NARRATIVE MODELLING: CONSTRUCTING PATHWAYS TO THE FUTURE

Paul Timms, Institute for Transport Studies, University of Leeds, UK.

P.M.Timms@its.leeds.ac.uk

David Watling, Institute for Transport Studies, University of Leeds, UK.

D.P.Watling@its.leeds.ac.uk

ABSTRACT

This paper introduces a new concept, *narrative modelling*, in transport modelling and provides a mathematical framework for the operationalisation of this concept. It describes how the purpose of narrative models is to construct alternative pathways to the future in situations which involve a high level of change, either in terms of individual behaviour or in terms of social context. In order to justify the need for a new type of modelling, the paper explains the theoretical defects of traditional transport models in terms of representing such change. In particular, it is argued that traditional transport modelling, with its base in positivist and neo-positivist philosophies of science, takes an "essentialist stance" in assuming that there is an essential behaviour of individuals which is both observable and constant over time. Such essentialist assumptions are highly pragmatic for predicting marginal and short-term changes in the transport system, and form the scientific basis of the many computer modelling packages currently in use throughout the world. However, their deficiencies are exposed in situations in which there is an interest in (or indeed a normative requirement for) deep structural change in individual and social behaviour, as is for example required in order to reduce the contribution of transport emissions to global warming.

Keywords: dynamic transport modelling, visions, philosophy, long term futures, essentialism

1. INTRODUCTION

Planning for future transport systems, say 20-30 years ahead, has been a mainstream part of transport practice for many decades, for example when forecasting the stream of economic benefits arising from some transport policy 'scheme'. When making such predictions, it is well–recognised that there is substantial uncertainty in many of the exogenous factors that are assumed to drive travel demand, such as GDP or demographic trends, and to reflect such uncertainty different scenarios based on different baseline assumptions may be assessed. In recent years, however, the demands on long-term transport planning have changed in nature, as we have moved toward addressing questions of long-term sustainability in the light of fossil fuel depletion, and in resilience of transport systems in the presence of a changing climate. In order to achieve such goals we typically will need to see major step-changes in the way we travel that are independent of economic or demographic factors. The question is, could we realistically bring about such changes, and how could we do so? The thesis of the present paper is that this brings about a new kind of uncertainty, an endogenous kind of uncertainty (i.e. in addition to the exogenous uncertainty already mentioned), as it is unclear how and whether travellers could adapt to such changes, and how and whether planning agencies could devise a realistic process of policy measures to bring about such change.

Such challenges are new to the transportation modelling community, and are ones for which, in our opinion, the 'social physics' and 'neo-classical economics' modelling paradigms that currently dominate transport planning practice are ill-suited (Timms, 2008). The basic problem with all such approaches is the premise of pre-determined, fixed, 'essential behaviour': whilst the 'external' factors driving travel decisions (such as transport supply) may change and cause adaptation in journey patterns, the individual behaviour of travellers is assumed fixed over time with respect to attitudes and values. The social physics approach, for example, is derived from the idea of treating individuals as analogous to particles or billiard balls interacting, isolated in a section of the world which is fixed or changing slowly in some predictable fashion. Keeping with this latter analogy, if a slight, well-controlled change is made to the angle of the billiard table, the effect may be quite complex and involve interactions between many of the balls, but still the physics governing the balls' "behaviour" (movement) remains the same.

This move away from the premise of pre-determined essential behaviour hits right at the basis of traditional forecasting, where the approach is effectively to extrapolate currently observed travel behaviour into a future that is determined by given exogenous changes and policy measures. In response to the environmental challenges described above, and the changes in traveller behaviour required for meeting such challenges, the key questions now are: would people really change their behaviour in such a manner, and why? Would a planning agency, politically, be able to bring about changes to the transport system that are consistent with new attitudes and values on the part of travellers, but that might need to be introduced before such attitudes and values actually emerge? This opens up the issue of what are the key *causal factors* that underlie the evolution of our future transport system? Thus, when moving away from the assumption of pre-determined, fixed essential behaviour, we have to ask: which are the main, relevant causal variables driving changes in behaviour? We do so while recognising that some of these variables might not be observable, or even if observable might not be measurable. Furthermore, since the actions of a planning agency are a key element, including their reactions to public response to any measures introduced, the question arises: why do we traditionally not represent the planning agencies as *actors* in transport planning models?

Section 2 of the present paper examines some of the philosophical issues underlying the comments in the previous discussion. This is followed, in Section 3 to 5, by the description of a general framework within which, in the future, we may construct dynamic transport models that include the factors mentioned above. In principle, the paper could stop at the end of Section 5, at which point we will have an outline of how we may construct new kinds of system-dynamics style forecasting approaches; such an outline provides a platform for the formulation, specification, calibration and implementation of new methods which provide a challenge to future applications of mathematical techniques in transportation analysis. The paper, however, does not stop at Section 5, and instead sets out in Sections 6 and 7 an alternative means (to traditional forecasting) of using these new methods for examining long-term futures, thus opening up further conceptual and mathematical challenges. Here, we propose the use of so-called *backcasting methods* as a means of devising dynamic trajectories that lead to normative end-states, known as *visions*. The reason for advocating this approach over the traditional forecasting methodology could be said to be one of pragmatism: given the enormous range of causal, dynamic processes that might drive our future systems in many different ways, how do we know which ones to focus on? If we do not focus, we are left with a problem of such high complexity and dimensionality that it seems potentially unmanageable. By focusing first on a long-term vision, on the other hand, our suggestion is that a sensible range of causal mechanisms (to achieve such a vision) might be more readily defined. In truth, this may be open to debate, and in that way Sections 3 to 5 can be read independently of Sections 6 and 7, yet we do believe there to be merit in connecting them in one overall framework. In order to provide a readily memorable name for the framework we are producing, we call it *narrative modelling*.

2. THE UNDERLYING PHILOSOPHY OF SCIENCE OF TRANSPORT MODELS

Despite the vast number of scientific papers devoted to transport modelling over the past 50 years, very little attention has been paid in the published literature to an explicit analysis of the philosophy of science underpinning such modelling. However, a discussion of such issues is given by Timms (2008), which provides the basis for the current section. In order to proceed with a philosophical analysis, it is helpful to view models as being constructed from three distinct elements: (1) theoretical concepts concerning human and system behaviour (such as static equilibria, perfectly-informed utility-maximisers and human gravity laws); (2) deductive logic (e.g. mathematical arguments and algorithms); and (3) empirical data (both ‘‘raw’’ and manipulated). On the one hand, the characterisation of model-type will depend upon which element (out of theory, logic and data) predominates, in terms of the attention that it receives in the mechanism of model-building. On the other hand, the philosophy of science underlying the model depends upon which element has priority in terms of truth-value. Since the deductive part of any model is, in practice, regarded as beyond question in terms of its truth-value, the philosophy of science essentially adjudicates between theory and observation, i.e. elements (1) and (3).

