium and long run will continue to attract people to use the car (perhaps different people). Demand is therefore not just the result of one variable and is affected by several dynamic feedback loops that many times need to be modelled to get a realistic estimation of the impact of a policy or measure.

16.4 THE 4-STEP MODEL: A TRADITIONAL AGGREGATE MODELLING APPROACH

As was mentioned above, in the case of spatially aggregated models a study area is divided into zones. Furthermore, the main transport modes (car, public transport and active modes) have pre-defined networks, which may have thousands of nodes and links. Each zone has its own centroid node, which is connected to the transport networks through connector links.

The 4-step modelling procedure that was applied for the first time in the USA in the 1950s (Ortúzar and Willumsen, 2011) is the following:

1st Step: Generation (production) and attraction – answering the question as to how many trips depart from a zone and how many arrive at each zone.
2nd Step: Distribution – from the trips that depart from each zone what are their destination zones?
3rd Step: Modal split – from the trips that start and end at different zones how many are done using each mode or combination of modes of transport?
4th Step: Assignment – which route is taken to get from an origin to the destination zone in the existing networks?

Trip generation models compute the total number of trips O_i departing from zone i in a certain period of time. That number is based on the characteristics of the zone concerned, like population size, retail area and employment. These characteristics are known as land-use variables. The popular Trip Generation handbook in the United States is a good source for relating trip generation factors and the number of trips for many common functions (Hooper and Institute of Transportation Engineers, 2017). Trip-attraction models compute the total number of trips D_j in the OD matrix that have their destination at a certain zone j.

The most classic distribution model has been derived from the gravity theory (Newton's laws about attraction between celestial bodies). In accessibility, though, a distribution model usually looks like the following expression where the constants that Newton estimated are replaced by parameters to be estimated for each application region:

$$T_{ij} = A_i \; O_i \; B_j \; D_j \, f(c_{ij}) \tag{16.2}$$

where T_{ij} is the number of trips between zones i and j, and O_i and D_j are the generation from zone i and the attraction from zone j, respectively, as derived from the generation and attraction model.

The balancing factors A_i and B_j for the zone of origin i and the zone of destination j ensure that the trip-distribution results are consistent with the results from the trip-generation and trip-attraction models. This results in what is called a 'doubly constrained model' since both O_i and D_j are respected. Single-constrained or unconstrained models are used as well but they are not discussed here.

In the impedance function $f\left(c_{ij}\right)$, c_{ij} represents the generalized travel costs between zone i and zone j. For example, $c_{ij} = \alpha \times \textit{travel distance} + \beta \times \textit{travel time} + \gamma \times \textit{toll charge}$ (where a, β and γ are weighting factors). In the generalized travel costs, times and other factors such as the number of transfers in public transport are all translated into costs. The translation takes place through the so-called value of time, which is the number of monetary units a traveller is willing to spend to decrease a unit of his/her travel time (see Chapter 15).

Modal split models divide the number of trips T_{ij} in trips per mode T_{ij}^m where m is the index of the modes of transport available between the OD pair $< i,j >$. Most often, discrete choice models are used for this (for a general introduction to the logit model, the most classical one, see Section 16.5 on disaggregated models). At the end of this step, there are as many trip matrices as there are modes in the region of study (or combinations of modes in multimodal transport).

Usually, the last step in this 4-step aggregated modelling approach is the allocation of trips to the network (trips assignment). Various methodologies are available for this. The first and most simple methodology is that of all-or-nothing. In this case, it is assumed that everyone takes the same, shortest route between i and j. Shortest is defined here in terms of travel time or generalized costs of travelling (as defined above). Such shortest paths are computed by using an algorithm, for example, the Dijkstra algorithm (Dijkstra, 1959). The second methodology is that of stochastic allocation, also called multiple routing. In this case, differences in the perception and taste of individuals are included in the model, therefore, distributing the travellers along the several possible competitive paths for each OD pair according to their perceived utility. The assignment can be done using a logit model, explained in the next section on human behaviour modelling, whereby the travellers are assigned to paths according to their probability of choosing each path of the choice set. The third and most used methodology, user equilibrium (UE) traffic assignment, is especially meant to be used for car networks as it takes traffic congestion into account. Congestion causes changes in the travel times on the road network. The relationship between the traffic intensity on a stretch of road, on the one hand, and its capacity, on the other hand, is described by a speed-flow curve (see Chapter 7). Because of delays due to congestion, the original free-flow shortest route between zone i and j will become less attractive. Finding all the routes and their number of travellers for each OD pair in an equilibrium situation is obtained by following the so-called first Wardrop principle: in stable conditions, all routes used between i and j have identical travel times so that no driver can improve his/her travel time by opting for a different route. If in this situation of congestion, the methodology of stochastic allocation is used as well, meaning that there is uncertainty on the perception of travel times, a fourth methodology emerges: the stochastic user equilibrium assignment. Under this approach, no driver can improve his or her perceived travel time by unilaterally changing routes. Models that take into account the departure time of the drivers are relatively more recent and belong to the dynamic traffic assignment methods. For further details, see for example Ortúzar and Willumsen (2011) or Sheffi, (1986).

The way the four steps have been presented makes it seem like the sequence from the first to the last step makes perfect sense, just like a traveller would first decide if he/she will travel or not (1st step), then where he/she would travel to (2nd step), finally deciding which mode to take (3rd step) and which path to follow (4th step). However, this may be deceiving: some of these decisions are highly interconnected. As an example, consider the effect of traffic congestion on the mode choice. If everyone would like to use their private car that would be physically impossible, since the network does not carry so many vehicles under an acceptable travel time. That is why in several 4-step model applications there is feedback from the trip assignment step to the mode choice step, especially in highly congested urban areas. And mode and destination choice are often made simultaneously *see* in the next section on disaggregated models how the destination choice (equivalent to the distribution step) can also be connected to mode choice.

Even today, the aggregated 4-step model is still widely used. Most large cities in the developed but also developing world run some type of 4-step method to help plan their transport system. The method is usually implemented in software such as PTV-VISUM, Omnitrans or Cube, to name a few.

Disaggregated models make better use of individual data compared to aggregated models. And nowadays, as explained above, big data is being collected about people's behaviour everywhere including cellphone usage data, which is a good proxy for location data (Demissie et al., 2013; Wang et al., 2018). Nevertheless, in many cases, those individual data have to be specifically collected for the study at hand. In addition, a disaggregated model has to be aggregated before it is ready for forecasting. Data for aggregated models at a zone level are often easier to estimate from routinely collected statistical data.

16.5 HUMAN BEHAVIOUR MODELLING

The disaggregated approach (Ben-Akiva and Lerman, 1985; Ortúzar and Willumsen, 2011) uses the individual or the household as the basic unit for the analysis. When participating in traffic and transport, an individual needs to choose between alternatives. His or her travel behaviour can be unravelled into many decisions, such as for instance:

1. To make a certain trip, or not to make it (generation).
2. The choice of the destination (distribution).
3. The choice of the means of transport (travel mode selection).
4. The choice of the route to be taken (route selection).
5. The choice of the time of day for the trip (time-of-day selection).

Except for the last one the other decisions can be associated with the classic 4-step model that has been explained in the previous section. The time of day decision can be seen as an improvement on the assignment of trips to the network, recognizing that some travellers may avoid travelling at their desired departure time due to traffic congestion.

