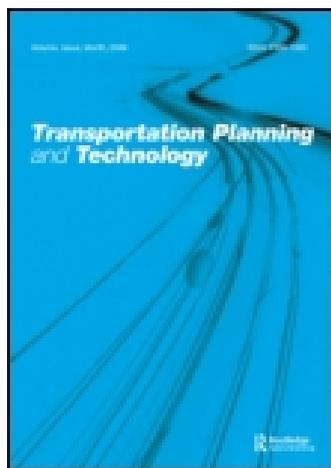


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Evaluation of diversion strategies using dynamic traffic assignment

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A framework for the evaluation of the effectiveness of traffic diversion strategies for non-recurrent congestion, based on predictive guidance and using dynamic traffic assignment, is presented. Predictive guidance is based on a short-term prediction of traffic conditions, incorporating user reaction to information and guidance. A case study of the Lower Westchester County network in New York State, using DynaMIT-P, is presented to illustrate the application of the framework. DynaMIT-P is capable of evaluating diversion strategies based on predicted conditions, which take into account drivers' response to traffic information. The case study simulates the operations of predictive variable message signs positioned in strategic locations. DynaMIT-P is calibrated for the study network and used to establish base conditions for two incident scenarios in the absence of advanced traveller information systems. The effectiveness of predictive diversion strategies is evaluated (using rigorous statistical tests) by comparing traffic conditions with and without diversion strategies. The empirical findings suggest that incident diversion strategies based on predictive guidance result in travel time savings and increased travel time reliability.

Keywords: incident management; response strategies; dynamic traffic assignment; travel time savings; travel time reliability

1. Introduction

It is well established in the literature that the provision of driver information has the potential to reduce congestion, especially under incident conditions (cf. Mahmassani 2001, Ben-Akiva *et al.* 2002). However, information may have adverse impacts if it is not accurate, timely or properly disseminated. A key concern with the dissemination of driver information is the phenomenon of overreaction. Prediction-based route guidance based on short-term forecasts of the state of the network, taking into account driver response to information, is expected to be more effective in minimizing overreaction than naive strategies based on historical or current traffic patterns.

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Theoretical and simulation-based analyses have generally confirmed the need for prediction-based guidance (cf. Ben-Akiva *et al.* 1991, Ben-Akiva *et al.* 1996). Furthermore, Balakrishna *et al.* (2004) confirm some existing findings on overreaction while providing valuable insights into the role played by critical parameters that control simulation-based guidance generation systems.

Clearly, to analyse the impact of information through in-vehicle units (IVUs), variable message signs (VMSs), highway advisory radio (HAR) messages or by other means, it is necessary to model accurately both traveller behavior and traffic dynamics. Recently developed simulation-based dynamic traffic assignment (DTA) systems – such as DynaMIT (Ben-Akiva *et al.* 2001a) and DYNASMART (Mahmassani 2001) – have traffic estimation and prediction capabilities, incorporating driver response to information. These systems, because of their predictive capabilities, can reduce or even eliminate the impact of overreaction which may occur if traffic information is provided without considering driver response to information (Ben-Akiva *et al.* 2002, Balakrishna *et al.* 2004).

Dia and Cottman (2006) used a microscopic simulation approach to evaluate the impacts of incident management strategies and the provision of real-time travel information in response to incidents. The presented strategies involved diversion towards alternative routes, combined with externally defined compliance rates. While microsimulation is a useful tool with many applications, it also has some limitations. Although microscopic simulation arguably provides a more accurate modeling of traffic dynamics than do mesoscopic or macroscopic tools, microscopic traffic simulation is currently useful only in the context of relatively small networks. As a result, routing decisions/diversions are usually based on intermediate destinations (defined at the boundaries of the microscopic network) and do not really represent actual origins and, more importantly, ultimate destinations. Hence, impacts of the simulated incident management strategies may be biased. DTA models on the other hand can model these impacts more accurately, as they can deal with larger networks and explicitly model demand at the origin–destination (OD) level.

Other approaches for traffic prediction models have also been developed. Sadek *et al.* (1999) presented a framework for the development of real-time traffic routing strategies. The authors used heuristic search algorithms, including simulated annealing and genetic algorithms. Sadek *et al.* (2001) examined the feasibility of applying case-based reasoning to the problem. Ishak and Al-Deek (2002) investigated the factors that have a significant impact on the forecasting accuracy of travel times using a non-linear time series traffic prediction model. The study was conducted using real-time data collected from Interstate-4 in Orlando, Florida.

Mahmassani (2001) presented an application of the DTA system DYNASMART to evaluate and compare the impacts of various information supply strategies under incident conditions. The emphasis of this research was in the evaluation of different types of information strategies. The first group of strategies provided descriptive information, such as prevailing trip times and associated current best paths were provided to users; different penetration levels were then modelled. Prescriptive information with multiple user classes was also presented, while a prescriptive system's optimal solution was also simulated as a benchmark case.

