TOWARDS DEVELOPING A TRAVEL TIME FORECASTING MODEL FOR LOCATION-BASED SERVICES: A REVIEW

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TOWARDS DEVELOPING A TRAVEL TIME FORECASTING MODEL WITH GIS FOR LBS: A REVIEW

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Abstract

Travel time forecasting models have been studied intensively as a subject of Intelligent Transportation Systems (ITS), particularly in the topics of advanced traffic management systems (ATMS) and advanced traveler information systems (ATIS). Now, the interests for the travel time forecasting models have been revived, particularly since the market for location-based services (LBS) are foreseen to be rapidly increasing. While the concept of travel time forecasting is relatively simple, it involves a notably complicated task to implement even a simple model. Thus, existing forecasting models are diverse in their original formulations, including mathematical optimizations, computer simulations, statistics, and artificial intelligence. A comprehensive literature review, therefore, would assist in formulating a more reliable travel time forecasting model.

On the other hand, geographic information systems (GIS) technologies primarily provide the capability of spatial and network database management, as well as technology management. Thus, GIS could support travel time forecasting in various ways by providing useful functions to both the managers in transportation management and information centers (TMICs) and private sector brokers for LBS. Thus, in developing a travel time forecasting model for LBS, GIS could play important roles in the management of real-time and historical traffic data, the integration of multiple subsystems, and the assistance of information management.

The purpose of this paper is to review various models and technologies that have been used for developing a travel time forecasting model with geographic information systems (GIS) technologies to be employed for location-based services (LBS). Reviewed forecasting models in this paper include historical profile approaches, time series models, nonparametric regression models, traffic simulations, dynamic traffic assignment models, and neural networks. The potential roles and functions of GIS in travel time forecasting for LBS are also discussed.

TOWARDS DEVELOPING A TRAVEL TIME FORECASTING MODEL WITH GIS FOR LBS: A REVIEW

I. Introduction

It is widely believed that about 80 percent of public and private decisions are related to some sort of spatial and locational consideration, leaving only few areas that are not affected by locational considerations. The Internet puts an unprecedented amount of locational information of all kinds at a user's fingertips, information that can be used for personal production activities in a mind-boggling variety of ways.

The location-based services (LBS) are the new face of the wireless Internet. Advertising and e-commerce consulting firms predicts that by 2005 LBS market will reach \$11-\$15 billion in revenue and as many as one billion Internet-enabled handsets will be in use[1]. With this growth potential, LBS present a substantial emerging market opportunity for wireless providers.[2]

While the market for LBS seems to be a rapidly emerging and some initial, but primitive services have been introduced in the market, there are many basic issues that have yet to be researched and developed in order to provide efficient services for users and providers. Upon reviewed technologies that made LBS feasible, the paper focuses on developing interface standards for multi-modal routing and navigation services for LBS as the international standard for the international organization for standards (ISO).

Travel time forecasting models primarily have two functional areas in LBS applications: traffic management and traveler information. While travel time forecasting systems assist in avoiding delayed controls of traffic flow in traffic management, predicted travel time information can support commercial vehicle operators and individual travelers who seek appropriate travel routes.

In general, travel time forecasting tasks are initiated by forecasting future traffic conditions such as traffic volumes, speeds, and occupancies, and thus research that deal with traffic

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[1] See Jim VanderMeer, 2001, "Location Content Drives Wireless Telecommunications", http://www.geoplace.com/bg/2001/0201/0201pay.asp
[2] http://www.isotc211.org/

forecasting is directly related to travel time forecasting. Future travel times can be directly predicted or indirectly estimated after forecasting traffic data, depending on the types of real-time data that comes from various traffic surveillance systems such as closed-circuit video cameras, loop detectors, and probe vehicles. For instance, loop detectors installed on highways can transmit traffic volume~~s~~ and speed~~s~~ to traffic management information centers (TMICs) or LBS brokers. Thus, future travel time information can be estimated after future traffic conditions are predicted, or future travel time can be predicted using estimated travel time information that is based on collected raw traffic data. Probe vehicles on arterial roads, on the other hand, can transmit link travel times as raw data to TMICs. Thus, future travel times can be predicted directly using the transmitted travel time data.

