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Traveller Behaviour: Decision-making in an Unpredictable World

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Abstract

This paper discusses the nature and consequences of uncertainty in transport systems. Drawing on work from a number of fields, it addresses travellers' abilities to predict variable phenomena, their perception of uncertainty, their attitude to risk and the various strategies they might adopt in response to uncertainty. It is argued that despite the increased interest in the representation of uncertainty in transport systems, most models treat uncertainty as a purely statistical issue and ignore the psychological aspects of response to uncertainty. The principle theories and models currently used to predict travellers' response to uncertainty are presented and number of alternative modelling approaches are outlined. It is argued that the current generation of predictive models do not provide an adequate basis for forecasting response to changes in the degree of uncertainty or for predicting the likely effect of providing additional information. A number of alternative modelling approaches are identified to deal with travellers' acquisition of information, the definition of their choice set and their choice between the available options. The use of heuristic approaches is recommended as an alternative to more conventional probabilistic methods.

1. Introduction

This paper is intended to provide an overview of the field rather than to report on new research findings. It seeks to provide a background for a discussion of travellers' responses to information from ITS sources and to suggest some approaches to modelling that response.

The paper will argue that, although the presence of uncertainty in transport systems is well known, most analyses of traveller behaviour treat it rather simplistically and most attempts to model it have seen uncertainty as a statistical issue which can be dealt with using fairly conventional probability theory rather than as a phenomenon which deserves detailed behavioural investigation. A recurring theme of the paper will be that, since it is *uncertainty in the mind of the traveller,* rather than variability in the system, which directly influences behaviour, we need to understand people's perception of and attitudes to uncertainty if we are to predict their responses to it. The study of variability in transport systems is an essential input to this process but it is not the end of the matter.

Interest in uncertainty and variability in transport systems is not new but has increased dramatically in recent years. We suggest that there are two fundamental reasons for this.

Firstly, we suggest that uncertainty has become a more serious problem due to the faster pace of life, the prevalence of just-in-time processes in industry and the increased problem of congestion – traffic growth has outstripped the available capacity and traffic engineers have responded by fine tuning the system leaving it with little spare capacity and so more prone to catastrophic failure. Secondly, we suggest that the advent of traveller information systems and other ITS developments has drawn attention to the fact that conventional models of transport systems and traveller behaviour were unable to fully capture the potential benefits of such systems. It was only when we began to try to model the implications of providing travellers with additional information that the conventional models' assumption of perfect information became absolutely untenable. If one is to model the impacts of ITS one must first address the question of how people behave with incomplete information. This naturally leads to an interest in decision making under uncertainty.

The paper will set the scene by discussing the nature and consequences of uncertainty facing travellers and will then discuss travellers' abilities to predict variable phenomena, their perception of and attitudes to the inevitable uncertainty about the choices available to them. Having outlined a number of strategies by which travellers might respond to uncertainty, attention will be turned to various alternative approaches to modelling these responses.

The dominant paradigm for the current generation of models is Expected Utility Theory (Von Neumann and Morgernstern, 1944). It has many attractions and the resulting model is attractively simple but is based on the rather questionable assumption that the decision maker is indifferent to risk. People are assumed to evaluate probabilities rationally without adding any emotional element which is not already encapsulated in the utilities.

Although transport analysts have done some useful work on response to uncertainty, the paper will draw particular attention to the much larger body of work in experimental economics and psychology. The paper will outline the principle theories and models currently used to predict travellers' response to uncertainty and will argue that the current generation of predictive models based on Expected Utility Theory do not provide an adequate basis for forecasting response to changes in the degree of uncertainty or, more specifically in the current context, for predicting the likely effect of providing additional information.

A number of alternative approaches are identified and although some are fairly complex and data-hungry, we will argue that incremental improvements to existing models may make it possible to incorporate key aspects of decision making under uncertainty. We will suggest a generalised model framework which, with a heuristic implementation, offers considerable advantages.

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The paper draws on an earlier version by the author (Bonsall, 2001). It expands on a number of the points made in the previous version and, with the addition of new material, seeks to provide a more complete treatment of the topic.

2. Variability in Transport Systems

2.1 Types of variability

Transport systems are characterised by variability. The most quoted, and most studied, examples relate to variability in journey durations but almost all attributes of a journey are subject to some degree of variability. The smoothness of the traffic flow, the stressfulness of the journey, the chance of being involved in an accident, of getting a parking space, of getting a seat on the bus, of successfully hailing a cab, of finding the lights on red, of stepping into something unmentionable on the way from the car park, and of finding one's car clamped, vandalised or stolen, are all subject to variation.

Some of the variability in transport systems is due to more or less predictable events such as public transport service schedules, planned road maintenance, the daily tide of commuter traffic, or the traffic associated with sporting fixtures or public holidays. But much of it results from seemingly random events such as road accidents, severe weather, technical failure/malfunctioning of equipment, or, most particularly, the behaviour of other people – be they fellow travellers, service operators or traffic wardens. Although most variabilities are beyond the control of the individual traveller, others, including the risk of an accident or breakdown or of getting lost, may be partly or wholly due to the traveller's own actions and, as we shall see, there may be reason to treat them differently in models.

Figure 1 indicates three different patterns of variability. The first might represent the probability of a binary event such as whether a given traffic light would be on red or whether a given stretch of road is subject to roadworks – the one varying in a matter of minutes and the other in months. The second might represent the annual fluctuation in lighting-up times or second-by-second variation in noise levels at the roadside. The third pattern might represent the distribution of journey durations perhaps varying second by second or perhaps over several months. Different patterns will be manifest over different timescales and with different degrees of predictability. Very few transport phenomena are invariant - although some may be stable for considerable periods of time and others may vary so marginally that they can be considered as invariant for all practical purposes.

Figure 1: About here

2.2 The consequences of variability

The consequences of variability are very context-dependent. At one level this is simply a matter of cause and effect – as when the consequences of a variation in demand or capacity depend crucially on the amount of spare capacity available. At another level, however, it reflects the circumstances of the traveller (the purpose of their journey, their ability to adjust their plans, their awareness of alternatives, etc) and, most crucially, their ability to predict the variation in question.

The consequences of an unexpected delay during a journey would probably be insignificant if the time could be made up later in the journey, but could be serious if the traveller was already late for an appointment. A late arrival would mean much more to a traveller who was due at an important meeting than to someone taking a leisurely drive.

Although some of the consequences of variation might appear to be binary (you are either late or on time, you either get a parking space or you do not), their *importance* will depend on the context in which the journey is being made (see Figure 2).

Figure 2: About here

2.3 The classic model of behavioural response to variable phenomena

Expected Utility Theory (Von Neumann and Morgenstern, 1944) provides a model of response to variable phenomena. The theory suggests that behaviour can be explained as the result of decision-makers choosing those actions which maximise the expected utility (EU) of all the available courses of action. The expected utility of each action will be the sum of the utilities of all the potential outcomes of that course of action multiplied by their respective probabilities – as summarised in equation 1.

$$EU_a = \sum_{o} (U_{oa} \cdot P_{oa}) \qquad (1)$$

Where EU_a is the expected utility of course of action a
U_{oa} is the utility of outcome o of action a
P_{oa} is the expected probability of outcome o of action a

Figure 3 is a diagrammatic representation of the way in which, in the context of a journey of uncertain duration, the probability of different durations is combined with the disutility associated with these durations to produce a distribution of expected utility.