Sundaram (2002) developed a methodological framework for the evaluation of intelligent transportation systems (ITSs) at the planning level and implemented it in DynaMIT-P – DynaMIT for short-term planning applications (Ben-Akiva *et al.*

2001b). The methodological framework captured both the within-day and day-to-day evolution of traffic and modelled traveller behavior and network performance in response to special events and situations such as incidents, weather emergencies, sport events, and work zones. Various scenarios involving instantaneous and predictive information were evaluated using DynaMIT-P based on a hypothetical incident on the Irvine, CA, network. The benefits of providing consistent predictive information (versus instantaneous) were demonstrated. However, this effect was avoided by using predictive VMS with a consistent guidance strategy. Other studies (cf. Oh and Jayakrishnan 2000) have also confirmed the intuitive expectation that *ceteris paribus* predictive VMS information leads to larger travel time gains when compared to instantaneous VMS information.

The optimal location of advanced traveller information system (ATIS) infrastructure is a related problem. Chiu *et al.* (2001) introduced a framework for finding an optimal set of locations to install a given number of VMS in a traffic network. The aim was to maximize the expected benefit of the available VMS under a variety of traffic incident situations. The model was constructed as a nested optimization problem in which there were two levels of decision-making. The upper level seeks to minimize the expected total user travel time over the space of stochastic incidents. A tabu search algorithm was employed at the upper level to generate potential solutions, which were then evaluated at the lower level by solving the user equilibrium dynamic traffic assignment problem via simulation.

The objective of the present paper is twofold: to present a framework for the application of DTA for the evaluation and/or development of diversion strategies and to evaluate the impact of predictive VMS information in situations of incident congestion. The simulation-based DTA system DynaMIT-P is used for the evaluation of diversion strategies through an extensive case study of the Lower Westchester County network in New York State.

The remainder of this paper is organized as follows. Section 2 presents the proposed framework, covering both the development of incident scenarios and the subsequent evaluation of diversion strategies. An overview of DTA requirements for incident management strategy evaluation is presented in Section 3, along with a description of the modeling aspects of DynaMIT-P that cover these requirements. Section 4 presents the results of an extensive application to the network of Lower Westchester County. The objective of the application is to evaluate the effectiveness of predictive VMS guidance (simulated using DynaMIT-P) under incident conditions. Section 5 summarizes and concludes the paper.

2. Framework for the evaluation of diversion strategies using DTA

The evaluation of diversion strategies using DTA (Figure 1) requires as a first step the calibration of the model and the establishment of base conditions. The type of infrastructure (e.g. VMS, HAR or IVU), the location and range, the type of information to be disseminated and the method for generating this information are key design characteristics and are also required as inputs. In the case of existing systems, the type of the system as well as the location and range may already be fixed. However, this process can be used in the planning phase of an ATIS deployment in order to determine optimal resource allocation (cf. Chiu *et al.* 2001).

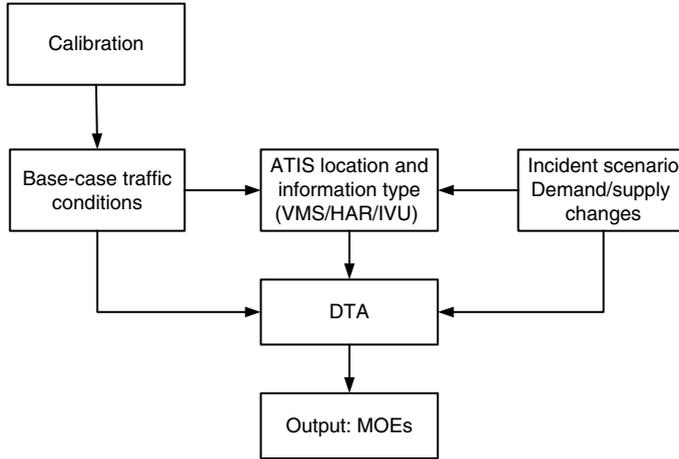


Figure 1. Evaluation of diversion strategies.

Various measures of effectiveness (MOEs), such as average travel times and their standard deviations, obtained during incident scenarios provide benchmark performance measures that establish reference points for quantifying the benefits of alternative response strategies.

2.1. Calibration

In general, DTA models include a number of parameters that need to be calibrated. These parameters include the (usually unknown) dynamic OD flows and route choice parameters on the demand side and capacities and speed–density relationship parameters on the supply side. Therefore, calibration of the unknown parameters and inputs of the demand and supply models within a DTA system is an important and crucial step in any application, as it ensures that the model accurately captures the traffic conditions prevailing in the network. It is defined as follows: *Given a set of initial values for various parameters and typically available (aggregate) measures of flows, speeds and densities at sensor locations, determine the OD flows, route choice parameters, capacities and speed–density relationships, so that the discrepancy between the DTA model output and observed values is minimized.*

Following Balakrishna *et al.* (2005), the calibration problem is formulated as an optimization problem:

$$\min_{\mathbf{x}, \beta, \gamma} \left[z_1 (\mathbf{M}^{\text{DTA}}, \mathbf{M}^{\text{obs}})^2 + z_2 (\mathbf{x}, \mathbf{x}^a)^2 + z_3 (\beta, \beta^a)^2 + z_4 (\gamma, \gamma^a)^2 \right] \quad (1)$$

where β represents the route choice parameters, γ represents the parameters in the supply simulator, \mathbf{X} are the OD flows, \mathbf{M}^{obs} are the observed measurements and \mathbf{M}^{DTA} are the DTA model outputs. Superscript α indicates a priori values and z_1 , z_2 , z_3 and z_4 are error functions. The objective function minimizes the discrepancy between various model outputs and observed (actual) measurements \mathbf{M} (e.g. flows and speeds can be used as measurements) as well as deviations from a priori values, appropriately weighted. Constraints can be added to the values of the estimated parameters to ensure that they lie in their allowed domain. For example OD flows

should be non-negative, while the travel time coefficient for the route choice model should be negative, as higher travel times tend to lower the perceived utility of the corresponding route. The above problem is solved iteratively using appropriate algorithms (Balakrishna *et al.* 2005).

