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# Incorporating Weather Impacts in Traffic Estimation and Prediction Systems

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## Final Report

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<tr><td colspan="4">16. Abstract<br>Dynamic Traffic Simulation-Assignment models are gaining wider acceptance and use to support transportation network planning and traffic operations decision-making. Significant improvements in traffic estimation capabilities and overall utilities of these systems for traffic management can be achieved by upgrading or adjusting them to account for the impacts of weather. This report presents the results of a study to develop weather-sensitive dynamic traffic assignment (DTA) models for Traffic Estimation and Prediction (TrEPS) application, which addresses both supply and demand aspects of the response to adverse weather, including user responses to various weather-specific interventions such as advisory information and control actions.</td></tr>
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## Executive Summary


Inclement weather can significantly degrade roadway traffic operations, reducing service levels and creating unsafe conditions. Advances in sensor technologies and continuing deployment of intelligent transportation system (ITS) architectures provide an important opportunity for traffic management agencies to anticipate, mitigate, and intervene through various advisory and control measures to better manage conditions in the presence of inclement weather. Achieving this potential requires tying weather forecasting and traffic management capabilities together in an integrated framework that captures the effect of weather and weather-related measures on traffic system performance.

Traffic analysis tools used in practice typically ignore the effect of weather, and hence lack essential features to support weather-related traffic management. This study overcomes this deficiency by developing weather-sensitive traffic prediction and estimation models and incorporating them in Traffic Estimation and Prediction (TrEPS) tools intended for online operation in traffic management centers (TMC) as well as for offline evaluation of contemplated measures.

The development of weather-sensitive TrEPS is built on (1) a synthesis of existing cross-disciplinary knowledge on traffic responses to weather conditions and the application of weather-responsive advisory and control strategies, and (2) a thorough review of existing corridor and network traffic estimation and prediction models and systems that incorporate weather impacts or that can be adjusted to account for weather conditions. The synthesis addresses both the impact of weather events on traffic system performance (supply side), as well as traveler behavioral responses to weather events and related traffic advisory information (demand side). Both aspects are incorporated in the models developed in the study.

The principal supply-side and demand-side elements affected by adverse weather are systematically identified and modeled in the framework of traffic estimation and prediction systems, in order to account for changing weather conditions, as well as the availability of traveler information systems and weather-responsive traffic control devices. Where possible, the models and relations developed have been calibrated using available observations of traffic and user behavior in conjunction with prevailing weather events. The proposed weather-related features have been implemented in the DYNASMART TrEPS, and demonstrated through successful application to a real world network, focusing on two aspects: (1) assessing the impacts of adverse weather on transportation networks; and (2) evaluating effectiveness of weather-related advisory/control strategies in alleviating traffic congestion due to adverse weather conditions.

The procedures implemented provide immediately applicable tools that capture knowledge accumulated to date in the growing body of literature regarding weather effects on traffic. The application to a real world network shows that the proposed model can be used to evaluate weather impacts on transportation networks and the effectiveness of weather-related variable message signs.

The high level framework for incorporating weather impacts in TrEPS, presented in this study, provides a direction for future development towards a modern approach to traffic management under adverse traffic that recognizes modern technological developments (e.g. weather sensing/forecasting, weather responsive traffic management). The work accomplished in this study advances the state of the art in incorporating weather effects in network analysis tools. Additional effort in two main areas is necessary to translate these advances into practice. The first entails actual implementation in the context of a regional planning and/or traffic operations agency to establish the model and calibrate it for application under a variety of local conditions and traffic patterns. The second area of development would focus on weather-related traffic management and control measures, and interfacing their actual deployment with the decision-support tools developed in this project.

