Advanced traveller information services in real-time traffic prediction models

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Abstract
The article deals with prediction models for freeway traffic control that can adequately handle the behavioral responses of travellers to real-time traffic information provision, specifically with respect to route choice. After a short overview of possible information measures, recent empirical evidence will be presented of impacts of Variable Message Signs on congestion levels on freeway segments. Crucial for any prediction system is consistency between information messages and predicted responses. A prediction systems architecture will be proposed that satisfies these consistency requirements. Based on a theoretical framework for dynamic route choice behaviour, a modelling approach is outlined to predict impacts of en-route information provision upon en-route diversion.

1. Introduction
Given the societal problems associated with the construction of new transport infrastructures, there is an increasing need to optimize the usage of the existing transport capacities. This is especially true for freeways. To minimize daily recurrent and non-recurrent congestion, a better distribution of travel demand among available travel alternatives is needed.

To improve freeway traffic conditions in both the long and short run, a large variety of control measures can be employed, such as ramp metering, variable speed limits etc. Another very promising class of measures to serve this purpose is providing information to travellers about current and future traffic conditions in order to assist them in making more efficient travel decisions. Such information services can be given before starting of during the trips, dealing with descriptive information about conditions such as congestion levels or travel durations, or with advice about advantageous routes to take or moments to depart.

An important question now is how individual travellers will react to such information provision and how these individual responses will influence traffic flow performance in networks. This knowledge is needed among other things to assist freeway network operators in maximizing traffic flow performance by real-time on-line traffic control. Therefore, for the effective real-time traffic control, traffic prediction models are needed that are responsive to both control and information measures.

We will first deal with the specification of real-time prediction models for freeway traffic control that can adequately handle the behavioral responses of travellers to real-time traffic information provision, specifically with respect to route choice. After a short overview of possible information measures, recent empirical evidence will be presented of impacts of Variable Message Signs about congestion levels on freeway segments in the Netherlands. Crucial for any prediction system is consistency between information messages and predicted responses. A prediction systems architecture will be proposed that satisfies these consistency requirements. Based on a theoretical framework for dynamic route choice behaviour, a modeling approach is outlined to predict impacts of en-route information provision upon en-route diversion. A more detailed elaboration of the presented exposition can be found in DYNA 1994.

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2. Information provision services and their impacts on flow

Increasingly, dynamic traffic information services become available to the traveller, especially to the freeway motorist. Examples of this type of up-to-date information on current or expected traffic conditions are:

- Television Broadcast Traffic Pages
- Telephone Traffic Services
- Highway Advisory Radio (HAR)
- Radio Data System/Traffic Message Channel (RDS/TMC)
- Road-side Variable Message Signs (VMS)
- In-car Navigation Systems and Route Guidance (IVNS)

The traffic messages mostly refer to current or duly expected congestion, queue lengths, delays, incidents or roadway changes at particular places.

Some of the suppliers of these services only try to assist the individual drivers in making more efficient travel decisions. Road authorities employing e.g. VMS, however, have as their first objective to optimize traffic conditions. These two objectives are not necessarily consistent. The provided information can be received at home or workplace, which helps for pre-trip route planning or departure timing, or may be received during the trip, possibly to be used for en-route diversion. For an overview of these travel information services, see e.g. ECMT 1995.

Drivers respond to these messages by adapting their travel or driving decisions such as route and departure time choice. In the aggregate, these behaviours in turn influence traffic flow conditions such as the spatial and temporal distribution and levels of congestion. Drivers' as well as traffic systems' reactions to dynamic information provision have been studied intensively by using simulation-type studies. Empirically derived evidence of responses however are relatively rare.

A general finding is that, depending on the particular situation, dynamic information provision leads to sensible adaptations of route and departure time choices and to significant changes in traffic conditions.

As an example, the impact of introduction of VMS on the Amsterdam Beltway will be presented (see figure 1). This motorway ring crosses the North Sea Canal to the west and to the east of Amsterdam respectively, both crossings being tunnels with limited capacity. The Coentunnel in the

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2 For an overview, see e.g. Adler et al. 1991.

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Figure 1: Amsterdam Ring Road with DRIP (situation 1991)
west is a real bottleneck that is severely congested every work day during many hours. The eastern Zeeburgertunnel, having a much higher capacity, only seldom exhibits congestion.