Figure 3: About here

Expected Utility Theory has many attractions and the resulting model is attractively simple but it is based on the rather questionable assumption that the decision maker is indifferent to risk. People are assumed to evaluate probabilities rationally without adding any emotional element which is not already encapsulated in the utilities (an assumption which we question in Section 3.4).

Implementation of the model also requires the analyst to know the shape of the probability distribution *as perceived by the decision maker.* If, as we will argue in section 3.3, it is unrealistic to assume that the decision maker might know the true probability distribution, it becomes necessary to predict what their perceived distribution might look like – the apparently simple model now seems rather less simple!

3. Unpredictability in Transport Systems

3.1 Variability and unpredictability

The terms ‘variability’ and ‘unpredictability’ are often used almost interchangeably but, although some of their causes and obvious manifestation may be similar, their consequences for traveller behaviour are quite different.

When a phenomenon is described as *variable* the implication is simply that it is subject to change. Variability is thus a descriptive label; if something is not constant then it is variable and the extent of its variability can, in theory if not in practice, be measured. Variability is often associated with uncertainty and unpredictability, in as much as variable phenomena are generally more difficult to predict, but there is no reason to assume that invariant phenomena can be predicted or that varying phenomena cannot be predicted.

Some phenomena affecting transport choices may be invariant but unknown to many travellers. For example, travellers who do not usually use public transport may be quite unaware of the fare payable for a particular journey and drivers who do not use a particular parking location may be unaware of the charge due. Other phenomena affecting transport choices may be variable but habitual travellers may come to recognise patterns in their variation. For example, regular travellers on a commuter route may come to recognise that the journey time varies within a particular range, that the worst of the congestion can be avoided by setting off at a particular time, and that speeds are reduced during adverse weather conditions. With reference to Figure 1, it is clear that some patterns are, by their very nature, easier to identify than others. If a pattern is detectable, and detected by the traveller, then that traveller might be in a position to use the shape of the probability distribution to inform his choices (as implied by Expected Utility Theory). If it is not detectable or detected then it cannot possibly inform the traveller’ choices.

If a phenomenon is described as *unpredictable* the implication is that its state at any given time cannot be known in advance. Unpredictability is a not simply a statistical concept and it may be difficult or impossible to measure. The state of predictability depends on the person doing the predicting; something may be regarded as predictable by one person but may seem completely unpredictable to another. Predictability is thus, in part, a question of perception; if someone regards something as unpredictable then, to him, it *is* unpredictable and he will behave accordingly (and vice versa).

3.2 Travellers’ abilities to predict – the role of experience and information

Travellers base their prediction of future system conditions on various sources of information. These include:

- personal experience;
- second hand experience and opinion from friends, colleagues, or the media; and
- information and advice provided by system managers or other agencies.

These sources are interpreted in the light of the traveller’s personal understanding of how the system works. Most travellers are aware of general “rules” (such as that travel times are longer when the weather is bad or the traffic is heavy), but many are unaware of more detailed phenomena affecting the performance of transport systems (such as the extent to which traffic signal settings vary from hour to hour and thus affect the likelihood of meeting a red signal at different times of day). A traveller’s understanding of how the system works is likely to reflect the amount of experience they have of that system and the amount of information at their disposal, but it will also depend on their intellectual curiosity/ability.

Personal experience is a powerful source of information (Toglia *et al*, 1992) but most people are quite happy to rely on second hand experience or opinions (Perkins, 1999). For example, it is commonly asserted that Bangkok is congested by people who have never visited the place! Second hand experience and opinion is particularly powerful if it derives from a respected source and is often repeated and, in such circumstances, may even outweigh a contrary personal experience (Asch, 1985).

Information and advice provided by system managers and other agencies might involve one or more of a number of alternative sources including; maps, timetables, roadside information, advice bureaux, TV/radio broadcasts, Internet pages and in-vehicle units. Such information can, of course, be of great value to travellers but their ability to make use of it is conditioned by their ability to access it, their ability to understand it and their preparedness to trust it. Research suggests that the credibility of the information depends on the degree to which it is corroborated by other sources of information, its inherent reasonableness, and the credibility of the source (see, for example, Bonsall and Parry, 1991, or Wardman *et al* 1997). The credibility of the source is likely to depend primarily on its track record of providing reliable information but there is some evidence to suggest (see, for example, Bonsall and Palmer, 1999) that travellers, suspecting the motives of some information providers, may be sceptical of the information or advice they provide (the classic example being the suspicion that highway authorities will exaggerate the seriousness of potential delays at road works because they want to reduce traffic at such sites to a minimum).

An experienced traveller will usually be better able to predict conditions in a transport system than will a newcomer because he will have better knowledge of:

- the established patterns (of congestion, service levels, etc) and of the ways in which they differ according to the time of day, day of the week or weather conditions;
- how to recognise the advance signs of disruption or change; and
- where to access information about the current state of the system (and how much trust to put in the sources of such information).

However, when established patterns are disrupted, the experienced traveller may find that his knowledge of those patterns is of little use. For example:

- if normal timetables are suspended (e.g. during a strike or technical breakdown);
- if capacities are disrupted by a radical change to the network (e.g. due to the closure of major link or during severe weather conditions);
- if the system has been re-engineered such that it becomes more (or less) vulnerable to disruption;
- if the pattern of demand is disrupted by a major event (e.g. a major sports fixture);
- if the behaviour of other users of the system changes radically (e.g. due to the unprecedented presence of a large number of visitors or if a significant number of drivers gain access to a new source of traffic information which causes them to alter their behaviour).

If established patterns are no longer valid for reasons such as those indicated above, the experienced traveller relying on experience of the “normal” situation may actually be more confused than someone without that knowledge.

Although travellers' ability to predict usually increases as more information is made available to them, a *lack* of information can sometimes give the traveller a false confidence in his ability to predict. For example, an experienced driver may be aware that the duration of a particular journey time is very weather-dependent, whereas a less experienced driver may assume that he can complete the journey in an hour whatever the weather conditions.

Although uncertainty in the mind of the traveller stems from complexity and variability in the transport system, it is more directly due to the fact that the traveller *believes* that some aspect of the system is characterised by uncertainty. Generally this will be because the traveller believes that the phenomenon is unpredictable or that he does not have access to the information which would enable him to make a confident prediction. These beliefs may or may not be correct, but it is the beliefs, rather than the reality, that will influence the traveller's behaviour – including the decision on whether to seek additional information. Some ITS systems, for example advanced traffic control systems, may be designed to reduce variability but most are designed to reduce uncertainty in the mind of the traveller.

3.3 Perceptions of variability

A traveller's knowledge or experience of the distribution of possible outcomes of any given course of action is typically very sparse and unlikely to be representative of the full distribution. On this basis alone we would argue that it is thus very unlikely that travellers can have an accurate perception of the relative frequencies with which particular outcomes might arise. But a further reason is that travellers' recollection of past events is subjective and selective. It is known that people are more likely to recall events which were out of the ordinary than those which were unremarkable (Graesser *et al*, 1980; Woll *et al*, 1982). There is also evidence to suggest that most people tend to recall occasions when things went particularly badly more readily than those when things went particularly well (see, for example, Robinson-Reigler and Winton, 1996). The traveller is more likely to remember the journeys when he missed the train or was late for the meeting than the ones when everything worked according to plan. This is bound to result in a distorted perception of the distribution of possible outcomes.

