■ 論 文 ■

# Using Traffic Prediction Models for Providing Predictive Traveler Information : Reviews & Prospects

## 교통정보 제공을 위한 교통예측모형의 활용

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목 차



요 약

본 논문은 현재 및 가까운 미래에 있을 교통정보의 제공에 관한 일반적인 가능성으로서 교통현상의 기술이 가능한 교통예측모형의 사용에 대한 총체적인 정리를 함과 함께 바람직한 모형의 제시가 주요 목적이다. 이를 위하여 우선 동적교통배정모형, 통계모형, 모의실험모형, 및 휴리스틱모형이 어떻게 교통정보제공을 위해서 사용될 수 있는지를 각 모형별 제반 특성적 측면에서 검토를 한다. 다음에 이러한 모형의 각종 요구사항이 분석되며, 더나아가 단기간 교통상황을 예측하기 위한 각 모형의 능력 및 장단점이 서술적인 관점에서 기술되어진다. 마지막으로, 이러한 각각의 장점을 수용할 수 있을 만한 포괄적인 예측모형의 전형이 그러한 모형을 구축함에 있어서 필요로하는 데이터의 요구조건과 함께 제시된다.

## Ⅰ. Introduction

In recent years, various ITS operational demonstration projects have been deployed worldwide in places like Chicago, Paris and Tokyo. The success of ITS subsystems such as Advanced Traveler Information Systems (ATIS) and Advanced Transportation Management Systems (ATMS) depends on the availability and dissemination of accurate and timely estimates and predictions of traffic conditions. Current ATIS depends almost exclusively on static and near-real time information. The next generation of ATIS systems will exploit the potential of traffic prediction models to develop value-added traveler information.

Traveler information providing is gradually becoming one of the corner stones of the ITS industry. While it is difficult to predict when the traveler information market will take off, various public agencies and private companies are investing significant resources to develop and operate various ATIS systems. As identified in the ITS user services, the predictive traveler information is indispensable, partly due to the following reasons: 1) the lack of sufficient sensoring devices to collect enough real-time information to cover major freeway and arterial streets; 2) the need to proactively predict traffic congestion and disseminate the predicted congestion information to travelers.

Although predictive traveler information is so important, there exists a big gap between the ATIS practitioners and researchers in terms of how the predictive traveler information should be obtained and disseminated. To bridge this gap, the objective of this paper is to identify the functional requirements and capabilities of prediction models with some near-term and mid-term perspectives for providing predictive traveler information in ATIS practice. This paper will also offer some insights and predictions on how the ATIS information providing, especially the predictive traffic information providing, would evolve based on the experiences of Information Service Providers (ISP) and ATIS modeling specialists.

The current practices of traveler information providing are first reviewed in Section 2. The perspective of near term and mid term practices of traveler information providing is offered in Section 3. The traffic prediction models are reviewed in Section 4. To develop operational prediction models for a traveler information system, the functional requirements, capabilities, and data needs must be defined. In this paper, these functional requirements and capabilities will be summarized in Section 5. A comparison of functional requirements and capabilities of these prediction models will be provided as well. In this comparison, a specific analysis will be made in terms of the advantages and disadvantages for each type of models. Furthermore, the roles of all prediction models will be discussed. Consequently, how the four types of prediction models can be integrated in an operational traffic prediction system will be investigated in Section 6. The data needs of the prediction models will be summarized in Section 7. Finally, some concluding remarks are presented in Section 8.

## Ⅱ. Current and Expected Future Traveler Information Providing Practices

Currently, traveler information providing is based on either static/historical information or real-time information. Almost no predictive traveler information is offered by either public transportation agency or Information Service Providers (ISP). 〈Table 1〉 presents the types of currently available multi-modal traveler information.

As outlined in the ITS System Architecture both in Korea and US, the ATIS system will evolve from real-time traveler information dissemination to real-time route guidance and route choice coordination in the next decades. Although the ultimate goal is clearly identified, it is unknown

〈Table 1〉 Types of Currently Available Multi-Modal Information

| Facility Classification | Information Type | | | |
|---|---|---|---|---|
| **Highway** | Static | Historical | Real-Time | Predictive |
| Freeway | √ | √ | √ | |
| Toll Road | √ | √ | | |
| Primary Arterial | √ | | | |
| Secondary Arterial | √ | | | |
| Local Street | √ | | | |
| **Others** | | | | |
| Bus | √ | | √* | √* |
| Subway | √ | | | |
| Other Rapid Transit | √ | | | |
| Ride Sharing | √ | | | |
| Railway | √ | | | |
| Transit Terminal | √ | | | |
| Airline | √ | | √ | √ |
| Airline Terminal | | | | |

* Available only when dynamic Bus Information System (BIS) is installed

how the current prototype ATIS systems will evolve into mature systems. Many technological and economic factors will affect this evolutionary process. Ultimately, the market needs, especially the traveler needs, will decide this evolutionary path. With some of the ATIS successes and failures in mind and after reviewing the major ATIS/ATMS research efforts, some objective predictions are made in 〈Tables 2-3〉 regarding when various types of highway information and multi-modal traveler information could be made available for major US cities. These tables are not intended to provide some guidelines for ATIS practitioners. But they are presented here in order to offer some perspectives and opinions from some ISP practitioners and ATIS researchers.