II. What is LBS?

LBS – sometimes called location-based mobile services (LBMS) – is an emerging technology combining information technology, GIS, positioning technology, ITS technology and Internet. LBS combine hardware devices, wireless communication networks, geographic information and software applications that provide location-related guidance for customers (see Figure 1). It differs from mobile position determination systems, such as global positioning systems (GPS), in that LBS provide much broader application-oriented location services, such as the following:

> “You are about to join a ten-kilometer traffic queue, turn right on Washington Street, 1 km ahead.”
>
> “Help, I’m having a heart attack!” or “Help, my car has broken down!”
>
> “I need to buy a dozen roses and a birthday cake. Where can I buy the least expensive ones while spending the minimum amount of time on my way home from the office?”

A typical example of LBS for personal navigation would include the followings:

A. Entering address to desired destination (Geocode).
B. Subscriber wishes to start from their current position and add one stop along the way (Gateway).
C. Determining the route (Route Determination).
D. Presenting route summary to subscriber.

E. Presenting turn-by-turn directions to subscriber.
F. Subscriber wants to see a map overview with the route shown (Presentation).
G. Subscriber is now in transit and wants to see maneuvers (Gateway and Presentation).

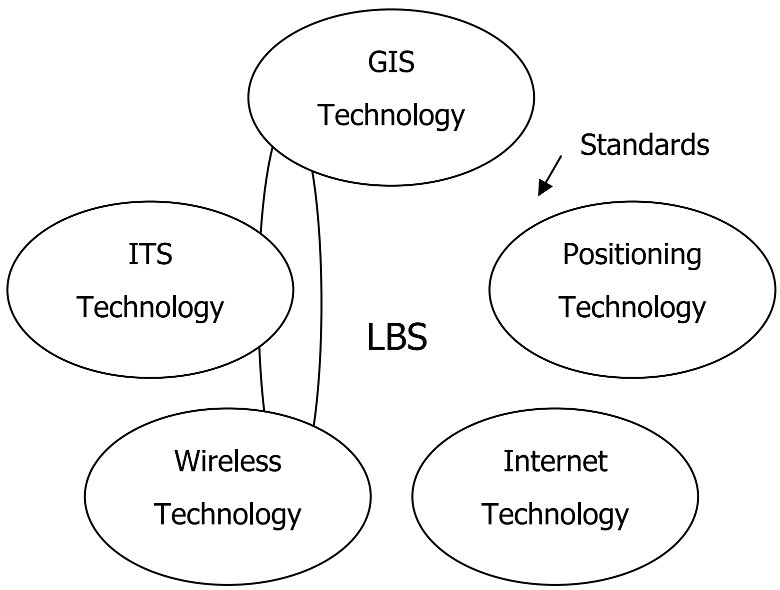

Figure 1: Technology Context of LBS

A typical example of LBS for finding Point of Interest (POI) would include the followings:

A. Subscriber wants to go to a nearby pizza restaurant. The address may be known (Gateway)
B. Subscriber wishes no more than 10 selections and no more than 2 miles from their current location.
C. Now search an online directory containing local restaurants (Directory)
D. The 10 restaurant choices are displayed. The subscriber’s position is also shown using such as a star (Presentation)
E. The subscriber selects a nearby location (Presentation).
F. Subscriber also selects starting address and obtains its location (Reverse Goecoding)
G. Determine the fastest route from starting location to the restaurant (Route Determination)
H. Subscriber displays the route and begins the trip to the restaurant (Presentation).

While most of these services are either available or will soon become available by commercial providers of LBS, the followings issues need to be researched for providing efficient and accurate location-based services for personal productivity:

1. Utilization of Real Time Data in Spatio-Temporal Context in GIS
2. Development of Spatio-Temporal Topology in GIS.
3. Development of Efficient Means to handle Large Data Set for LBS
4. Interoperability among Contents Providers and Interface Standardization for Efficient Request-Response Services.
5. Efficient and Cost-effective Means to collect Real-Time traffic data.
6. Development of Alternative Theories for utilizing Population Data vs Sample Data in GIS
7. Development of routing and navigation models for LBS
8. Development of Heuristic Solution Algorithms for routing and navigation models for LBS.

Among those, the following sections describe issues related to providing services for routing and navigation in LBS and issues related to solving such complex functions in few seconds to be able to respond to users' requests.

3. Travel Time Forecasting in ITS

While many researchers have studied travel time forecasting issues (Sen et al., 1997; Palacharla and Nelson, 1995; Sisiopiku et al., 1994; Yasui et al., 1994; Shbaklo et al., 1992), a number of researchers (Smith and Demetsky, 1997; Uchida and Yamasita, 1997; Ben-Akiva et al., 1995, 1994, 1993; Camus et al., 1995; Kaysi et al., 1993; Vythoulkas, 1992; Davis and Nihan, 1991; Moorthy and Ratcliffe, 1988; You and Kim 1999, 2000) have also studied traffic forecasting issues due to various types of real-time traffic data. This research focuses on both traffic and travel time forecasting efforts, so that a travel time forecasting model can be applied for a broad range of real-time traffic data types.