A more fundamental question is whether the ordinary traveller's perception of probabilities of different outcomes bears any relationship to the kind of distribution functions used by analysts.

Attempts to study travellers' perceptions of the distribution of probabilities are fraught with difficulties because it is impossible to know what their full experience has been and any attempt to ask their assistance in logging some part of that experience risks over-sensitising them to the phenomena. The risk of undue sensitisation is also present in laboratory-based experiments. A particular problem confronting research in this area is finding a way to characterise uncertainty in ways understood by the traveller unused to mathematical representations of probability. Although Polak and Jones (1993) had some success with fairly scientific representations of the distributions, Bonsall and Palmer (1998) found that travellers were happier to characterise their experience in terms of 'headline' outcomes (e.g. 'on a good day' 'on a bad day' and 'on a normal day').

It seems that many people perceive probability distributions as a small set of discrete outcomes each having an associated, all be it fuzzy, chance of fulfilment. This conclusion would invite analysis using heuristics or fuzzy logic rather than more conventional statistical approaches.

3.4 Travellers' attitudes to uncertainty and risk

Travellers' choices among the available options will reflect their perception of the costs and benefits associated with each option. If the costs or benefits are perceived to be uncertain then the choice will be influenced by the traveller's attitude to that uncertainty. The key issue is their attitude to risk. Suppose that a traveller is faced with the choice of three modes of transport and that the probability distributions for their arrival times at the destination are as shown in Figure 4. Which one would the traveller choose?

Figure 4: About here

According to the distributions, mode **A** is most likely to arrive at *T1* but might arrive as late as *T5.* Mode **B** is most likely to arrive at *T2* and is certain to have arrived before *T4.* Mode **C** is most likely to arrive at *T3* but could arrive as early as *T0* or as late as *T6*. Assuming that the traveller wants to arrive as soon as possible, he should choose **A** if he wants the mode which is *likely* to arrive earliest but **C** if he wants the mode that *could* arrive the earliest. If the traveller wants to avoid being later than *T4* he should choose **B**, If he wants to arrive earlier than *T5* he could safely choose **A** or **B** (but with a preference for **A** since it is *likely* to arrive earliest). The actual choice will depend not only on the consequences of arriving at different times but also on the traveller's perception of the probabilities involved and his attitude to risk.

However, as noted by Edwards (1962), Kahneman and Tversky (1979), Schoemaker(1980) and many others, it is well established that people do not respond to probabilities in a strictly rational manner. For example, most people behave as if they are exaggerating low probabilities (*vide* the popularity of lotteries and the fear of flying) and most people behave as if they are unaware of the differences between low probabilities (for example, most people would treat odds of 1:1,000,000 and 1:10,000,000 as virtually identical). These behaviours may reflect an ignorance of the underlying odds or a misunderstanding of the laws of probability but most seem to be associated with personality traits; optimists like to gamble – they are risk-seeking, while pessimists do not like risking loss (or failure to win) - they are risk-averse.

We referred in Section 2.2 to the fact that the consequences of an unexpected delay during a journey would probably be insignificant if the time could be made up later in the journey. This may be true in an objective sense but, for someone who is very risk averse, the experience of that delay, however inconsequential, might be sufficient to affect their behaviour next time they make the journey.

Figure 5 shows how attitudes to risk might be represented via marginal utility curves. Curve *a* is the perceived probability of a given event (in this case the probability of a given journey duration). Curve *b* shows how the utility of each journey duration might be affected for someone who is risk seeking (the marginal utility is zero for outcomes which are no better than the most likely but are increasingly positive for outcomes that are better than that). Curve *c* shows the same thing for someone who is risk averse (the marginal utility is zero for outcomes which are no worse than the most likely but is increasingly negative for outcomes which are worse than that).

Figure 5: About here

Figure 6 is equivalent to Figure 3 and shows how an attitude-to-risk surface such as curve *c* in Figure 5, might be combined with the probabilities and outcomes to produce a risk-weighted expected utility distribution.

Figure 6: About here

Attitudes to risk vary from person to person, and any given person's attitude varies according to circumstances and their emotional state, but some general tendencies are apparent. For example, it is generally held that females are more risk averse than males (see for example, Eckel and Grossman, 2002) and it appears that risks are perceived more keenly if one does not have control over them – a tendency which causes people travelling by train or bus to build more slack time into their schedules than is generally allowed by people who are driving (Koskenoja, 1996).

Kahneman and Tversky (1979) suggest that, other things being equal, there will be a tendency towards risk-averse behaviour when the outcomes involve gains and towards risk-seeking behaviour when the outcomes involve losses. They developed Prospect Theory, and more recently, Cumulative Prospect Theory (Tversky and Kahneman, 1992) to explain some of the commonly observed departures from the behaviour that would result from strictly rational assessments of probabilities. The key tenet of Prospect Theory is that decisions are context-dependent and that the evaluation of risky prospects involves a sequential assessment of outcomes during which process the prospects are disassembled, simplified and reassembled with gains and losses being identified in respect of some common reference point. Prospect Theory is clearly more difficult to work with than Expected Utility theory but would appear to have a much sounder behavioural basis. In place of the assumption that people will assess perceived probabilities in a strictly rational manner, Prospect Theory allows for a subjective weighting of perceived probabilities reflecting the decision maker's attitude to risk.

Studies in experimental economics emphasise the role of gambling or risk-seeking behaviour and there is a very extensive literature on the subject (see, for example, issues of the journal *Games and Economic Behaviour,* the *Journal of Risk and Uncertainty Organisation Behavior and Human Decision Processes,* or the *Journal of Economic*

Behavior and Organisation). Application of the methods used in experimental economics to the study of driver behaviour are rare but include work by Powell and Davis (1996) and Denant-Boemont and Petiot (2003). Although the strategies adopted by participants in games of chance constructed by experimental economists may not reflect real-life behaviour and any interpretation of that data as evidence of real-life risk seeking is therefore bound to be controversial, the behavioural tendencies revealed by such work have strong anecdotal echoes. Powell and Davis assumed that interurban route choice strategies could be interpreted as "games" played by drivers seeking to outperform the expected duration for the journey in question. Denant-Boemont and Petiot found some evidence to suggest that drivers would generally prefer to risk an uncertain journey duration rather than pay a toll which would have guaranteed a certain journey duration.

Another interesting example is provided by the work of Cho (1998) who used SP questions to examine drivers' responses to imprecisely defined tolls. Although the results showed a general preference for routes with fixed tolls rather than uncertain tolls, this preference seemed to *decrease* as the degree of uncertainty increased. It was clear that some respondents, particularly males, were showing a distinct preference for the most *uncertain* tolls. Cho sought to explain this result using Prospect Theory but found the theory unsatisfactory as an explanation of why a general preference for the certain prospect should co-exist with an increasing preference for the increasingly uncertain prospect. Bonsall (2000a) sought alternative explanations for the result but eventually concluded that, despite the absence of any exaggerated incentive to gamble, some respondents had a real preference for the more uncertain prospect *simply because it offered greater risk*.

4. Travellers' Strategies for Dealing with Perceived Uncertainty

We will now consider the strategies which travellers might adopt to deal with perceived uncertainties. We distinguish five main types of strategy:

- seeking to reduce the uncertainty by accessing additional information;
- seeking to reduce the uncertainty by advance planning;
- seeking to reduce the consequences of the uncertainty;
- accepting the uncertainty and seeking to make the best decision in the light of it; and
- seeking to capitalise on the uncertainty.