Positivism

Arguably, the main philosophy actually used in transport modelling has been *positivism*. Essentially, positivism prioritizes observed data over theoretical concepts, in the sense that the former are considered to be more believable than the latter. In this case, the main function of theoretical concepts is to provide mechanisms for generating mathematical forms/structures for the model. If the concepts cease to be useful in this respect, they are disposable, since they have no inherent importance in their own right. Frequently, in the history of transport modelling, we see a specific mathematical model form surviving whilst its associated theory changes, and such changes would be consistent with a positivist attitude towards models. Positivism in transport modelling is typically accompanied by the predictive approach of *naïve instrumentalism*, by which the validity of any model is solely determined by the numerical accuracy of its predictions. An operationalisation of this overall approach is expressed succinctly by Bell in terms of a *theory-model cycle*:

> The theory gives rise to the model. It is the predictive value of the model that governs its acceptance by practitioners. If a model is widely accepted but the original theory falls into disrepute (as happened with gravity type models), ivory tower academics in search of greater fame (and/or promotion) will search for alternative theories to underpin the model (Bell, 1997, p. 36).

One point to note here, though, is that Bell uses the term *predictive value* rather than predictive accuracy. We will return to this issue below.

A common example of an observation-based positivist approach is one which attempts to find law-like regularities between observations, and project these regularities into the future. Such law like regularities will typically, even if only implicitly, make assumptions about *behavioural essentialism* of the type mentioned in Section 1. However, as already mentioned by the comparison with billiard balls, such approaches are questionable in applications which deal with people rather than inanimate objects, given the potential of people to change their behaviour. As explained by Polak (1987):

> The notion that phenomena in the social world (such as travel and transport behaviour) operate in accordance with ‘laws’, comparable in character to the laws of

> the physical world, is an attractive and popular idea. It promises the possibility of theories and models of social phenomena as powerful and comprehensive as those that exist for physical phenomena. One suspects that many transport modellers may adhere to a similar philosophy…However, it is simply not possible to accept the idea that transport phenomena are subject to patterns of empirical regularities that have a 'law-like' interpretation. The phenomena of the physical world are in general inanimate and passive; they do not consciously interact with or have an active understanding of the world around them (Polak, 1987, pp. 65–66).

Polak's analysis provides a strong argument against the assumption of ''eternal'' law-like regularities that can be determined from observations, and hence against what might be referred to as *pure positivism*. A reading of the transport modelling literature would appear to indicate that this type of pure positivism was in fact widely abandoned in the 1970s, to be replaced by a weaker approach that can be termed *pragmatic positivism*, which continued to use most of the techniques associated with pure positivism whilst jettisoning its strong philosophical basis[1]. This change implicitly recognised that the exactness of the physical sciences could not be reproduced in social science applications such as transport modelling. Pragmatic positivism downplays (though does not abandon) the importance of accuracy in model validation, emphasising more a loosely conceived idea of *model usefulness*. An indication of this development is provided by the concept of predictive value (as opposed to predictive accuracy) raised in the quote given above by Bell (1997). Bell provides a further elaboration of this concept:

> The usefulness of predictions is not necessarily a question of their accuracy. All models are simplifications of reality with some effects included and some excluded. It is, however, important that the model be *policy sensitive* (Bell, 1997, p. 36).

From the definitions given above, the difference between pragmatic positivism and pure positivism involves issues about model validity rather than model technique (i.e. it concerns how much we believe in the results of a model rather than how the results are generated). To explore this idea further it is helpful to distinguish between models making short term predictions and those making long term predictions.

Short term and long term predictions

We would argue that the replacement of pure positivism by pragmatic positivism has had little practical consequence for models making short term predictions, but is rather more significant for models making long term predictions. Pragmatic positivism has two key attractions for the former type of model. Firstly, due to the shortness of the interval between

[1] It could be argued that pragmatic positivism should simply be termed pragmatism. However, this would miss the point concerning the underlying continuity of (positivist) techniques (as opposed to philosophies) between the pre-1970s and post-1970s modelling eras. We would argue that if techniques developed in the latter era had been created anew in line with a pragmatist philosophy, they would have had a very different form to those that actually were developed, and would in fact have been more consistent with the communicative approaches that we describe below.

the time of making the prediction and the future time horizon for which the prediction is being made, it is likely that the human mobility behaviour being represented will ''not change very much'' in this interval. Hence, even if the formal belief in constant law-like regularities (pure positivism) is abandoned, the pragmatic application of techniques associated with such a belief (pragmatic positivism) is likely to provide useful approximations. Secondly, also due to this short time interval, model predictions can soon be checked against real life observations. As a result, short term models can be calibrated and recalibrated continuously in order that they produce predictions that fit with such observations. Thus, whatever their initial underlying theory of human behaviour, the resulting models can be ''forced'' by this recalibration process to produce results that are sufficiently accurate (in the view of the model user) for the successful day-to-day application of the models. For models making long term predictions, though, these two advantages do not apply. As a result, pragmatic positivism is significantly weaker as an approach for long term modelling than it is for short term modelling.

Realism

In distinction to a philosophy that emphasises the predominance of data over theory (i.e. positivism), *realism* is a philosophy that emphasises the real-life existence of theoretical concepts underlying data, frequently concentrating upon finding *causal factors*. In general there are many varieties of realism, which differ in highly complex ways, and an attempt to make a comprehensive summary of these varieties (across all sciences) would be beyond the scope of this paper. However, the application of realism in transport modelling (as experienced until now) can be described quite straightforwardly. This application has concentrated upon the assumption of the real-life existence of theoretical concepts such as static equilibria, perfectly-informed utility-maximisers and human gravity laws. Since the phenomena represented by these concepts can, in practice, be observed trivially to be nonexistent (e.g. nobody can always be perfectly-informed), we refer to this type of realism as *naïve realism*. In our opinion, a transport modeller has two basic options for defending such an approach. The first option is to say that, although static equilibria and perfectly informed utility maximisers do not actually exist, such concepts are useful tools for organising and manipulating data, and hence for the process of model-building. Whilst this is a valid argument, it moves the philosophical basis towards positivism and away from realism. A second argument is to view these concepts as *idealizations*, which do not correspond so much to ''real things out there'' but rather to the (imagined) limits or extremes of real things (i.e. nobody can be better informed than a perfectly-informed person and no system can be more equilibrated than a perfect equilibrium). However, this interpretation moves the philosophical basis of the concepts from realism to *social constructivism* (the philosophy which emphasises social agreement concerning concepts, as opposed to their objective reality). This line of thinking is explored further by Timms (2008) with respect to the use of metaphors in transport modelling.

In summary, we would say that a position of naïve realism is unsustainable. However, the usefulness of conceptualising this philosophical position is that it opens up the possibility that other theoretical concepts (not yet adopted in transport modelling) might in future supply the real underlying causal factors sought by the realist transport modeller.