Among various ITS applications, there are two important applications that can primarily and immediately utilize travel time forecasting models for LBS: advanced traffic management systems (ATMS) and advanced traveler information systems (ATIS). In conventional ATMS and ATIS applications, which do not consider travel time forecasting, both applications estimate current travel time. Real-time traffic data are transmitted from traffic surveillance systems to TMICs.

Transmitted real-time traffic data are processed and current link travel times are estimated. Estimated link travel times are disseminated within TMICs and sent to external users via communication networks, including local area network (LAN), the Internet, and wireless communications.

Nonetheless, these estimated current travel times from conventional ATMS and ATIS are not exactly current when users utilize them on road networks. In fact, these estimated travel times are delayed information in a strict sense due to the dynamic nature of network traffic. Without exception, traffic conditions change rapidly and dynamically as time goes by, and thus traffic conditions cannot be the same as the conditions when travel times are initially estimated in TMICs. With this concept in mind, it is understood that predicted travel times might reduce the gaps between current travel time estimation and actual travel times. Therefore, it is recognized that travel time forecasting models be utilized as an important module in ATMS and ATIS applications.

In general, travel time forecasting models could reduce the difference between estimated and actual link travel times. For example, real-time traffic data are initially transmitted to traffic management and information centers, and stored in historical databases. Transmitted raw traffic data and historical data are then screened, filtered, and fused in data preprocessing modules, after which a travel time forecasting module performs short-term link travel time predictions. Predicted link travel times are finally disseminated within a TMIC and sent to external users.

Travel time forecasting models could play more important roles when LBS applications intend to provide shortest path information to travelers. Predicted travel times can be used to calculate shortest paths as shown in Figure 2. TMICs search shortest paths between user-defined origins and destinations using predicted link travel times. Travel time forecasting models require tremendous amounts of calculations, and thus high performance computers are necessary to reduce computation time. Thus, conceptual applications discussed in this section assume that travel time forecasting tasks are performed in TMICs or LBS brokers.

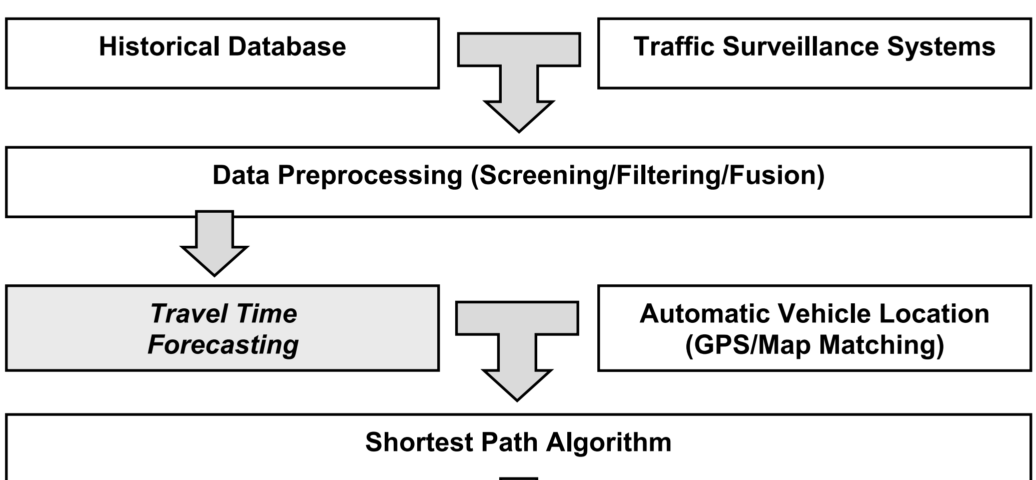

Figure 2. A Possible Application of Travel Time Forecasting with Shortest Paths Algorithms

3. Existing Travel Time Forecasting Models

For many years, various types of travel time forecasting models have been developed, including historical profile approaches, time series models, neural networks, nonparametric regression models, traffic simulation models, and dynamic traffic assignment (DTA) models. By analyzing the original formulations of these existing models, they can be categorized as statistical models, mathematical optimizations, computer simulations, and artificial intelligence models.