For explaining these decisions there is the need for a model to indicate the alternative that the individual will select from the set of alternatives offered. A rational individual will prefer the alternative that will yield the highest utility. Utility is a construct in economics that reflects the satisfaction or benefit that individuals gain from choosing a certain choice alternative. This utility cannot be measured or observed directly. Instead, the planners or analysts infer what is the utility of each alternative by observing how frequently the individuals choose it. Furthermore, the planner assumes that total utility consists of the sum of a deterministic component and a stochastic component. The deterministic component is a function of all variables that the analyst/planner can collect about the choice and the decision-maker such as the characteristics of transport mode *i* that are relevant for the individual (like speed, costs and comfort) and the individual's socio-economic characteristics (like gender, age, education and income). The stochastic component describes what cannot be observed by the planner meaning that, by knowing all variables in the deterministic part of utility, the analyst still cannot explain and predict an individual's choice exactly. However, he/she can assign a probability that each alternative is chosen. From here, a Random Utility Maximization principle arises to explain human choices. From the assumptions made regarding the stochastic component different choice modelling structures are generated.

The most used choice model is the multinomial logit model:

$$P_i = \frac{e^{V_i}}{\sum_{j \in M} e^{V_j}} \tag{16.3}$$

where P_i is the probability that the individual will select alternative i, V_i is the deterministic or systematic part of the utility of alternative i and M is the set of all the alternatives.

In the case of applying choice models for explaining transport mode choice, all the variables defined above can be plugged into the systematic component of the utility function. The utility functions determining the probabilities will then look like this example of a choice between public transport and car:

$$V_{PT} = \beta_0 + \beta_1 TT_{PT} + \beta_2 TC_{PT} + \beta_3 WT_{PT} + \beta_4 TrT_{PT} + \beta_5 CO \tag{16.4}$$

$$V_{Car} = \beta_6 TT_{Car} + \beta_7 TC_{Car} + \beta_8 PrC_{Car} \tag{16.5}$$

where TT_{PT} is the travel time of PT, TC_{PT} is the travel cost of PT, WT_{PT} is the waiting time for PT, TrT_{PT} is the transfer time of PT, CO is a dummy variable that takes the value 1 if the person has a private car and 0 if not, TT_{Car} is the travel time of car, TC_{Car} is the travel cost of car, and PrC_{Car} is the parking cost.

The β coefficients in the utility functions indicate how the various variables affect the utility of each specific transport mode. The larger a coefficient is in relation to the others, the more it affects the utility an individual derives from the travel mode concerned. Negative coefficients indicate that the corresponding variable decreases the utility of the transport mode, for example, all the coefficients of cost and time are expected to be negative. The coefficient for the dummy variable *CO* should be negative as well since having a car should lead people to use less public transport. β_0 is the so-called alternative specific coefficient (ASC) which measures the average unexplained part of the utility, that is, the mean of the error term. A positive or negative value of this coefficient gives clues to aspects that are not being expressed in the existing utility functions, like for example a positive or negative attitude toward a particular mode.

The values of the beta coefficients are determined by using statistical estimation techniques. Most estimation is done by maximum likelihood. The basis for this is a random sample of trips actually made (called 'revealed preference' data) or trips that respondents say they would make in hypothetical choice situations (called 'stated preference' data).

It can be demonstrated that the natural logarithm of the denominator of the multinomial logit expression (16.3) $ln\left(\sum_{j\in M} e^{V_j}\right)$, also called the 'logsum term', is the maximum expected utility that can be obtained from the choice of those modes for a particular trip for the average decision-maker (Ben-Akiva and Lerman, 1985). It can also be demonstrated that this is the expected consumer surplus in economic theory for choosing to consume a certain product, here a mode of transport (de Jong et al., 2005).

A trip distribution model can also be a logit model. In such a model the choices are not the modes, but the destinations. Here, also, characteristics can be identified that affect the likelihood of the individual selecting destination *d* from a collection of possible destinations *D*. On the one hand, the effort required from the individual to reach a certain destination plays a part, and on the other hand, there is the attractiveness of a destination. Interestingly it can be demonstrated that if an exponential impedance function $f\left(c_{ij}\right)$ is used in the trip distribution gravitational method (explained in the previous section) this becomes a multinomial logit destination choice model (Anas, 1983).

In a model where a multinomial logit structure is used to explain the destination choices, the logsum term, which as explained above is the maximum expected utility from the choice situation, becomes a measure of accessibility in the region since it weights the different destinations according to their reachability and desirability to the average citizen (Geurs and van Wee, 2004). As mentioned, variables that describe the travel to the destination as well as the characteristics of the destination should be used.

Since the choice of the transport modes is most often also a multimodal logit model, location and mode choices can be joined in a so-called nested model. Because there are several alternatives to travel to the same destination, the transport effort required to get to *d* can be expressed as a weighted sum of the effort using each travel mode to get to *d*. Here once again one can use the so-called logsum (or "inclusive value" as referred to by other researchers) variable which is determined from the underlying modal split model, thus forming a nested logit model of the joint choice of location and mode of transport (Ben-Akiva and Lerman, 1985). To evaluate if such a choice structure compared to a simpler one makes sense, the typical validation procedures of a nested logit model can be used (Train, 2003).

The way in which destinations and modes of transport are chosen can vary with the trip motive. Regarding commuter trips, most likely, an individual will first choose a destination (workplace) and next a travel mode. In this case, the two steps can be kept separate with travel impedance playing a lesser role in explaining the destination choice. However regarding shopping trips, for example, the choices of destination and travel mode may be simultaneous, comparing options like travelling by car to a suburban shopping mall or by tram to the city centre.

When modelling an individual's trip frequencies in a disaggregated trip-generation model, various explanatory variables can be distinguished. Socio-economic characteristics like income, profession and age have been demonstrated to be important determinants. Furthermore, characteristics of the household that the individual is a part of, like the number of members of the household and whether or not there are children, are important. Besides, factors like the accessibility of destinations from the individual's residence and the attractiveness of making a trip from the residence (sometimes) play a part.

A disaggregated model for time-of-day selection usually uses the current time of departure and several periods (e.g. per quarter of an hour) before and after as alternatives. The utility of each alternative period is a function of the travel time and the travel costs in that period. If there is a lot of congestion, the travel time will be high. Travel costs can get high if a peak charge is introduced, for example. High travel time or costs diminish the utility of such a period and with it the likelihood that that particular period will be selected for a trip.

Various other disaggregated models exist besides the logit model. In the logit model, it is assumed that the stochastic component of the utility follows an extreme value distribution (a family of continuous probability distributions) (Hensher et al., 2005). One alternative is the 'probit' model, in which the stochastic component follows a normal distribution. Furthermore, over the last few years, the mixed logit model has become very popular, especially among researchers. In this model, the β coefficients do not have a fixed value; instead, they are individual-specific, following a certain statistical distribution over the population with a mean and a standard deviation (Hensher et al., 2005; Ortúzar and Willumsen, 2011). Because of its complexity, the mixed logit model is better suited for describing behaviour than for predicting future behaviour. Other models that are not within the family of logit models or are not based on the principle of random utility maximization have also been proposed such as random regret minimization (Chorus, 2012).