Communicative rationality

In parallel to the 50-year development in transport modelling described above, there has been a thriving development in planning theory. Of particular relevance to the philosophical issues described in this paper has been the growth in interest in the concept of *planning as a communicative activity*. Essentially, this concept focuses upon the communication that takes place between various social actors within the planning process. As with many other social scientific concepts, ‘‘planning as communication’’ can be interpreted both normatively and descriptively. As a normative concept, where it is frequently referred to as *communicative rationality*, it underpins the design of methods by which agreement is sought, on a consensus basis, between those affected by the planning process. As such, it has much relevance to methods of public participation in transport planning. Communicative rationality is discussed by Langmyhr (2000), Willson (2001), Langmyhr (2001), Willson et al. (2003), and Khisty and Arslan (2005). Although not actually mentioning communicative rationality, papers by Kane and Del Mistro (2003) and Lokopoulos and Scholz (2004) cover similar ground, in that they propose transport planning methods that emphasise communication and negotiation. Communicative rationality is typically contrasted with instrumental rationality, in which emphasis is placed upon a technocratic process through which planning decisions can be made ‘‘objectively’’ through the comparison of modelled predictions of the effects of alternative potential transport schemes. Willson et al. (2003) describe how communicative rationality is based upon the *Continental tradition* of philosophy, whilst instrumental rationality is based upon the *Anglo/American tradition*, and in fact the Continental philosopher Habermas is frequently mentioned in the papers cited above. With respect to transport modelling in communicative planning, Willson (2001) writes:

> Data analysis and modelling are crucial elements of communicative planning but they are in the service of deliberative processes, not ends in themselves. They serve group purposes, not a unitary decision maker. To function as discourse, models are quick-response so they become part of the flow of conversation in which decisions are made and plans are developed (Willson, 2001, p. 22).

An emphasis upon communicative rationality thus leads directly to consideration of models as communication tools, focussing as much (if not more) upon gaining a mutual understanding of transport phenomena as upon prediction. Furthermore, the use of models in such processes could incorporate the hypothetical responses of planners, politicians and the voting public to various transport scenarios predicted by the models (as in current gaming models, but for real-life locations), thus overcoming the problem of invisibility of such actors within mainstream transport models (as mentioned above in Section 1). The philosophical basis for such an overall approach could be termed *communicative philosophy*. Following the comment by Willson et al. (2003) above, such an approach would benefit from insights from Continental philosophy.

Subjectivism

In a strict sense, the move towards communicative planning is independent of whether the models used in such planning are considered to be accurate. However, if doubts exist about the accuracy of models (as would be expected to be the case of long term models, for reasons given above), then the logic of communicative planning would dictate that these doubts should be revealed by anyone in the planning process using such models. It is then a short step to expect the model-user to reveal the extent to which she/he believes in the validity of the model being used, particularly in situations where an (accurate) measure of uncertainty cannot realistically be provided. Such thinking underlies a *subjectivist philosophy* towards modelling, discussed by Timms (2008) in the context of maximum entropy models, and is consistent with a view on modelling put forward by Willumsen (1990):

> An essential feature of modelling activities is the frame of reference or viewpoint employed. A model is a simplified representation of an aspect of reality from a *particular point of view*. A model highlights certain aspects of reality and leaves aside others. What is included is partly determined by the problem in hand and partly by the subjective preferences of the modeller (Willumsen, 1990, p. 288).

In comparison to maximum entropy as a method for applying a subjectivist philosophy, it can be argued that Bayesian methods provide a more sophisticated approach to subjective modelling, due to the greater flexibility (in terms of prior probability distributions) afforded to the modeller when expressing their subjective belief. Sheppard (2001) provides some insight as to why Bayesian approaches reflect various lines of development that are currently topical in particular fields of social science research (though not yet in transport modelling):

> Bayesian analysis…explicitly recognizes that investigators cannot be separated from objects of analysis. Indeed, it could even be seen as a reflexive approach to investigation, more generally associated with hermeneutics and feminism than with statistics, because it invites the investigator to make his or her situated knowledge part of, and a subject for, analysis (Sheppard 2001, p. 544).

Summary and way forward

This section has described a number of related issues concerning the philosophy of transport modelling and planning. Firstly, it was suggested that a positivist philosophy was inadequate for transport modelling, particularly for those models making long term predictions. Secondly, an alternative realist approach was considered. However, whilst realism has the potential to provide a strong (causal) basis for transport modelling in the future, its potential has not yet been achieved. Thirdly, it was pointed out that, due to the movement towards communicative rationality in transport planning, it would be appropriate to adopt a communicative philosophy for transport modelling. Finally, it was suggested that, given the (widely recognised) uncertainty associated with transport modelling, the type of communicative philosophy to be developed should have a subjective orientation, whereby the modeller makes explicit his/her belief in the validity of the model being used. Such approaches have previously been applied in maximum entropy and Bayesian techniques.

Various ways forward for modelling can be identified following the thoughts given in this section. Timms (2008) examines models as if they are linguistic phenomena, basing this analysis upon theories of metaphor, narrative and aesthetics. The current paper views the subject from a different (but complementary) perspective by considering how current modelling paradigms can be "opened up" in order to avoid the restrictions put on them by the various restrictions described above. As stated in Section 1, we refer to this approach as *narrative modelling*. The description of narrative modelling provides, in Sections 3 to 5, a general mathematical framework within which, in the future, we may construct dynamic transport models that do not make essentialist assumptions about travel behaviour and which can represent planners and policy-makers as actors. Furthermore, it describes in Sections 6 and 7 how this framework can be combined with techniques of *backcasting* and *visioning*.

3. PRELIMINARY NOTATION: TRANSPORT AS A STOCHASTIC, DYNAMIC PROCESS

As a preliminary to what we shall subsequently discuss, it is useful to first briefly define some basic, standard notation for representing the evolution of any transport system, using the theoretical device of a stochastic, dynamic process. Time will be represented as discrete epochs, which we shall refer to as years. At any year t, the probabilistic state of the transport system (and its driving factors) will be represented using a vector random variable $\mathbf{X}(t)$ whose elements are discrete random variables. We shall discuss this more below, as in fact this is a rather flexible definition, but for quantitative variables the point is that we might consider these elements as taking values that are integers (e.g. 0/1 indicators), total counts (integer aggregates) or 'bins' (0-10, 10-20, etc.), rather than continuously divisible quantities as is often assumed in traffic flow models or trip matrices. Moreover, we assume there are sensible constraints that mean we need consider only a finite number of such possible states that could arise (even though this finite number could be very large). Then, we have a discrete-time stochastic process with a discrete, finite state-space S containing the possible states of $\mathbf{X}(t)$.

Although not a necessary restriction, as an aid to specification we will make the quite typical assumption in using such processes that it satisfies the Markov property:

$$\Pr(\mathbf{X}^{(t)} \mid \mathbf{X}^{(t-1)}, \mathbf{X}^{(t-2)}, \ldots, \mathbf{X}^{(0)}) = \Pr(\mathbf{X}^{(t)} \mid \mathbf{X}^{(t-1)}, \mathbf{X}^{(t-2)}, \ldots, \mathbf{X}^{(t-m)}) \qquad (3.1)$$

for some given integer $m \geq 1$. That is to say, only at most the last m states affect the evolution of the system at any one period of time. A technical point to note is that such an m-dependent process may be converted to a 1-dependent process by introducing the concatenated variable:

$$\mathbf{Y}^{(t)} = \left(\mathbf{X}^{(t)}, \mathbf{X}^{(t-1)}, \ldots, \mathbf{X}^{(t-m+1)}\right) \in S^m \qquad (3.2)$$

then the transition probabilities defining the process may equivalently be represented in $\mathbf{Y}^{(t)} \in S^m$ as:

$$\begin{aligned} \Pr(\mathbf{Y}^{(t)} \mid \mathbf{Y}^{(t-1)}) &= \Pr(\mathbf{X}^{(t)}, \mathbf{X}^{(t-2)}, \ldots, \mathbf{X}^{(t-m+1)} \mid \mathbf{X}^{(t-1)}, \mathbf{X}^{(t-2)}, \ldots, \mathbf{X}^{(t-m)}) \\ &= \Pr(\mathbf{X}^{(t)} \mid \mathbf{X}^{(t-1)}, \mathbf{X}^{(t-2)}, \ldots, \mathbf{X}^{(t-m)}) \end{aligned} \qquad (3.3)$$

so that theoretically at least, representing a dependence on m previous states is no more difficult than representing a dependence on only the most recent state, we just need to think in terms of the concatenated state variable $\mathbf{Y}^{(t)} \in S^m$ instead of $\mathbf{X}^{(t)} \in S$.