In a multi-modal traveler information system, transit information providing is much simpler than highway information providing. Furthermore, other

〈Table 2〉 Types of Multi-Modal Information Available for Near-Term (2-5 Years)

| Facility Classification | Information Type | | | |
|---|---|---|---|---|
| **Highway** | Static | Historical | Real-Time | Predictive |
| Freeway | √ | √ | √ | √ |
| Toll Road | √ | √ | √ | √ |
| Arterial | √ | | | √ |
| Other Arterials | √ | | | |
| Local Street | √ | | | |
| **Others** | | | | |
| Bus | √ | √ | | √ |
| Subway | √ | √ | √ | √ |
| Other Rapid Transit | √ | √ | √ | √ |
| Ride Sharing | √ | | | |
| Railway | √ | √ | √ | √ |
| Transit Terminal | √ | | | |
| Airline | √ | | √ | √ |
| Airline Terminal | √ | | | |

〈Table 3〉 Types of Multi-Modal Information Available for Mid-Term (5-10 Years)

| Facility Classification | Information Type | | | |
|---|---|---|---|---|
| **Highway** | Static | Historical | Real-Time | Predictive |
| Freeway | √ | √ | √ | √ |
| Toll Road | √ | √ | √ | √ |
| Arterial | √ | √ | √ | √ |
| Other Arterials | √ | | | √ |
| Local Street | √ | | | √ |
| **Others** | | | | |
| Bus | √ | √ | √ | √ |
| Subway | √ | √ | √ | √ |
| Other Rapid Transit | √ | √ | √ | √ |
| Ride Sharing | √ | √ | √ | |
| Railway | √ | √ | √ | √ |
| Transit Terminal | √ | √ | √ | |
| Airline | √ | √ | √ | √ |
| Airline Terminal | √ | √ | √ | |

modes, such as airline, would be much easier to provide various static, historical, real-time, and predictive information than highway. Therefore, in the following discussion, the major focus on predictive traveler information will be put on highway instead of other modes.

## Ⅲ. Review of Traffic Prediction Models

The traffic prediction models for a Traffic Information System will mainly provide predictive information on link travel time and route travel time as well as link/route flow variables. In these models, links represent streets and nodes represent intersections. To achieve on-line real-time operations, these models must be easy, fast, and reliable. Furthermore, it is desirable that the output or outbound forecast information on link/route travel times would have prediction probability of accuracy, which is similar to weather forecast. To serve a traveler information system, there are basically four types of prediction models: 1) Dynamic Traffic Assignment (DTA) models; 2) statistical models; 3) simulation models; and 4) heuristic models. Among these models, the DTA models and statistical models are expected to be the most promising for providing short term travel time prediction and forecasting. This is because two models are sound in mathematical background, more adaptable to reproduce traffic trends, manageable in handling the data and outputs, and more realistic in representing the real-world demand and supply conditions. These models will be reviewed in the following.

### 1. Dynamic Traffic Assignment (DTA) Models

With the support of the Federal Highway Administration and the management of Oak Ridge National Laboratory, the development of a real time dynamic traffic assignment (DTA) system is currently under way. For a DTA model, the fundamental route choice behavior is based on the following criterion that each traveler uses the route that minimizes his/her actual travel time when departing from the origin to his/her destination. This route choice criterion is termed ideal *dynamic user-optimal* (DUO). For any O-D pair, under ideal DUO route choice conditions vehicles departing the origin at the same time must arrive at the destination at the same time.

In a basic DTA problem, it is generally assumed that the time-dependent origin-destination trip pattern is known *a priori*. In other words, the departure times of travelers are given. The ideal *dynamic user-optimal* (DUO) route choice problem is to determine the dynamic trajectories of link states and inflow and exit flow at each instant of time resulting from drivers using minimal-time routes, given the network, the link travel time functions (or link travel time determination method) and the time-dependent O-D departure rate requirements. Other types of DTA problems are generalizations based on different applications and purposes. For each of the applications, a DTA model may have a different set of data needs and computational requirements. For example, the use of DTA models for planning/evaluation purposes can afford to have longer computer run-times and more specific data inputs. However, for on-line prediction, computer run-times and data inputs may be under more stringent requirements.

There are in general two different approaches for developing DTA models: simulation-based or analytic-based, depending on the formulation approach, solution property and modeling granularity. Many of the existing DTA models belong to the first category (Mahmassani et al. 1993, and Ben-Akiva et al, 1997). More or less, each of the simulation DTA models premises on the assumption that vehicles are assigned to their individually-determined time-dependent minimal travel time routes. Some simulation models use more general assumptions which are based on time-dependent minimal travel cost or marginal cost route searching and assignment. The simulation DTA models contend that their approaches would approximate the dynamic user-optimal (DUO) or dynamic system-optimal (DSO) route flows and route travel times. However, there is no guarantee that simulation DTA models will actually arrive at the optimal solution with DUO or DSO properties, or even at a solution with well-understood properties. For example, the final solution often changes by simply changing the random seed numbers associated with the simulation. Since traffic management or control always assume some sort of objective, such as minimizing total system delay, the lack of well-defined solution properties of simulation DTA models is a major modeling deficiency.