# 1. Introduction

The disruptive effect of inclement weather on traffic is well known to most drivers and travelers, and is a challenging issue to traffic engineers and managers. In addition to its staggering impact on safety (it is estimated that about 28% of all highway crashes and 19% of all fatalities involve weather-related adverse road conditions as a factor), adverse weather results in reduced service capacity (often at the most critical of times), diminished reliability of travel, reflected in considerable variability and unpredictability, and greater risk of accident involvement. It is well documented that weather exerts significant impact on several key traffic flow parameters, such as free flow speed and capacity (e.g. Kockelman, 1998; Smith et al. (2004) and a recent FHWA report (Hranac et al., 2006) summarizing empirical studies on traffic flow in inclement weather). In addition, adverse weather often affects tripmaker decisions of travel mode, route, timing, destination, or even whether to make the trip at all (e.g. telecommute or teleshop instead). Thus, weather affects both the supply and demand sides of transportation. Recognizing it into transportation operations and management has the potential to improve the performance of the transportation system at times where such improvement is most critically needed.

Yet, an assessment of current and past practice, as well as of the major reference documents typically used by practicing traffic engineers, quickly reveals that there is little out there to guide traffic planners and engineers in dealing with adverse weather on a regular basis. There appears to be a perception that there is not much that one could do to deal with such situations, other than caution drivers to stay home, drive slowly, or be more alert. This perception may be rooted in three inter-related causes: (1) absence of specific actions and measures, and accepted conditions for their application, that could be deployed specifically to manage traffic under adverse weather; (2) lack of tools to support such management decisions, including analysis/evaluation of the impact of contemplated actions and design of interventions, both off-line and on-line; and (3) insufficient understanding of the [qualitative and quantitative] effects of adverse weather of varying characteristics on traffic flow, on the performance of different types of facilities with varying geometric and operational features, and on the response of users to the weather phenomena as well as to contemplated control and management actions.

Advances in sensor technologies and continuing deployment of intelligent transportation system (ITS) architectures provide an important opportunity to anticipate, mitigate, and intervene through various advisory and control measures to improve traffic conditions in the presence of inclement weather. The premise of ITS is the ability to sense prevailing conditions, anticipate unfolding future conditions, and rapidly devise actions to optimize system performance in real-time. Dealing with adverse weather requires not only sensing of traffic conditions, but also the ability to forecast the weather in real-time for operational purposes. Recognizing the importance of tying weather and traffic management together in areas exposed to extreme weather situations, such as hurricanes and floods, some Traffic Management Centers (TMC) co-locate the weather service personnel with the usual traffic management agencies (police, traffic operators, Emergency Medical Services). Another relevant initiative is the *Clarus* weather data system, intended to provide traffic management centers with accurate real-time weather information (Pisano and Goodwin, 2002; Mixon-Hill Inc. et al., 2005; Pisano, Alfelor, et al., 2005; FHWA Clarus web site, at http://www.its.dot.gov/clarus/index.htm). The weather information, along with the traffic information obtained from ITS sensors, enable promising new opportunities to improve traffic operations and management under inclement weather conditions. In addition, the Clarus system will eventually be coordinated with IntelliDrive$^{SM}$ systems such that both vehicular information as well as weather data can be obtained for traffic management.

A critical methodological capability in the above architecture is a Traffic Estimation and Prediction System (TrEPS). Because the dynamics of traffic systems are complex, many situations call for strategies that anticipate unfolding conditions instead of adopting a purely reactive approach. Real-time simulation of the traffic network forms the basis of a state prediction capability that fuses historical data with sensor information, and uses a description of how traffic behaves in networks to predict future conditions, and accordingly develop control measures. The estimated state of the network and predicted future states, in terms of flows, travel times, and other time-varying performance characteristics, are used in the on-line generation and real-time evaluation of a wide range of measures, including information supply to users, VMS displays, coordinated signal timing for diversion paths, as well as weather-related interventions (through variable speed displays, advisory information, signal timing adjustments and so on). The core of the descriptive DTA capability is a traffic simulation model, intended to capture the dynamics of traffic flow movement in the network (Jayakrishnan et al. 1994; Mahmassani 1998, 2001).