A common special case of the problem involves the estimation of the OD flows \mathbf{x}_h for interval h . In this case the general formulation reduces to

$$\mathbf{x}_h = \operatorname{argmin} \left[z_1(\mathbf{x}_h, \mathbf{x}_h^a) + z_2 \left(\sum_{p=h-p'} \mathbf{a}_h^p \mathbf{x}_p, \mathbf{y}_h^a \right) \right] \quad (2)$$

Function z_1 measures the Euclidean distance of the estimated flows \mathbf{x}_h from their a priori values \mathbf{x}_h^a , while z_2 measures the distance of the measured counts y_h from their simulated counterparts. The assignment matrices \mathbf{a}_h^p required by the OD estimation module are outputs of the supply simulator of the DTA model and are functions of the as-yet-unknown OD flows, the equilibrium travel times on each link (tt_l^{eq}), the route choice parameters β and the supply-side parameters γ :

$$\mathbf{a}_h^p = g(\mathbf{x}_p, \beta, \gamma, \text{tt}_l^{\text{eq}}) \quad (3)$$

The determination of consistent ‘equilibrium’ travel times is part of the calibration process. Equilibrium is achieved when motorists follow the perceived shortest path to their destination. Travel times on those paths are time-dependent. These equilibrium travel times are themselves a function of the OD flows, route choice parameters and supply-side parameters:

$$\text{tt}_l^{\text{eq}} = h(\beta, \gamma, \mathbf{x}_p) \quad (4)$$

Equations (2)–(4) clearly demonstrate the fixed-point nature of the calibration problem. An iterative approach is therefore used to converge to a consistent calibration of the parameters and ‘equilibrium’ conditions (Sundaram 2002, Balakrishna *et al.* 2005).

2.2. Evaluation of strategies

The objective of incident management is to apply diversion strategies that will ultimately reduce the travel delays due to the incident. The main concept is usually the more effective utilization of the residual capacity of secondary routes that are not heavily used by drivers under regular conditions by shifting travellers to these routes. The various strategies may be evaluated based on a number of suitable MOEs, including, for example:

- Travel times and delays on the affected ODs, paths and links
- Reliability/uncertainty of travel times (and resulting guidance), which has been shown to have an impact on pre-trip and en-route drivers’ behavior (cf. Abdel-Aty *et al.* 1997, Mahmassani and Liu 1999, Toledo and Beinhaker 2006)
- Impact on secondary roads
- Distribution of travel times and other MOEs over time and space, e.g. by time of day, by departure time interval or by OD pair.

3. DynaMIT DTA model for evaluation of incident management strategies

DynaMIT-P is a short-term planning tool for the evaluation of ITS strategies that combines detailed representation of demand, supply, and algorithms that capture their interactions. The primary objective of DynaMIT-P is to assist planners in short-term planning applications. Such applications are related to infrastructure-related, operational or informational changes. In response to altering traffic conditions caused by such changes, travellers make adjustments to their travel choices. These adjustments in turn change traffic conditions. DynaMIT-P is designed to model these interactions and assess the performance of the network and the benefits to travellers under various proposed infrastructure, operational or information strategies. DynaMIT-P is capable of handling several types of information (e.g. pre-trip/en-route, descriptive/prescriptive). Route choice is based on discrete choice models (Antoniou *et al.* 1997). DynaMIT-P and DynaMIT-R (its operational, real-time counterpart) have been extensively validated for several real networks (cf. Sundaram 2002, Balakrishna *et al.* 2004, 2005, Antoniou *et al.* 2007).

DynaMIT-P consists of two main components: a demand simulator and a supply simulator. The two components are used iteratively to capture the demand–supply interactions as illustrated in Figure 2 (Ben-Akiva *et al.* 2002).

The demand simulator estimates dynamic OD flows and captures travellers' decisions in terms of departure time, mode and route choices (Antoniou *et al.* 1997). An initial estimate of demand is directly derived from available data (e.g. from planning models or prior surveys). The supply simulator explicitly simulates the interaction between the demand and the network.

Because of the above structure and characteristics, DynaMIT-P is very well suited for the off-line generation of libraries of incident diversion strategies and the evaluation of ATIS prior to their actual online deployment by simulating a wide range of information generation approaches and diversion strategies. DynaMIT-P satisfies all the requirements with respect to the representation of both incident scenarios and ATIS infrastructure, as well as the route choice and path generation process (discussed in the previous section).