The second approach is analytic-based dynamic traffic assignment models. Contrary to simulation DTA models, solutions of analytical DTA models have well-defined and understood properties for both the DUO and DSO cases. This is a very important point because it is generally believed that DUO and DSO route flows and route travel times are fundamental to the prediction and control of traffic management systems, especially for dynamic route guidance and traffic signal control purposes. In contrast to their superior solution properties, one major drawback of analytical DTA models lies with their simplification of some complex traffic representations.

In several sophisticated simulation and analytical DTA systems, travelers are stratified into several classes, depending on their route choice criteria. For instance, travelers can be stratified into three classes as follows: (i) predetermined or fixed routes; (ii) stochastic dynamic user-optimal principle (SDUO); and (iii) dynamic user-optimal principle (DUO). Class (i) represents travelers who either do not have real-time traffic information and hence continue their intended routes, or refuse to change their routing plans. Class (ii) can be used to describe those who determine their routes according to what is perceived to be the lowest travel time when they depart. Class (iii) represents travelers who have access to real-time traffic information, and are able to evaluate route choice attributes identically and without error. The details of this travelers classification can be referred to Ran et al (1996) and Peeta and Mahmassani (1995).

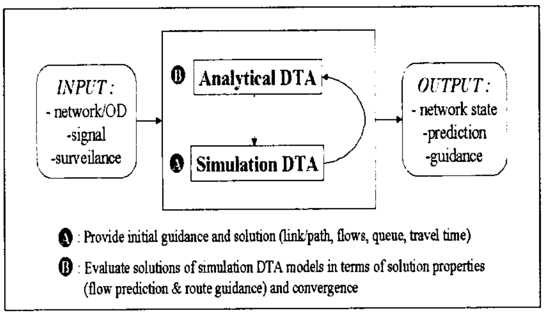
There are many similarities and differences between analytical DTA models and simulation DTA models. The fundamental differences of the two types of models could be summarized in terms of two aspects: 1) solution granularity and 2) solution property. In general, the solution granularities of the two types of DTA models are determined by their natures. By definition, simulation DTA models are microscopic or mesoscopic and analytical DTA models are macroscopic. If simulation DTA models use the analytical DTA approach to ensure its solution property and convergence, it will become an analytical DTA model. On the other hand, if an analytical DTA model considers the detailed vehicle movement and uses the granularity of simulation DTA models, it will approach the simulation DTA model. However, its computational complexity will increase. While it is unfeasible to develop a super model to include all the advantages of both analytical DTA and simulation DTA models and avoid the disadvantages of both models, it is reasonable to develop both types of models in parallel and develop an interface in-between to ensure that the advantages of both types of models could be reserved and utilized in an integrated DTA system.

It is desirable that the analytical DTA models could be used to define simulation boundaries for simulation DTA models so that each simulation iteration is implemented in a much smaller and well-defined region. Furthermore, it is also desirable that the analytical DTA models could be used to define the solution direction for simulation DTA models so that each simulation iteration is implemented in the right direction toward the desired optimal DTA solutions. The intermediate solution points of simulation are determined and evaluated by using the analytical DTA models. In the meantime, the solution boundaries for the simulation are also determined by using the analytical DTA models. This will present a good integration of both analytical DTA models and simulation DTA models so that advantages of both models could be utilized and disadvantages of both models could be avoided. In other words, the analytical DTA models could be used as a benchmark evaluation tool for simulation DTA models, while simulation DTA models could be used to provide vehicle-specific routing and prediction. But the possible incompatibilities between these two kinds of models are expected and should be taken care of when we try to integrate them into one system.

In the following, some recommendations for future studies will be presented to implement such an integration. At this point in time, it is important that both approaches should be given equal opportunity for further development. Given the brisk pace of the development of faster computers, and the possibility of building better solution algorithms, it is optimistic that the integrated DTA system will become a standard tool for providing predictive traffic information in a traveler information system in a few years.

It is also important that the roles of both analytical and simulation DTA models in an integrated operational DTA system are analyzed and an integrated system of both analytical and simulation DTA models is developed. To serve the need of developing an operational DTA system, it is desirable to ensure that the current simulation DTA models have valid solution properties. In other words, it is necessary to guarantee that the solution process of the simulation DTA models will lead to the desired optimal DTA solution in a reasonably fast speed. An integrated approach should be designed to ensure such a solution process. Furthermore, the analytical DTA models could be further refined to serve the needs of evaluating the simulation DTA models.