As already indicated in Section 16.4, the results of disaggregated models need to be aggregated before they can be used for forecasting. A description of an aggregation procedure is beyond the scope of this chapter (see Ben-Akiva and Lerman, 1985; Ortúzar and Willumsen, 2011). After aggregated OD matrices have been obtained through that process these can be used for the traffic assignment, in the same way as described above for aggregated models.

16.6 VALIDATION OF MODELS

Validation is defined as the assessment of whether or not the model describes reality correctly. The question is phrased simply, but the answer is usually complicated (Cambridge Systematics, 2010). For validation purposes, designers use independent data not used during the construction of the model. They want to know the reliability of the model for a wide range of situations.

Aspects that have to be taken care of during validation of a transport model may be:

1. Application scope. For example, when using a peak model designed for working days, model users cannot expect the model to perform well for peak travel during holidays.
2. Qualitative criteria. For example, for which policy measures should the model be suitable in general?
3. The level of validation. On which road links should the model be able to calculate delays due to congestion? All roads or just a few important roads under scrutiny? The model designers must also define their levels of confidence in the forecasts that they judge to be acceptable.

The analysis of the non-conformities of the model with the requirements in terms of model validation will ideally give clues about needed improvements:

1. At the lowest level, additional model parameters could be added.
2. At the level of computation, the accuracy could be increased, for example by calculating with more digits or taking smaller time steps (in dynamic models).
3. In iterative model-solving algorithms, the step size could be reduced or the number of iterations could be increased.
4. The mathematical model might not sufficiently adhere to the conceptual model and hence might need to be enhanced.
5. Finally, at the highest level, the conceptual model might need some modifications because the dependencies are not correctly modelled or because the theory needs amendment.

16.7 SOME EXAMPLES OF MODELS

In this section, we present three models. We first describe the LMS, the national Dutch model system, being an example of a state-of-the-art mainstream strategic transport model. This is followed by ILUTE, a state-of-the-art agent-based LUTI model. Finally we present DYNAMO, an example of an impact model, in this case a model for car ownership, energy use and emissions.

16.7.1 The Dutch National Model System

The Dutch National Model System (in Dutch: Landelijk Model Systeem – LMS) is an internationally renowned, unique instrument for designing transportation policies. Rijkswaterstaat, the public works department of the Dutch Ministry of Infrastructure and the Environment, has been using it since 1986. Besides the LMS there are four regional models, together covering the whole of The Netherlands and fully consistent with the LMS (Rijkswaterstaat, 2017).

The LMS is a disaggregated model system (modelling individual decisions) that can estimate future traffic flows, both on the trunk-road network and in public transport. The LMS is a spatial model, which means that The Netherlands and small parts of bordering countries have been compartmented into about 1500 zones, each with its characteristics (e.g. employment, number of students, income, size of the working population in the base year). These characteristics were mainly derived from statistics prepared by the CBS (the Dutch Central Statistical Office). For the forecasting year, these data were derived from scenarios designed by the Dutch planning agencies PBL (environment) and CPB (economy), partly based on other models.

When using the model, the following steps can be distinguished:

- Step 1: Choice behaviour for each type of household

  The model starts with the choice behaviour of individuals or households. Households decide on car ownership. An individual makes a comparative assessment of travel costs versus travel time for the different modes of transport. For example, using the car in the morning peak hours will take more time than making the same trip at a later point in time. These choices are based on behaviour actually observed (RP data; see Section 16.2), as found either in the trip diaries from the annual OVIN, the Dutch national travel survey (CBS, 2021), or derived from the responses from a study in which individuals were asked to state what their behaviour might be in reaction to a change (SP data; see Section 16.2). The latter applies to the planned introduction of a per kilometre tax (road pricing), for example.
- Step 2: Type of travellers in the base year

  Using the choices made by individuals and households, the LMS establishes what are called traveller types. What are the characteristics of the people making the choices? The following characteristics may be distinguished, among others, by: age (grouped into 18 classes), gender (2 classes), car availability (5 classes), participation in society (working, retired, etc., 5 classes), income (10 classes), education level (4 classes) and owner of a student OV-chipcard (a public transport smart card) or not (2 classes). For households, there is a similar classification. This is done for every zone, in both the base year and the forecasting year, and is necessary for being able to estimate future traffic flows. For example, if the number of people over 50 years of age in 2030 is twice as large, *ceteris paribus* the model takes into account an increase in the number of trips made especially by people in that age group.
- Step 3: Applying the choice models

  In step 2 the traveller types and their choice behaviour have been generated. In this step, the choice models are computed. The following choices are taken into account:
  1. the choice to obtain a driving licence and to own a car;
  2. the decision as to whether or not to make a trip;
  3. the selection of the travel destination, the travel mode, the time of day, station choice and access/egress mode choice;
  4. for car drivers the selection of the route to take. For people travelling by train, bus or tram/metro the assignment to lines is done using a commercially available software package.

  In addition, for car drivers and train passengers, time of day choices are included. The LMS thus mainly consists of four choice models which are directly related to the choices listed above. To determine the transport demand, the first three choice models, in particular, are important. The LMS brings the transport supply from the network data. Using the driving licence and car ownership model, the LMS determines car ownership per household and zone but uses the DYNAMO forecast (see 'DYNAMO' below in 16.7.3) for the whole of The Netherlands as a constraint. The car ownership model, therefore, works as a distribution model for a given external national total. The LMS determines the choice of destination, travel mode, station choice and access and egress mode choice and time of day based on the tour generation and accessibility. Except for the choice of the route, all LMS choice models are disaggregated logit models.

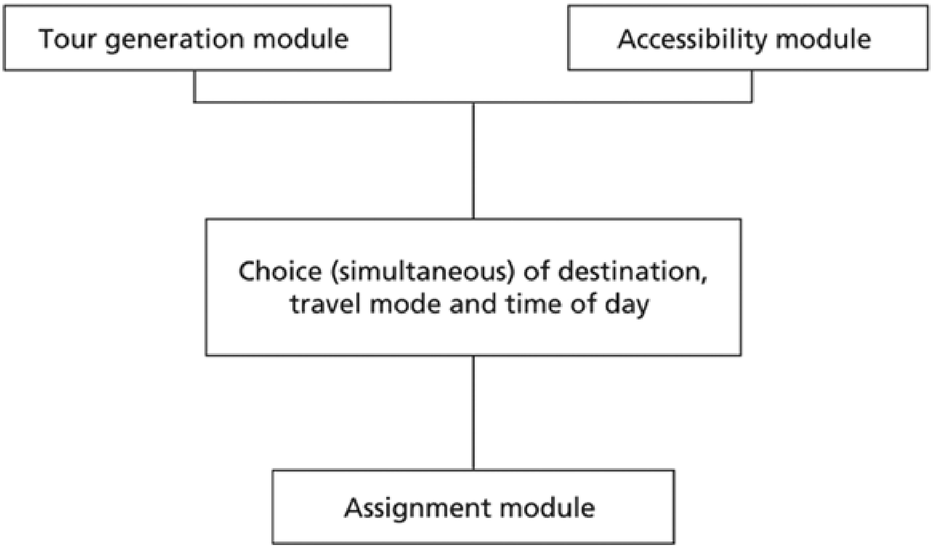


Figure 16.1 Coherence between various choice modules from the LMS

Figure 16.1 shows the coherence between various choice modules from the LMS. Note that the figure includes the dominant modules, but not all. In addition, the LMS has a time-of-day module, models for secondary destinations and non-home-based trips, a model for border crossing car traffic and a model for destinations (or origins) of air travellers including the mode choice for getting to the airport or the destination within The Netherlands.