3.1. Representation of incident scenarios

The considered incident scenarios are captured in DynaMIT-P by modifying the relevant inputs on the supply or demand side and evaluating the network

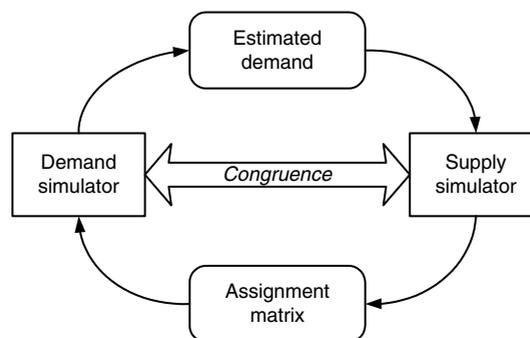


Figure 2. Demand–supply interactions within DynaMIT-P.

performances under modified inputs. Changes on the supply side are made primarily to the segment capacities. For example a lane closure due to an accident and its impacts for a temporary period are captured by reducing the capacity of the corresponding segment for the appropriate time interval. DynaMIT-P's traffic simulator is mesoscopic in nature. As a result, segment capacity is an input that can be modified according to the prevailing traffic conditions or disruptions (e.g. incidents, work zones, special events, adverse weather conditions). More detail regarding the modeling of capacity in DynaMIT-P can be found in Ben-Akiva *et al.* (2002).

Any changes on the demand side are captured by updating the appropriate OD matrices. A typical example of changes in the demand inputs would be the increase in demand due to special events such as baseball games, music concerts or holidays. Special events may not directly affect the supply side but will in general affect the demand patterns in the network. For example a major sports or arts event would provide a significant attraction of demand towards the venue (before the event) and from the venue (after the event). Similarly, major holidays might result to sudden changes to the demand pattern in the network. Incidents (both planned and unplanned) may also affect demand as people modify their departure time or mode in response to these incidents.

3.2. Representation of ATIS infrastructure

DynaMIT-P is capable of representing a variety of ATIS infrastructure, ranging from VMSs and HAR to IVUs. Furthermore, DynaMIT-P can simulate several types of each system, based on the scope of the information provided and the method used for generating it. For example a VMS system is providing drivers with instantaneous information if it is simply broadcasting the latest measured travel time information. On the other hand, a VMS is providing predictive information if it is broadcasting travel time information that has been obtained as a result of a short-term prediction process.

If the information that is provided by the VMS is based on the current traffic conditions, it is likely to be outdated by the time drivers have reached their destination. It is also very likely to result in overreaction. Predictive information has the potential to avoid these problems. However, prediction has to take into account the response of drivers to the information provided. Hence, systems that broadcast predictive information anticipate the evolution of traffic patterns in the near future and provide drivers with information and guidance that is consistent with the traffic conditions that they will encounter when they reach their destination.

The problem of generating predictive traffic information that incorporates user response to information is not a trivial task. In DynaMIT, it is formulated as a fixed-point problem and an Method of Successive Averages (MSA)-type algorithm is used for its solution. Bottom *et al.* (1999) provide a rigorous mathematical formulation of the guidance generation process as a fixed-point problem and suggest algorithmic approaches for its solution. An algorithmic investigation of the problem is also available in Bierlaire and Crittin (2006).

3.3. Route choice and response to information

DynaMIT-P explicitly models driver response to information. Pre-trip departure time and path choice, as well as en-route path choice, are captured through discrete choice models (Antoniou *et al.* 1997). Path choice decisions are based on the Path-Size Logit model (Ramming 2002, Ben-Akiva and Bierlaire 2003) to account for driver perceptions of overlapping paths. Many factors affect drivers' response to information (whether predictive or instantaneous), such as the range and timeliness of the information, the socioeconomic characteristics of the travellers that receive the information and the time of day (Polydoropoulou *et al.* 1994, 1996, Bonsall and Merrall 1997, Wardman *et al.* 1997, Polydoropoulou and Ben-Akiva 1999, Chatterjee *et al.* 2000, Ishak and Al-Deek 2002, Tsirimpa *et al.* 2007). The default utility specification of the models included in DynaMIT-P for pre-trip and en-route path choice uses travel time and includes a freeway bias component.

Drivers are originally assigned habitual paths based on historical travel times. Those drivers without access to en-route information (e.g. via VMS, HAR or IVU) follow their habitual path to their destination, irrespective of the prevailing traffic conditions. Drivers with access to IVU or those that are within the range of VMS and HAR become aware of the prevailing (respectively predicted) traffic conditions and can use this information to update their habitual routes. This results in updated route choices for the informed drivers.

3.4. Path generation

The choice set for the route choice model is based on an extensive list of pre-calculated 'reasonable' paths from every node to the various destinations, maintained by DynaMIT. The path choice set generation involves the computation of a large set of feasible paths connecting every OD pair of interest. While the set of shortest paths between every OD pair might capture driver behavior, changing traffic patterns can increase the attractiveness of other paths. Incidents, for example, can block the shortest route and force drivers onto less attractive paths. A good set of paths is therefore essential in both planning and real-time applications. DynaMIT-P employs three steps in its path generation algorithm:

- *Shortest path computation*: Shortest paths between nodes and all destination nodes are calculated and added to the choice set.
- *Link elimination*: Each link in the shortest path tree is eliminated, one at a time, and the corresponding shortest paths are computed. The shortest paths generated with the link elimination are added to the choice set. This step ensures that choice set includes alternatives (if they exist) even when an incident completely blocks a link.
- *Random perturbation*: This step further augments the path set. The impedances of the links are perturbed randomly to simulate varying travel times. Another set of shortest paths is computed and appended to the existing set. The number of random perturbations performed is controlled by the user.