As shown in ⟨Figure 1⟩, in an integrated DTA system, analytical DTA models could be used as a benchmark evaluation tool for simulation DTA models. For example, analytical DTA models could function as a target for dynamic route guidance. An analytical DTA model could provide a solution of dynamic routing based on either dynamic user-optimal (DUO) or stochastic dynamic user-optimal (SDUO) criterion. The dynamic O-D matrices and state estimates from the dynamic state estimators are used as input for the analytical DTA model. After the analytical DTA model solves either DUO or SDUO link flows and travel times, it generates DUO or SDUO routes and corresponding route flows for each O-D pair. The generated routes and route flow information are used as binding criterion for the simulation DTA model. The simulation DTA model then implements detailed route and link flow assignment and generates a new set of route flows and link flows. After the simulation DTA model finishes its iterations, the synchronization and consistency check module compares the DUO or SDUO routes and route flows from both analytical DTA model and simulation DTA model. If there is a large discrepancy, the simulation DTA model needs to be executed again and a new loop needs to be completed. If the discrepancy is acceptable, then output from the simulation DTA model is used as the network traffic prediction and the routing plan for dynamic route guidance.




⟨Figure 1⟩ Integration of Analytical DTA and Simulation DTA Models (Ran, 1997)

## 2. Statistical Models

The statistical models use the information on flow conditions in the immediate past to estimate future values of travel time and flow. The statistical models predict traffic flow characteristics by identifying regularities in traffic flows and traffic flow patterns over time. Statistical models may be based on information from a single link or from multiple links. The single link models predict flow on a link from previous flow data on that link. Multiple link models predict flow on a link from flow data on that link and neighboring links. When link flow is determined, the link travel time can be calculated by using link travel time function.

As a simple statistical model, the historic profile approach is based on the assumption that an historic profile can be developed for volume or travel time for each link, which represents the average traffic characteristics at each time period over days which have a similar profile. An important component of the historic approach is the classification of days into day types with similar profiles.

### Single Link Models

The statistical models for single link can be further stratified into: 1) time lag models; and 2) models with dynamic adjustment. Time lagged linear models use previous time period values of flow on a particular day to predict future flow values on the same day. These models assume that the relationship between the current and past flow values is invariant with respect to time. For instance, the time series methods can be used for short-term volume forecasting and a typical Box-Jenkins analysis can be used for occupancy and volume data analysis. Kim (1994) reviewed this type of traffic prediction researches and Davis and Nihan (1991) used k-nearest neighbor approach (k-NN), which is a non-parametric regression method, in forecasting the freeway traffic. Danech-Pajouh and Aron (1991) devised a variation of statistical method for predicting urban motorway traffic using three step analysis, comprised of the analysis of historical data, modeling, and forecasting activities.

The time lag models could be enhanced with classification of day types and traffic conditions. This approach is a time series analysis in which the available data is classified into categories according to pre-selected criteria and a separate model is estimated for each category.

With the day type classification, the type of day is used as a primary factor for classifying the data. The classification can be based either on a-priori expectations that there are differences between day types or can be based on analytic classification using cluster analysis techniques or other similar methods. The idea of clustering similar day patterns is appealing. However, when used for prediction, the problem with this approach is that it is difficult to identify the appropriate day class using data from a small number of time periods at the beginning of the current day. Thus, the day classification may only be available too late in the day to support the prediction procedure.

With classification based on traffic conditions, this approach classifies the data based on a comparison of conditions with previously defined traffic condition patterns. For example, the classification scheme could be based on the cause of congestion:

a) Spontaneous congestion, which occurs without any decrease in traffic capacity.
b) Accident congestion.
c) Maintenance congestion.

Instead of having a discrete classification scheme with separate models to represent different relationships among classes, the statistical models with dynamic adjustment use a continuous adjustment of model parameters over time. The approach is based on the premise that time-variate models can provide better predictions than time-invariate models.

Multiple Link Models

The multiple link model is an extension of the single link model, where traffic flow prediction on a link is based on previous flow information from that link and from other neighboring links. The neighboring links may be upstream or downstream links, or may comprise all links in the immediate vicinity of the link under consideration. In general, the cross-correlation techniques, non-parametric regression method, and the Kalman filtering approach can be used. Basics of Kalman Filter and some applications can be referred to Grewal and Andrews (1993) and Okutani and Stephanedes (1984), respectively.

A major problem with single-link and multiple-link models is that the predictions generated by these methods tend toward the mean value of flow. Thus, these approaches tend to stop (or reverse) the development of any trends during prediction. Consequently, the models may not be useful in situations where there is a trend in the volume profile over an extended period of time, such as when upstream flow increases in the presence of a downstream incident.

ADVANCE Model

The ADVANCE Project (Sen et al, 1993, and Liu and Sen, 1994) has developed a very comprehensive statistical travel time prediction model. In the ADVANCE statistical model, expected travel time over a given time interval is viewed as a sum of three components: one component that can be estimated long in advance, based on day-type, time of day, etc.; a second component that can be added to the first component and can be forecast based on quantities known just before the forecast is made; and a third component that needs to be treated as randomly varying. The most dominant part of this last component is due to traffic signal cycles. An unbiased estimate of the first component is called a static estimate and an estimate of the sum of the first two components is called a dynamic estimate. An estimate of the first component may be used as a default estimate when the second component is not available.