For the assignment of the car trips, QBLOK is used (Significance, 2021). The essential difference between QBLOK and other equilibrium assignments (see Section 16.4) is the calculation of the link travel times. During the calculation of the travel time on a link, QBLOK takes into account the inflow from the preceding links. The inflow on the link is constrained when there is congestion on the preceding links. It is also investigated whether blockades occur. These limit the maximum outflow from a link, owing to the distribution of congestion over the network. A blockade occurs when traffic on a link is halted by a bottleneck elsewhere, but will not pass that particular bottleneck itself.

- Step 4: Types of travellers in the forecasting year

  After the choice models have all been run the model can compute the situation in a future year. The model now determines the size and composition of the future traveller population for each location in The Netherlands, thereby using all input on demographic and socio-economic data as well as spatial developments. The model thus computes the types of travellers in 2030, for example.
- Step 5: Changed circumstances

  In this step, the planned policy options that may affect the choice behaviour are taken into account. An example of such a policy option is increasing the frequency of railway connections between Amsterdam and Rotterdam. This may mean that more people may opt for public transport. A second example is making parking in Rotterdam more expensive, in which case people would use the tram more often and leave their car at home. A further example is widening a stretch of the A4 motorway (connecting Amsterdam and Rotterdam via The Hague), in which case the trip to work would take less time (at least in the short run), so car owners would rather travel by car on this route.
- Step 6: Forecast: new travelling behaviour

  The model computes both the short and the long-term changes in the choice behaviour. A heavier load of traffic on a stretch of the road means, in the short run, that people opt for a different route, whereas in the long run, they will opt for a different time of departure, while in the even longer run they will opt for a different travel mode and ultimately maybe even for a different destination. The model forecasts the number of travellers for each transport mode as well as the number of kilometres they travel. It also computes the transport flows within and between zones. Finally, the model allocates these trips to the trunk-road network and public transport.

  In order to be able to run the LMS, input is required. As could be deduced from the outline presented above, this input consists of:

  1. road networks, including, for example, toll charges;
  2. public transport networks;
  3. parking costs;
  4. socio-economic and employment data for each zone, both in the base year and in the forecast year;
  5. driving licence and car ownership data;
  6. a description of passenger mobility and freight transport in the base year including OD matrices for the modes car driver, train, bus and tram/metro.

  The LMS distinguishes various transport modes: car driver, car passenger, train, bus, tram/metro, bicycle, walk, and finally bus/tram/metro as access transport for the train.

There are 11 travel purposes distinguished in the LMS, covering commuting, business, school and private travel. Some travel purposes are non-home-based. There are nine times of day distinguished, covering peak, off-peak, evening and night. The number of day periods is this large because the peaks widen more and more. To be ahead of traffic jams motorists leave earlier or later. For the benefit of a correct prediction of the travel time losses due to traffic jams, it is essential to predict the distribution across times of day as precisely as possible.

The output of the LMS consists of:

1. Forecasts about passenger mobility in The Netherlands in the forecast year. For the transport modes and travel purposes listed, as well as for the time of day, the LMS distinguishes: morning peak, evening peak and the remainder of the day.
2. Forecasts of the load on the trunk-road network in the forecast year. In the assignment, the LMS distinguishes commute, business, other and freight, and as vehicle types car, short delivery van, long delivery van, lorries with medium length and long lorries. Synthetic results concerning tours, kilometres travelled, travel times, etc. are available for combinations of mode and travel purpose. A simple example is presented in Figure 16.2 where traffic intensity is represented in vehicles per day for 2021.

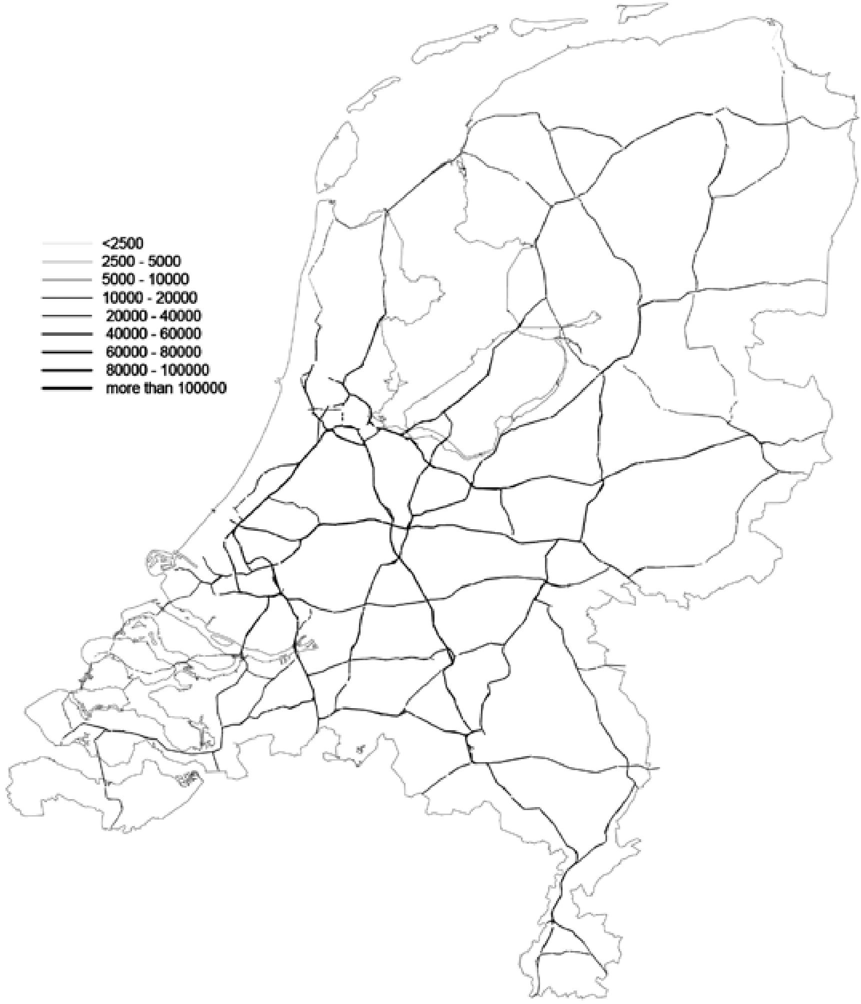


Figure 16.2 Example of an intensity forecast in vehicles per day for 2021, in The Netherlands

In what regards to the quality of the model, ten years after the completion of the LMS, in 1996, this was tested by way of an audit (Bates et al., 1996), followed by another audit in 2012 (Tavasszy et al., 2012). Bates et al. (1996) concluded that the LMS had been prepared using the latest academic insights. Tavasszy et al. (2012) concluded that the model is fit-for-purpose, although they spotted some weaknesses with respect to public transport modelling and some limitations concerning the ability to answer complex policy questions. On various occasions, further quality checks were conducted by comparing the forecasts to the actual developments (de Jong et al., 2008; Gunn and van der Hoorn, 1998). In this way, the 1986 forecasts for 1996 were compared with the 1996 reality. Except for the fact that the model underestimated the growth of the recreational traffic, the quality of the forecasts proved to be reasonable. Backcasting has been performed successfully on the scope of the TIGRIS-XL model development which uses the LMS as a backbone.[1]

Since then, the development of household incomes has been incorporated into the model. In 2010 a comparison was made for the total mobility growth which was well predicted. Car driver kilometres were overestimated; those of car passengers and walking/cycling were underestimated. A large part of the less good forecasts was caused by unexpected developments in society outside of the realm of transportation. In particular, both the population and the workforce (particularly women) grew more than expected. Incomes per household increased less than expected. The anticipated pricing measures (road pricing, kilometre charge) did not materialize. Public transport increased strongly through the introduction of a free public transport pass for students. The biggest matter of concern was the underestimation of the growth of road congestion. Therefore the periods of the day have been refined in the later LMS. The assignment method QBLOK has been improved as well. Transport models are in constant evolution taking advantage of the progress in scientific research as well as practice with these tools *see* also Chapter 14 for uncertainties about future developments.