The algorithm also examines the final path set for uniqueness and eliminates unreasonably long paths. While the path tree is not recomputed in the event of an

incident, the combination of the shortest paths' computation, link elimination, and random perturbation ensures that all ODs will be connected even in the event of a severe incident on any link of the network (provided that such a path actually exists).

4. Case study

The objective of the case study is to demonstrate the application of the framework presented in Section 2 for the evaluation of the effectiveness of predictive VMS guidance, simulated by DynaMIT-P, in response to incidents. While traffic estimation and prediction systems that can support ATIS and provide them with predictive guidance are under evaluation, testing and deployment, the use of such systems is very limited. It is anticipated that a series of practical showcase studies demonstrating the benefits of such systems could propel them and support their wide-spread deployment.

A congested network north of New York City was used in this case study. The DynaMIT-P calibration results for the study network are outlined and the reference traffic conditions are established. The impact of two incidents is then presented, along with the traffic conditions resulting from the provision of predictive traffic information (simulated by DynaMIT-P). The nature of the mitigation of traffic delays due to predictive diversion strategies is also investigated.

4.1. Network

The case study is based on a freeway and parkway network from the Lower Westchester County, NY. Drivers experience heavy traffic conditions, especially during commute periods. The main arteries in the network include the New York State Thruway (I-87), the New England Thruway (I-95), the Cross Westchester Expressway (I-287), the Cross County Parkway, the Hutchinson River Parkway, the Sprain Brook Parkway, the Saw Mill River Parkway, the Bronx River Parkway and the Taconic State Parkway. Four adjoining arterials (Tuchahoe Road, Ardsley Road, Hartsdale Road and Weaver Street) and Routes 9, 22, 100 and 119 provide alternate routes (Figure 3).

The network representation of the study area comprises 1659 directed links, further subdivided into 2421 segments that capture changing link characteristics. Data available for calibration include counts, speeds and occupancies from 58 sensors and a static, planning-level, OD matrix (provided by the New York State Department of Transportation). There are 579 OD pairs in the network.

4.2. Calibration

As noted previously, DTA models such as DynaMIT involve a number of demand and supply parameters that need to be calibrated. The demand simulator is primarily composed of the driver behavioral models and the OD estimation and prediction model. DynaMIT relies on probabilistic discrete choice models to model driver decisions. Utility theory along with the Path-Size Logit model (cf. Ben-Akiva and Bierlaire 1999) is employed to evaluate these probabilities. DynaMIT was calibrated using surveillance and historical data using the methodology outlined earlier.

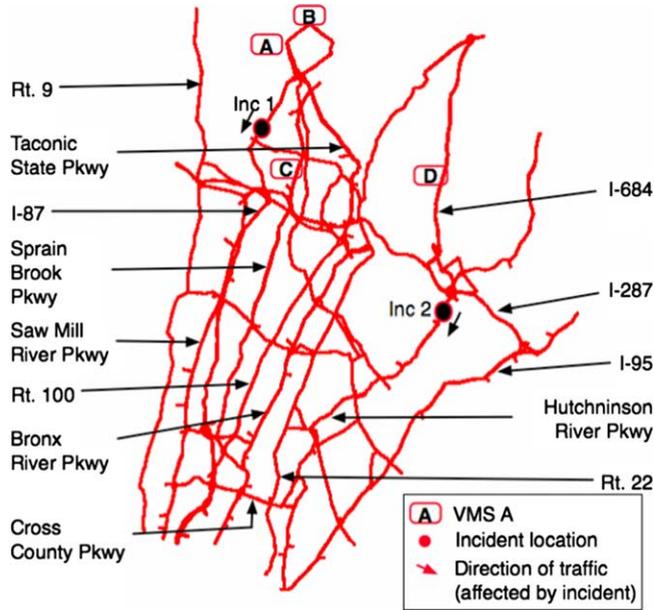


Figure 3. Lower Westchester County network, including VMS and incident locations.

A sequential calibration approach has been chosen, with the supply and demand calibration steps being performed separately.

An important step in the calibration process was the generation of a good set of paths for each OD pair of interest. Optimal parameters for the path generation algorithm were identified so as to capture most of the feasible paths for every OD pair. A suitable path set was obtained using 40 random draws to complement the set of link-elimination-based shortest paths from every link to a destination node. Recognizing many drivers' preference to favour freeway paths, an internal freeway 'bias' of 0.6 was used to force the path generation algorithm into preferring paths with longer freeway sections. The random draws helped augmented this set with arterial paths. Manual inspection confirmed that most of the practical alternatives had been selected in the path generation stage. The final set contained a total of 7541 paths between 579 OD paths.

A small number of parameters need to be calibrated for the route choice model, mainly the travel time coefficient and the freeway bias. Several iterations were performed in conjunction with the OD estimation step to determine an optimal set of parameters for the route choice model. A grid search was performed on the two parameters (coefficient of travel time and freeway bias) and the optimal values were found to be equal to -0.025 and 0.80 , respectively. These are intuitive and reasonable values. Obviously, one would expect the travel time coefficient to have a negative sign, while the freeway bias would be a positive number between 0 and 1.