4. SPECIFICATION OF THE STATE VARIABLE

The Markov process description introduced in Section 3 is entirely generic, it could apply to any physical, economic or social system. What we shall do in this section is to start to add context to this description in terms of our interest in long-range transport planning. In particular, we shall turn attention to the state variable $\mathbf{X}^{(t)} \in S$, where as noted earlier S is a discrete state space with a finite number of states. Elements of $\mathbf{X}^{(t)}$ comprise variables describing:

- the actual travel demand realised in year t, disaggregated as needed by mode, origin/destination(s), user group (e.g. socio-economic group, peer group, trip purpose);
- the policy measures of relevant transport planning agencies realised in year t, as well as those announced in year t for future implementation; and
- the underlying *causal* factors at time t that will drive both travellers' decisions and the decisions of the transport planning agencies in times t+1 and beyond.

Such a specification has two elements of novelty relative to conventional transport planning approaches. Firstly, we directly represent transport planners and policy-makers as 'agents', with their own distinct perceptions, and factors causing these perceptions, that will influence the implementation of any transport policy measure. In this way, a policy measure is not an abstract intervention, whereby a new road or road pricing system magically appears overnight. Rather, we represent the reality that the implementation of a measure is typically the result of a political process, involving interaction with the public in terms of their support or otherwise.

The second element of novelty is the focus on causal factors: the 'deep factors' that truly drive decisions of both the public and planners. Many such causal factors will not be directly observable through surveillance or surveys. This breaks with the traditional transport planning approach, where the focus is on *observable* factors that may be correlated (crosssectionally, or longitudinally with change). Our contention is that the focus on what is observable omits many of the most important variables that shape the transport system, such as political will, the attitudes of the public, changing societal/social norms and the perception of less tangible qualities such as aesthetic qualities. Although attempts have in the past been made to measure these factors using proxy variables, such attempts typically are limited by the fact that the appropriateness of a particular proxy is usually restricted to a specific time and place. While our alternative focus on factors that are unobservable might at first seem unusual, we should also equally raise questions over observability when we apply conventional transport forecasting approaches. Since we are looking at long-term futures, it might well be questioned: what do we mean to suggest that *anything* is observable: i.e. can the future be observed? In traditional transport forecasting, the implicit assumption is made that all unobservable causal factors will remain constant through time in the future (even if we do not actually believe this is likely), and that just a small number of explanatory factors (e.g. GDP, demographics, economic valuations) will change in some deterministic way over time, by extrapolating from past trends. Such a modelling approach thus drastically limits the 'degrees of freedom' for representing change in future transport patterns, and thus specifically for representing *desirable* changes. If, on the other hand, the approach represents the full range of causal factors, then we potentially have an enormous range of 'levers' at our disposal, both in the way that planners communicate their intentions and interact with the public, and in potentially seeing how 'society' shapes the transport options that are available.

While it may thus be argued that it brings significant advantages, a focus on causal processes whose past history has been frequently unobservable (and which are impossible to observe in the future without time travel) inevitably brings with it several new problems. How might we actually specify such causal relationships? How could we use 'past evidence' to support such relationships? What actually do we *mean* by the time-dependent trajectories of modelled behaviour that result from using such relationships? What is the most appropriate way to *use* such trajectories in long range planning? Each of these questions deserves some dedicated discussion, so we shall address all these factors explicitly in the following sections.

For the present section, we consider the impact on *specification* of the state variable. In particular, as we will need to specify relationships about which we are likely to have at best a *qualitative* understanding, it is our expectation that all components of $\mathbf{X}^{(t)}$ will be qualitative. We suggest that a qualitative description will also be relevant even for measurable variables (such as cost, travel time or the demand for travel), with qualitative states representing ranges for these variables, e.g. 'low', 'medium' and 'high'. While it is entirely possible to retain a mixed quantitative/qualitative definition of the state variable within the framework described, we feel that this is likely to encourage a spurious sense of accuracy in the specification of the causal relationships. In any case it can be argued that conventional transport forecasting approaches, based on quantification and continuous trade-offs (e.g. between time and money), already admit a degree of spurious accuracy when specifying long-term future relationships.

5. SPECIFICATION OF THE TRANSITION PROBABILITIES

In Section 3 we introduced the notion of transport as a stochastic dynamic process, evolving over years, with the state variable (as defined in Section 4) at year t denoted by $\mathbf{X}^{(t)} \in S$, and the concatenated variable $\mathbf{Y}^{(t)} = (\mathbf{X}^{(t)}, \mathbf{X}^{(t-1)},\ldots,\mathbf{X}^{(t-m+1)})$ representing the evolution over a sequence of m years ending at year t, for given fixed m. Based on the Markov assumption, the evolution of the process is thus governed by the equation:

$$\Pr(\mathbf{Y}^{(t)}) = \Pr(\mathbf{Y}^{(t)} \,\big|\, \mathbf{Y}^{(t-1)})\ \Pr(\mathbf{Y}^{(t-1)}) \qquad (\,for\ t = 1,2,\ldots)\ . \tag{5.1}$$

That is to say, given an initial probability distribution $\Pr(\mathbf{Y}^{(0)})$ (representing the present year 0 and the m-1 previous years), then the equation above describes how the probabilities of the system states will evolve over each step in time. The key to the model is thus the specification of the so-called transition probabilities $\Pr(\mathbf{Y}^{(t)}/\,\mathbf{Y}^{(t-1)})$; for specification purposes, it is usually more convenient to work with the equivalent probabilities $\Pr(\mathbf{X}^{(t)}/\,\mathbf{Y}^{(t-1)})$.