4.1 Reducing uncertainty by accessing additional information

Faced with uncertainty, a wise traveller will put some effort into seeking better information before considering whether and how to adjust his behaviour. The action required will depend on the circumstances but the following examples serve to illustrate the point.

- *Experiment with a number of transport alternatives (modes, routes, times of travel) in order to assess their relative attractiveness.* This strategy is expensive but may be very appropriate for people who have recently moved their home or workplace.
- *Invest in up-to-date maps, timetables etc*. This action is particularly relevant for newcomers to an area or following changes to the transport network of services provided.

- *Subscribe to a traffic information service.* This strategy might suit travellers for whom schedule-adherence is likely to be an important consideration and for whom access to real-time traffic information may therefore be particularly important
- *Seek information or advice from a telephone enquiry line, Teletext service or Internet site prior to departure.* This is already the norm for many users of long distance public transport services and, with the increasing quality of information available, may become the norm for more local journeys.

Active information acquisition requires an investment of time and other resources and the traveller must consider whether the investment is likely to be justified. The costs and benefits of information searches have attracted attention in many fields and a considerable literature has resulted. (See, for example, Richardson, 1978; Gemunden, 1985; Walker and Ben Akiva, 1994). The following strategies for information acquisition have been identified and are clearly relevant in the context of travellers' decisions to access ITS services :

- *Devote a predetermined amount of resource to the search and then stop* (e.g. spend ten minutes studying train timetables).
- *Continue seeking extra information until a predetermined goal is met* (e.g. until an airline offering flights to Japan for less than $1000 is found). A satisficing strategy of this kind may, of course, lead to an endless search!
- *Continue as long as there is a reasonable prospect of reward from continuing*. This strategy appears logical, and allows for decreasing rates of return, but requires a reliable method of predicting the likelihood of a successful outcome if the search is continued.

4.2 Advance planning in order to reduce uncertainty

Strategies designed to reduce uncertainty are most likely to be adopted by people who abhor uncertainty and on journeys for which uncertainty could have serious consequences. They might include the following:

- *Making maximum use of existing knowledge* (eg by choosing to use modes, routes, or times with which the traveller is already familiar or for which information is readily available). Route choice studies (e.g. Bonsall et al 1997) have revealed that drivers making unfamiliar journeys generally seek to make maximum use of routes with which they are already familiar. Other work has suggested that female drivers are less willing than males to depart from familiar or signposted routes (Bonsall, 1992; Khattak et al, 1993; Emmerink et al, 1996) and that drivers' reluctance to depart from familiar routes is greatest when they are under time pressure (Bonsall et al, 2000).
- *Deliberately avoiding modes, routes and times which are known to be subject to disruption or instability* - even if they might otherwise be more attractive than the alternatives (eg avoiding travel by plane in foggy conditions, by road during peak periods or too late to be sure of getting a parking space at the destination).
- *Taking sensible advance precautions* (eg making sure that the vehicle is properly maintained and that, if driving in an unfamiliar area, a route has been planned, the relevant maps marked up and the subscription to the traffic information service has been paid).

An appreciation of these strategies is important when analysing the uptake, impact and performance of ITS services but they are rarely included in models or even sought in surveys.

4.3 Seeking to reduce the consequences of uncertainty

These strategies may be categorised according to whether they involve advance planning or whether they represent ad hoc responses to an emerging situation.

Strategies which require advance planning include the following:

- *Building a safety margin into the schedule*. This is the classic strategy for reducing the potential consequences of unexpected delay. It was clear from Pells' (1987) review of research and analysis in this area in the late 1980's that scheduled safety margins were widely used and tended to be largest where the uncertainty was greatest or the consequences of late arrival were most serious.
- *Deliberate adoption of a lifestyle which minimises participation in time-critical activities* - for example by accepting employment only if it allows flexitime working, by eschewing the use of timetabled transport services and by avoiding commitments to fixed appointments.

Strategies which represent responses to adverse conditions already encountered on the current journey might include the following:

- *Speeding up or slowing down* depending on whether one is behind or ahead of schedule.
- *Changing lane, route or mode* if the current one seems likely to continue to under-perform.
- *Alerting people at the destination to the likelihood of a delayed arrival.* The widespread adoption of mobile communications makes this strategy very attractive and anecdotal evidence suggests that this is allowing people to reduce their scheduled safety margins but little research has yet been done to verify this.
- *Multi-tasking to make up for lost time.* Again, this strategy is facilitated by the availability of mobile communications and may require modellers to rethink the treatment of travel time as unproductive.
- *Abandoning the journey* if conditions are so bad that the original purpose of the journey can no longer be met (e.g. if there is now no prospect of catching the plane) or, more generally, if the effort and resources likely to be required to complete the journey seem likely to outweigh the benefits of doing so.

With the exception of rescheduling of departure time to include a safety margin and, more recently, the dynamic adjustment of speed or route, few of these responses are included in models or even sought in surveys.

4.4 Making the best decision in the light of the uncertainty

These strategies require an initial assessment of the situation to determine the likely outcomes of each action and then a pragmatic decision on how best to proceed. As will be clear from the preceding sections, the initial assessment of likely outcomes is far from straightforward but, once it is complete, the possible courses of action might include the following:

- *Choose on the basis of the full probability distribution of outcomes for each option.* If the choice is based on the relative utilities of the different options then this strategy requires maximisation of the expected utility (as per equation 1 earlier in the paper). If the choice is based only on journey time, it would imply minimisation of expected journey time.
- *Choose on the basis of the most probable outcome for each option.* For example, decide between alternative modes on the basis of the single most likely journey time for each option.
- *Choose on the basis of the most pessimistic outcome for each option.* For example, decide between alternative routes on the basis of their worst-case journey times.
- *Choose on the basis of the most optimistic outcome for each option.* For example, choose the route that would be the quickest if there were no delays.

The first of these strategies is the one normally assumed in predictive modelling – despite its somewhat unrealistic assumptions about the abilities of individuals to comprehend the shape of the distributions of probability and disutility.

4.5 Capitalising on the uncertainty

Some people thrive on the uncertainty involved in travelling and seem to get a buzz from confronting it. Such people may obtain satisfaction by seeing their journey as a competition; the challenge being to use their skills to compete with some imaginary opponent (the clock? the system? the driver of the car who barged into the queue in front of them? themselves on the previous day?). For such people, the existence of uncertainty in the transport system is a bonus. As was illustrated in Figure 5, risk seekers may experience increased utility if they succeed in their game of chance and may not suffer correspondingly when they lose. The behaviour of risk seekers is likely to be characterised by attempts to gain relative advancement and this is likely to be manifest as *frequent lane-changing, use of circuitous routes, frequent changes of route, making fast-getaways from traffic lights,* and so on.

These phenomena are widely observed and may be taken simply as examples of aggressive behaviour. However, if they reflect an attempt to capitalise on the uncertainty within transport systems, they may be influenced by changes in the level of uncertainty consequent on changes in the supply of capacity or the provision of ITS facilities and services. As such they would need to be considered in any analysis of the full impacts of ITS deployment.