- **Statistical Models** include historical profile approaches, time series models and nonparametric regression models. Like many other scientific areas that utilize statistics as a tool for analysis and forecasting, transportation professionals have used statistical models in forecasting travel times as well. Without exception, all statistical models for forecasting travel time require historical data because they are based on analyzing time series data by applying elementary to applied and advanced statistical methods.

- **Mathematical Optimizations** include dynamic traffic assignment models. Dynamic traffic assignment models are relatively difficult to formulate, and require iterative optimization techniques to obtain solutions like many other optimization applications in the field of operations research. Thus, high performance computers are usually required to reduce computation time.

- **Computer Simulations** include traffic simulation models. Traffic simulation models simulate the characteristics of vehicle movements on road networks. After formulating mathematical equations for characteristics (i.e., variables) of traffic behavior, simulation parameters are calibrated. Thus, precise analyses toward the nature of road networks are necessary to obtain reasonable simulation results. These models also require high performance computers to expedite simulation processes.

- **Artificial Intelligence Models** include neural network models that imitate human brain cells. Based on the nature of considered problems, the number of layers and connections among input, hidden, and output layers are predefined. Connection weights among layers are estimated based on network learning procedures (for example, supervised and unsupervised learning). Most of neural network forecasting models perform predictions based on learned information from historical data patterns. Thus, these models generally produce better results when the pattern learning is performed more frequently.

Table 1 shows researches related to travel time forecasting in the four categories. The most widely applied methods are the statistical models. They have been applied in the field of traffic forecasting since the early 1970s. Early applications utilized simple historical profile approaches, but they have adopted other advanced approaches such as time series and nonparametric regression models later on. Traffic simulation models have been developed much earlier than their applications in travel time forecasting, but the massive computation in simulating traffic behaviors has hindered their applications in travel time forecasting for many years.

Table 1. Types of Traffic Forecasting Models

Types	Models	Applications
Statistical Models	Historical Profile Approaches	- Kreer, 1975 - Stephanedes et al., 1981 - Jeffrey et al., 1987 - Kaysi et al., 1993

	Time Series Models	- Moorthy and Ratcliffe, 1988 - Davis et al., 1990 - Vythoulkas, 1992 - Ben-Akiva et al., 1993; 1995 - Shimizu et al., 1995 - Yasui et al., 1995 - Smith and Demetsky, 1997 - Uchida and Yamasita, 1997
	Nonparametric Regression Models	- Davis and Nihan, 1991 - Smith and Demetsky, 1997
	Hybrid Model	- You and Kim, 2000
Computer Simulations	Traffic Simulations	- Junchaya et al., 1992 - Berkbigler et al., 1997 - Yang, Q., 1997 - McShane et al., 1998 - Nagel et al., 1998 - Bush, 1999
Mathematical Optimizations	Dynamic Traffic Assignment Models	- Mahmassani et al., 1991 - Ben-Akiva et al., 1993, 1994, 1995 - Gilmore and Abe, 1995 - Ran and Boyce, 1996 - Sadek et al., 1997
Artificial Intelligence Models	Neural Networks	- Dougherty et al., 1993 - Dochy et al., 1995 - Gilmore and Abe, 1995 - Palacharla and Nelson, 1995 - Smith and Demetsky, 1997

As a result, some formulations in simulating traffic behaviors have adopted parallel computing technologies (Bush, 1999; Nagel et al., 1998; Berkbigler et al., 1997). Neural network models became popular in travel time forecasting during the 1990s, and the recent development of neural network models have a strong influence in forecasting travel time. Nevertheless, their current formulations are still difficult to deal with real-time applications due to complex learning processes.

3.1. Historical Profile Approaches

The historical profile approach is based on the assumption that a historical profile can be obtained for traffic volume or travel time (Shbaklo et al., 1992). It solely relies upon the cyclical nature of traffic flow. For instance, this approach simply uses an average of past traffic volume to forecast future traffic volume. The advantage of this approach is its relatively easy implementation and its fast computation speed. However, this approach has a serious disadvantage due to its static nature; i.e., if traffic incidents occur, it has no way to react to the changes (Smith and Demetsky, 1997). This approach has been tested in many traffic management and information systems such as the Urban Traffic Control System (UTCS) (Kreer, 1975; Stephanedes et al., 1981), as well as in several traveler information systems in Europe including AUTOGUIDE (Jeffrey et al., 1987) and LISB (Kaysi et al., 1993).

3.2. Time Series Models

Time series models have been used particularly for short term travel time forecasting. These methods include various time-series analysis such as autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA). In order to enhance forecasting accuracy, many research projects have also adopted data filtering methods such as Kalman filtering, fixed interval smoother, and m-interval polynomial approximation Kalman filtering.