Recognizing the need for prediction in advanced traffic management systems, the FHWA funded R&D into the methodological foundations of simulation-based DTA for TrEPS application, and subsequently supported the development of two prototypes, DYNASMART-X and DynaMIT, both of which adopted similar methodological decisions with regard to the underlying simulation logic—specifically, to use a mesoscopic approach in which individual particles (vehicles) move according to local speeds determined consistently with (macroscopic) relations among averages of speed and density. This mesoscopic approach for network-level TrEPS defines the state of the art in this domain. However, these tools have to date only been calibrated and tested under "normal" weather conditions. In other words, no provision has been made to explicitly capture the behavioral phenomena that determine traffic patterns under adverse weather, predict how traffic might be impacted by such weather, and how it might respond to various advisory and regulatory interventions aimed at managing traffic during such conditions. Therefore, while a major need for on-line estimation and prediction arises precisely because of unanticipated weather perturbations, the tools developed for such applications did not initially have the ability to represent traffic behavior under such conditions, or in response to the possible interventions.

To address the above-mentioned deficiency this project is aimed at developing weather-sensitive traffic prediction and estimation models and incorporate them in existing traffic estimation and prediction systems. In particular, the following tasks are performed to achieve these goals:

- Review and summarize existing knowledge on traffic responses to weather conditions and the application of weather-responsive advisory and control strategies, including both pre-trip decisions (i.e., departure time, mode choice and route choice) and en-route traffic behavior (i.e., speed, speed variance, volume, etc.)
- Review and summarize existing corridor and network traffic estimation and prediction models and systems that incorporate weather impacts or that can be adjusted to account for weather conditions.
- Develop traffic estimation and prediction models at the corridor and network levels that account for traffic response to inclement weather with and without the presence of advisory and control strategies.
- Incorporate models of traffic response to inclement weather in existing corridor and network traffic prediction and estimation system to account for changing weather conditions as well as the availability of traveler information systems and weather-responsive traffic management and control devices.

The remainder of this report is organized as follows. A literature review is presented in Chapter 2, which covers two major aspects: (1) impact of weather events on traffic system performance (supply side); (2) traveler behavioral responses to weather events and related traffic advisory information (demand side). This is followed by a review of existing traffic prediction/estimation models and systems in Chapter 3, which can be used for both planning and real-time traffic management applications at the corridor and network levels (i.e., DYNASMART, DynaMIT). Chapter 4 presents a methodology to model the weather impact in DYNASMART. The principal supply-side and demand-side elements that would be affected by adverse weather are identified and modeled in the framework of traffic estimation and prediction systems. These proposed weather-related features are implemented in DYNASMART, as described in Chapter 5. In Chapter 6, calibration procedures as well as the results are presented. Chapter 7 demonstrates the application of the weather-sensitive traffic estimation and prediction model to a real world network, focusing on two aspects: (1) assessing the impacts of adverse weather on transportation networks; and (2) evaluating effectiveness of weather-related advisory/control strategies in alleviating traffic congestion due to adverse weather conditions. Finally, Chapter 8 concludes the project and discusses further research directions.

# 2. Literature review

This chapter presents the review of the literature regarding traffic responses to weather events and the application of weather responsive traffic advisory and control strategies. The review focuses on two main areas of the literature: (1) impact of weather events on traffic system performance (i.e. supply side impacts), and (2) traveler responses to weather events and related traffic advisory information (i.e. demand side impacts). These two areas are generally unconnected in the literature. The first area developed primarily in the traffic flow theory/traffic engineering community, whereas the second has been the purview of travel behavior researchers and demand analysts. This study is among the first to combine and juxtapose these two hitherto separate domains, recognizing that behavioral responses and system performance interact in determining the manner in which weather events and weather-related information interact in determining traffic flows and associated travel times through a network.

As has been recognized since the inception of this study, the literature is considerably richer in regard to the supply-side relative to the demand-side. This is in part due to the greater relative ease of measurement and observation in the traffic arena, compared to the demand area, which often requires direct participation of the respondent in a tracking and/or interview process. This section first presents the traffic performance-related material, followed by contributions to the behavior area.