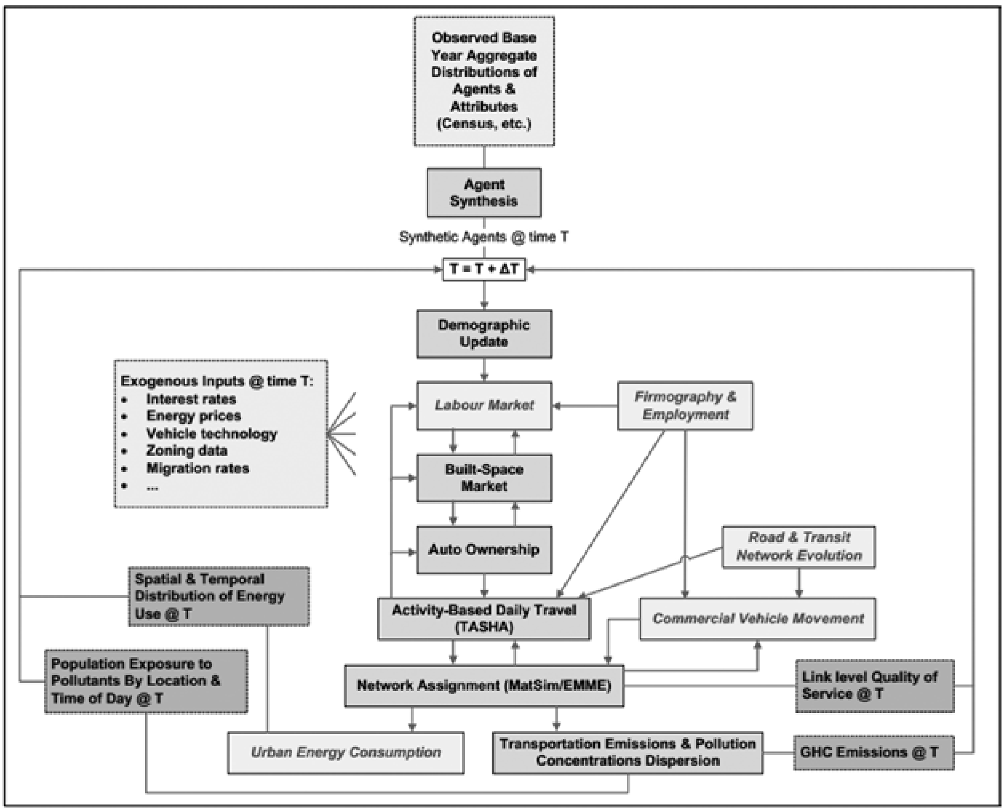
16.7.2 ILUTE: An Agent-Based LUTI Model

A state-of-the-art example of an ABM that is also a LUTI model (see Section 16.2) is the ILUTE model (Salvini and Miller, 2005). The ILUTE model is an agent-based LUTI model of the whole region of Toronto-Hamilton in Canada where the system state is evolved from an initial base case to some future end state in discrete time steps. The system state is defined in terms of the individual persons, households, housing units, firms, etc. (so-called agents) that collectively define the urban region state. The project led by Eric Miller of Toronto University has been developing for the past three decades with many contributions from different researchers on several of its modules.

The model has the following main modules (Figure 16.3):

1. a demographics module whose objective is to model how the population and households evolve over time including births, deaths and migration as well as marriages and divorces, among other life events (Chingcuanco and Miller, 2018);
2. a housing market component that explains endogenously the supply of housing by type and location with their corresponding prices (Farooq and Miller, 2012);

3. household automobile ownership which is dynamically updated using models of household vehicle transactions (Mohammadian and Miller, 2003);
4. an activity generator for the agents called Travel Activity Scheduler for Household Agents (TASHA) that runs the activities of the synthetic population in the regions (Roorda et al., 2008);
5. a method to assign the trips resulting from the agents' movements to modes of transport (public transport and car) as well as to the paths in the networks. This process can be executed using traditional aggregated traffic assignment methods as explained above or even be fed into an agent-based dynamic traffic simulation model like MATSim (see Section 16.2).



Source: Harmon (2013).

Figure 16.3 The ILUTE model structure

Preliminary models have been tested for adding a labour market into the model (Harmon and Miller, 2020) and there is also the intention to implement some form of firms' characteristics recognizing the importance of the location of companies in explaining the dynamics of the population in terms of mobility, but also in terms of choosing places to live. At the time of writing this chapter (Autumn 2022) this has not yet been accomplished (Chingcuanco and Miller, 2018).

Several of these modules use the principle of random utility maximization for simulating choices coupled with specific procedures to enhance the realism of those choices. For example, regarding house choice, it is well known that a decision-maker does not consider at the same time all the available houses on the market. Often a home seeker will first consider specific areas on which s/he is willing to move as well as house characteristics that are compatible with his/her lifestyle before checking specific houses. Therefore the choice set is much more limited than the whole number of houses on the market.

Because of its disaggregated dynamic and spatial nature, ILUTE allows following each agent across time as it evolves regarding his/her workplace, household composition, modes of transport, chosen paths, etc. This provides a unique opportunity to study how policies may affect different populations in different ways. For example, ILUTE has been used to model the population exposure to pollution in the region of Toronto by coupling the traffic network with a model for pollutant emissions and dispersion. Since the agents can be traced it's possible to know the total amount of pollution they have been exposed to in all their daily activities (Hatzopoulou et al., 2007).

16.7.3 DYNAMO

DYNAMO (Meurs and Haaijer, 2006) is a model to forecast the size, composition and use of the Dutch passenger car fleet for the period 2003–40, together with the resulting emissions. It is a dynamic model, which means that the effects in one year affect results in the next. The heart of the model is an equilibrium module where the prices for second-hand cars emerge in such a way that demand and supply are in equilibrium each year, both for the fleet as a whole and for individual household types. Size, use and composition of the car fleet are functions of the household and car characteristics (like the fixed and variable car expenses, among other things).

The model needs the following input

1. the number of cars per household;
2. the type of fuel;
3. the weight category;
4. car age;
5. fuel consumption;
6. type of owner (private, lease or company cars);
7. car use (the number of kilometres driven);
8. types of households (relative to the types of cars), which are defined by four characteristics: the size of the household, number of working people, age of the oldest individual in the household and real disposable household income;
9. income effects on car use and car choice for each group of households;
10. effects of the fleet composition and corresponding usage on government income (raised through taxes).

Figure 16.4 represents the DYNAMO model's structure.