A time series is defined as a set of statistical observations, arranged in chronological order. For instance, an observed traffic volume series consists of two parts: the series generated by the real process and the noise that is not directly related to the real process. Therefore, elimination of the noise, which is the result of outside disturbances, is the main target of time series models (Moorthy and Ratcliffe, 1988). In order to eliminate the noise, autoregressive (AR) and moving average (MA) models have been mainly utilized. Based on these basic models, it has been shown that any discrete stationary time series can be analyzed using an autoregressive moving average (ARMA) model. Later the Box-Jenkins model was introduced based on ARMA (Box and Jenkins, 1977). An improved ARMA, Box-Jenkins model, is called an autoregressive integrated moving average model (ARIMA), and does not require a fixed initial pattern, which is used in previous models. ARIMA models have been applied to the UTCS and freeway volume forecasting (Davis et al., 1990; Smith and Demetsky, 1997).

One of the most advanced time series methods, Kalman filtering, has also been utilized to minimize estimation errors in time series analyses (Ben-Akiva et al., 1995, 1993; Shimizu et al., 1995; Vythoulkas, 1992). In addition, a vector autoregressive moving average (VARMA) model has been applied to a multivariate time series analysis by segmenting road network and considering correlation between road segments (Uchida and Yamasita, 1997).

3.3. Neural Networks

Neural networks have been developed mainly in the field of artificial intelligence. A neural network is an information processing system that is non-algorithmic, non-digital, and intensely parallel. Because neural networks are capable of learning how to classify and associate input and output patterns, they are distinguished from other traditional computing systems. Their learning capabilities make themselves a suitable approach for solving complicated problems like estimating current travel times from traffic flow patterns (Palacharla and Nelson, 1995). Recently, neural networks have gained a significant attention for transportation applications such as traffic flow modeling, traffic signal control, and transportation planning (Gilmore and Abe, 1995; Smith and Demetsky, 1997; Dochy et al., 1995). Among a number of neural network paradigms, back-propagation, a multi-layer learning regime, has been often applied to forecast traffic flow and congestion because of its ability to model relationships among continuously valued variables (Smith and Demetsky, 1997; Dougherty et al., 1993).

3.4. Nonparametric Regression Analysis

Nonparametric regression can be thought of as a dynamic clustering model, which attempts to identify groups of past cases whose input values or states are similar to the state of the system at prediction time. It is considered dynamic because it defines a group of similar past cases (or the neighborhood) around the current input state, instead of defining a number of groupings prior to the time of prediction. Nonparametric regression is applicable to analyzing multiple links, which is an extension of single link analysis where traffic flow prediction on a link is based on previous flow information from that link and from other neighboring links (Shbaklo et al., 1992). Nonetheless, few nonparametric regression models have been used in travel time forecasting due to the complexity of search tasks for "neighbors" (Smith and Demetsky, 1997; Davis and Nihan, 1991). Thus, nonparametric regression models generally require an effective and efficient search algorithm with a well-structured data model.

3.5. Traffic Simulation Models

Simulation models are designed to mimic the behavior of real-world systems. Transportation researchers have developed various types of traffic simulation models such as discrete time/discrete event models, micro/mesoscopic/macro models, and deterministic/stochastic models. In fact, most traffic simulation models are discrete time models, which segment time into a succession of known time interval (McShane et al., 1998; Lieberman and Rathi, 1997). Most of traffic simulation models are micro models as well as stochastic models. Though simulation-based models are capable of analyzing various types of situations, they require estimating the entering and exiting traffic flows when they are used in travel time forecasting (Smith and Demetsky, 1997). Table 2 shows representative traffic simulation models.

3.6. Dynamic Traffic Assignment Models

Dynamic traffic assignment (DTA) models have evolved from traditional static equilibrium assignment models. In general, traffic assignment models can be categorized as two distinctive types: descriptive and normative models. The descriptive models attempt to capture how the users behave given a set of traffic conditions (i.e., user optimal). Whereas, normative models seek to determine how the system should behave in order to optimize some system-wide criteria (i.e., system optimal) (Mahmassani et al., 1991; Ran and Boyce, 1996).