Since we need to know how the system will change from any given previous sequence of m states state to its current state, this amount to a specification of the probabilities:

$$\mathrm{p_{ij}}^{(t)} \;=\; \Pr(\mathbf{X}^{(t)} = \mathbf{x}_{\mathrm{j}} \,\big|\, \mathbf{Y}^{(t-1)} = \mathbf{y}_{\mathrm{i}}) \qquad \text{(for t = 1,2,…; i = 1,2,…,}N^m\text{; j = 1,2,…,N)} \tag{5.2}$$

where we have identified the finite number of possible discrete X states in S by the notation:

$$\mathrm{S} = \left\{\mathbf{x}_{\mathrm{j}} : \mathrm{j} = 1,2,\ldots,\mathrm{N}\right\} \tag{5.3}$$

and the finite number of possible (m-sequence) **Y** states in set S^m by the notation:

$$\mathrm{S}^{\mathrm{m}} = \left\{\mathbf{y}_{\mathrm{i}} : \mathrm{i} = 1,2,\ldots,\mathrm{N}^{\mathrm{m}}\right\}. \tag{5.4}$$

It is common in many fields of application to adopt a simplified version of this model in which the probabilities $\mathrm{p_{ij}}^{(t)}$ are constant over time (independent of t), leading to a so-called time-homogeneous process. Indeed, this has been the case for the applications of the stochastic process approach seen in transport to date (e.g. Cantarella & Cascetta, 1995; Watling, 1996, and the references therein). A way of understanding this assumption would be to say that the laws governing the system are constant over time — particularly the laws governing its transitions from one time period to the next — it is just the stimuli to these laws that change (from previous system states). We use the word 'law' deliberately here, given the predominance of concepts in transport modelling that have their origin in the physical sciences; in physics, it is reasonable to assume that the same laws of gravity, motion and force will operate in a hundred years time as will operate today, so the constancy with time is natural. The common context of the transport references cited in this paragraph was the day-to-day dynamics of road networks, where it was assumed over the short-term that any 'laws' we observe today may hold over, say, the next few months. Again, time homogeneity seems reasonable, although in this case (unlike the case of physical laws) the assumption should be seen as an approximation to reality rather than an accurate representation.

Our present context, however, namely long-range transport planning over several decades, we believe to be potentially quite different. The 'laws' we are talking about here include the behaviour of individuals (in responding to their experiences and perceptions), shaped by societal values, norms and attitudes. There are many examples in the past where we have seen these latter factors change over such a time-scale, such as attitudes to smoking in public, to consuming alcohol before driving, to the images we find acceptable for television, and of course attitudes to personal mobility and the distance separation of our homes from the work place. Thus, we might expect attitudes to land-use changes and changes in public transport provision to be quite different today, to the attitudes that would be expected of individuals thirty years ago. Indeed, we have seen growing interest in issues such as travel awareness programmes as a transport policy measure; unless our models of the future reflect such factors, then we are missing out an important tool for influencing transport systems in desirable ways. It seems rather natural, too, to represent such evolving attitudes as an unfolding process, depending on our experience: our attitudes to making longer journeys to work changed partly because we had experience of making more longer-distance journeys, as workplace, home and other activities became more separated in many urban areas.

The attitudes of individual travellers are not the only reason to propose a time-dependence in the 'laws' underlying our mathematical process. The state variable also includes the actions of transport planning agencies, and the nature of these actions is conditioned by the prevailing approach to 'governance' and decision-making. In the UK, the recent interest in road user charging measures through the Transport Innovation Fund has seen quite different approaches to local decision-making (notably in Edinburgh and Manchester), whereby direct public approval (as opposed to, say, consultation or challenge through public enquiry) is seen as a pre-requisite to the implementation of the measure. Many of the long-term future transport problems are likely to involve step-changes in policy of at least a similar level of controversy; therefore, as modellers selecting the most important factors to represent, it seems difficult to neglect the potentially changing future nature of local decision-making, given our evidence of how strongly this may shape and/or constrain actual implementation of measures.

A third issue that seems pertinent to consider is the distinction between *endogenous factors* and *exogenous factors*, Endogenous factors are those which are represented as both having impacts on the local transport system (i.e. the system being modelled) as well as being affected by changes in the system. Examples of such factors described above are travellers' attitudes and local transport decision-making processes, On the other hand, exogenous factors, whilst also having an impact on the local transport system, are assumed not to be affected by changes in such a system. Examples of such factors are population size, GDP and transport policy on a 'higher than local' level (e.g. regional, national, European). It must be emphasised that the distinction between endogenous and exogenous is not one found strictly in reality: changes in a local transport system can potentially have effects on all 'exogenous' factors, even though in many cases this effect is very small. Rather, the distinction is a modelling device to make the modelling problem more manageable. As in traditional transport modelling practice, it is assumed in this paper that exogenous factors are dependent on absolute time t.

In order better to highlight the different sources of dependence discussed in the issues above, we shall now propose a more specific representation of the state variable, an example that builds on Section 4. Specifically we shall suppose that $\mathbf{X}^{(t)}$ has four kinds of (vector) component:

$$\mathbf{X}^{(t)} = \left(\mathbf{D}^{(t)}, \mathbf{E}^{(t)}, \mathbf{L}^{(t)}, \mathbf{S}^{(t)}\right) \tag{5.5}$$

and that each of these vector components decomposes itself into n vector components:

$$\mathbf{D}^{(t)} = \left(\mathbf{D}_1{}^{(t)}, \mathbf{D}_2{}^{(t)}, \ldots, \mathbf{D}_n{}^{(t)}\right) \qquad \mathbf{E}^{(t)} = \left(\mathbf{E}_1{}^{(t)}, \mathbf{E}_2{}^{(t)}, \ldots, \mathbf{E}_n{}^{(t)}\right) \tag{5.6}$$

$$\mathbf{L}^{(t)} = \left(\mathbf{L}_1{}^{(t)}, \mathbf{L}_2{}^{(t)}, \ldots, \mathbf{L}_n{}^{(t)}\right) \qquad \mathbf{S}^{(t)} = \left(\mathbf{S}_1{}^{(t)}, \mathbf{S}_2{}^{(t)}, \ldots, \mathbf{S}_n{}^{(t)}\right). \tag{5.7}$$

The latter component-wise separation represents the distinct groups of actors involved in the transport system, including groups of travellers, groups of businesses, planning organisations, and any other potentially influential group. The variables $\mathbf{D}_k{}^{(t)}$ denote the *decisions* of actor-group k in year t, such as travel decisions of travellers, and decisions of planners on future policy measures to implement. The variables $\mathbf{E}_k{}^{(t)}$ represent the *experiential* components as perceived by actor-group k in year t. For example, for a traveller group the experiential variables may represent their feeling of convenience or safety associated with their chosen travel option(s) in period t, and for a planning agency the experiential variables may reflect the reactions of the public to the planning decisions made in period t. The variables $\mathbf{L}_k{}^{(t)}$ represent the *learnt experience* of group k in their cumulative experience up to and including year t. The variables $\mathbf{S}_k{}^{(t)}$ represent *shaping* parameters for actor-group k, namely those factors/parameters which contribute to the way in which decisions will be made in subsequent time periods (i.e. time period t + 1 and beyond). For example, $\mathbf{S}_k{}^{(t)}$ may reflect endogenously-influenced factors, such as evolving 'social norms' in the spirit of the Theory of Planned Behaviour (see, e.g., Jopson, 2004 for a transport application), or exogenous factors such as technological advances, energy insecurity or the state of the economy.