## 2.1 Traffic Performance under Weather Events

Since the early 1950's (Tanner, 1952), it has been recognized that weather conditions affect driver behavior and the manner in which a transportation system needs to be operated. By modifying speeds, headways as well as other parameters, drivers' reactions impact the overall system performance. This section presents a detailed literature review on the classification of inclement weather conditions and their translation into measurable objective parameters. The impact of such conditions on speed-flow-density relationships is first introduced. Such impact is associated with a change in capacity, delay, volume and speed, and reflects drivers' behavior on a given road section. Once the change in these parameters is better understood, the control aspect of the study is analyzed; research studies linking weather effects to signal timing, unsignalized intersections and variable message signs (VMS) are reviewed.

### 2.1.1 Weather Conditions

The impact of “weather conditions” on transportation systems is a general term that may pose some confusion. Researchers have used different classification schemes for weather conditions, because these conditions differ considerably in type and in magnitude (Rakha et al., 2007). Some weather conditions are extreme in nature (tornados, floods, typhoons, hurricanes etc.) and thus may trigger a different response by the drivers. Such extreme conditions are outside the immediate focus of the present study. Other inclement weather conditions (light and heavy rain, light and heavy snow etc.) offer a less compressed time frame to the decision makers, and allow drivers to retain an acceptable amount of control on their vehicles; this control may be less than under “normal everyday” situation due to physical factors such as visibility, physical discomfort (cold or hot temperatures) and reduced pavement friction with the tires when there is precipitation or icy conditions prevail.

As mentioned earlier, most existing studies do not describe all “weather conditions” in the form of measurable objective parameters, making it difficult to explain or quantify the effect of such conditions on the transportation systems and their users. Martin et al. (2000) suggested that before analyzing the impact of such conditions, four dimensions need to be considered:

1. Severity of the condition
2. Duration
3. Geographic area of influence
4. Traffic flow or the demand served by the network

According to the literature, most inclement conditions can be classified into one of three types: “rain”, “snow” and “others” (wind, fog etc.). These in their turn differ in intensity (light versus heavy). In reviewing previous research efforts, Rakha et al. (2007) reported the influence of these conditions on speed and volume as summarized in Table 2-1through Table 2-4.

**Table 2-1 Rain Effects on Speed**

| | Speed Reduction | | |
|---|---|---|---|
| Researcher | Ibrahim and Hall | Kyte et al. | Smith et al. |
| Location | Toronto, Ontario | Idaho | Hampton Roads, Virginia |
| Year | 1994 | 2001 | 2004 |
| Light Rain | 1.9-12.9 km/hr (1.2-8 mph) | 9.5 km/hr (5.9 mph) | 3-5% |
| Heavy Rain | 4.8-16.1 km/h (3-10 mph) | 9.5 km/hr (5.9 mph) | 3-5% |

*Source: Rakha et al., 2007*

**Table 2-2 Snow Effects on Volume**

| | Volume Reduction | | |
|---|---|---|---|
| | Freeway | | Arterial |
| Researcher | Hanbali and Kuemmel | Knapp | Maki |
| Location | Illinois, Minnesota, New York, Wisconsin | Iowa | Minneapolis, Minnesota |
| Year | 1992 | 1995-1998 | 1999 |
| Light Snow | 7-31% | - | - |
| Heavy Snow | 11-47% | 16-47% | 15-30% |

*Source: Rakha et al., 2007*

**Table 2-3 Snow Effects on Speed**

| | Speed Reduction | | | |
|---|---|---|---|---|
| | Freeway | | Arterial | |
| Researcher | Ibrahim and Hall | Kyte et al. | Maki | Perrin |
| Location | Toronto, Ontario | Idaho | Minneapolis, Minnesota | Salt Lake City, Utah |
| Year | 1994 | 2001 | 1999 | 2001 |
| Light Snow | 0.97 km/hr (0.6mph) | 16.4 km/hr (10.19 mph) | - | 13% |
| Heavy Snow | 37-41.8 km/hr (23-26mph) | 16.4 km/hr (10.19 mph) | 40% | 25-30% |