The current version of DynaMIT employs a sequential generalized least squares-based OD estimation module. The external inputs to the model include link counts and the historical database of OD flows. The historical flows are coupled with the concept of flow deviations in order to effectively capture the information contained in the past estimates. The key inputs generated internally are the time-dependent

assignment matrices. While the matrices α_h^p are generated by the supply simulator, the historical database has to be created offline. The OD estimation and prediction algorithm is also based on an autoregressive process that captures spatial and temporal correlations between the OD flows.

The key calibration parameters for the OD estimation and prediction model are as follows:

- The historical database of OD flows, x_h^H . For each of the 16 time intervals (a calibration period of 6:00–10:00 a.m. was assumed, and each interval had a duration of 15 minutes), this corresponds to 579 parameters. Therefore a total of 9264 OD flows were estimated through a sequential estimation process; i.e. the OD flows for each interval were estimated before moving to the estimation of the OD flows for the next interval.
- The variance–covariance matrix associated with the indirect measurement errors V_h and W_h . These were assumed to possess a diagonal structure in order to ensure that the limited available data would provide enough observations to estimate the elements of these matrices. Furthermore, the structure of the error covariances was assumed to remain constant across the peak period, i.e. only one matrix V and W was computed.
- The matrices f_h^p of autoregressive factors. The autoregressive process was assumed to be of degree 1, meaning that the deviation of flow between the OD pair r from their historical values does not depend on the prior interval flow deviations between the OD pair r .

For a more detailed coverage of the OD estimation and prediction model, the reader is referred to Balakrishna (2002).

The supply simulator obtains aggregate measures of network performance by simulating the movement of drivers on the road network. Detailed mesoscopic models capture traffic dynamics and accurately model the build-up and dissipation of lane-specific queues and spillbacks. The links in the network are subdivided into segments to capture changing section geometries. Each segment contains a moving part (with vehicles moving at certain speeds) and a queuing part. The movement of vehicles in the moving part is governed by macroscopic speed–density relationships that take the following form:

$$v = v_{\max} \left[1 - \left(\frac{k - k_{\min}}{k_{\text{jam}}} \right)^\beta \right]^\alpha \tag{5}$$

where v is the speed of the vehicle (in mph), v_{\max} is the speed on the segment under free-flow traffic conditions, k is the current segment density (in vehicles/mile/lane), k_{\min} is the minimum density beyond which free-flow conditions begin to break down, k_{jam} is the jam density, and α and β are segment-specific coefficients.

The movement of vehicles from one segment to the next is governed by a set of capacity calculations. The primary quantities of interest are the input and output capacities of the various segments. These capacities are compared with the available physical space on the downstream segments before allowing vehicles to cross segment boundaries. A constraint on either capacity or space would cause vehicles to queue.

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An important calibration step is therefore the computation of segment capacities that truly approximate the allowed turning movements, signal logic and sectional geometry of the network.

The key calibration parameters on the supply side are as follows:

- Segment-specific speed–density parameters (v_{\max} , k_{\min} , k_{jam} , β and α).
- Lane group capacities on freeway and arterial segments.
- Lane group capacities at intersections based on signal control logic.

The network segments have been classified into three groups, and different speed–density relationships have been estimated for each group (shown in Table 1). The values for the capacities of the network segments have been computed based on the *Highway Capacity Manual* (HCM 2000). In particular, the resulting values for the freeways are 2200 vehicles per hour per lane (vphpl), while for the arterials (Tuchahoe Road, Ardsley Road, Hartsdale Road and Weaver Street) and Routes 9, 22 and 100, the values were set to 1900 vphpl. Ramp capacities were set to 1600 or 1800 vphpl depending on the location and geometry of the ramp.

Clearly, calibrated model parameters are network specific and as such the data presented cannot be considered transferable or applicable to another network or application.

The calibration results are shown in Figure 4. For each of the four figures, the estimated and observed (field) sensor counts per lane for each hour in the peak period (6:00–10:00 a.m.) are compared in a scatter plot. The (calibrated, observed) points of individual sensors follow the ‘45° line’, indicating a good fit and ability to replicate observed conditions.

In addition, the validity of DynaMIT-P was evaluated using the normalized mean square error (RMSN) on the estimated versus observed counts. The RMSN is given by

$$\text{RMSN} = \frac{\sqrt{N \sum_{i=1 \dots N} (x_i - \hat{x}_i)^2}}{\sum_{i=1 \dots N} x_i} \quad (6)$$

where N is the number of counts, x are the observed counts and \hat{x} are their simulated counterparts. The RMSN values for this case study were 0.0863 for 6:00–7:00 a.m., 0.0851 for 7:00–8:00 a.m., 0.1181 for 8:00–9:00 a.m., and 0.1048 for 9:00–10:00 a.m.

Table 1. Speed–density relationship parameters by road type.

