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IVHS

Intelligent Vehicle-Highway Systems

An Iterative Routing / Assignment Method for Anticipatory Real-Time Route Guidance

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1 Anticipatory Route Guidance

A central idea in Intelligent Vehicle/Highway Systems (IVHS) research is the improvement of traffic network performance, both in system-wide measures and in travel times of individual vehicles, by providing route guidance to drivers in real time based on real-time measurements of traffic conditions. In particular, user-optimal route guidance attempts to route each driver onto the path that minimizes his personal travel time. These fastest paths are easily calculated in a static network model, where fixed travel times are known for each link in the network. However, link travel times can change rapidly over time, especially at peak periods of traffic demand. Therefore accurate route guidance requires fastest-path calculation in a dynamic network, where link travel time is a function of the time at which the link is entered. We call route guidance consisting of shortest paths under time-dependent link travel times *anticipatory*, looking ahead to the future conditions to be experienced by the driver during his trip. Time-dependent fastest path calculation requires forecasts of time-dependent link travel times from the moment of the current routing decision up to some near-term time horizon.

The problem of forecasting future link travel times and network congestion conditions is one of dynamic traffic assignment. Dynamic traffic assignment typically takes inputs of network structure and capacity, relations between link volumes and link travel times either explicitly by impedance functions or implicitly by link outflow rate constraints, and volume of demand for travel between various origin/destination pairs, with travel demands and perhaps other inputs varying over a time horizon such as a rushhour period. Outputs may include time-dependent link volumes and travel times, delays, pollution outputs, and other measures of travel quality. For examples see [1,3,4,7]. In contrast, earlier static assignment models assumed all inputs to be fixed over time; for reviews see [2,6]. Assignment models have been used mainly for long-term transportation planning of issues such as increasing network capacity by construction of new roadways. However, advances in communication and computing technology and the scarcity of space for new roads have turned the focus to dynamic assignment in order to better utilize existing roadways.

If the link travel time outputs of dynamic traffic assigment are used to compute anticipatory route guidance which is then disseminated to drivers in real time, in general these drivers may follow routes different from those they would have chosen without route guidance. Therefore, traffic conditions may evolve differently under anticipatory route guidance than they would have otherwise, *invalidating the forecasts from the traffic assignment and hence the route guidance itself.* In this paper, we apply an iterative routing-assignment method to seek forecasts that, when disseminated as route guidance, cause themselves to be realized by vehicles in the network, implying that the route guidance was calculated from correct information about the future of the traffic network. We analyze the iterative procedure in a test network representing an aggregated city roadway system, considering the effects of the proportion of vehicles receiving anticipatory route guidance (the *market penetration*) on the existence of these stable forecasts and the benefits they provide both to the anticipatory vehicles and to the system as a whole. We conclude that anticipatory route guidance provides benefits at levels of market penetration up to a high threshold and that the results of efforts to increase this threshold identify needed extensions to the iterative procedure.

2 The Iterative Routing-Assignment Procedure

As we stated above, providing anticipatory route guidance to vehicles alters their choice of path, tending to invalidate the forecasts from which the route guidance was calculated. A natural way to proceed is to iterate between forecasting and assignment. We begin with a set of forecast travel times and calculate route guidance information. We then perform traffic assignment based on the assumption that a specified proportion of traffic follows anticipatory routing. This assignment provides new forecasts; we terminate the iterative process if the new forecasts are sufficiently close to the old, and otherwise continue with new anticipatory guidance information. The resulting feedback loop is illustrated in Figure 1.

Dynamic traffic assignment is often considered to mean solving optimally a mathematical program expressing a user-equilibrium condition guaranteeing that no vehicle is routed in such a way that it could reduce its trip travel time by changing routes. Dynamic equilibrium models (e.g. [3,4]) do not distinguish vehicles by their ability to receive real-time guidance