5. Approaches to Modelling Decision Making under Uncertainty

5.1 Introduction

The preceding sections have established the ubiquity of uncertainty in the transport system and the potential complexity of travellers' response to it. It was noted that a number of the potential responses involve processes and actions which are usually ignored in analyses of traveller behaviour and that some of the potential responses to uncertainty involve advance action by the traveller. We will now explore the implications that this has for modelling of traveller behaviour, paying particular attention to the representation of the impact of ITS systems.

5.2 Models which help define the choice set

5.2.1 Restriction of the choice set

One of the consequences of limited knowledge is that the traveller will be unaware of all the options available. In such circumstances the choice would be made from a restricted choice set. Equation 2 is a formal statement of such a model but without specifying the nature of the restriction.

$$\boldsymbol{j} = {}^{\boldsymbol{argmax}} \; \{ \boldsymbol{U_k},\, \boldsymbol{K} \in C \} \tag{2}$$

Where: $\boldsymbol{j}$ is the chosen option
$\boldsymbol{U_k}$ is the utility of option $\boldsymbol{k}$
$\boldsymbol{C}$ is the restricted choice set to which $\boldsymbol{k}$ belongs.

The restriction, $\boldsymbol{K} \in C$, could be binary (with $\boldsymbol{K}$ either belonging or not belonging to the set $\boldsymbol{C}$) or probabilistic (such that the probability of $\boldsymbol{K}$ being included is a function of some attribute). If the restriction is intended to reflect limited knowledge it might be proxied by excluding, or setting a high probability of excluding, options which are unlikely to be known to the traveller. For example, in the context of route choice, one might omit links which are not on signposted routes, or which involve substantial diversion from the straight-line route.

Restriction of the choice set may of course be voluntary; one of the responses to uncertainty identified in Section 4.1 was that the traveller might deliberately exclude options characterised by an unacceptable degree of uncertainty. For example, options liable to unpredictable non-trivial variation in journey times might be excluded when choosing a mode or route by which to travel to an important appointment.

Tversky's (1972) elimination-by-aspects (EBA) model provides an example of one mechanism by which the choice set might be restricted. The EBA model provides for options to be eliminated from further consideration if they fail to meet specified criteria in respect of one or more of their attributes. Such a model could provide a direct representation of an attitude to risk which implied rejection of any option for which there is a significant (to be defined) probability of, for example, arriving later than a given time or costing more than a specified amount. The critical values should, of course, be allowed to vary between groups or individuals and might be different for different journey purposes.

Application of elimination rules, whether EBA or some other, might be followed by use of a more conventional optimisation model to choose between any remaining options.

5.2.2 Representing imperfect knowledge

Restriction of the choice set allows for the situation where a traveller is unaware of all the options available or decides to consider only some of them but it does not allow for the case where the traveller is aware of all the options but misperceives their attributes. A number of authors have sought to model the impact of imperfect knowledge on route choice by distinguishing between drivers on the basis of their assumed level access to information. One approach has been to allow informed drivers to choose options on the basis of the best estimate of actual generalised costs while uninformed drivers are assumed to make their choices according to some heuristic (e.g. signposted routes, free-flow costs, or minimum distance routes – see McDonald *et al*, 1995). Another approach, which we will revisit in section 5.3.1, has been to apply more "error" to the choices of unfamiliar drivers. But before considering this approach we should perhaps pay further attention to models of learning and information acquisition.

5.2.3 Models of information acquisition

The traveller's choice set, and his perception of the attributes of options within it, is necessarily conditioned by his knowledge of the system. This knowledge will be a result of experience gained, other information acquired passively or information obtained following a deliberate and active search.

Several models have sought to represent driver perception of network performance as the result of experience gained. Such models generally take the form of day-on-day simulations wherein conditions, and behaviour, change from one day to the next. A record is kept of the conditions experienced by each 'traveller' and he is assumed to use his accumulated experience to form an expectation of conditions and to behave accordingly. Notable examples of this approach include Ben-Akiva et al (1991), Cascetta and Cantarella (1991), Hu and Mahmassani (1994), Liu et al (1995), Emmerink *et al* (1995) and Jha *et al* (1998). Although this approach could be used to build up an assumed perception of the distribution of the phenomenon in question (typically the journey time to be expected on a particular mode or route), most of these models assume that the synthetic traveller uses his accumulated experience to derive a single expected value.

There are a large number of ways in which the synthetic traveller might draw a single value from his accumulated experience. For example:

- the mean value experienced in the last *n* days (assuming the traveller has a limited memory),
- the modal value experienced (assuming that the traveller is persuaded by "the most usual" value),
- the lowest value experienced (assuming an optimistic traveller);
- the highest value experienced (assuming a pessimistic traveller);
- an exponentially-smoothed mean of the values experienced (assuming that the traveller gives greater weight to his most recent experience), or
- the result of a Bayesian progression.

The creation and analysis of individual histories of journey times could, of course, be extended to cover other journey attributes and might begin to use evidence, such as that collected by van der Waerden *et al* (2003), on the influence of key events and incidents on choice-set composition. However, despite reductions in the computing, the construction of personal histories for synthesised travellers remains a relatively expensive approach even when limited to journey times and it can clearly be argued (see, for example, Bonsall, 2000b) that, until we know more about how travellers interpret their experiences, the computer budget would be more productively devoted to other aspects of the modelling process.

We turn now to the representation of active attempts to acquire information. A number of information acquisition strategies were outlined in Section 4.1 and models can be constructed for each of these. A satisficing strategy might be simulated via a sequence of conditional probabilities or heuristic rules, or the outcome might be derived analytically, with the investment to reach that outcome being derived probabilistically. A fixed investment search could be modelled by optimising among a constrained set of sources. A rational-investment search might be modelled via utility-maximising procedures.

Polak and Jones (1993) and Hato *et al* (1999) used logit equations to predict the probability that a particular information source will be accessed. They concluded that the utility of the information source depended on the service attributes (cost, accuracy, accessibility), the individual's characteristics (age, gender), and the trip characteristics (purpose, usual degree of congestion). Walker and Ben Akiva (1994) produced a sequential model of the search process and sought to calibrate this via laboratory simulation.

A full representation of the information acquisition process would need to include the following stages (although some may not be relevant in all circumstances):

- recognition of the value of obtaining additional information (the information deficit),
- recognition that it is possible to obtain additional information;
- decision to seek additional information;
- identification of potential sources of additional information;
- opinion on the credibility of potential sources of additional information;
- decision to access potential sources of additional information;
- degree of success in accessing additional information from those sources;
- degree of success in understanding the new information;
- opinion on the credibility of the new information;
- synthesis of new information with pre-existing knowledge and beliefs;
- use of synthesised information to form expectations.

5.3 Representation of the disutility of options in the choice set

This section will illustrate a number of approaches to the definition of the utility of each of the available options. It is assumed that the choice between options would be made on the basis of their relative utilities.