	Free-flow speed u_f (mph)	Minimum speed u_{\min} (mph)	Jam density k_{jam} (vpmpl)	Minimum density k_{\min} (vpmpl)	Parameter α	Parameter β
Freeways	65	20	0.125	0.015625	2.0	0.5
Arterials	50	20	0.0625	0.00625	1.5	0.32
Ramps	45	20	0.125	0.0125	1.5	0.3

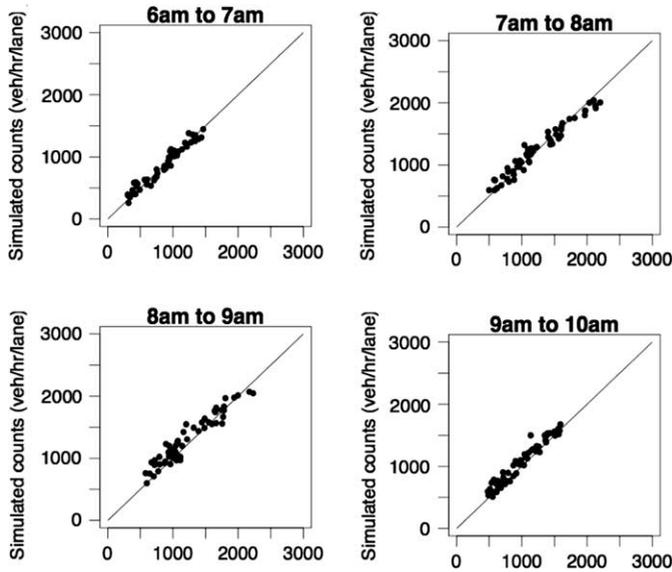


Figure 4. Calibration results.

4.3. Evaluation of predictive guidance

Earlier work has showed that the use of instantaneous VMS has little impact (Oh and Jayakrishnan 2000, Sundaram 2002). Hence, only predictive VMS was used in the case study. Traffic statistics obtained with and without ATIS information were compared, and the improvement (attributed to the impact of the ATIS information) was identified. A simulation of the base case (where no incident is present) was used as the reference scenario.

The analysis took place during the morning peak period (7:00–9:30 a.m.) during which the main direction of traffic is southbound (towards New York City). Scenario 1 involves an incident in the southbound direction of the Saw Mill River Parkway in the north of Cross-Westchester Expressway (I-287). The duration of the incident is 65 minutes (from 7:45 to 8:50 a.m.) and results in a capacity reduction of 80%. Scenario 2 deals with an incident in the southbound direction of the Hutchinson River Parkway. The duration of this incident is 65 minutes (from 7:15 to 8:20 a.m.) and also results in a capacity reduction of 80%. The locations of these incidents, as well as the locations of the relevant VMSs, are shown in Figure 3. The VMS provided descriptive guidance, based on predicted travel times, to drivers within its range.

Travel time is used to evaluate the impact of the incidents and the effectiveness of the predictive guidance provided. In the no-incident case, the average travel time for the main OD pairs is 1665 seconds. In the first incident scenario, and for the case without guidance, the average travel time for the main OD pairs increased by 16.6% to 1942 seconds. In the presence of VMS-disseminated predictive guidance, the average travel time increased by only 9.8% (to 1828 seconds). The variability of the average travel time is also affected by the predictive guidance. In the case of the incident without information, the standard deviation of the travel time increased by 48.3%, while when predictive guidance is provided the increase is only 19.5%. This implies that 41% of the delay and 60% of the increase in the standard deviation due

to the incident have been eliminated through the provision of predictive traffic information disseminated via VMS devices.

In the second scenario and in the case without VMS, the average travel time for the main OD pairs increased by 13.5% (from 1665 seconds in the no-incident case to 1890 seconds). In the presence of VMS, the average travel time increased by only 5.1% (to 1750 seconds). Similarly, the standard deviation of the travel time increased by 27% in the case of the incident without information, while when predictive guidance is provided the increase is only 15.6%. This implies that in this case, 62% of the delay and 42% of the increase in the standard deviation due to the incident have been eliminated through the provision of predictive traffic information disseminated via VMS devices.

The above differences in average travel times are also statistically significant. A two-sample test on the mean values μ was used to test the null hypothesis $H_0: \mu_1 - \mu_2 = 0$ against the alternative $H_a: \mu_1 - \mu_2 \neq 0$. The test statistics obtained are between 11.4 and 31.4, while the critical value for a two-tailed test at the 0.5% significance level is 3.09. Hence, the null hypothesis of equal means is rejected. Like most traffic measures, travel times are non-negative, and as such the normality assumption (implied in such statistical tests) may be challenged. The normality of traffic measures such as travel times and speeds is often assumed for the purposes of statistical tests and analyses (cf. Dimitriou *et al.* 2007). Ko and Guensler (2005) discuss the conditions under which the normality assumption would be applicable, e.g. when large samples are available, in which case some central limit theorem could be invoked. This is an issue that should be further researched; however, for the purposes of this study, the tests presented provide some additional measurable evidence.

Figure 5 illustrates the frequency distribution of travel times for the various scenarios and cases. As a result of the first incident, a significant number of vehicles with lower travel times (1500–2000 seconds) in the base case (no incident) have shifted to higher travel times (3000–5000 seconds) during the incident when no information is available. However, when information is provided, the number of drivers experiencing travel times greater than 3000 seconds decreases by more than half. On the other hand, a larger number of drivers experience travel times between 1000 and 3000 seconds. Similarly, as a result of the second incident, a significant number of vehicles with lower travel times (1000–2000 seconds) in the base case have shifted to higher travel times (2000–3500 seconds) in the incident case with no information. When information is provided, the number of drivers experiencing travel times greater than 2000 seconds has decreased considerably, while, on the other hand, more drivers experience travel times between 1000 and 2000 seconds (compared to the case of the incident without information).