*Source: Rakha et al., 2007*

**Table 2-4 Summary of Weather Impact on Macroscopic Traffic Parameters**

| Factors\Reduction | Volume | Maximum Observed Flow | Capacity | Speed |
|---|---|---|---|---|
| Rain | - | 0-20% | 4-47% | - |
| Snow | 7-47% | 5-10% | 30% | 13-40% |
| Wind | - | - | - | 10% |

*Source: Rakha et al., 2007*

### 2.1.2 Human Factors

As mentioned earlier, parameters directly linking weather conditions (visibility factor, pavement friction factor) to the driving task (perception and execution) are rarely used. Previous studies have focused mainly on two parameters, visibility and traction.

*Visibility*

While perceiving a stimulus to which drivers need to react, visibility plays an important role in understanding driver behavior during inclement weather conditions. A limited amount of research focused explicitly on visibility as a factor impacting traffic flow. Mostly, low visibility has been implied by the presence of heavy rain or snow conditions that reduces the sight distance of the drivers. Brilon and Ponzlet (1996) studied visibility in the context of daylight versus darkness. Based on data collected in Germany, a 13% to 47% reduction in capacity was observed in darkness compared to daylight conditions.

On the other hand, Kyte et al. (2001) explicitly defined a critical visibility distance of 0.3 km (0.18 mile), below which the speed was reduced by 0.77 km/hr (0.48 mph) for every 0.01 km (0.0062 mile) reduction in visibility. In contrast to such results, Snowden et al. (1998) found that, based on a laboratory simulation, drivers tended to underestimate their speed under more foggy environmental conditions. Accordingly, drivers subconsciously increase their speed as they get used to the surrounding environment.

*Traction*

During the execution of a given response by the drivers (accelerating, decelerating, steering), traction reflects the friction that exists between the tires and the pavement. Explicit friction measurement (friction coefficient) has not been associated with different weather conditions that are classified in section 2.1.1. To study the impact of snow and ice on the highway system, the Federal Highway Administration (FHWA) offered a weather classification scheme with seven categories in ascending severity ID's. These categories are closely related to the pavement conditions as well as the resulting speed reduction (Table 2-5).

It should be noted that, while capturing the weather impact on the perception (visibility) and the execution (traction) aspect of driver behavior, few researchers focused on the judgment aspect (reaction time, weight on different alternatives). Some studies (Zeitlin, 1995) suggested that weather affected drivers' ability to make quick decisions.

**Table 2-5 Speed Reduction based on Pavement Conditions**

| Condition | Severity ID | Percent Speed Reduction |
|---|---|---|
| Dry | 1 | 0% |
| Wet | 2 | 0% |
| Wet and Snowing | 3 | 13% |
| Wet and Slushy | 4 | 22% |
| Slushy in wheel Paths | 5 | 30% |
| Snowy and Sticking | 6 | 35% |
| Snowing and Packed | 7 | 42% |

*Source: FHWA, 1977*

A more elaborate multi-dimensional study was introduced by Rakha et al. (2007). For the three main macroscopic parameters, namely, maximum flow rate $q_c$ and corresponding speed $u_c$ , and free-flow speed $u_f$ , a weather adjustment factor (WAF) is predicted for a given precipitation type (i.e. rain or snow), intensity level, and visibility level. The prediction model is given in the following form:

$$F = c_1 + c_2 i + c_3 i^2 + c_4 v + c_5 v^2 + c_6 iv \qquad (2\text{-}1)$$

where

$F = WAF$

$i$ = precipitation intensity (cm/h)

$v$ = visibility (km)

$iv$ = interaction term

$c_1, c_2, c_3, c_4, c_5, c_6$ = model coefficients

Using data collected in the Twin Cities, Minnesota, the WAF's were plotted for both rain and snow conditions. The results are shown in Figure 2-1 and Figure 2-2.