An on-line travel time prediction procedure has been developed in the ADVANCE model, which is used for various scenarios, including road closures, presence of incidents, and absence of road closures and incidents.

## 3. Other Prediction models

Simulation Models

Rigorously speaking, simulation models cannot be used for traffic flow prediction purposes as they require the input of traffic flow values for the simulation time period and lack of the dynamic route choice behavior considerations. However, simulation models provide a method to estimate travel times once traffic flow volumes have been predicted by other means. In other words, simulation provides an alternative to field calibration of the relationship among flow, occupancy, and travel time. While it is possible to envision a case where a simulation model can be implemented in real time (i.e., receiving flow predictions, simulating the network, and producing travel time predictions), none of today's candidate models such as TRAF-NETSIM (Rathi and Santiago, 1989) or SATURN (Van Vliet, 1987) are suitable for real-time implementation. Changes in the structure of the source code and modeling philosophy must be considered to render such models useful for on-line applications.

More recent versions of simulation models may include INTEGRATION (Van Aerde et al., 1992), CONTRAM (Leonard et al., 1989), and DYNASMART (Mahmassani and Peeta, 1992). The INTEGRATION model assigns vehicles sequentially to paths by taking into account the congestion caused by the vehicles already assigned to the network. As the vehicles reach intersections, the paths of vehicles are reassigned based on the travel times at that instant. Hence, the model keeps reassigning paths based on instantaneous travel times. Nonetheless, the model has depicted the computational feasibility of the combined assignment/simulation approach. The CONTRAM model iteratively assigns packets of vehicles to paths after accounting for the dynamic travel times due to the congestion by other vehicles on the network. The iterations are continued until suitable convergence criteria have been met or the paths do not change from the previous iteration. The path of each packet is simulated to update the queues and the travel times before the assignment of the next packet. Although not bad in performance, the model is only quasi-dynamic in the sense that it has relatively long time intervals. The variations in driver behavior are not addressed satisfactorily in the model. Finally, the DYASMART model, with some modifications attached recently, basically captures the details of the traffic and network characteristics. The dynamic travel times along the links generated by the simulation model are used in determining the dynamic shortest paths while assigning flows to paths in the assignment model The paths determined by the assignment model are used in the simulation model to move vehicles between origins and destinations. This iterative scheme is repeated until the convergence is achieved. The model can deal with a mix of drivers with and without routing information and with different driver behavior patterns. A shortcoming in this model is its inability to properly utilize the real-time sensor information.

In some cases, simulation models can be used for prediction purposes for small freeway corridors under stringent conditions. This would require the refinement of the simulation models. The simulated predictions are expectations of travel times. Simulation models can account for the control environment in which trips take place, including traffic signals, stop signs, lane channelization, and the like. These features provide some advantages for simulation models to play a role in prediction problems for freeway corridors with few or without route choice options and OD requirements.

#### Heuristic Models

The heuristic models are similar to the statistical models except that heuristical rules are used for the predication of flow variables instead of formal statistical models. For example, Hoffmann and Janko (1990) used the historical profile as the basis for a heuristic short-term prediction procedure. Dougherty et al (1992) investigated the use of neural networks in predicting traffic flow. One of the major advantages of the heuristic models is the computational requirements and CPU time are relatively small. Moreover, this approach is flexible in specifying the projected flow pattern given information up to the current time interval. The flexibility arises from the ability to formulate different heuristic rules corresponding traffic flow patterns in recent periods. The criteria for determining appropriate projection profile can be based on an expert system. Heuristics also have been employed to solve the nonconvex optimization formulations as is the case in analytical model. As an example, Janson (1991) has developed a heuristic to get an approximate solution to the optimization formulation. The properties of this type of heuristics are not well understood and it can lead to anomalous results. The heuristic employs the same simple flow relationships used by the optimization formulation.

## Ⅳ. Functional Requirements and Capabilities of Prediction Models

〈Table 4〉 summarizes the functional requirements and capabilities for on-line prediction models. These requirements and capabilities are presented based on the applications of prediction models for ATIS and ATMS systems. Furthermore, a comparison of the four types of prediction models is conducted. The advantages and disadvantages of the models could be shown. Depending on the application purpose, some prediction models may be more suitable that others. Specifically, DTA models have superior solution properties, but are complex to develop, require substantial computational requirements, and are difficult to understand. Statistical models have their advantages: they are relatively easy to develop, have small computational requirements, and permit understanding even to the novice. The major drawback of statistical models is that they cannot perform network-wide prediction. Simulation models are relatively easy and have milder-to-large computational requirements. But their major drawback is that no dynamic route choice behavior is considered. Thus, its application in traffic prediction is limited to well-defined freeway segment or corridor where route choice is minimized. The major advantages of the heuristic models are that the computational requirements and CPU time are relatively small, and the approach is flexible. However, the major drawback is defined by its own nature--lack of well-defined solution properties and have heuristic criteria only.

There are many unsolved issues associated with the on-line prediction models. The functional requirements and capabilities basically illustrate the majority of these issues. Among them, there are some urgent ones which should be solved in near term in order to be applied for on-line prediction.