In November 1991 a Dynamic Route Information Panel (DRIP) has been placed at the northern entrance to the ring. This panel displays the actual congestion condition in both tunnels using messages about non-existence of a queue or the actual queue lengths respectively in units of a kilometre. Also lane closures or other special circumstances can be displayed. An extensive before-and-after study has been carried out by repeatedly interviewing individual drivers about their choices and trip characteristics as well as by measuring traffic flow characteristics on the ring.

It appears that about 33% of the drivers entering the ring from the north have routing options, the choice of which possibly is being somehow influenced by DRIP messages. On average about one-fifth of these free-choice drivers change route because of the DRIP messages. An unexpected outcome was that drivers not only deviate from their intended route when the DRIP message shows that the preferred route is congested but many drivers also switch if the sign shows that there is no congestion at all. Apparently, many drivers formerly avoided to use their shortest alternative because of the probability of getting in a queue. In order to be sure they formerly accepted a detour. The longer the displayed queue lengths, the more drivers switch. In the very peak at 8 a.m., with queue lengths of 4 kilometre or more, about 12% of all drivers approaching the ring from the north switch route.

If congested, the Coentunnel now is less used than before (-4%) but if uncongested its usage is now higher than formerly (+10%). On a daily basis total flow through the Coentunnel increased (+6%) despite the fact that this tunnel is a severe bottleneck since years for many hours of the day. The frequency with which drivers coming from the north get stuck in a queue, significantly decreased from 78% before to 52% after DRIP installation (-33%). This is also reflected in the congestion data: the percentage of time with congestion during morning peak (6 to 10 a.m.) decreased from 61% to 48% (-20%).

But much more significant is the decrease in queue lengths (see Figure 2), total queue severity (measured in kilometre minutes) decreased from 350 to 230 (-34%). Consequently, driving speeds on the ring increased. The average door-to-door travel time gain for all entering drivers appeared to be 8%. This gain is larger for route switchers, especially for those switching from their intended Zeeburgertunnel route to the

Figure 2: Average queue length at Coentunnel before and after DRIP installation

\(^2\) BGC 1993; Van Berkum & Van der Mede 1993
Coentunnel route in cases of a no-congestion message. The travel time gain can be composed of both a smaller travelling distance and less congestion time loss. The study shows that in congested situations already relatively small changes in flows can lead to considerable changes in travel times.

It is important to note that also the non-switching drivers (mostly because of lack of alternatives) benefit from the information provision; they experience travel time gains due to the decrease in congestion levels. Similar convincing empirical findings about the impact of DRIP’s were found recently in the Paris region.*

The question now is how to incorporate these findings in real-time prediction models of traffic flow that are to be used in developing and evaluating strategies of traffic control and information provision in freeway networks.

3. Freeway traffic predictions for real-time control

In order to maximize safety, efficiency, reliability and other objectives related to freeway traffic flow there is a need for a real-time traffic control system for freeways. Such a control system on the one hand activates control measures which directly influence supply conditions. Examples are ramp metering, speed limits, lane closures, tidal flow, etc.. The selection of appropriate control measures is a dynamic process dependent on projections of the time-varying demand and flow conditions. At the same time the control system activates real-time information provision to travellers and drivers about current or expected flow conditions in the network, including control measures. Examples are variable message signs, highway advisory radio, in-car route guidance etc.. Also the selection of appropriate information measures is a dynamic process dependent on projections of the time-varying demand and flow conditions.

To support such a real-time control, suitable prediction models are needed enabling the prediction of the likely impacts of sets of anticipated control and information measures envisaged for a certain planning horizon. This concerns the impacts upon behaviour of travellers and drivers as well as upon supply conditions. Both classes of impacts determine how the traffic flow control objectives are affected which results in choosing the optimal course of control actions.

The predictions may refer to future periods ranging from five minutes to one hour ahead. These predictions are more or less continuously updated, e.g. at five-minute intervals because they are a function of demand and flow conditions, partly measured on-line. Key features of such a prediction system are its dynamics, its on-line operation, inclusion of dynamic information provision, and its consistency between predictions and actions. The dynamics among other things imply that the following aspects are modelled: the development of travel demand over time, the dynamic evolution of traffic flow in the network, the anticipation and responses of travellers to future conditions they will encounter, part of which may be communicated to them by information provision.