5.3.1 *The application of random error terms to the mean cost of each option*

A commonly adopted mechanism for allowing for uncertainty in a model is simply to add a random error term to the cost (or perceived cost) of the option. The size and distribution of this error term would be derived as part of the calibration of the model and could be manipulated to represent different levels of knowledge – with larger error terms representing less perfect knowledge. Equation 3 shows the case where the disutility of option is made up of its mean cost plus a random error term. Equation 4 shows the case where the mean cost is multiplied by the random error term. Other variants could of course be defined.

$$U_a = \overline{X_a} + \varepsilon \tag{3}$$

$$U_a = \varepsilon \overline{X_a} \tag{4}$$

Where:

U_a is the disutility of alternative a (as used in a utility maximising model)

$\overline{X_a}$ is the mean cost of alternative a

ε is a randomly distributed error term

Equations 3 and 4 reflect the usual approach whereby one error term is applied to the entire cost but, since this implies the same degree of uncertainty about all components of the cost, a case is sometimes made for applying separate error terms to the different components (as per equation 5). This would allow separate weighting of uncertainty in, say, travel time and out-of-pocket costs.

$$U_a = \sum_n \alpha_n \left(\overline{x}_{an} + \varepsilon_n \overline{x}_{an} \right) \tag{5}$$

Where:

α_n is the weight applied to the nth component of the cost of alternative a

$\overline{x}_{an}$ is the mean cost of the nth component of the cost of an alternative a

ε_n is a randomly distributed error term applied to the nth component of the cost of alternative a

Although the use of randomly distributed error terms has some attractions as a way of representing uncertainty, it is perhaps more appropriate for representing uncertainty in the model (i.e. error, miss-measurement or miss-specification by the analyst) than uncertainty in the mind of the traveller because it cannot hope to capture any of the complexity or subtlety of traveller attitudes or response. Constraints on the error term might allow for a crude representation of risk aversion (e.g. if it were constrained to be positive in equation 3, or greater than 1 in equations 4 or 5, it would introduce a positive relationship between uncertainty and disutility) but this would fall far short of what is required.

5.3.2 Methods based on the mode of the cost distribution

Equations 3, 4 and 5 made use of the mean value of the cost distribution. This may be an intuitively attractive approach since it makes use of the whole distribution but it lacks credibility as a behavioural model because it presupposes that the decision makers would or could know what the mean value is. It might be more realistic to assume that they are aware of the most frequently experienced value and so an alternative approach might be to allow the utility to be based on the modal (most likely) value of the cost distribution – as shown in equation 6.

$$u_a = sup.(X_a) + \varepsilon \tag{6}$$

Where: $sup.(X_a)$ is the most likely (i.e. modal) value of the cost of alternative a

An alternative, and more behaviourally valid approach might be to base the choice on the cost which is *perceived* to be the most likely as in equation 7.

$$u_a = sup.p.(X_a) + \varepsilon \qquad (7)$$

Where: $sup.p.(X_a)$ is perceived to be the most likely (i.e. modal) value of the cost of alternative a

Variants on equations 6 and 7 could of course be specified with multiplicative error terms or with separate treatment of different components of cost (i.e. as per equations 4 and 5) but the representation of attitudes to risk would still be quite limited.

5.3.3 Methods which make use of statistical measures of variability in the cost distribution

An obvious method of representing uncertainties in decision models is simply to add a term to the calculated utility to represent the statistical uncertainty associated with a given alternative. This approach could be applied using the true, objectively measured, cost distribution or some subjective representation - if such were available. Equation 8 shows the use of the mean together with the variance but other measures could of course be used.

$$U_a = \overline{X_a} + \beta SX_a \qquad (8)$$

Where: SX_a is the variance of the distribution of cost of alternative a
β is the weight put on the uncertainty inherent in the cost of an alternative

Equation 9 indicates how this method might be extended to allow the uncertainty associated with individual components of the generalised cost of an alternative.

$$U_a = \sum_n \alpha_n \overline{X}_{a\,n} + \beta_n SX_{a\,n} \qquad (9)$$

Where: α_n is the weight put on the mean value of the nth component of cost of an alternative
β_n is the weight put on the uncertainty inherent in the value of the nth component of cost of an alternative
(if X_n is journey time, then α_n will be the value of journey time and β_n will be the value of uncertainty in journey time)

Variants of this model have been widely used (see for example, Hendrickson and Kocur, 1981; Small, 1982, Arnott et al, 1990; and Noland and Small, 1995) although most applications have excluded all components of generalised cost other than journey time (i.e. they only have one $\alpha\overline{X_a} + \beta SX_a$ term in equation 9). The main attraction of this model has been its simplicity and the ease with which it can be used to explore the impacts of different levels of uncertainty (by redefining SX_n) and different attitudes to it (by varying α_n and β_n) within the population of travellers.

Emmerink et al (1998) developed a model based on a stochastic variant of equation 9 wherein individual traveller's values of α and β are allowed to vary. The model was used to explore the effect of providing traffic information to some or all the drivers in a network (an effect represented in the model by reducing the SX term for those drivers receiving the information). The authors applied what they regarded as 'reasonable' limits to the value of β; they deemed that β should lie above zero on the grounds that travellers would not be "risk-loving" in respect of journey time and that it should be less than α because "it is unlikely that travellers would be so risk-averse" (they relaxed this latter constraint in later work but continued to assert that such extreme risk aversion would be confined to minorities). The work on attitudes to risk outlined in Section 3.4 of this paper gives reason to believe both constraints should be set aside for some groups within a population.

The model outlined in equation 9 has great attractions as a practical exploratory tool but its representation of the distribution of uncertainty via a single measure of dispersion is obviously fairly simplistic and makes it difficult to explore, for example, more complex attitudes to risk and uncertainty.

5.3.4 Expected utility approaches

The classic expected utility approach, introduced in equation 1, seeks to combine the probability distribution with the utility distribution but ignores the question of the decision maker's attitude to uncertainty or his perception of it. Polak (1987) sought to go further by combining the attitude to risk with the utility distribution itself. This approach is computationally tractable for easily parameterised distributions and it may be pragmatically justified if questionnaire respondents are unable to distinguish between utility and risk. However, if one wishes to allow more complex distributions, to use measurable utilities, or to explore the transferability of attitudes to risk between different contexts, this combined approach will not suffice.

5.3.5 A general model of utility

Equation 10 may offer a way forward. It shows how the approach summarised in equation 9 might be generalised to allow for a more complete representation of the perceived distribution of probabilities. For each component of cost it represents the perceived distribution of possible outcomes as a number of discrete elements each of which is deemed to have been estimated by the traveller with a given level of confidence. Separate weights are applied to the value of each element and to the confidence which the traveller places on his estimate of that element.

$$U_a = \sum_e \sum_n \alpha_{en} X_{aen} + \beta_{en} CX_{aen} \qquad (10)$$

Where: X_{aen} is the value of the eth element of the of the perceived distribution of the value of the nth component of the cost of alternative a

CX_{aen} is the confidence placed on the value of X_{aen}

α_{en} is the weight put on the eth element of the perceived distribution of the value of the nth component of the cost of an alternative.

β_{en} is the weight put on the confidence placed on the value of X_{aen}

By splitting the distribution into discrete elements (e) it becomes possible to allow for discontinuous ("lumpy") perceptions of probabilities by travellers. For example, although the cost distribution might be represented as a large number of small increments, it might more realistically be represented via a small number of "headline" measures such as the mean, mode, median, maximum and minimum.

By allowing different attitudinal weights to be applied to each of these elements of the distribution it is possible to allow the decision maker to put more emphasis on, say, his estimate of the 75th percentile of a travel time distribution than of, say, its mean.

By including the traveller's confidence in his estimation of each of the specified cost element values, the method allows account to be taken of the perceived uncertainty of the various elements of the cost distribution and, since different weights can be put on the confidence associated with each element, it is possible to allow the decision maker to put more emphasis on, say, his confidence in the mode of a travel time distribution than in, say, its median.