Now, based on standard laws of conditional probabilities, we may decompose our transition probabilities as follows:

$$\begin{aligned}\Pr(\mathbf{X}^{(t)} \mid \mathbf{Y}^{(t-1)}) &\equiv \Pr(\mathbf{D}^{(t)},\mathbf{E}^{(t)},\mathbf{L}^{(t)},\mathbf{S}^{(t)} \mid \mathbf{Y}^{(t-1)}) \\ &= \Pr(\mathbf{D}^{(t)} \mid \mathbf{Y}^{(t-1)})\ \Pr(\mathbf{E}^{(t)},\mathbf{L}^{(t)},\mathbf{S}^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)}) \\ &= \Pr(\mathbf{D}^{(t)} \mid \mathbf{Y}^{(t-1)})\ \Pr(\mathbf{E}^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)})\ \Pr(\mathbf{L}^{(t)},\mathbf{S}^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)},\mathbf{E}^{(t)}) \\ &= \Pr(\mathbf{D}^{(t)} \mid \mathbf{Y}^{(t-1)})\ \Pr(\mathbf{E}^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)})\ \Pr(\mathbf{L}^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)},\mathbf{E}^{(t)}) \\ &\qquad \Pr(\mathbf{S}^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)},\mathbf{E}^{(t)},\mathbf{L}^{(t)}). \qquad (5.8)\end{aligned}$$

This decomposition requires no additional assumptions, but why do we wish to make such a decomposition? The reason is that this provides, we believe, a natural means for *specifying* the transitions in our system. Before explaining this, let us make some additional assumptions that, while not necessary, we believe will further aid the specification process:

- For k = 1,2,…,n, the variables $\mathbf{D}_k^{(t)} \mid \mathbf{Y}^{(t-1)}$ are mutually statistically independent.
- For k = 1,2,…,n, the variables $\mathbf{E}_k^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)}$ are mutually statistically independent.
- For k = 1,2,…,n, the variables $\mathbf{L}_k^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)},\mathbf{E}^{(t)}$ are mutually independent.
- For k = 1,2,…,n, the variables $\mathbf{S}_k^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)},\mathbf{E}^{(t)},\mathbf{L}^{(t)}$ are mutually independent.

Thus, (5.8) may be written as:

$$\begin{aligned}\Pr(\mathbf{X}^{(t)} \mid \mathbf{Y}^{(t-1)}) &= \left(\prod_{k=1}^{n} \Pr(\mathbf{D}_k^{(t)} \mid \mathbf{Y}^{(t-1)})\right) \times \left(\prod_{k=1}^{n} \Pr(\mathbf{E}_k^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)})\right) \\ &\times \left(\prod_{k=1}^{n} \Pr(\mathbf{L}_k^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)},\mathbf{E}^{(t)})\right) \times \left(\prod_{k=1}^{n} \Pr(\mathbf{S}_k^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)},\mathbf{E}^{(t)},\mathbf{L}^{(t)})\right). \qquad (5.9)\end{aligned}$$

We propose this to be a useful decomposition since:

- It is logical to define $\mathbf{D}_k^{(t)} \mid \mathbf{Y}^{(t-1)}$ as being independent of $\mathbf{E}_k^{(t)}$, $\mathbf{L}_k^{(t)}$ and $\mathbf{S}_k^{(t)}$ in the *current* period t, as we assume these latter factors are updated *after* the decision and travel experience is made in period t. Instead, the dependence of $\mathbf{D}_k^{(t)}$ on experience, learning and shaping as formed in periods *previous* to period t is captured through the conditioning on $\mathbf{Y}^{(t-1)}$ which is formed from $\mathbf{X}^{(t-1)} = \left(\mathbf{D}^{(t-1)},\mathbf{E}^{(t-1)},\mathbf{L}^{(t-1)},\mathbf{S}^{(t-1)}\right)$ and earlier periods.
- It is logical to define the perceived experience $\mathbf{E}_k^{(t)} \mid \mathbf{Y}^{(t-1)},\mathbf{D}^{(t)}$ as depending only on the actual decisions of (all) actors $\mathbf{D}^{(t)}$ at time t (note that this does not depend on just the decisions of group k, due to factors such as private car congestion, bus crowding, and the link to the perception of safety of walking/cycling to the number of people walking/cycling in an area/road). Note that the dependence of perception on the 'shaping'

factors is already reflected by the conditioning on $\mathbf{Y}^{(t-1)}$ which includes $\mathbf{S}_k^{(t-1)}$ and earlier periods.

- It is logical to define learning $\mathbf{L}_k^{(t)} \big| \mathbf{Y}^{(t-1)}, \mathbf{D}^{(t)}, \mathbf{E}^{(t)}$ as depending only on experience and decisions (the latter additionally could capture habitual tendencies to make a decision, independent of the experience).
- The 'shaping' will be influenced by exogenous factors and potentially by all endogenous factors across all groups (e.g. one 'group' may be influenced by another group's learning in the case of friends, peers or work colleagues exchanging experiences). Thus it is logical that the shaping is updated based on potentially all of $\mathbf{D}^{(t)}$, $\mathbf{E}^{(t)}$ and $\mathbf{L}^{(t)}$.
- The four assumptions of conditional independence across groups imply that, given the conditioned factors (which *do* reflect between-group interactions), the actors make their decisions, learn and are shaped independently *within* a period. The interactions between actors is reflected by noting that the conditioned variables are not just about group k, but conditioned on all groups. Note that, for example, this implies a lag of one time period before planners find out the actual impact on travel demand of any policy measures. It also means that we implicitly assume travellers are 'captive' to a group throughout time t.

The four main terms in (5.8) (and equivalently, (5.9)) might be described, by analogy to conventional transport planning approaches, as respectively a 'demand model', a 'supply model', a 'learning model' (no analogy in conventional approaches), and a model that specifies the parameters and exogenous factors to the demand model. By breaking the transition probabilities down in this way into a product of conditionally independent terms, then we may better judge which of the underlying 'laws' we may wish to assume as being invariant in time, and which may be time-dependent. For example, it might be assumed that—given the same set of past experiences, external factors and social norms—travellers in the future would behave similarly to travellers today, which would suggest that the probability matrix specifying $\Pr(\mathbf{D}_k^{(t)} \big| \mathbf{Y}^{(t-1)} = \mathbf{y})$ should be time-homogeneous, independent of t, and dependent only on **y**. We might similarly wish to argue that the relation between (perceived) 'experience' and demand is the closest we get to a physical law in transport, and thereby the probabilities in $\Pr(\mathbf{E}_k^{(t)} \big| \mathbf{Y}^{(t-1)} = \mathbf{y}, \mathbf{D}^{(t)} = \mathbf{d})$ could be assumed time-homogeneous, with actual experience dependent on **d** and perceptual bias based on **y**, but with both dependencies independent of time t. If the same time-homogeneity argument could be made for the way we learn from experience, i.e. that $\Pr(\mathbf{L}_k^{(t)} \big| \mathbf{Y}^{(t-1)} = \mathbf{y}, \mathbf{D}^{(t)} = \mathbf{d}, \mathbf{E}^{(t)} = \mathbf{e})$ depends on (**y**,**d**,**e**) but not t, then the only potential source of time inhomogeneity in the whole process could be through the shaping variables. For simplicity, in some cases it might be argued that these are entirely exogenous variables, meaning that the probability matrix defining $\Pr(\mathbf{S}_k^{(t)} \big| \mathbf{Y}^{(t-1)} = \mathbf{y}, \mathbf{D}^{(t)} = \mathbf{d}, \mathbf{E}^{(t)} = \mathbf{e}, \mathbf{L}^{(t)} = \mathbf{l})$ is independent of (**y**,**d**,**e**,**l**), but depends on absolute time t in some exogenously-specified manner. It is not intended to suggest that all these restrictions would be valid in all cases, but it serves to illustrate how quite simple component-wise assumptions can lead to complex, time-inhomogeneous behaviour at the level of the overall defining transition probabilities. The main point is that the given decomposition serves as a means of focusing the modeller on explicitly deciding which components might be assumed time-homogeneous and which are not.