The on-line application context means that only on-the-spot measured data, e.g. from loops or video cameras, can be used such as on/off ramp as well as link volumes, speeds and occupation densities. This implies that barely any traveller specific data needed for choice predictions are observable except on vehicle type. On the other hand, time series of such traffic data are available, also historic
ones. The on-line measurements enable a gradually improvement of successive predictions for future periods which makes application of adaptive within-trip route choice modelling useful.

![Diagram](image)

Figure 3: Causes of interdependencies between control and prediction system variables

The consistency requirement, which means that the outcomes of the planned control and information measures are in accordance with the responses of drivers when these measures are executed, is not a trivial property. Control actions depend on flow conditions, but flow conditions depend on control measures via the drivers’ reactions to these. If e.g. a lane closure is envisaged due to expected flow conditions, a prediction can be made of the resulting traffic flow conditions on the remaining lanes downstream, given the starting conditions.

However, the starting conditions in turn depend on the behavioral reactions of the drivers to the lane closure measure, such as speed changes, lane changes etc. Many of such chicken-egg fixed-point problems need to be solved. By adding information provision measures the consistency problem becomes even more complex (see figure 3). The need for information provision depends on the expected flow conditions and therefore also on the intended control measures. But the latter two states depend in turn on the information given to the drivers. The operator might e.g. consider to give somewhere upstream ahead of a fork information on expected congestion conditions due to the lane closure. These conditions however depend on whether and how this information is given.

This consistency requirement is an extension of the well known service-demand equilibrium property of traffic assignment models, and it is envisaged that in order to meet this requirement a procedure can be used that is parallel to procedures that are used in some traffic assignment models.

4. Stages in a dynamic control system development

Achieving the desired dynamic prediction system most probably will need a number of intermediate development steps to take. In this respect, depending on the level of feedback to transport network and travellers and on the assumed anticipation level of travellers, we can distinguish at least five levels of forecasting and control.

1. Static forecasting

Other than distinguishing between peak and off-peak, no differentiation in time is made in the forecasting procedure, nor is the procedure updated with on-
line data. This kind of forecasts are used for planning purposes. This is the current state in the Netherlands, some locally optimized ramp meters excepted.

II. Dynamic forecasting, no dynamic control
The traffic forecast is continuously updated with on-line or at least time-differentiated data. This makes more accurate forecasts possible than static forecasting, however the forecasting system is not directly influencing the traffic system (see figure 4 without DIS and Control boxes).

III. Dynamic forecasting and dynamic control, no information supply to travellers
Some form of optimal control is applied, based on dynamic forecasting. Anticipating behaviour still plays a role, since travellers learn from their experiences, which may be influenced by a control system. There is however no direct feedback from the forecasts to the traveller (see figure 4 without DIS boxes).

IV. Dynamic forecasting and dynamic control, information supply to travellers about current conditions
In this case a driver information system (DIS) may operate independent from the control system. Distributed messages are only based on current traffic data and are thus also input to the forecasting system. This situation is identical to the previous one, except for the fact that an extra feedback loop has been added. The DRIP's in Amsterdam as employed today fit in this category, since travellers are only informed about current conditions.

V. Dynamic forecasting and control, information supply to travellers about expected conditions (see figure 4)
In this ultimate version of the system, traffic forecasts are followed up by suitable DIS messages about future control measures and traffic conditions. These messages will influence travellers, therefore ideally the supplied DIS messages should be taken into account while forecasting. The potential benefits of
this system are larger, because information to travellers is provided more timely, so travellers have even more possibilities to adjust their trips to the forecasted situation. On the other hand, this may seriously affect the reliability of the forecasting system.

When comparing options IV (supplying information on current conditions) and V (supplying information on expected conditions) the main difference is probably the reliability of information. When information on the current situation is supplied, the quality is probably good. However, travellers will have to extrapolate this information to a time interval that applies to their journey. In theory this task can be better performed by a forecasting system. On the other hand, leaving the interpretation of information to the travellers, will cause dispersion over different routes, which can be a desirable effect.