By differentiating between the different components of cost (n) it becomes possible to put more weight on, say, the mean than the mode when considering out-of-pocket-costs but more weight on the mode than the mean when considering journey times.

The α_{en} and β_{en} coefficients represent the traveller's attitude to risk for a given attribute n. Different sets of coefficients might be sought for different types of people or for different journey contexts. However, it is possible that attitudes to risk are transferable between attributes, person types and contexts and, indeed, one of the benefits of this formulation is that it allows the analyst to see if there is any transferability between a given respondent's apparent attitude to risk while travelling and his attitude to risk in other contexts.

The introduction of additional information, such as that coming from a new traffic advice service, could be represented within equation 10 in various ways; perhaps by changing the expected value of a key cost element, perhaps by increasing the confidence associated with that element or perhaps by applying a revised set of weights deemed to reflect the different weighting put on values derived from information received from a traffic advice service.

Although, in its full specification, this definition of utility would require an impractical amount of data, its value lies in the fact that, it can be simplified as far as is necessary to match the available data. For example, if journey time were found to be the only attribute of interest and if the cost distribution were found to represented quite adequately by its mode, the utility could be calculated from only two items of data - the most likely journey time and the perceived likelihood of this time occurring – with a generic coefficient for each. A utility maximisation model using such a simplified specification of utility could perhaps be replaced by a simple heuristic (for example, "Select, from among those options whose most likely journeys times are likely to occur with a probability of at least 0.5, the option with the shortest expected journey time").

Such heuristics not only require less data, but they actually accord quite closely with human decision making processes. Decision makers must use heuristics when faced with data which is too complex or uncertain for them to process analytically (see Tversky and Kahneman, 1974). The representation of decision making processes via statistical models should be seen as a means of aggregation over different heuristics rather than as an attempt to replicate actual decision making. The argument against using simplified statistical models is twofold; firstly, because concentration on the aggregate picture may make it difficult to understand the process of decision making and so leave the analyst ill-placed to predict the effect of changes in base conditions and secondly because use of a statistical model may obscure important non-linearities and other irregularities which are actually present at the aggregate level.

Recent years have seen several attempts, in transport modelling as much as elsewhere, to identify and represent the heuristics used by individual decision makers – with particular interest in the extent to which people use fuzzy, rather than precise, definitions (see, for example, Lotan and Koutsopoulos, 1993, Henn, 2000). The use of heuristic models and fuzzy logic to explore traveller response to uncertainty has obvious attractions and the general model of utility presented in equation 10 might offer a framework for such work.

6. Concluding Comments

We have argued that uncertainty is the norm in transport systems, that its consequences are complex and situation-dependent, and that it cannot be ignored if we want to understand traveller behaviour – particularly in the context of the introduction of ITS. We have suggested that travellers' perceptions of probabilities are necessarily incomplete and imperfect and that attitudes to risk vary from person to person and from situation to situation. We have emphasised that it is *the uncertainty that exists in the mind of the traveller*, together with *their attitude to that uncertainty*, which determine behaviour. We have noted that the response strategy adopted by a given individual may have more to do with their personality type than with a rational assessment of the situation.

We have outlined a number of strategies that travellers might adopt in response to perceived uncertainty and have suggested that different strategies might be used by different people or even by the same person in different situations. Many of the potential responses to uncertainty in the transport system relate to actions which have not usually been included in analyses of traveller behaviour and many of them imply actions, or even lifestyle decisions, in advance of a given journey.

Although much remains to be discovered about the psychology of response to uncertainty, a great deal is already known and the main gap is not so much in the understanding of the behavioural factors but in our ability to model them. The key question is, given the complexity of the problem and the difficulties involved in obtaining the necessary data, at what level of detail is it appropriate to model?

Our review of modelling approaches has indicated a number of some ways in which elements of the behavioural response to uncertainty might be modelled. We have suggested that, by using a model framework that allows a traveller's attitudes to risk to be separated from his perception of probability and his attitude to outcomes, it may become possible to identify transferable patterns in attitudes to risk. If such patterns can be found they would advance our understanding of traveller behaviour and be of great help in the specification and calibration of predictive models.

We have suggested that some of the conventional methods, particularly the classic expected utility model, are rather limiting but that the use of heuristics and fuzzy logic may open the way to more behaviourally-valid approaches.

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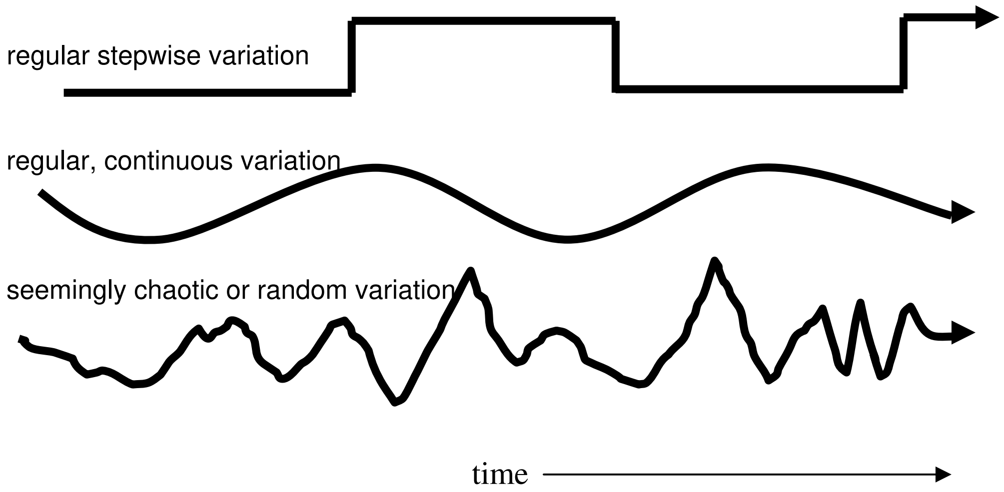
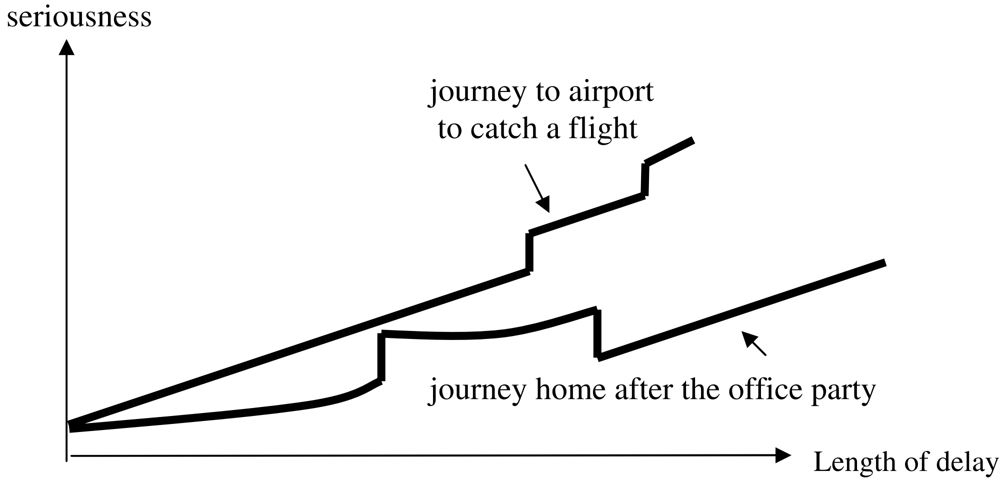


Figure 1: Patterns of Variability



Notes:
In the case of the journey to an airport, the seriousness of the delay increases at first gradually (reflecting extra travel time and fuel consumption and reduced time to relax in the departure lounge), then increases in steps (as the passenger progressively misses the chance to reserve a window seat, to buy duty-free goods and, eventually is too late to board).
In the case of the journey home after the office party, the seriousness of the delay increases gradually at first then jumps when it is clear that partner will have gone to bed, rises gently as driver gets tireder, then decreases as breakfast bars begin to open!