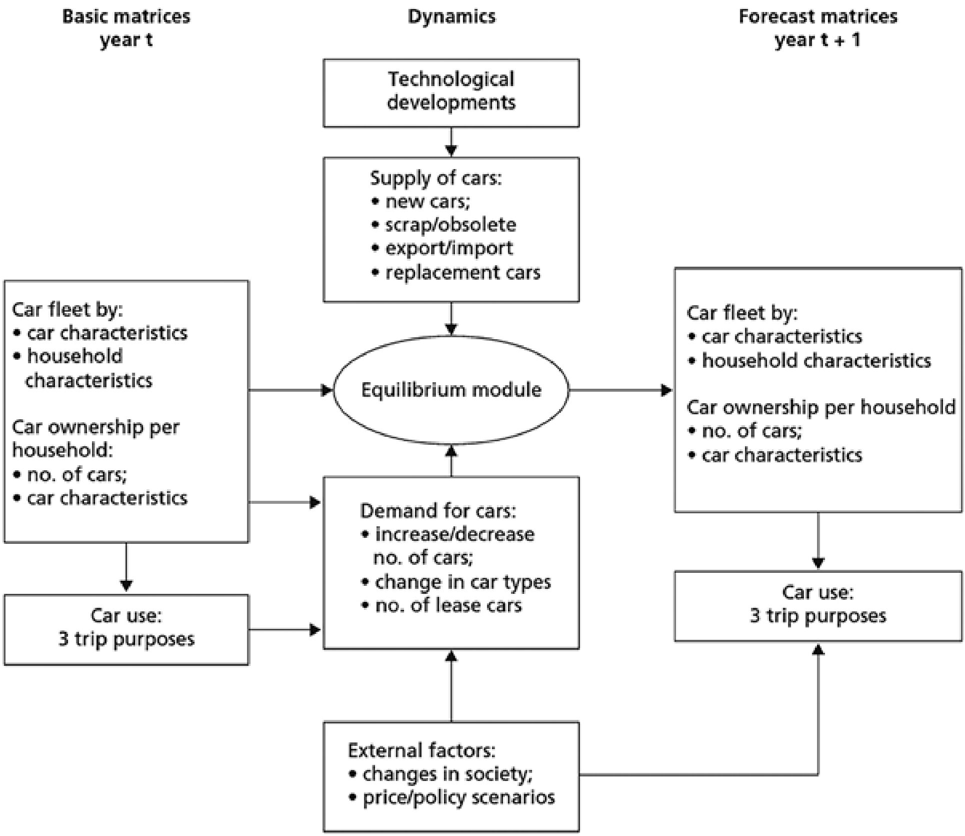


Figure 16.4 Structure of the DYNAMO model

16.8 WHAT CAN AND WHAT CAN'T A TRANSPORT MODEL BE USED FOR?

The main reason for using transport models is that they provide an insight into the magnitude of effects of developments or policy measures on transportation and on indicators that convey something about the quality characteristics or the effects of transportation. Examples of quality characteristics and effects are pollutant emissions, the level of congestion or long-term suburbanization. This may involve the effects of demographic, economic, spatial or infrastructural developments *see* also Figure 2.1 in Chapter 2 about how travel behaviour leads to various societal impacts (on environment, safety, accessibility, health and well-being).

Whether or not it is advisable to answer a research question or solve a policy issue using a model cannot be answered in a general way. In some situations, it may be sufficient to use the results of earlier empirical research or simulations carried out previously. In other cases, new model simulations may be required. Much depends on the amount of time available for answering the question, and on whether any (and if so how much) money is available for new studies and what the outcomes will be used for. The greater the potential effect of system changes, the higher the expenditures (in time and money) that will be made available, and the sooner model simulations will come into the picture. In general, it is important to weigh possible extra costs against the enhanced quality of the answer to be produced in a study. For some questions, a rough estimation of the magnitude of effects may suffice, whereas for other questions a higher quality, more precise output is required.

Furthermore, it is important to set up a structure of a model corresponding to the real world. The structure of a model should be compared to a schematic conceptual representation of that particular part of reality that is relevant for answering the questions. An example elucidates this. Suppose policy-makers want to know the effect of the acquisition of more fuel-efficient types of cars on pollutant emissions. The effect of more fuel-efficient cars is, on the one hand, a decrease per kilometre in the average fuel use and some emissions and, on the other hand, an increase in the number of kilometres, as the fuel costs of more fuel-efficient cars are, on average, lower. A model that first models car ownership and car use ignoring fuel efficiency in the costs of travelling will overestimate the effect of a more fuel-efficient car fleet on the reduction in fuel use and emissions (see also Chapters 2 and 6 for such relationships). In another example, suppose that policy-makers want to know the effect of ABS on traffic safety. Presumably, ABS will lead to different driving behaviour. A model that does not take this into account overestimates the positive effect of ABS on traffic safety. Put differently, researchers who aim to support policy-making first need to get an idea of what will change in practice and how these changes will affect human behaviour, and next need to establish whether these changes can adequately be modelled by the model they would like to use. This is an important advantage of the use of models, or rather, of considering the use of models: it stimulates thinking about how to conceptualize the complexity of the system that needs to be modelled. Just that activity alone is a long way to understanding potential problems and avoiding undesired impacts on society.

Besides, it should be realized that most models are better able to study the effect of relatively small changes than to study the effect of major changes. The effect of an increase in fuel prices of half a euro can be estimated reasonably well by using the current models, whereas that would not hold for an increase by five euros. Greater changes are outside the boundaries of the usual behaviour of the agents in the transport system which may lead to bigger adaptations not yet seen in the system itself before. A good example would be the oil crisis of 1973 during which the Western world had to resort to ways of organizing transportation that were not being used systematically before, like car sharing (Correia and Viegas, 2011).

An important advantage of using models is that they enable us to make the research or policy questions more explicit. The researcher who poses the question needs to make a general question concrete. A question like 'What happens if fuel prices increase?' is very vague. A model forces the researcher to make the question explicit, otherwise simulations are impossible. Therefore the researcher needs to answer questions like: Which kinds of fuel are becoming more expensive? And to what extent? When will the price increase become effective? For which year, or for which years? Which effects does one want to measure? Only the effect on car use? Or also the effect on car ownership, the use of other means of transport, mobility behaviour, emissions of pollutant emissions, or noise pollution? Of course, a research question always has to be concretized, but the use of model simulations can be very helpful in doing so.

A further advantage of using models is that, usually, a model can be used quickly to compute the effects on variants for socio-economic developments and policy variants. Because expressly only a few variables are changed and the other factors are kept constant, comparability of those variants is warranted, and the right conclusions can be drawn as to the effects of the supposed changes.

Another advantage is that the comparability of the results from individual studies can be enhanced by using models. Various studies on the same issue often (seemingly) arrive at different results. For example, many studies have been carried out on the effects of increases in fuel prices. The effects are rather diverse: when expressed in the fuel price elasticity of car use, the range goes from −0.1 to −1.0. Models that can be used to compute the effects of increasing fuel prices teach us that the effects will be larger for people with lower incomes when compared to people with higher incomes. A study carried out in Portugal in 1980 would, therefore, in principle, show a higher price sensitivity than would a study carried out in the US in 2000. Furthermore, models show that the effect of an increase in (solely) the price of petrol will be less if other, cheaper kinds of fuel are available. So the effect of an increase in the price of petrol will be larger if no LPG is available and if the price difference, when compared to diesel oil, is limited. If we look at the effect of fuel price increases on the demand for fuel, model simulations teach us that, in the short run, the only effect is a decrease in car usage. In the long run, however, a further effect will be that people acquire more fuel-efficient cars if fuel prices increase. In some cases, this phenomenon also explains part of the seeming differences in the study results. In the even longer run, a further effect may be that people will select a different place to work or to live, which will increase the effect on car use (a LUTI model is required for this). On the other hand, in most countries, incomes are gradually increasing, which partly counterbalances the effects of price increases. Therefore model simulations can mean that researchers get a better insight into the causes of differences between empirical studies.