5. A conceptual model for information supply responses

As a preparation to a real-time route choice modeling approach that adequately treats dynamic information supply responses, we will make system level V more specific. To that end we introduce a mathematical notation (see table 1). Sometimes conceptual variables will be used. These variables should be interpreted as vectors that represent a certain aspect of the traffic system (printed in bold). If more detail is required, indices are added to define starting period of trip, current period, OD-pair, etc. All processes are defined dynamically. Time is discretized in periods of equal length T.

<table>
<thead>
<tr>
<th>Indices:</th>
<th>Variables:</th>
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<tbody>
<tr>
<td>s</td>
<td>d: OD-demand</td>
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<tr>
<td>starting period</td>
<td>f: path flows</td>
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<tr>
<td>f</td>
<td>x: link volumes</td>
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<tr>
<td>current period</td>
<td>b: routing fractions</td>
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<td>k</td>
<td>z: link travel delays</td>
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<tr>
<td>path</td>
<td>e: information vector</td>
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<td>q</td>
<td>g: filtered information flow</td>
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<tr>
<td>link</td>
<td>c: control vector</td>
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<td>a</td>
<td>s: link path incidence map</td>
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<td>information component</td>
<td>i: information availability map</td>
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Figure 5 shows the distinguished system variables and their dependencies.

Figure 5: Schematic representation of traffic system dependencies

The OD-demands are given by $d$, $d_{ls}$ represents the OD-demand for group $l$, starting in period $s$. A group is assumed to be homogeneous with respect to OD-pair, route-choice set and other relevant properties for route choice behaviour. The OD-demand $d$ is assumed to be an exogenous input.

The OD-demands are distributed over different route alternatives, resulting in path-flows $f$. $f_{kls}$ represents the flow on path $k$, starting period $s$. The path-flow $f$ is derived from the OD demand $d$ and the route choice proportions $b$, so: $f = f(d, b)$.

The split- or route choice proportions $b$ denote the ratios of each group that contribute to a flow. $b_{lks}$ gives the contribution of group $l$ to flow $k$ starting in period $s$. This definition includes within-trip rerouting, i.e. pre-trip route choice proportions may differ from $b$.

$$f_{kls} = \sum_l d_{ls} b_{lks}$$

The route choice proportions $b$ depend partly on the perceived (historic) route attribute values and partly on the received information. The content of received information is defined by the information vector $I$ and the information availability
map $\delta$. Since the route choice proportions also include within-trip route choice, route choice proportions may also depend on experienced travel delays $c$.

$$b = b(I_b, c)$$

Link volumes are represented with the symbol $x$. $x_{qt}$ is the link volume on link $q$ during time period $t$.

There is a relationship between the path-flows and the link volumes. This relationship is defined by a dynamic link-path incidence map $\tau$. $\tau_{qkst}$ represents the contribution of path flow $k$ to link $q$, if the starting period of the trip is $s$ and the current period is $t$.

$$x_{qt} = \Sigma_{k,s} \tau_{qkst} f_{ks}$$

This map $\tau$ is therefore an exclusive function of the delays encountered on the links that constitute the path, $\tau_{qkst} = \tau(s)$. The link volumes $x$ thus are derived from the path-flows and the delays encountered in the networks. These delays are incorporated in the link-path incidence map $\tau$: $x = x(f(s))$.

Travel times or delays on links are indicated with the symbol $c$. $c_{qt}$ is the delay on link $q$ during period $t$. Link travel delays $c$ depend primarily on link volumes $x$, but are also affected by the control vector $C$. $c = c(x, C)$. The set of control actions is represented by $C$. $C_{yt}$ is the $y_{yt}$ control component applied in period $t$.

Information intended for travellers is represented with $I$. $I_{zt}$ is the $z$th information component displayed, broadcasted or distributed otherwise during period $t$. As far as the information provision $I$ and traffic control $C$ are the result of automated procedures, they are responsive to projections of all relevant system variables. For now we will assume that control and information provision are dependent on projections of link volumes, $\hat{x}$, $I = I(\hat{x})$, $C = C(\hat{x})$.

The information availability is specified with the availability map $\delta$. This map defines which information is available to which group of travellers (characterized by path and departure time). $\delta_{zst} = 1$ if information component $z$ provided during period $t$ is available to travellers on path $k$ starting in period $s$, and zero otherwise. Assuming that the fact whether or not a traveller receives a message depends on the time and place of the traveller at the moment of supplying the message, the information map can be derived from the link-path incidence map: $\delta = \delta(t)$.