〈Table 4〉 Functional Requirements and Capabilities of Prediction models

| | DTA Model | Statistical Model | Simulation Model | Heuristic Model |
|---|---|---|---|---|
| ◆ **Representation of Network Traffic** | | | | |
| - Flow conservation/propagation | √ | | √ | |
| - Queue, oversaturation and spillback | √ | | √ | |
| - First-In-First-Out (FIFO) | √ | | √ | |
| - Background traffic (predetermined routes, transit, HOV, etc.) | √ | | √ | |
| - Empirical/analytical travel time functions by turning movements: freeway, arterial, ramps, etc. | √ | √ | √ | √ |
| - Traffic signals/ramp controls | √ | | √ | |
| - Temporal travel demand and supply | √ | | √ | |
| - Capacity changes from incidents, lane closures and changes of signal timing | √ | √ | √ | √ |
| - Various information dissemination strategies: CMS, RF broadcasts, route guidance, etc. | √ | | √ | |
| - Market penetration of ATIS equipment | √ | | √ | |
| ◆ **Traveler Behavior/Characteristics** | | | | |
| - Dynamic user-optimal (DUO) route choice | √ | | | |
| - Multi-class of travelers: ATIS equipped vehicles, knowledge of network, age, HOV, compliance, etc. | √ | | √ | |
| - Multi-class of drivers: aggressive, cautious, etc. | √ | | √ | |
| - Multi-class of vehicles: car, truck, bus, HOV (restricted use of lane/roads) | √ | | √ | |
| - Utility functions: weighting travel time, operating cost, preferences | √ | | | |
| - Different route choice criteria: fixed route | √ | | √ | |
| - Different route choice criteria: Stochastic DUO | √ | | | |

〈Table 4〉 Functional Requirements and Capabilities of Prediction models (Continued)

| | DTA Model | Statistical Model | Simulation Model | Heuristic Model |
|---|---|---|---|---|
| ◆ **Theoretical Foundation** | | | | |
| - DUO route choice models (Time-dependent shortest-path and routing coordination under congestion) | √ | | | |
| - Routing based on current and predicted network conditions (look-ahead) | √ | | | |
| - Stochastic dynamic user-optimal: randomness of link travel times or capacities, knowledge, compliance, perceptions, etc. | √ | | | |
| - Departure/arrival time choice | √ | | | |
| - Mode choice | √ | | | |
| - Destination choice - trip distribution | √ | | | |
| - Combined dynamic travel choice | √ | | | |
| - Combined with congestion pricing | √ | | | |
| ◆ **Computational Issues** | | | | |
| - CPU times: (a) short, (b) medium, (c) long | (b)-(c) | (a) | (b)-(c) | (a) |
| - Hardware platform: workstation, PC | √ | √ | √ | √ |
| - Memory requirement | large | Small | Large | small |
| - Applicable networks | large | N/A | Small | N/A |
| ◆ **Deployment/Application: How can TIC use these models?** | | | | |
| 1) On-Line Application | | | | |
| a) Real-time information acquisition and assimilation | √ | √ | √ | √ |
| b) Synthetic O-D | √ | | √ | |
| c) link travel time functions/capacities | √ | √ | √ | √ |
| d) Fusion with other models for providing link travel times, queues and flows | √ | √ | √ | √ |
| e) Compatible with real-time ATMS control strategies (signal/ramp control) | √ | | √ | |
| f) Interact with information sources (probes, surveillance systems, historical data, etc.) | √ | √ | √ | √ |
| g) Interact with field validation/correction module | √ | √ | √ | √ |
| h) Interface with other ATMS/ATIS modules (surveillance, incident detection, control) | √ | √ | √ | √ |
| 2) Calibration: adjustment of model output vs. real time data | | | | |
| a. Self calibration | √ | √ | √ | √ |
| b. Run time consideration | √ | √ | √ | √ |
| c. Rolling horizon procedure | √ | | | |
| d. Other considerations: | | | | |
| a) Adaptable to various TIC/TMC architectures (distributed, decentralized, centralized, etc.) | √ | √ | √ | √ |
| b) User-friendly interface | √ | √ | √ | √ |
| c) Adaptive or en-route routing (from current origin to destination) | √ | | | |
| 3) Post route generation: create time-dependent shortest routes under congestion after solving models | √ | | | |