A drawback of model use is that their usage can be overestimated. A model is nothing more than a tool, and one should refrain from attaching too much absolute value to its results. Especially if the result of simulations is that certain government objectives are, or are not, achieved by a small margin only, these simulations have a great impact on the policy-makers' way of thinking. It is hardly relevant whether a certain package of policy measures, according to the model and in a certain context, will only just, or will only just not, lead to achieving a goal in 2040. For example, consider the objective of reducing NO_x emissions. The message then is first and foremost that, in that context, the package will lead to NO_x emissions in the magnitude of the set aim. And, in the case of air pollution, some people often assume the results to have a great degree of certainty, even though these results are relatively uncertain.

Researchers may sometimes attach too much weight to a model's results. They often hide behind the model and then make statements like 'Well, that is what the model has come up with.' Once again, a model is no more than a tool. The researcher answers a research question and in doing so he/she is responsible for whether or not to use a model and, if so, in which way, and how to use and interpret the results.

16.9 CONCLUSIONS

The major conclusions to be drawn in this chapter are the following.

1. A model is a simplified representation of a part of a real system.
2. Transportation models are first and foremost a means to gain insights into the effects of various developments (like policy developments) on transportation.
3. There are many kinds of models. They can be classified, among other things, by the transport mode they focus on (e.g. passenger cars, public transport), the period of time they focus on, the technical characteristics (e.g. dynamic versus static models), or the question as to whether or not they contain spatially varying data.
4. Aggregated models such as the 4-step method have been used extensively for the past decades to support transport policy decisions in urban areas. With the need to study more complex measures and their interaction effects in a dynamic context disaggregated models started to be used supported by the advances in computational speed.
5. Whether or not it is advisable to answer a certain research or policy question by using a model cannot easily be established. It requires adequately weighing the available alternatives as well as the pros and cons of model simulations and the relevant alternatives.

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NOTE

1. Historische forecast TIGRIS-XL (https://significance.nl).

REFERENCES

Anas, A. (1983), 'Discrete choice theory, information theory and the multinomial logit and gravity models', *Transportation Research Part B: Methodological*, 17, 13–23. https://doi.org/10.1016/0191–2615(83)90023–1

Axhausen, K.W. (2016), *The Multi-Agent Transport Simulation MATSim*, Switzerland: Ubiquity Press. https://doi.org/10.5334/baw

Bates, J., M. Dasgupta, N. Daha, G.R.M. Jansen and M.J.M. van der Vlist (1996), *Audit of the Dutch National Model: Final Report*, Report INRO-VVG 1996–29, Delft: TNO INRO.

Ben-Akiva, M. and S. Lerman (1985), *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press series in transportation studies, 9, Cambridge, MA: MIT Press.

Brownstone, D., D.S. Bunch and K. Train (2000), 'Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles', *Transportation Research Part B: Methodological*, 34, 315–38. https://doi.org/10.1016/S0191–2615(99)00031–4

Cambridge Systematics, Inc. (2010), *Travel Model Validation and Reasonability Checking Manual Second Edition*. Federal Highway Administration.

CBS (2021), *Dutch National Travel Survey*. CBS. www.cbs.nl/en-gb/onze-diensten/methods/surveys/korte-onderzoeksbeschrijvingen/dutch-national-travel-survey (accessed 28 December 2021).

Chambliss F. and R. Schutt (2019), 'Causation and experimental design', in Daniel F. Chambliss, Russel K. Schutt (Eds.), *Making Sense of the Social World: Methods of Investigation*, London: SAGE, 130–61.

Chingcuanco, F. and E.J. Miller (2018), 'The ILUTE Demographic Microsimulation Model for the Greater Toronto-Hamilton Area: Current Operational Status and Historical Validation', *GeoComputational Analysis and Modelling of Regional Systems,* Cham: Springer, 167–87. https://link.springer.com/chapter/10.1007/978-3-319-59511-5_10

Chorus, C. (2012), 'Random Regret Minimization: An Overview of Model Properties and Empirical Evidence', *Transport Reviews*, 32(1), 75–92. https://doi.org/10.1080/01441647.2011.609947

Correia, G. and J.M. Viegas (2011), 'Carpooling and carpool clubs: Clarifying concepts and assessing value enhancement possibilities through a Stated Preference web survey in Lisbon, Portugal', *Transportation Research Part A: Policy and Practice*, 45(2), 81–90. https://doi.org/10.1016/j.tra.2010.11.001

Cullinane, S. and K. Cullinane (2003), 'Car dependence in a public transport dominated city: evidence from Hong Kong', *Transportation Research Part D: Transport and Environment*, 8(2), 129–38. https://doi.org/10.1016/S1361–9209(02)00037–8

de Jong, G., M. Pieters, A. Daly, I. Graafland-Essers, E. Kroes and C. Koopmans (2005), *Using the Logsum as an Evaluation Measure*. Leiden: RAND.

de Jong, G., J.G. Tuinenga and M. Kouwenhoven (2008), 'Prognoses van het Landelijk Model Systeem: komen ze uit?', *Colloquium Vervoersplanologisch Speurwerk*, 1–14.

Demissie, M.G., G.H. de A. Correia and C. Bento (2013), 'Exploring cellular network handover information for urban mobility analysis', *Journal of Transport Geography*, 31, 164–70. https://doi.org/10.1016/j.jtrangeo.2013.06.016

Demissie, M.G., G.H. de A. Correia and C. Bento (2015), 'Analysis of the pattern and intensity of urban activities through aggregate cellphone usage', *Transportmetrica A: Transport Science*, 11(6), 502–24. https://doi.org/10.1080/23249935.2015.1019591

Dijkstra, E.W. (1959), 'A note on two problems in connexion with graphs', *Numerische Mathematik*, 1, 269–71. https://doi.org/10.1007/BF01386390

Fagnant, D.J., K.M. Kockelman and P. Bansal (2016), 'Operations of a shared autonomous vehicle fleet for the Austin, Texas Market', *Transportation Research Record: Journal of the Transportation Research Board*, (1) 98–106. https://doi.org/10.3141/2536–12

Farooq, B. and E.J. Miller (2012), 'Towards integrated land use and transportation: A dynamic disequilibrium based microsimulation framework for built space markets', *Transportation Research Part A: Policy and Practice*, 46(7), 1030–53. https://doi.org/10.1016/j.tra.2012.04.005

Geurs, K. and J. Ritsema van Eck (2004), 'Editorial: Special issue: Land Use Transport Interaction Modelling', *European Journal of Transport and Infrastructure Research*, 4. https://doi.org/10.18757/ejtir.2004.4.3.4267

Geurs, K.T. and B. van Wee (2004), 'Accessibility evaluation of land-use and transport strategies: Review and research directions', *Journal of Transport Geography*, 12, 127–40. https://doi.org/10.1016/j.jtrangeo.2003.10.005

Gunn, H. and A. van der Hoorn (1998), 'The predictive power of operational demand models', *Proceedings of the Seminar Transportation Planning Methods. European Transport Conference*, Loughborough University, 249–64.