Table 2 presents the average travel times and their standard deviation under each of the scenarios by departure-time interval. In the case of the first incident scenario, average travel times for the affected travellers departing between 7:45 and 8:45 a.m. (incident duration) have increased by more than 50%. When predictive guidance is provided through VMS, the average travel times for these departure time intervals have increased by only 30% and never exceed 40%. Vehicles departing between 7:45 and 8:15 a.m. have experienced particularly major savings (more than 13%) due to the predictive guidance. Furthermore, the variability of the travel times, expressed in Table 2 through their standard deviation, is also considerably reduced (with the

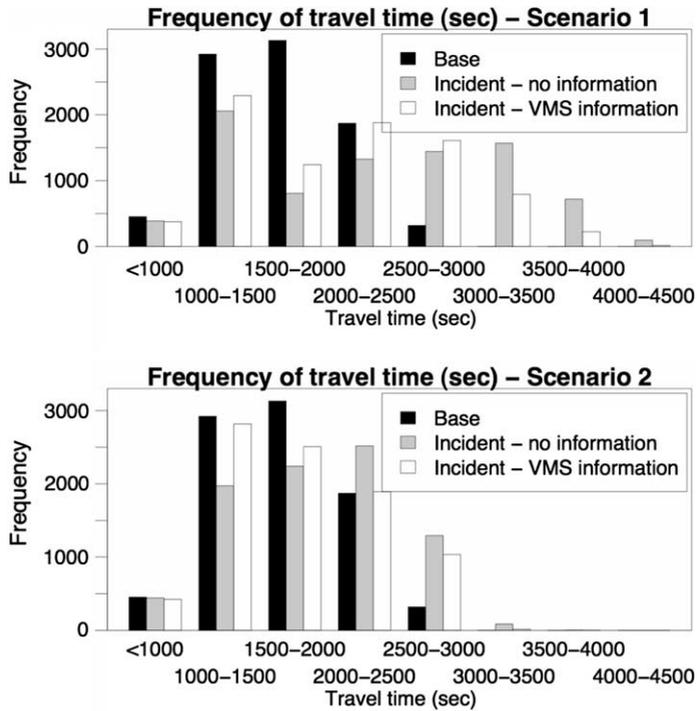


Figure 5. Frequency of experienced travel times.

exception of the time interval 9:00–9:15 a.m.). As a result of the incident in the second scenario, average travel times for travellers departing between 7:45 and 9:00 a.m. have increased by 11–23%. After using VMS messages, the average travel times for these departure time intervals have increased by only between 4% and 16% (relative to the no-incident base case). Furthermore, the variability of the travel times is also considerably reduced (with the exception of the time interval 7:45–8:00 a.m.).

5. Conclusions

This paper has discussed the impact of predictive guidance in reducing average travel time and travel time variability during incidents. A framework for the development of incident scenarios and diversion strategies was presented and a traffic estimation and prediction model, DynaMIT-P, was used to demonstrate its application. DynaMIT-P is capable of simulating and evaluating a wide range of ATIS systems and information generation strategies.

The core of this paper is an extensive case study in the network of Lower Westchester County, NY. The DynaMIT-P system was calibrated to capture the base case conditions and the impact of two incident scenarios. The results of the case study showed that predictive VMS is effective in incident scenarios as it shifts a significant number of vehicles from routes with higher travel times to routes with lower travel times, resulting in more efficient utilization of the network capacity and consequently reduction in delays. Furthermore, the variability of the experienced

Table 2. Average travel time and standard deviations.

	Average travel time (seconds)			Travel time standard deviation (seconds)		
	Base	No info	VMS	Base	No info	VMS
Scenario 1						
7.00–7.15	1057	1098	1052	92	224	90
7.15–7.30	1271	1474	1252	117	389	121
7.30–7.45	1503	1719	1484	185	315	145
7.45–8.00	1750	2031	1827	184	197	200
8.00–8.15	1869	2294	2164	212	397	351
8.15–8.30	2088	2315	2228	295	454	375
8.30–8.45	2164	2399	2302	310	427	365
8.45–9.00	2075	2307	2230	302	446	339
9.00–9.15	1869	1998	1875	366	384	273
9.15–9.30	1442	1650	1462	317	327	192
Total	1665	1890	1750	455	578	526
Scenario 2						
7.00–7.15	1057	1098	1052	92	224	90
7.15–7.30	1271	1474	1252	117	389	121
7.30–7.45	1503	1719	1484	185	315	145
7.45–8.00	1750	2031	1827	184	197	200
8.00–8.15	1869	2294	2164	212	397	351
8.15–8.30	2088	2315	2228	295	454	375
8.30–8.45	2164	2399	2302	310	427	365
8.45–9.00	2075	2307	2230	302	446	339
9.00–9.15	1869	1998	1875	366	384	273
9.15–9.30	1442	1650	1462	317	327	192
Total	1665	1890	1750	455	578	526

travel times is reduced as a result of the provision of predictive guidance through ATIS infrastructure.

As the case study does not cover all aspects of the presented methodology, further applications could be targeted in covering these aspects, such as adapting the OD matrix to capture special events or modeling of the information provided by HAR and IVU. Further research may also focus on the application of this approach in conjunction with methodologies for optimal placing of VMS in the network or for the optimization of response strategies due to incidents.

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