The combination of information vector and information availability map determines the filtered information flow, $I_b$. The information flow $I_b$ is what actually influences a traveller. Whether or not a specific information component has influence on any decision of a traveller depends on whether the time trajectory of the traveller and the time frame associated with the information component (for example time of broadcasting) coincide. The information flow is
hence a function of the information vector and the information availability map: 
\[ \mathbf{I}_g = I_g(\mathbf{I}, \mathbf{\delta}) \]

The on-line Dyna prediction models are part of the real system. The predicted traffic state \( \mathbf{\hat{x}} \) is primarily a function of observed link intensities: 
\[ \mathbf{\hat{x}} = \mathbf{\hat{x}}(\mathbf{x}) \, . \]

6. Outline of an on-line route choice prediction model

We need route choice models that can predict route choice proportions of the OD-demands over available routes based on actual knowledge levels among travellers. These models need to be dynamic and information responsive. At every prediction update, the route choice proportions for the OD-trips of a given starting period have to be calculated again in order to account for changes in flow conditions and information supply. For a particular trip this means that parts of the predicted pre-trip route choice to the destination may be changed several times at updating moments during the trip for the remaining part to the destination. For a general review of route choice behaviour and modelling see Bovy & Stern 1990.

Since the displayed messages are time dependent, all travellers do not necessarily receive the same messages. Therefore it is necessary to combine predicted time-network trajectories of travellers with proposed time-message trajectories of the VMS system in order to determine the information availability for each traveller.

![Diagram of route choice prediction model](image)

Figure 6: Integration of DNL and route choice module

The framework shown in figure 6 can be applied. It shows how the Dynamic Network Loading (DNL) module can be integrated with a dynamic route choice module. The DNL takes as an input a dynamic OD-matrix and a dynamic routing matrix. For every (departure) time-slice, a separate OD-matrix and routing matrix is available. The route choice module produces a routing matrix. This matrix contains for each combination of departure period, OD-pair and route alternative the projected usage fractions.

Predicting route choices involves various steps such as choice set generation and determination of the perceived attributes of the alternatives as well as the trade-off process between these. We confine ourselves here to the latter two issues.
To model the trade-off process various competing theories are available such as conflict theory\(^6\), satisficing theory\(^7\), and utility maximization. The essential aspect however always is that drivers use perceived knowledge of route attributes in their decisions. A dominant factor is travel time, but other traffic condition attributes such as congestion, travel time reliability, etc., play a role too.

Actual knowledge levels depend on prior knowledge and availability of messages. Since messages are distributed dynamically, the within-trip knowledge of travellers may differ from pre-trip knowledge. This may lead to within-trip route choice that deviates from pre-trip route choice, and necessitates sequential route choice models. Further, the knowledge of travellers is subject to an updating process. In this context it is important to note that messages usually contain only indirect information on the attributes on which travellers are assumed to base their route choice, especially if the message is of a descriptive nature. An important question therefore is how perceptions of route attributes are changed due to information supply.

A message may contain descriptive or prescriptive information. In both cases the message will be the result of predictions by the control system, translated into a message for the driver. The driver interprets the message after receiving it. During the process of encoding and interpretation some information is lost. Let's take an example of a descriptive messages such as the DRIP. The control system encodes the measured or predicted congestion situation into a queue length, while the drivers translate the displayed queue length into less or extra travel time than expected before.

7. A practical route choice model

It is assumed that individuals judge route alternatives by their expected attribute values. The utility of each alternative is a function of its expected route attributes.

\[
U_{nk} = \sum_j a_j z_{jk} + e_{nk} \quad (1)
\]

\(U_{nk}\): utility of route alternative \(k\) for person \(n\)
\(z_{jk}\): expected attribute value for attribute \(j\), route \(k\) and person \(n\)
\(a_j\): weight factor for attribute \(j\)
\(e_{nk}\): individual error term and non-specified attributes

In this model the weight factors are equal for each individual, while the perceived attribute values are traveller-specific.