Harmon, A. (2013), *A Microsimulated Industrial and Occupation-Based Labour Market Model for Use in the Integrated Land Use, Transportation, Environment (ILUTE) Modelling System*, Master's Thesis, University of Toronto.

Harmon, A. and E.J. Miller (2020), 'Microsimulating labour market job-worker matching', *Journal of Ambient Intelligence and Humanized Computing*, 11, 993–1006. https://doi.org/10.1007/s12652–019–01206–4

Hatzopoulou, M., E.J. Miller and B. Santos (2007), 'Integrating Vehicle Emission Modeling with Activity-Based Travel Demand Modeling', *Transportation Research Record: Journal of the Transportation Research Board*, 2011, (1) 29–39. https://doi.org/10.3141/2011–04

Hensher, D.A., J.M. Rose and W.H. Green (2005), *Applied Choice Analysis – A Primer*, Cambridge: Cambridge University Press.

Hooper, K.G. and Institute of Transportation Engineers (2017), *Trip Generation Handbook*, Washington, DC: Institute of Transportation Engineers.

Iacono, M., D. Levinson and A. El-Geneidy (2008), 'Models of Transportation and Land Use Change: A Guide to the Territory', *Journal of Planning Literature*, 22, 323–40. https://doi.org/10.1177/0885412207314010

Ibraeva, A., B. van Wee, G.H. de A. Correia and A. Pais Antunes (2021), 'Longitudinal macro-analysis of car-use changes resulting from a TOD-type project: The case of Metro do Porto (Portugal)', *Journal of Transport Geography*, 92, 103036. https://doi.org/10.1016/j.jtrangeo.2021.103036

Legêne, M.F., W.L. Auping, G.H. de A. Correia and B. van Arem (2020), 'Spatial impact of automated driving in urban areas', *Journal of Simulation*, 14, 295–303. https://doi.org/10.1080/17477778.2020.1806747

Lopes, A.S., C.F.G. Loureiro and B. van Wee (2019), 'LUTI operational models review based on the proposition of an a priori ALUTI conceptual model', *Transport Reviews*, 39, 204–25. https://doi.org/10.1080/01441647.2018.1442890

Lowry, I.S. (1964), *A Model of Metropolis*, RM-4035-RC. Abingdon: Routledge.

Lunke, E.B., N. Fearnley and J. Aarhaug (2021), 'Public transport competitiveness vs. the car: Impact of relative journey time and service attributes', *Research in Transportation Economics*, 90, 101098. https://doi.org/10.1016/j.retrec.2021.101098

Meurs, H. and R. Haaijer (2006), 'DYNAMO: a new dynamic model for the Dutch passenger car market', *Colloquium Vervoersplanologisch Speurwerk,* Amsterdam.

Mohammadian, A. and E.J. Miller (2003), 'Dynamic Modeling of Household Automobile Transactions', *Transportation Research Record: Journal of the Transportation Research Board*, 1831, 98–105. https://doi.org/10.3141/1831–11

Ortúzar, J. de D. and L.G. Willumsen (2011), *Modelling Transport*, Chichester: Wiley. https://doi.org/10.1002/9781119993308

Rijkswaterstaat (2017), *Traffic and Transport: National Model System (LMS)*. Ministerie van Infrastructuur en Waterstaat. https://puc.overheid.nl/rijkswaterstaat/doc/PUC_156019_31/ (accessed 28 December 2021).

Roorda, M.J., E.J. Miller and K.M.N. Habib (2008), 'Validation of TASHA: A 24-h activity scheduling microsimulation model', *Transportation Research Part A: Policy and Practice*, 42, 360–75. https://doi.org/10.1016/j.tra.2007.10.004

Salvini, P. and E.J. Miller (2005), 'ILUTE: An Operational Prototype of a Comprehensive Microsimulation Model of Urban Systems', *Networks and Spatial Economics*, 5, 217–34. https://doi.org/10.1007/s11067–005–2630–5

Sheffi, Y. (1986), 'Urban transportation networks: Equilibrium analysis with mathematical programming methods', *Transportation Research Part A: General*, 20, 76–77. https://doi.org/10.1016/0191–2607(86)90023–3

Significance (2021), *Documentatie van GM4 Deel D7–6*, Programma QBLOK4 (versie 4.21).

Smith, B., D. Olaru, J. Jabeen and S. Greaves (2017), 'Electric vehicles adoption: Environmental enthusiast bias in discrete choice models', *Transportation Research Part D: Transport and Environment*, 51, 290–303. https://doi.org/10.1016/j.trd.2017.01.008

Steg, L. (2003), 'Can public transport compete with the private car?', *IATSS Research*, 27, 27–35. https://doi.org/10.1016/S0386–1112(14)60141–2

Tavasszy, L.A., M. Snelder, M. Duijnisveld, R. Haaijer, H. Meurs, R. van Nes, E. Verroen, C. Schie, J. Bates and B. Jansen (2012), *Audit LMS en NRM syntheserapport*. Delft: TNO. https://research.tudelft.nl/en/publications/audit-lms-en-nrm-syntheserapport

Tavasszy, L.A. and G. de Jong (2014), *Modelling Freight Transport*, London and Waltham: Elsevier.

Thoen, S., L. Tavasszy, M. de Bok, G.H. de A. Correia and R. van Duin (2020), 'Descriptive modeling of freight tour formation: A shipment-based approach', *Transportation Research Part E: Logistics and Transportation Review*, 140, 101989. https://doi.org/10.1016/j.tre.2020.101989

Train, K.E. (2003), *Discrete Choice Methods with Simulation, Discrete Choice Methods with Simulation*, Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511753930

Wang, C., M.A. Quddus and S.G. Ison (2013), 'The effect of traffic and road characteristics on road safety: A review and future research direction', *Safety Science*, 57, 264–75. https://doi.org/10.1016/j.ssci.2013.02.012

Wang, S., G.H. de A. Correia, and H.X. Lin (2019), 'Exploring the Performance of Different On-Demand Transit Services Provided by a Fleet of Shared Automated Vehicles: An Agent-Based Model', *Journal of Advanced Transportation*, 2019, 1–16. https://doi.org/10.1155/2019/7878042

Wang, Y., G.H. de A. Correia, E. de Romph and B.F. Santos (2018), 'Road Network Design in a Developing Country Using Mobile Phone Data: An Application to Senegal', *IEEE Intelligent Transportation Systems Magazine*, 31, 1–1. https://doi.org/10.1109/MITS.2018.2879168

Yap, M.D.M.D., G.H. de A. Correia and B. van Arem (2016), 'Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips', *Transportation Research Part A: Policy and Practice*, 94, 1–16. https://doi.org/10.1016/j.tra.2016.09.003

Zondag, B., M. de Bok, K.T. Geurs and E. Molenwijk (2015), 'Accessibility modeling and evaluation: The TIGRIS XL land-use and transport interaction model for the Netherlands', *Computers, Environment and Urban Systems*, 49, 115–25. https://doi.org/10.1016/J.COMPENVURBSYS.2014.06.001