6. FORMING VISIONS OF DESIRABLE TRANSPORT SYSTEMS

In Sections 3 to 5, a new approach to *forecasting* transport systems has been proposed, where i) travellers are no longer assumed to have essential, pre-determined behaviour, ii) the causal processes of change are represented, and iii) planning agencies are explicitly represented as actors with evolving behaviour. We leave it to the reader to decide whether to conclude the paper at the end of Section 5 in that spirit. Our proposal, however, is that while changing the nature of our modelling methods, we might also consider changing the planning paradigm. This is more of a pragmatic argument. Firstly, the focus of data collection and calibration in traditional forecasting is on reproducing or fitting to the (base) current situation, or in understanding the behavioural drivers of the current populace. This means that we tend to be conservative in imagining the processes of change, since as humans living in the present we are naturally conditioned by current factors, and there is frequently no strong motivation in the planning/modelling process to imagine ourselves out of our current condition. Secondly, the approaches proposed so far require us to specify the causal factors underlying the future evolution of the transport system: but which causal factors? There are so many, and their relation is complex to understand, that it makes sense to focus on key factors relevant to where we *desire* our transport system to be. That is to say, we believe that introducing a normative view of the transport system will assist in constructing such causal models.

In particular, we propose to adopt the technique of *backcasting*, a method that has attracted growing interest in the context of planning for long-term futures: see Dreborg (1996) for a general overview, with specific recent examples from the transport sector given by Hickman and Banister (2007), Akerman and Höjer (2006), and Dubois et al (2010). To avoid ambiguity, as alternative meanings are adopted for this term, our meaning of backcasting is a method by which we begin by defining a desirable future state (independently of considerations of the present), and then examine the process by which such a state may be attained. We refer to the desirable future state as a *vision*; in Section 7, we then examine the process by which such a vision may be attained (for an overview of visioning methodology see Van der Helm, 2009).

Formally, we link the concept of a vision to our state variable defined in Sections 4 and 5 by defining a vision V(a,b) to be:

(a) a sub-set of the state space S, i.e. $V(a,b) \subseteq S$; and
(b) relevant to a time interval $a \leq t \leq b$.

That is to say, a vision as a whole may be potentially vaguer, less well refined than a single state of the dynamical system we have been considering, both in terms of its definition of variables and its relevance to a particular point in time. On the other hand it must comprise a set of feasible states that individually specify all relevant variables and causal factors in S. In practice, the process of definition is likely, we believe, to be the reverse of this, in that the definition of V(a,b) will be the pre-cursor to defining a relevant, potentially more sharply defined S (see Section 7). It is noted that this definition of a vision includes as a special case the possibility that V(a,b) consists of a single state in S relating to a particular time period (by selecting a and b appropriately), so that we can make the vision as detailed as we desire.

But how to choose between the many potential visions that could be defined? A vision is consciously a normative concept, in that it will define how someone (the planner, the public, …) envisages a transport system operating that satisfies some pre-defined set of objectives. Commonly, the list of objectives we may end up defining may seem to be contradictory, potentially pulling in different directions: we may wish to promote sustainable travel, to have a pleasant environment for walking in the city, but on the other hand we may wish to stimulate the local economy and to provide good parking opportunities for car travellers visiting the city. Whether such objectives truly are contradictory is something that the modelling approach will assist in addressing, but at the first stage of defining the vision, it seems possible to apply several 'consistency' checks to the vision, to ensure that it has some plausibility based on the mechanisms assumed to be in operation. For example, if the vision involves high degrees of walking and cycling for the journey-to-work, is this consistent with the journey lengths implied by the assumed land-use? Or if the vision is based on income growth/redistribution, is this consistent with the assumed vehicle ownership levels/costs? In the vision, how consistent are the kinds of transport policy measure assumed to be in place with the assumed socio-political 'background'? What technological factors influence travel, and how widespread is their penetration in the population? Is the infrastructure available for alternative modes consistent with the assumed journey times and demand levels for those modes?

As can be seen from these examples, the questions of consistency range from familiar questions (e.g. the last is effectively a supply-demand consistency question, only applied to a future imaginary scenario) to quite deep, difficult questions about the nature of society, and to 'futures' questions where we may have to imagine the potential impact of technologies that may be entirely new or not yet in widespread use. It might be noted that while it seems that we have created a problem altogether more difficult than our traditional forecasting problems, all of these issues are *implicitly* contained in any forecasts we make by traditional means: it is just that our assumptions about their nature and impact is not generally made explicit.

In practice, though, how might we judge such 'consistency'? As stated above, we cannot have certainty about the future: the best we can hope to know are the processes that drove the past and present. We can of course speculate as to whether these processes will continue in the future, perhaps helped by finding out how (present) writers might envisage the future. If we make the explicit judgement that we can assume (some degree of) temporal transferability of these processes, to what extent can we cite past *evidence* for informing our judgement of the consistency of a vision? Since our vision will typically relate to a particular locale (rather than the whole world), we also have the potential for assuming spatial transferability of evidence: could City A in 2010 in some respects provide evidence of what City B might 'look like' in 2030? We use the term *evidence* here as it encompasses a wide range of potential sources, covering quantitative and qualitative data, but also historical stories/accounts of processes that took place in the past. This judgement of evidence (for both the visions and, later, for the processes in Section 7) replaces our tasks of calibration and validation that are required for traditional modelling, whereby considerable effort is expended on finding quantitative data and calibrating travel decision models. In such modelling, the focus is on collecting data to calibrate explanatory models to the present (or to examine how current individuals respond to hypothetical deviations from the present, as in stated preference), whereas in the visions approach the focus is on gathering evidence to judge the consistency of the visions and to support the assumed causal processes described in Section 7.

A final point to note is that while we refer in this section to a single vision, it is not unusual in backcasting approaches to propose several alternative visions, perhaps each associated with a particular choice from several 'background scenarios' and 'policy interventions'. Thus, we would need to conduct consistency checks for each such vision.

7. FORMING A NARRATIVE MODEL OF CHANGE TOWARDS A VISION

So far in this paper we have described (a) a method of constructing a stochastic, dynamic process of the transport system, based on assumed causal relationships largely described as transition probabilities between qualitative states (Sections 3 to 5), and (b) the concept of a vision, a normative judgement on a desirable future transport system, that is formally a collection of such states related to a period of time in the future. The vision thus gives us a target (a basket of 'end-point' states $V(a,b) \subseteq S$ at a basket of time periods $a \leq t \leq b$) , we can observe the current situation ($\mathbf{x}(0) \in S$), and therefore the stochastic dynamic process gives us (in principle, at least) a means of connecting the current situation with the desired vision. However, since we have described the construction of the vision independently from the construction of the dynamic process, it is pertinent to ask: how can we be sure that *any* of the trajectories of our dynamic process lead to the vision? (Perhaps as we are talking in terms of probability, we might refine this question to ask whether any trajectory attains the vision with a non-negligible probability?) Or, alternatively, what should we do if we find that many different trajectories may lead to the same vision?