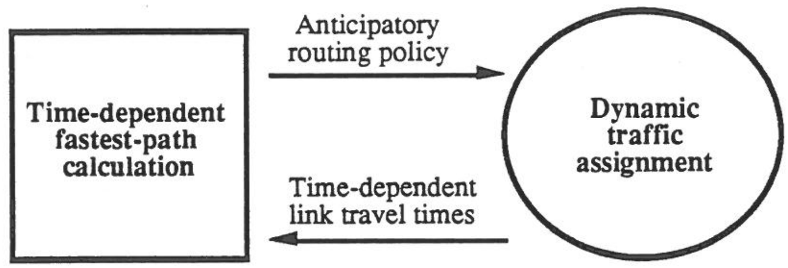


Figure 1: Feedback between link travel time forecasts and anticipatory route guidance.

information. Since we wish to study the effects of market penetration, we cannot use these models. In addition, equilibrium models assume link travel time to be a function solely of the volume on that link, ignoring the interaction between links which is a crucial component of congestion behavior. Other models ([1,7]) are based on a system-optimal condition, determining assignments that minimize the total travel time of all vehicles. Such assignments may delay some drivers in order to gain net reductions in travel time for the system, raising issues of user compliance that are beyond the scope of the current study. Therefore, we must look beyond mathematical programs for assignment. We will instead apply the INTEGRATION traffic simulation [8]. INTEGRATION was created by M. Van Aerde for investigation of congestion due to interactions between freeway corridors and surface street areas. Traffic is modelled microscopically, maintaining information for each vehicle in the network including location, origin and destination nodes, and ability to receive route guidance. The separation of traffic into classes of route guidance capability makes INTEGRATION well-suited for the assignment portion of the iterative process.

Route guidance calculation is implemented by standard methods for calculating shortest paths in networks. Although the standard methods were proposed for static networks, they calculate time-dependent fastest paths with no added computational effort if it is always true that of two drivers who travel the same link, the one who enters the link first is able to exit first (Kaufman and Smith [5]). Since situations where a driver can shorten the duration of his trip by delaying arrival at some intermediate point are rare, this assumption is appropriate. With the time horizon broken into discrete periods, the fastest-path calculation determines route guidance information consisting of the optimal next link to be taken by a vehicle as a function of its current node location and destination and the current time epoch. We refer to the complete set of optimal next link data as a *routing policy*.

INTEGRATION was written with two vehicle classes of route guidance capability. The first class represents *background* vehicles with no real-time guidance; these vehicles always follow the path that would be fastest if the network were empty. The second class of *quasi-dynamic* vehicles have real-time guidance based on a static network model, following the routes that would be fastest if the most recently observed link travel times were to hold for the entire time horizon. The static shortest paths are updated in each time period and the quasi-dynamic vehicles are permitted to change paths each time they reach nodes. We have added anticipatory (i.e. *fully dynamic*) traffic as a third class. In each time period, vehicles reaching nodes choose their next link according the anticipatory route guidance calculated from the previous iteration's forecasts.

The iterative process begins by running INTEGRATION without anticipatory traffic, creating an initial set of forecast data. We enter the feedback loop by calculating the corresponding anticipatory routing policy and running the simulation with the anticipatory traffic, producing new forecasts. If the new forecasts agree with the old, we terminate with convergence. Otherwise we iterate, creating new route guidance and new forecasts until a termination condition occurs. Because there are finitely many links departing each node, there are finitely many route guidance policies that can occur. Hence, the iteration fails the convergence criterion ad infinitum only if cycling occurs, i.e., some set of forecasts and corresponding route guidance policy do not reproduce themselves in the next iteration but do reoccur in a later iteration. Therefore, we add a cycling termination criterion, checking whether a new set of forecasts coincides with any previous set.

A set of forecasts and the corresponding routing policy which cause termination with convergence (i.e. reproduce themselves) will be called a *fixed point* of the iterative routing/assignment process. It is evident that allowing for the approximating character of the discretization of the time horizon, a fixed point gives user-optimal routings. The fixed-point routing policy sends the anticipatory vehicles onto paths that are optimal if the corresponding forecasts are correct. Since the set of forecasts is also a fixed point, they do give the times experienced in the network, hence the routing policy is truly user-optimal.

Kaufman and Smith demonstrated average trip time savings for fully dynamic routing of 9% over quasi-dynamic vehicles and 24% over background vehicles in a small single origin, single destination network. However, the market penetration was kept small enough that the anticipatory route guidance did not affect link travel times, hence no iterative process was required. Furthermore, the study had no bearing on system-wide benefits since the savings for anticipatory vehicles was overwhelmed by the much larger volume of non-anticipatory traffic.