Table 2. Representative Traffic Simulation Models (Lieberman and Rathi, 1997)

Type / Model	Discrete Time	Discrete Event	Micro	Mesoscopic	Macro	Deterministic	Stochastic
NETSIM	x		x				x

NETFLO 1		x		x			x
NETFLO 2	x				x	x	
FREFLO	x				x	x	
ROADSIM	x		x				x
FRESIM	x		x				x
CORSIM	x		x				x
INTEGRATION	x		x				x
DYNASMART	x			x		x	
CARSIM	x		x				x
TRANSIMS	x			x			x

Unlike static assignment models, dynamic models assume link flows and link trip times change over the duration of the peak period, so that they are appropriate for real-time traffic control during peak periods on congested networks, where constant steady-state conditions hardly occur. Thus, DTA models have been used for relatively long term travel time forecasting. To apply DTA models in forecasting travel time, it is necessary to estimate dynamic travel demand, and hence obtaining dynamic origin-destination (OD) tables is a major issue for a successful DTA model. To improve existing DTA models, which are mostly based on static user equilibrium and system optimal traffic assignment models, several models have adopted genetic algorithms and neural networks (Sadek et al., 1997; Gilmore and Abe, 1995).

4. A Comparison of Existing Travel Time Forecasting Models

It is difficult to decide a suitable method in travel time forecasting because existing models have both advantages and disadvantages as shown in Table 3. For instance, time series and simulation models are relatively accurate for very short-term (i.e., less than 15 minutes) predictions, but they become unreliable when prediction time periods get longer and longer (i.e., more than 15 minutes). In a study, DTA models have been considered in travel time forecasting for 15 to 60 minutes time interval (Ben-Akiva et al., 1995). However, dynamic assignment formulations have often encountered problems with regard to their tractability and solvability in realistic network settings (Sen et al., 1997; Mahmassani et al., 1991).

Table 3. Advantages and Disadvantages of Travel Time Forecasting Models (Adapted from Smith and Demetsky, 1997; Sen et al., 1997)

Model	Advantages	Disadvantages
Historical Profile Approach	- Relatively easy to implement - Fast execution speed	- Difficult to respond to traffic incidents
Time Series Analysis	- Many applications - Well-defined model formulation	- Difficult to handle missing data
Neural Network	- Suitable for complex, non-linear relationships	- Forecasting in black box - Complex training procedure
Nonparametric Regression Analysis	- Pattern recognition application - Requires no assumption of underlying relationship	- Complexity of search in identifying "neighbors"
Traffic Simulation	- Possible to simulate various situations	- Requires traffic flow prediction in priori
Dynamic Traffic Assignment	- Various types of models available - Models are relatively well known	- Not suitable to Micro-simulation

Toward developing a more reliable travel time forecasting model, a generalized comparison has been conducted, based on six evaluation categories: (1) Utilization of Historical Database, (2) Capability of Online Data Use, (3) Transferability of Forecasting Algorithm, (4) Effectiveness of Forecasting Algorithm, (5) Accuracy of Forecasting Algorithm, and (6) Capability of Forecasting with Traffic Incidents.

- **Utilization of Historical Database**: Historical profile approaches, nonparametric regression models, and time series models utilize historical databases relatively well. For instance, historical profile approaches compute historical averages of traffic data using historical databases. Within historical databases, nonparametric regression models search similar conditions that occurred in the past. Time series models can perform autoregressive (AR) and moving average (MA) analyses using time series data stored in historical databases.

- **Capability of Online Data Use**: A travel time forecasting model should be able to promptly produce outputs using real-time data. In general, historical profile approaches involve static models that do not consider real-time data. Time series models should persistently accomplish complicated parameter estimations, and neural networks have to learn input patterns continuously. Moreover, DTA models require complex dynamic O-D estimations whenever input data are changed. Therefore, with time series models, neural networks, and DTA models it is difficult to utilize real time data with currently available computing technologies. On the other hand, nonparametric regression models, which are based on pattern recognition techniques that search similar conditions that have occurred in the past, do not require any assumptions, and thus they can effectively utilize real-time data. However, nonparametric regression models need a well-designed search algorithm for large size historical databases to reduce search time.

- **Transferability of Forecasting Algorithm**: A forecasting model needs to be adopted easily among TMICs that are usually equipped with various types of computer systems. It is economical that a forecasting model is readily customized among these centers. DTA models, time series models, traffic simulation models, and neural networks usually require intensive calibration processes for different road networks. On the other hand, historical profile approaches and nonparametric regression models do not require any assumption, and thus they can be applied in travel time forecasting with relatively simple calibration processes.