To consider these questions, let us first if we consider a different, simpler problem, and then draw the analogy. Suppose that rather than looking into the future, we were looking into the past, and our task was to explain the processes of change by which the current transport situation arose from how it was 20 years ago (or perhaps even going back to Victorian times?). A historian or social geographer analysing such a question would typically propose some causal process of change: such a process would describe the pathway from the situation in the past to the present day. To be an effective narrative of how the past connects to the present day, then clearly the causal links in the chain have to be successful in linking the past to the present; if they were not, then the historian would revise her description of the causal processes until the narrative did indeed connect up in this way. Thus, in creating the narrative, the historian is given some free rein in choosing the causal dynamic process, its choice is openly subjective; but on the other hand she will only convince others of its plausibility if she can find corroborative evidence to support it. Therefore, the approach is still evidence-based, but the historian is free to select her sources of evidence and causal mechanisms as the basis for her subjective narrative. Scientifically, we might feel somewhat uncomfortable with this notion, but it should be appreciated that the processes we are considering here are much more difficult to understand—with the causal mechanisms rarely explicitly documented—than (say) the problem of devising mathematical models to optimize/'tune' the engine management system of a car to operate over a journey: in the latter case the 'physics' and science rightly takes over. In contrast, accounts of conflicts even in the recent past, even the causes of present world-wide conflicts and disputes, are open to considerable debate; our point is that the task of unravelling the historical development of a transport system over many decades is much more similar to this kind of problem than it is to the engine management problem.

If we now return to our original problem, of looking into the long-term future rather than the past, then we are faced with an even more difficult problem in understanding our transport systems, as we do not have the corroborative evidence of the future that we can draw on for our analysis of history. Therefore it does not seem appropriate to set higher standards for examining long-term futures than it does for understanding long-term histories. In a directly analogous way, we see the construction of the state-space, state variables, causal mechanism and transition probabilities as the development of a subjective narrative, drawing on evidence of the past and of other locales where possible, to devise a story that now links the present with some subjectively-desirable future outcome, the vision. Mathematically, this says nothing in conflict with the presentation of earlier sections: the point we are making is about the *use* of these tools, whereby the planner (or some other body?) creates what we term a *narrative model*, namely the dynamic, causal, qualitative process that links the present to the vision.

So, to conclude, what are the implications of adopting such an approach for planning, and how does it contrast with the more familiar forecasting? Firstly, in our approach the task is not to identify which futures are more likely, but which are most desirable (the visions). 'Likeliness' only enters as a plausibility check, in that when defining the narrative model, the dynamic trajectory must have a 'reasonable' probability of occurring. Secondly, the proposed approach would naturally form part of a communicative planning process, whereby alternative visions and narratives might be considered and discussed with the public and other bodies. Thirdly, as noted in §5, it may be desirable to consider several different visions as part of the planning process. It is entirely feasible that we may associate different narrative dynamic models with different visions, for example including the representation of different causal processes, not only different policy measures. This may be contrasted with traditional forecasting whereby we would use one model to assess several schemes, and where certainly the end-state does not affect the choice of model. Finally, it should be recognised that although as we have stated the vision definition naturally precedes (and influences) the specification of the dynamic narrative model, in practice there may be a feedback: if no plausible process can be defined that reaches the given vision, then we may need to return to refine the vision.

8. CONCLUDING REMARKS

A discussion has been presented concerning deficiencies in current transport modelling paradigms. This discussion has been backed up by a philosophical analysis in Section 2. It has been pointed out that there are a number of ways forward for transport modelling that can help overcome these deficiencies. The description of one way forward, which we name *narrative modelling*, has taken up the bulk of the paper, presenting a framework for transport modelling that we believe is better suited to contemporary, long-range planning needs than are prevailing approaches in the field. Whether the structure proposed in Sections 3 to 5 is used to forecast or to backcast (Sections 6 and 7), we believe it sets out a range of new, relevant, future mathematical challenges for the transport field, in terms of algorithms, specification, estimation, optimization and conceptualisation of transport systems.

ACKNOWLEDGEMENTS

We gratefully acknowledge EPSRC support, originally via a Platform Grant (gow.epsrc.ac.uk: GR/S46291/01) and more recently through the Visions2030 project (visions2030.org.uk). We also thank researchers involved in Visions2030, and practitioners who have participated in the workshops, for comments on various aspects raised in this paper.

REFERENCES

Akerman, J., and Höjer, M. (2006). How Much Transport Can the Climate Stand?—Sweden on a Sustainable Path in 2050. *Energy Policy* 34, 1944-1957.

Bell, M.G.H. (1997) The games transportation academics play. *Transportation* 24, 33–42

Cantarella G.E., and Cascetta, E. (1995). Dynamic Processes and Equilibrium in Transportation Networks: Towards a Unifying Theory. *Transportation Science* 29, 305–329.

Dreborg, K.H. (1996). Essence of Backcasting. *Futures* 28(9), 813-828.

Dubois, G., Peeters, P., Ceron J.-P and Gössling, S. (2010). The Future Tourism Mobility of the World Population: Emission Growth Versus Climate Policy. *Transportation Research A*. In press.

Hickman, R., and Banister, D. (2007). Looking over the Horizon: Transport and Reduced CO2 Emissions in the UK by 2030. *Transport Policy* 14, 377-387.

Jopson, A. 2004. The Role of Norms in Mode Choice. 3rd Int Conf on Traffic & Transportation Psychology., 5th -9th September 2004, Nottingham, available at: http://eprints.whiterose.ac.uk/2501

Kane, L., and Del Mistro, R. (2003) Changes in transport planning policy: changes in transport planning methodology? *Transportation* 30, 113–131

Khisty, C.J., and Arslan, T. (2005) Possibilities of steering the transportation planning process in the face of bounded rationality and unbounded uncertainty. *Transportation Research* C 13, 77–92

Langmyhr, T. (2000) The rhetorical side of transport planning. *European Planning Studies* 8(5), 669–684

Langmyhr, T. (2001) The rationality of transport investment packages. *Transportation* 28, 157–178

Loukopoulos, P., Scholz, R.W. (2004) Sustainable future urban mobility: using 'area development negotiations' for scenario assessment and participatory strategic planning. *Environment and Planning A* 36, 2203–2226

Pfaffenbichler, P., Emberger, G., and Shepherd, S. (2008). The Integrated Dynamic Land-Use and Transport Model MARS. *Networks & Spatial Economics* 8, 183–200.

Polak, J. (1987) A comment on Supernak's critique of transport modelling. *Transportation* 14, 63–72

Sheppard, E. (2001) Quantitative geography: representations, practices and possibilities. *Environment and Planning D* 19, 535–554

Timms, P. (2008). Transport Models, Philosophy and Language. *Transportation* 35, 395-410.

Van der Helm, R. (2009). The Vision Phenomenon: Towards a Theoretical Underpinning of Visions of the Future and the Process of Envisioning. *Futures* 41, 96-104.

Watling, D.P. (1996). Asymmetric Problems and Stochastic Process Models of Traffic Assignment. *Transportation Research* 30B, 339–357.

Willson, R. (2001) Assessing communicative rationality as a transportation planning paradigm. *Transportation* 28, 1–31 (2001)

Willson, R.W., Payne, M., Smith, E. (2003) Does discussion enhance rationality? *Journal of the American Planning Association* 69(4), 354–367

Willumsen, L.G. (1990) Urban traffic modelling with limited data. In: Dimitriou, H.T. (ed.) *Transport Planning for Third World Cities*. Routledge, London