In Figure 2-1, the vertical lines show that only rain intensity, not visibility, influences free-flow speed and speed at capacity. No significant effect was recorded for the capacity measure. Notice that under "rain conditions", only atmospheric weather parameters (no traction related parameters) affect the three macroscopic traffic parameters. This is consistent with the zero reduction in speed for wet conditions reported in Table 2-5 (Severity ID 2). On the other hand, more significant impact can be seen in "snow conditions". Capacity is reported to be independent of snow intensity (horizontal lines, Figure 2-2). As for the non-linear plots (Figure 2-2), they indicate that other parameters (mostly related to pavement conditions) may impact the free-flow speed and the speed at capacity and are not captured in the model.

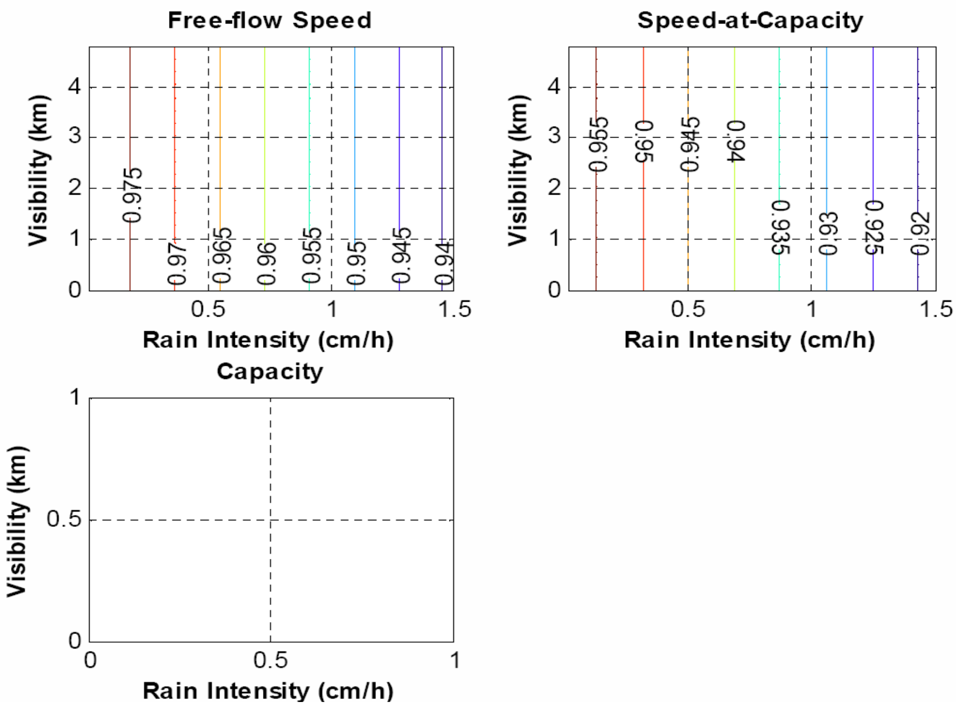



**Figure 2-1 Variation in WAFs as a Function of Visibility and Rain Intensity Levels;**

*Source: Rakha et al., 2007*

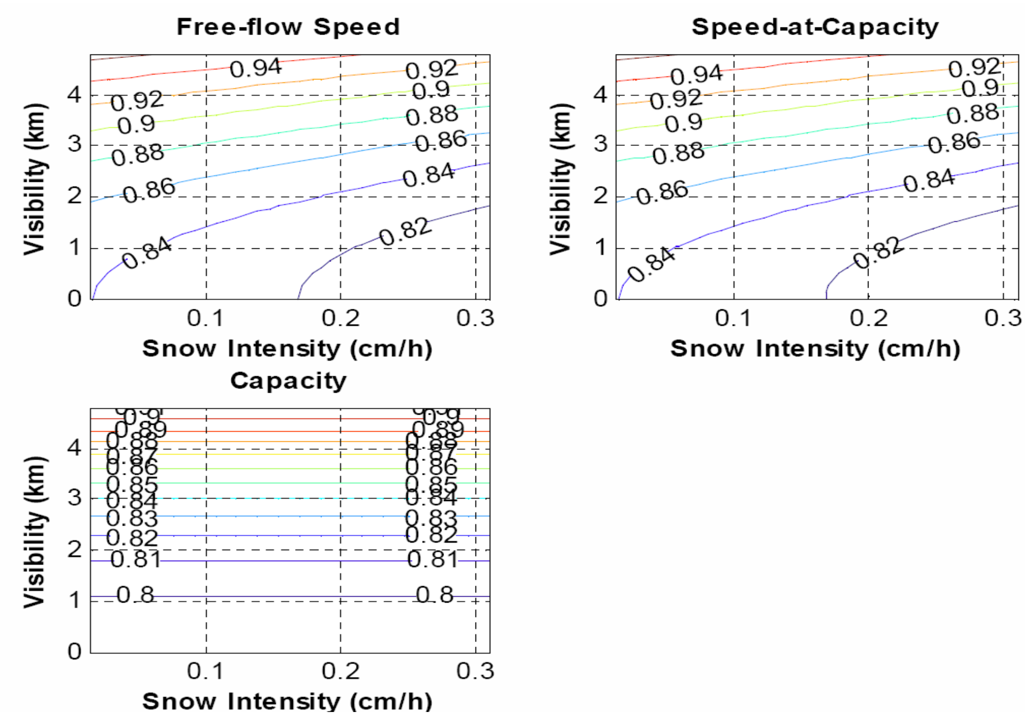



**Figure 2-2 Variation in WAFs as a Function of Visibility and Snow Intensity Levels;**

*Source: Rakha et al., 2007*

### 2.1.3 Traffic Flow Characteristics

After reviewing the different classification schemes of inclement weather conditions, the impact of such conditions on traffic flow relationships is discussed in this section.