3 Test Network and Initial Feedback Results

The iterative routing/assignment process was tested on the network shown in Figure 2. The network has six zones, i.e., nodes that function as trip origins and destinations, represented as large numbered squares. The zone in the center of the network is intended to represent the center of a metropolitan region, and the five zones on the outer ring represent outlying concentrations of population or industry. Intermediate nodes at which no vehicle either starts

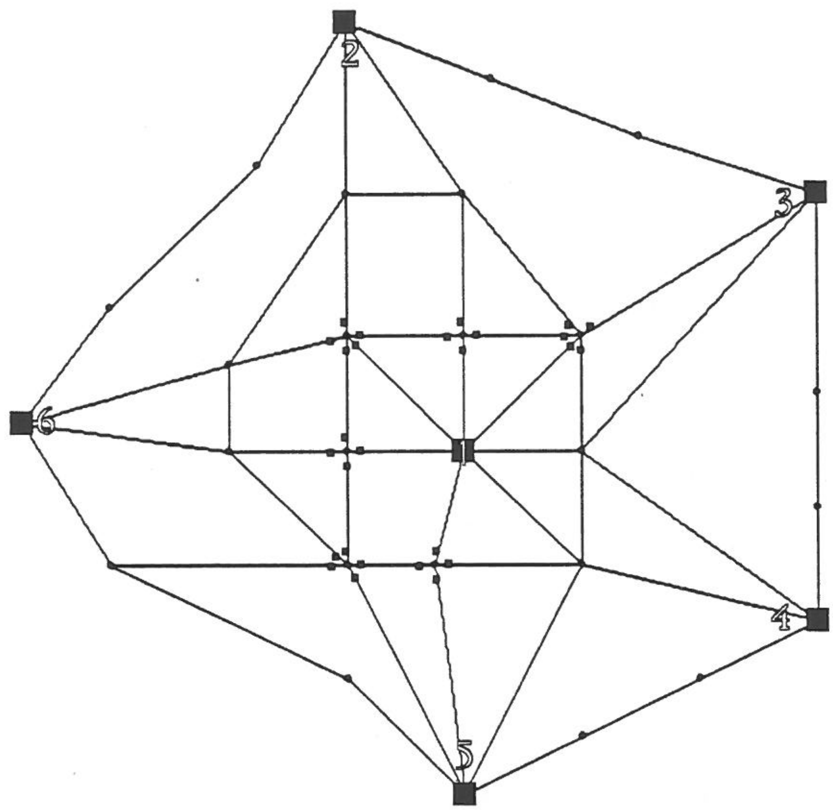


Figure 2: Test network for iterative routing/assignment

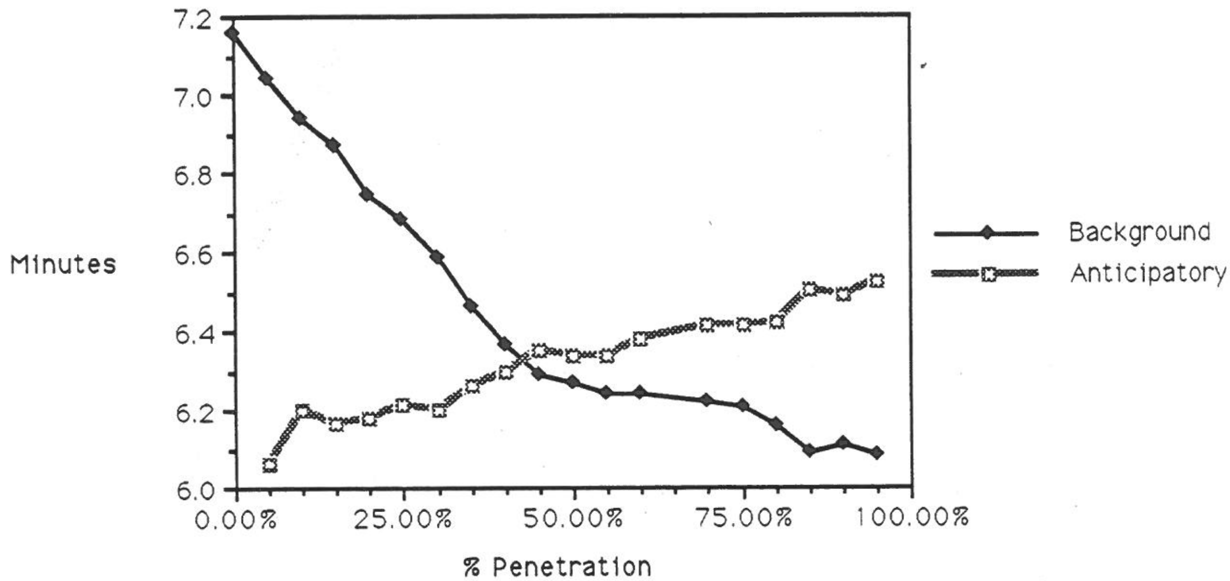
or ends a trip are shown as smaller circles. The links on the outer ring of the network are high-speed high-capacity freeway links, while links closer to the center are slower, smaller arterial links. The clusters of small squares surrounding certain nodes represent traffic signals.