- **Effectiveness of Forecasting Algorithm**: Computation time strongly affects the success of a forecasting model development. For instance, forecasting results should be calculated at least within a specified forecasting range. Thus total computation time should be no longer than 15 minutes to perform a "15-minute ahead" forecasting. It is always necessary to minimize computation time, so that the forecasted results can be disseminated within TMICs and to public. In real-time applications, high performance and parallel processing capable computer systems are often considered for neural networks that require continuous network learning processes with real time data inputs, and for DTA models that repeatedly calculate dynamic O-D tables. In traffic simulation models, the computing time grows quickly when input road networks become larger. Nonparametric regression models require relatively simple calculations, but they have to optimize search processes to minimize computation time (Smith and Demetsky, 1997).

- **Accuracy of Forecasting Algorithm**: A forecasting algorithm should be able to produce accurate forecasting results. In general, neural networks are relatively accurate when they learn input networks sufficiently (Weigend and Gershenfeld, 1994). Nonetheless, computation time in neural networks grows rapidly when results that are more accurate are required; i.e., more network learning processes are required. Like neural networks, nonparametric regression models have shown relatively accurate forecasting results while their computation times are much shorter than neural networks' as shown in Figure 5 and Table 4 (nonparametric regression models are categorized as local linear models in the table) (Weigend and Gershenfeld, 1994).

- **Capability of Forecasting with Traffic Incidents**: A forecasting model should be able to deal with traffic incidents. In this category, none of the existing models is satisfactory. Historical profile approaches and time series models have difficulty in dealing with online traffic data with incidents. Nonparametric regression models, neural networks, traffic simulation models, and DTA models need to be modified and enhanced to deal with traffic incidents.

In order to shed light on the issue of adopting a core-forecasting algorithm for the development of a travel time forecasting model, which requires the use of historical database and real-time data concurrently, Table 5 shows a generalized comparison. Basically, historical profile approaches do not consider real-time data. Therefore, they could not be the core algorithms in developing a travel time forecasting model that utilizes real-time data. DTA models, time series models and traffic simulation models require intensive computations and complex parameter estimations. Thus, they are extremely cumbersome to implement among TMICs, particularly in dealing with real-time data. Neural networks show relatively accurate output as shown in Table 4, but they require complex network learning algorithms and additional computations for real-time data input.

On the other hand, nonparametric regression models provide relatively simple forecasting mechanisms with reasonably high forecasting accuracy as shown in Table 4. However, in order to implement an effective nonparametric regression model with limited computer resources, it is necessary to optimize its complex search processes. In addition, a supplementary algorithm should be developed to make nonparametric regression models capable of dealing with traffic incidents, which could cause conventional nonparametric regression models to generate inaccurate forecasting results.

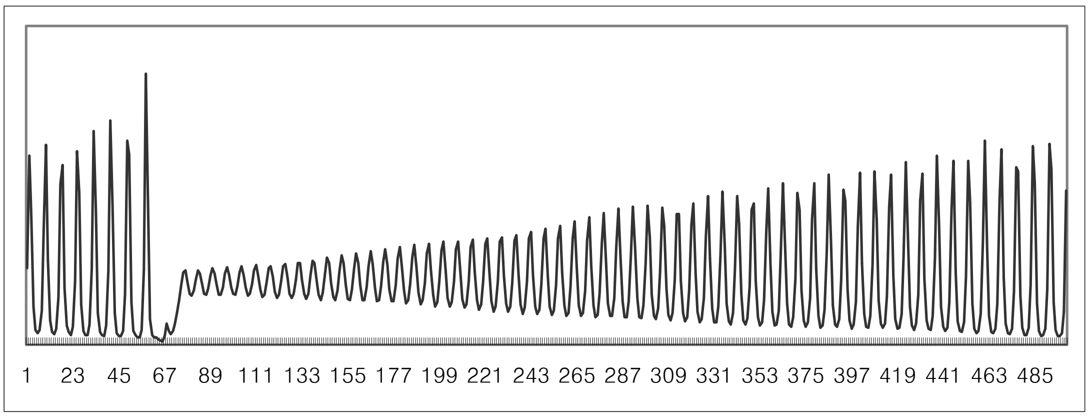

Figure 1. A Section of the Santa Fe Time Series Forecasting Competition: Data Set A (Weigend and Gershenfeld, 1994)

Table 4. Entries received for the Prediction of Data Set A in the Santa Fe Time Series Competition (adapted from Weigend and Gershenfeld, 1994)

Entry[3]	**Method**	**Type**	**Computer**	**Time**	**NMSE(100)**[4]
W	NN	1-12-12-1; Lag 25,5,5	SPARC 2	12 hrs	0.028
Sa	Local linear	Low-Pass Embedding, 4 *k*-NN	DEC 3100	20 min	0.080
M	NN	Feedforward, 50-350-50-50	386 PC	5 days	0.38
A	Local linear	30 *k*-NN	SPARC 2	1 min	0.71
McL	NN	Feedforward, 200-100-1	CRAY Y-MP	3 hrs	0.77

[3] Anonymous identification for participants of the competition.