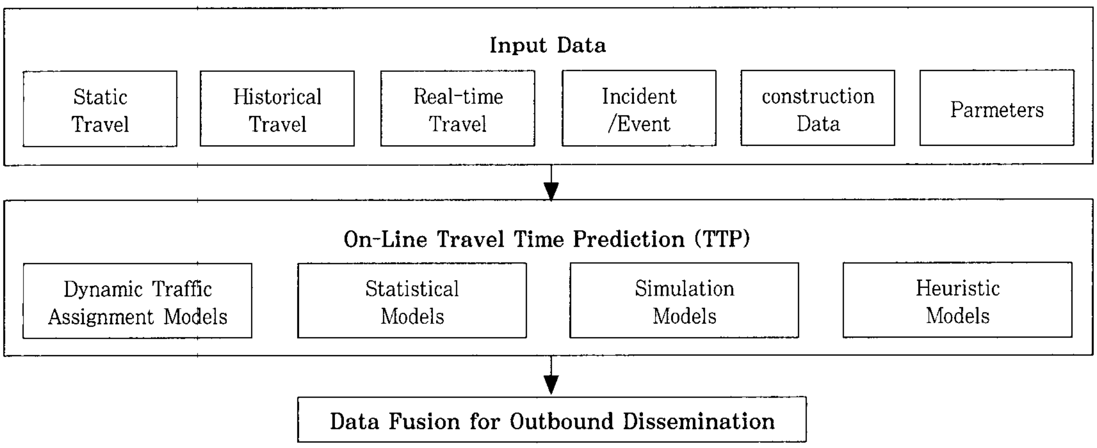
〈Table 4〉 Functional Requirements and Capabilities of Prediction models (Continued)

| | DTA Model | Statistical Model | Simulation Model | Heuristic Model |
|---|---|---|---|---|
| ◆ **Future Potential Applications** | | | | |
| - Real-time interface with traffic control strategies | √ | | √ | |
| - Simultaneous optimization of prediction/ routing and traffic control/coordination (ramp metering, signal control, etc.) | √ | | | |
| - Combined prediction for intermodal networks | √ | | | |
| - Prediction for AHS network | √ | | | |
| - Prediction under congestion pricing | √ | | | |

## V. A General Traffic Prediction Procedure

Travel time prediction is the major task in the on-line traffic prediction. To serve this on-line traffic prediction purpose, various input data should be prepared. In other words, the databases of static, historical, and real-time link and route travel times should be obtained. The static link travel time can be estimated by using the link travel time functions or a static traffic assignment model. The route travel time is calculated by adding the static link travel times over the route. Subsequently, the historical link travel time profile can be estimated by using the historical detector occupancy data or other data collected. A time series model could be used to serve this need. The real-time link travel time can be estimated by using the detector occupancy data or other real-time data. The route travel time is calculated by adding the current link travel times over the route. Thus, the route travel time is instantaneous travel time based on prevailing traffic conditions. This is what is used in current practice in traveler information providing.

As shown in 〈Figure 2〉 when the incident data, event data, and construction data are prepared, the on-line prediction could start. The incident/event and construction activity will significantly affect the travel time prediction and result in modifications of some of the prediction models. Furthermore, to use any of the four types of prediction models, the input databases required could be different. The associated parameters are also significantly different. For example, when a dynamic traffic assignment model is used to design this prediction




〈Figure 2〉 Travel Time Prediction in A Traffic Information System module, a time-dependent O-D matrix is required, which is normally not available for the highway network and should be estimated. Sometimes, a combination of the four types of prediction models could be used in one Traffic Information System. For such a scenario, a data fusion process is needed to integrate the output from different traffic prediction models.

Moreover, in order to produce more reliable and accurate predictive travel time information for travelers, a fusion process is necessary to integrate static, historical, real-time, and predictive travel times. This data fusion process could use a fuzzy logic model and take several steps. For instance, the first step in the fusion process is to fuse static and historical link travel time data. The static database normally has a full coverage of the highway network, while the historical database may have sparse coverage of the highway network. In other words, this fusion process is to improve some of the travel time estimates of the static database by using the partial historical database.

There are various real-time travel time information sources for a highway network, including detectors, video camera, and probe vehicles. Some links of the highway network may have overlapping coverage of several real-time information sources, while other links may have only one real-time information source, or may not have real-time information sources at all. This step is to fuse these on-line real-time link travel time data together in order to provide a more complete coverage of the highway network.

Since only one part of the highway network links have on-line travel time data, the travel time prediction models could be used to generate meaningful dynamic estimates and predictions for all highway network links. This step is to fuse the above two databases together in order to produce a new dynamic database which has the full coverage of the highway network.

The final step is to construct dynamic forecast which is equivalent to estimating the difference between static/historical and dynamic travel times. Since future static estimates will be known in advance, the final dynamic travel time forecasts will be generated by fusing static/historical estimates and dynamic estimate/prediction. This dynamic forecast database could be used for outbound dissemination.

## Ⅵ. Data Needs of Prediction Models

Prediction models describe time-dependent processes on a physical system in the near future. Consequently, these models require accurate descriptions of the characteristics of vehicles, the roadway system, and the traffic control system. These elements vary over physical space and time.

Among the characteristics that vary over space are traffic geometry (number of lanes, number and length of turning pockets, etc.), types of links (surface street or freeway), and some elements of traffic behavior (such as gap acceptance). Characteristics that vary over time include traffic volumes, turning movements, travel times, traffic regulations, and signal timing. Route choice decisions will vary over time and space. The input for a prediction model should be arranged to facilitate description of this variation in data. The spatial or geometric description of the traffic environment is represented as a network which consists of a set of link-node descriptions, where links represent urban streets and nodes represent intersections. The temporal or time-dependent components consist of traffic volumes, turn movement percentages, travel times, and parking regulations. These could remain fixed for user specified time periods or intervals.