The simulation duration is twenty-seven minutes, divided into one-minute intervals. Total traffic volume is nearly two thousand vehicles, all entering early enough that they finish their trips before the simulation ends. The vehicles are divided into seven classes by origin/destination pair, representing uptown/downtown traffic ($2 \leftrightarrow 5$), crosstown traffic ($3 \leftrightarrow 6$, $4 \leftrightarrow 6$), and suburb-downtown traffic ($6 \rightarrow 1$). The rate of vehicles entering the network starts low, increases to a peak and then decays, simulating time-dependent travel demand. All vehicles are either background (no route guidance) or anticipatory.

3.1 Benefits to anticipatory vehicles

In Figure 3 we report the average trip duration for both background and anticipatory vehicles as a function of market penetration (percentage of anticipatory vehicles), tested in increments

Figure 3: Average trip durations: background vs. anticipatory vehicles (actual-time accounting)

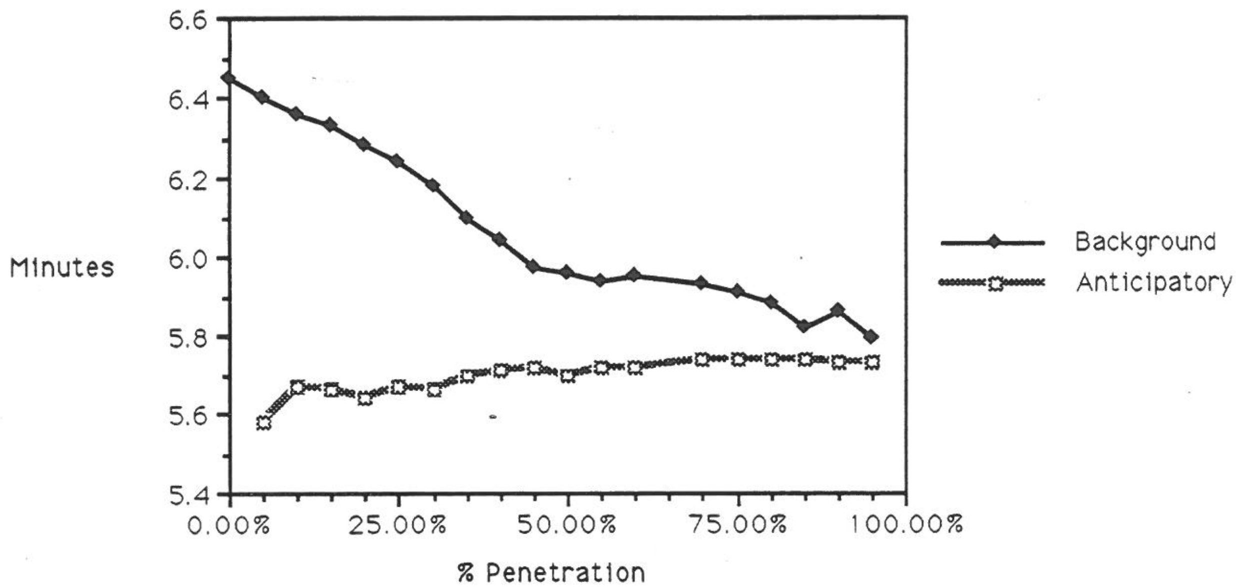


of 5%. No data are reported at penetrations of 65% and 100%, where the iterative process cycled and no fixed points were found. As penetration increases from 5%, the savings in anticipatory trip time decreases from a peak of 14%, and background vehicles average faster trip times at and beyond a penetration threshold of 45%. The existence of this threshold is in apparent contradiction to our earlier claim that a fixed point necessarily corresponds to a user-optimal routing policy for anticipatory traffic.