[4] Normalized Mean Square Errors (NMSE) are computed using the predicted values $\hat{x}_k$ as follows:

$$NMSE = \frac{\sum_{k \in T} \left(observation_k - prediction_k\right)^2}{\sum_{k \in T} \left(observation_k - mean_T\right)^2} \approx \frac{1}{\hat{\sigma}_T^2} \frac{1}{N} \sum_{k \in T} \left(x_k - \hat{x}_k\right)^2$$

where $k = 1 \ldots N$ enumerates the points in the withheld test set T, and $mean_T$ and $\hat{\sigma}_T^2$ denote the sample average and sample variance of the observed values (targets) in T. A value of NMSE = 1 corresponds to simply predicting the average.

N	NN	Feedforward, 50-20-1	SPARC 1	3 weeks	1.0
Can	NN	Recurrent, 4-4c-1	VAX 8530	1 hrs	1.4
P	Local linear	Time Delay	Sun	10 min	1.3
Sw	NN	Feedforward	SPARC 2	20 hrs	1.5
Y	NN	Feedforward, Weight-Decay	SPARC 1	30 min	1.5
Car	Linear	Wiener filter, width 100	MIPS 3230	30 min	1.9

(NN: Neural Network, *k*-NN: *k*-Nearest Neighbor)

5. Potential Roles of GIS in Travel Time Forecasting for LBS

Upon reviewing various functions of GIS-based applications (Nygard et al., 1995; Choi and Kim, 1994; Azad and Cook, 1993; Gillespie, 1993; Ries, 1993; Loukes, 1992; Abkowitz et al., 1990), data management, technology management, and information management -- the three important roles of GIS could be employed to support the operation of a travel time forecasting model.

- *Data Management*: Travel time forecasting requires various types of traffic data including traffic speed, traffic volume, occupancy rate, number of lanes, and so forth. Therefore, GIS should be able to provide mechanisms for data aggregation and manipulation.

- *Technology Management*: Travel time forecasting requires various functions including display, computation, and analysis. Therefore, GIS should provide flexible tools to integrate and customize the required functions. Moreover, GIS should support a travel time forecasting model to deal with various types of raw traffic data from loop detector, mobile communication, and Global Positioning Systems (GPS).

- *Information Management*: After forecasting future travel times, the results are validated and classified, so that traffic management and information centers can utilize them to manage network traffic. It is expected that GIS will eventually become an information gateway to the public, through various types of communication tools such as the Internet, telecommunications, broadcasting, etc.

Table 5. Generalized Comparison of Existing Forecasting Models

Evaluation Category / Model	Database	Capability of Online Data Use	Transferability of Forecasting Algorithm	Effectiveness of Forecasting Algorithm	Accuracy of Forecasting Algorithm	Capability of Forecasting with Traffic Incidents
		×	O	O	×	×
	O	Δ	×	Δ	Δ	×
Neural Networks	O	Δ	×	×	O	Δ
Nonparametric Regression	O	O	O	Δ	O	Δ
Traffic Simulation	Δ	O	Δ	Δ	Δ	Δ
Dynamic Traffic Assignment Models	Δ	O	×	×	Δ	Δ

(O) Excellent; (Δ) Good; (×) Poor

In addition, it is also expected that GIS provide important functions to expedite the development of a travel time forecasting model as follows:

- Creating and editing traffic networks with topology,
- Assisting in both managing and visualizing historical and real-time traffic data,
- Providing user environments through graphic user interfaces,
- Supporting application development environments for the integration of forecasting algorithms, and
- Providing flexible spatial data analysis tools using search and query tools when a forecasting model is implemented.

6. Summary

In this paper, preliminary discussions regarding both existing travel time forecasting models and GIS technologies have been made for the development of a reliable travel time forecasting model. The characteristics of travel time forecasting models have been presented and existing travel time forecasting models have been reviewed. In addition, the theoretical aspects of GIS implementation have been discussed to identify the potential roles of GIS in travel time forecasting. In the future research, it is recommended that findings in this research be further analyzed and compared for a more reliable travel time forecasting model, which could effectively utilize the existing forecasting models with GIS technologies in an integrated system framework.

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