In the following we concentrate on the modification of prior perceptions as a result of information received during the trip. Consider the example of the variable message sign. Motorists that are informed by this medium, adapt their perceptions of link attributes. As a result the utilities of route alternatives are influenced. Drawing on earlier work in this field\(^8\), an inference method is proposed, based on the principle of exponential weighing. We assume travellers apply a prediction model to estimate future conditions/attribute values given their experience and received information.

Let \(z_{jk}^a\) be the \textit{a priori} expected value for attribute \(j\) of route alternative \(k\) for person \(n\). Let \(z_{jk}^e\) be the expected value for attribute \(j\) of route alternative \(k\) for
person n based solely on information received during the trip. Finally, let $z_{kn}^+$ be the updated a priori value. The exponential weighing method comes down to:

$$z_{kn}^+ = \beta_{jk} z_{kn}^- + (1-\beta_{jk}) z_{kn}^-$$  \hspace{1cm} (2)

Assuming a high level of experience among travellers, $z_{kn}^-$ may be replaced by functions evaluated on the basis of average historic values. $z_{kn}^-$ is considered to correspond with the values from the perspective of a memoryless or non-experienced traveller. Assuming that these are not biased, the expected value of $z_{kn}^-$ equals $z_{kn}^-$. The perceived attribute value can be defined as the historic value plus a correction term that depends on the content of a received message being better or worse than average.

Again using the DRIP as an example, let's consider the attribute travel time of the route alternative through the Zeeburgertunnel. The DRIP may display a queue length of 1,2,3,... km for this tunnel. For every time of day there is a certain historic average of displayed queue length, for example 2 km for the time period considered. So when the sign displays 3 km, this is 'worse' than average, if the sign displays 1 km, this is 'better' than average.

The attribute 'travel-time through Zeeburgertunnel' is now derived using:

$$z_{kn}^- = z_{kn}^- + \tau_{jk} (d_{jk}^- d_{jk}^-)$$  \hspace{1cm} (3)

$d_{jk}^-$: displayed queue length
$d_{jk}^-$: average displayed queue length
$\tau_{jk}$: parameter

Combining equations (2) and (3) leads to:

$$z_{kn}^+ = z_{kn}^- + (1-\beta_{jk}) \tau_{jk} (d_{jk}^- d_{jk}^-)$$  \hspace{1cm} (4)

Combining (1) and (4) eventually leads to:

$$U_{kn} = \sum_j \alpha_j z_{kn}^- + \sum_j (1-\beta_{jk}) \tau_{jk} (d_{jk}^- d_{jk}^-)$$  \hspace{1cm} (5)

Defining the historic average of the utility for alternative k and group n with:

$$U_{kn}^- = \sum_j \alpha_j d_{jk}^-$$

and the parameters $h_{jk}$ with: $h_{jk} = \alpha_j (1-\beta_{jk}) \tau_{jk}$, equation (5) changes in:

$$U_{kn} = U_{kn}^- + \sum_j h_{jk} (d_{jk}^- d_{jk}^-)$$

Estimates of $U_{kn}^-$ may be derived from historic data. The parameters $\alpha_j, \beta_{jk}$ and $\tau_{jk}$ are a part of the model specification, but will not be estimated. Instead the aggregates $\mu_{jk}$ will be estimated. For testing and calibration of this mechanism data are needed about provided information and behavioral reactions. It is
envisaged to collect these data by using laboratory experiments like travel simulators and stated preference techniques such as FASTCARS developed in Adler et al. 1993.

8. Conclusions

A framework has been presented for inclusion of dynamic information provision to drivers into real-time traffic flow prediction models for freeways. Information provision about current or future traffic conditions as well as route guidance generates a process of behavioral responses such as information acquisition, compliance and trip choices. For the sake of simplicity, the paper was confined to modelling adaptive route choice using variable message signs as an illustration. The proposed logic can however easily be extended to other types of information provision.

A serious challenge to modelling is the required consistency in predictions and measures. This stems from the circularity where predictions of behavioral responses depend on the measures taken and information provided, whereas at the same time these measures depend on the behavioral reactions. For the moment it is assumed that iterative techniques may solve this problem. A key element in the proposed approach is the route attribute perception update mechanism. Parameters of this behavioral model can be estimated using travel simulators, such as e.g. developed in Adler et al. 1993.
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