To resolve the contradiction, recall that the anticipatory fastest path computation assumes forecasts of link travel time as a function of the time of *entry* to the link. INTEGRATION produces these forecasts by using the vehicles in the simulation as traffic probes. That is, at the moment when a vehicle exits a link, the travel time it experienced is reported to the set of forecast data. Therefore the forecasts are of link travel times as a function of the time of *exit* from the link, implying an inconsistency between the two parts of the feedback loop.

We describe the computation of the average trip times in Figure 3, recording the link travel times of each vehicle as it departs a link, as *actual-time accounting.* Figure 4 shows the average trip times calculated under *probe accounting*, using the fixed-point probe forecasts instead of the actual link times. That is, under probe accounting we calculate trip durations by assuming that a vehicle entering a link at time t experiences the link travel time that

Figure 4: Average trip durations (probe accounting)



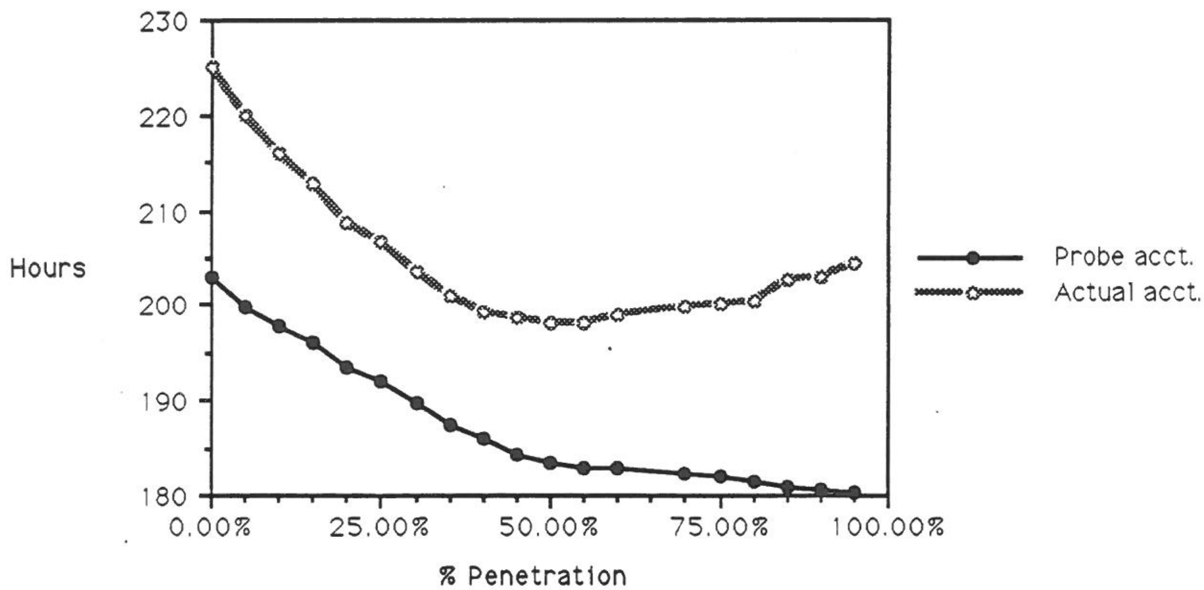
was forecast by a vehicle exiting the link at time t in the previous iteration. Therefore this accounting method is consistent with fastest-path calculation using the end-of-link forecasts output from INTEGRATION. The probe-accounting average trip times do satisfy the claim that a fixed point implies anticipatory user-optimality at all penetration levels.