The input generally begins with a data stream providing a basic description of the run performed (run control). This is followed by a set of data divided into time periods or intervals, each of which has model-specific information for each kind of traffic network or link being studied (model data). The various data records used by a prediction model generally consist of the elements shown in 〈Table 5〉.

〈Table 5〉 Data Requirements for Prediction Models

| Items \ Models | DTA Models | Statistical Models | Simulation Models | Heuristic Models |
|---|---|---|---|---|
| Geo-coding and other GIS data | √ | | | |
| Run control data | √ | √ | √ | √ |
| Reports and output specifications | √ | √ | √ | √ |
| Network data (Zonal data, Link data, etc.) | √ | √ | √ | √ |
| HOV lane records | √ | | √ | |
| Demand data(Time-dependent OD Matrices) | √ | | √ | |
| Traveler behavior parameters | √ | | √ | |
| Ramp control data | √ | | √ | |
| Vehicle characteristics specification | √ | | √ | |
| Traffic parameters | √ | √ | √ | √ |
| Sign and signal control records | √ | | √ | |
| Detector characteristics specification | √ | √ | √ | √ |
| Traffic volumes records | √ | √ | √ | √ |
| Turning movement records | √ | √ | √ | √ |
| Bus operation records | √ | | √ | |
| Approach geometry records | √ | | √ | |
| Incidents, construction, events, and parking maneuver records | √ | √ | √ | √ |
| Surveillance data (detector, probe, video) | | | √ | |
| Graphics records | √ | | √ | |

Several data sources can be used to gather the information needed for prediction model calibration or input. Information on the physical properties can be obtained from GIS database or collected by on-site visits. Such information includes link lengths (measured from stopline to stopline), number of lanes, lane channelization, existence of turning pockets, length and type (right or left) of turning pockets, and locations of detectors. Field traffic flow data is also necessary to be collected for the specific time period of interest in the form of 1-5 minutes or shorter time interval. Entry flows and turning movement percentages can be given for each individual time interval. Traffic conditions are assumed to remain stationary within each time interval. At the same time, signal phasing information can be obtained from an on-line database made available by a Traffic Management Center (TMC).

The effectiveness of any type of strategy applied towards the prediction of traffic congestion depends heavily on the accuracy and the credibility of the data sources used. Among other data sources currently available, loop detector systems can provide large quantities of high quality data, while video camera and probe vehicle can provide supplemental data for better highway information coverage.

Various types of real-time traffic data will be collected from various sources. The real-time traffic data will have different format. Some data may be incomplete or have errors. It is necessary to accomplish the data screening and conversion in order to produce a usable database of real-time traffic data. After collecting the initial raw real-time data from the above various sources, data screening must be accomplished via reasonableness checking. The outliers will be deleted. The real-time data include detector data, incident data, probe data, construction and event data, video data, and qualitative congestion information. The identification of the highway network and data sources has to be coordinated closely with the traveler information dissemination and travel time estimation/prediction. Not all data can be used directly by a Traffic Information Center (TIC) or ISP and their estimation and prediction modules. A standard format has to be specified for all real-time data. Then, all data from the above sources will be converted into one uniform database, which has the real-time information on travel time, speed, incident, construction, and event. The database used in ISPs data dissemination modules and subsequent estimation and prediction software must be consistent with the database developed for the TIC Host Server, which is usually maintained by a public agency or public-private partnership.

## Ⅶ. Concluding Remarks

This paper reviewed current practices of traveler information providing and provided some perspectives regarding the possible near term milestones in traveler information providing. To provide predictive traveler information in the near future, various prediction models are needed. This paper reviewed four types of prediction models: 1) dynamic traffic assignment (DTA) model; 2) statistical model; 3) simulation model; and 4) heuristic model. The DTA model estimates and predicts route flows and route travel times by using time-dependent O-D matrices, travel time functions, and assumed traveler route choice behavior. The statistical model predicts flows or travel times based on analysis from a single link or from multiple links. The simulation model simulates microscopic vehicle movement or macroscopic flow movement on links and in a network so as to predict traffic flows and travel times. The heuristic model is similar to the statistical model, but is based on the formulation of heuristic prediction rules.

The functional requirements and capabilities of the four types of prediction models were discussed and summarized. Some of the advantages and disadvantages of these models were compared with reference to short-term travel time prediction. Furthermore, a comprehensive prediction procedure was presented, which combines the four types of prediction models. The data requirements for each type of prediction model were summarized and compared.

This paper provided some insights into the current and near future traveler information providing. While it is hard to predict which prediction model will prevail in the future, it is generally expected that the DTA model and the statistical model would become the major prediction tools, and the simulation model and the heuristic model will provide a supplemental function in the short term traffic prediction. As shown in the functional requirements and capabilities, the earlier work only provides a foundation for prediction methods and concepts and there is a considerable need for deeper investigation and further development of alternative approaches for short-term travel time prediction.

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