Figure 2: Seriousness of the consequences of an unexpected delay (illustrative – from Bonsall, 2001)

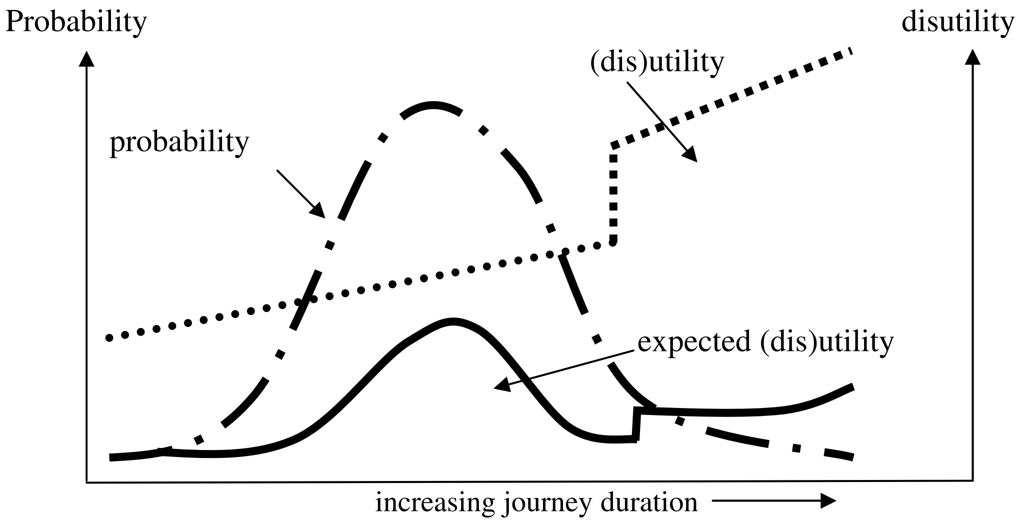


Figure 3: Combination of probability and utility to produce expected utility

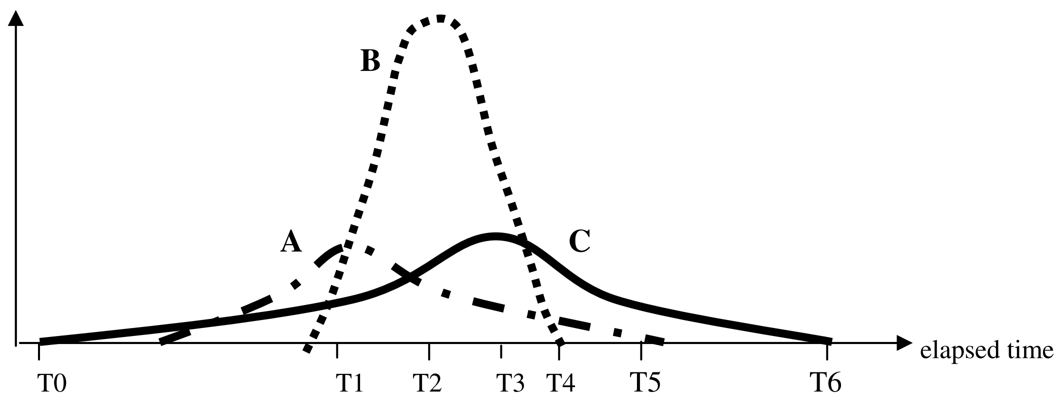


Figure 4: Choice between modes with differing probability distributions (illustrative)

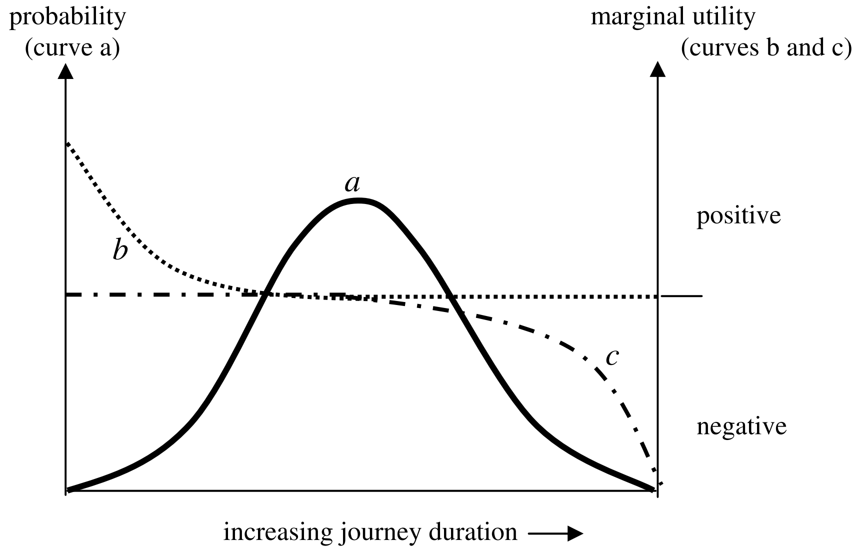
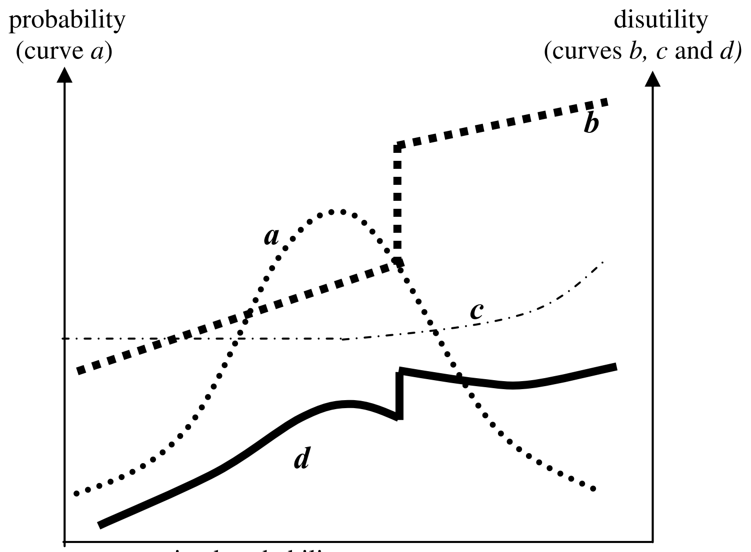


Figure 5: Graphical representation of different attitudes to risk



a = perceived probability
b = disutility
c = attitude to risk (risk averse) - note that, since we are dealing with disutilities rather than utilities, the curve is the reverse of that shown in Figure 5,
d = expected disutility

Figure 6: Expected disutility as a function of probability, disutility and attitude-to-risk