To benefit from anticipatory route guidance at all penetration levels in actual-time accounting, we must change our forecasting procedure to produce link travel time data as a function of time of entry to the link. This would be done by "backdating" the probe data, reporting a link travel time at the moment the link is exited, but recording it as a forecast relating it to the time when that vehicle entered the link. We are unable to report on trip times under backdated forecasting because it has consistently caused cycling, i.e., fixed-point forecasts are not available.

3.2 System benefits

Figure 5 shows the total travel time in the network as a function of market penetration, measured under both actual-time and probe accounting. Under actual accounting, total system time decreases until market penetration reaches 55%, and increases at greater penetrations. The probe-accounting system time is better behaved, with system benefits increasing to 10% as penetration increases to 95%. Therefore, it may be that fixed-point backdated forecasts would also induce greater actual-time system benefits at high penetrations. Even then, how-

Figure 5: Total travel time



ever, total system time may increase as penetration increases, as it is well known that models that achieve user-optimality may do so at the expense of system-optimality in static traffic models. The same has been shown for dynamic models in a compact example (Wunderlich [9]).

3.3 Conclusions: Contributions and Future Research Needs

The above computational experience indicates that the iterative routing/assignment algorithm produces anticipatory route guidance that improves the travel time of both the individual drivers receiving anticipatory guidance and the system as a whole at market penetrations of anticipatory route guidance of up to about 50%. This improves the attractiveness of real-time route guidance technology, since estimates of the maximum beneficial market penetration under non-anticipatory routing are typically about 15%. We now consider several future topics that may enhance the benefits we have identified.

3.3.1 Existence and computation of fixed points

Under probe accounting, calculating average trip times for each routing class as though the link travel time forecasts were beginning-of-link instead of end-of-link, anticipatory route guidance benefitted the drivers receiving it regardless of market penetration. Therefore, to have anticipatory routing provide benefits at all or nearly all penetration levels under actual accounting, we need to find fixed points for backdated forecasts. In general, the existence and efficient computation of fixed points for the general assignment/routing method is of interest.

3.3.2 All-or-nothing routing

The anticipatory route guidance currently takes the form of a single optimal next link at each time period for each pair of current node and destination. That is, all anticipatory traffic with the same destination reaching the same node during a single time period is routed together onto the same next link. This makes it more difficult to synthesize the link travel times experienced by each of these vehicles into one forecast for the link travel time in that period. Since most or all of the traffic in the network is following the same route guidance at high levels of market penetration, the network performance measures are especially sensitive to inaccuracy in forecasting. Therefore, policies with more balanced flows, routing vehicles along more than one path may improve network performance measures. Furthermore, if we express routing policies not as single optimal next links but as the proportion of vehicles routed on several optimal next links, the space of routing policies becomes a continuous space in which concepts of continuous mappings apply, perhaps making fixed-point theory more applicable.

3.3.3 Real-time forecasting/Adaptive routing

The current formulation of the iterative routing/assigment procedure requires the assignment portion of the feedback loop to use the entire anticipatory routing policy determined from the forecasts produced in the previous iteration. Suppose such a set of forecasts is very far from being a fixed point, so that a certain route appears very attractive to anticipatory traffic throughout the entire time horizon. Then early in the simulation, this route becomes heavily loaded with anticipatory traffic. Because the anticipatory routing policy can be changed only outside the assignment (simulation) phase of the iterative process, anticipatory traffic continues to be routed to this now-congested route. We would realize greater success by incorporating a real-time forecasting feature into the simulation that would adapt to the early congestion on the apparently attractive route and adjust the anticipatory route guidance of vehicles entering the network later.

This research issue is in fact crucial to anticipatory real-time route guidance. When a system of this type is to be implemented in actual traffic networks, it must be able to receive continuous updates of network traffic conditions and recalculate forecasts of future network conditions and appropriate guidance information throughout at least the peak periods of travel demand. In particular the system must be able to respond to reports of incidents such as lane closures causing capacity reductions. The unforeseen nature of these incidents invalidates some or all of the forecasts that had been maintained previously and requires immediate reevaluation of anticipatory route guidance. Therefore the need for an assignment model that is capable of its own real-time forecasting and adaptive routing is significant both from a computational standpoint of avoiding unnecessary oscillation in the iterative process and from a implementation standpoint of reacting to actual real-time information.

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