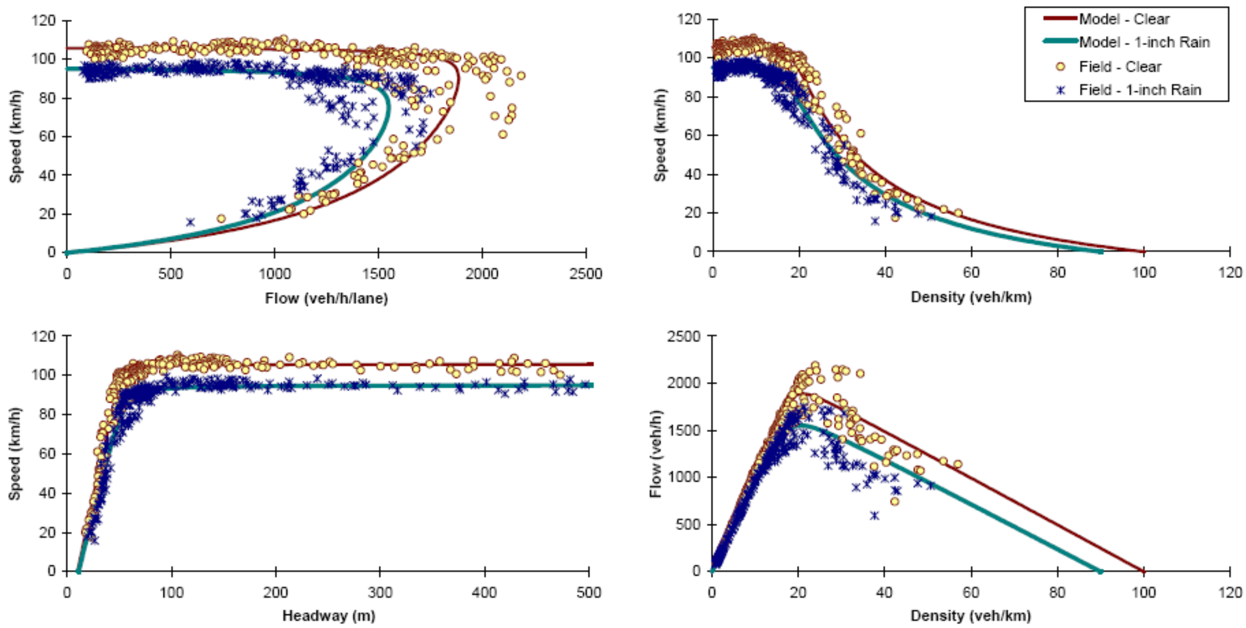
*Speed-Flow-Density Relationships*

The speed-flow-density relationships used in current applications do not explicitly take into consideration the effect of weather and the corresponding departure from "dry and clear conditions". A singe calibrated flow-density curve is normally used for a given location during the entire year, irrespective of the amount of rain or snow falling, the level of visibility/darkness, the pavement conditions and the temperatures. Salonen and Puttonen (1982) studied the relationship between adverse weather and safety. They found that darkness results in a reduction of operating speed by 5 km/hr. In terms of capacity, Jones and Goolsby (1969, 1970) indicated a 14% reduction during rain; no information was provided on the severity of the rain. This severity had an important impact on such reduction as reported by Keltsch and Cleveland (1971). An average of 8% reduction was reported.

Ibrahim and Hall (1994) used a dummy variable multiple regression analysis technique to test the significance in the differences in traffic conditions between different weather conditions. The data used was collected on the Queen Elizabeth Way in Missisauga, Ontario. The three measures available were speed, volume and occupancy. Detailed weather records were available from the Pearson International Airport. The weather conditions were classified under: clear, light rain, heavy rain, light snow and snow storms. The weather data used were those for the months of October, November and December 1990, and for January and February 1991. The focus was on the off-peak weekday duration (10 AM – 4 PM). Even though two functional forms were tested for the flow-occupancy relationship (linear versus quadratic), the linear model was chosen for testing the weather effects. For the speed-flow function, based on the regression analysis, the light rain caused a drop in the free-flow speed of a maximum of 2km/hr and a change of slope between -1.67 to -4.67 m/veh. At a maximum flow of 40 veh/min (2400 veh/hr), an average drop of 13 km/hr is observed compared to clear conditions. For the light snow conditions, the free-flow speed drops by 3 km/hr and the change of slope is between -1.58 and -1.92 m/veh. At the 2400 veh/hr level, the above gives an 8 km/hr drop in speed. It should be noted that, in light precipitation, even though the changes are statistically significant, the scattering of the data points makes the above conclusions difficult to apply.

For the heavy precipitation scenarios, the changes in the speed-flow-occupancy functions are more noticeable. During heavy rain, the free-flow speeds drop by 5 to 10 km/hr and the slope changes by an amount ranging between -1.67 to -4.67 m/veh. Heavy snow causes a drop of free-flow speed of 38 to 50 km/hr and the change is slope varies between –1.67and -5.08 m/veh. Near capacity (2400 veh/hr), the speeds can be reduced by more than 60 km/hr. In terms of flow-occupancy relationship, heavy rain caused a reduction in the maximum flow by 10 to 20% and heavy rains caused a reduction of 30 to 48%.

Consistently with the above studies, Rakha et al. (2007) reported no change in the functional form (linear, quadratic etc.) relating flows, speeds and densities. The authors in this study used the Van-Aerde's model (1995) calibrated using data from Baltimore, Maryland, Seattle, Washington and the Twin-Cities, Minnesota. As seen in Figure 2-3 only three main macroscopic parameters change in value (free-flow speed, flow at capacity and speed at capacity).




| Parameter | Normal | Inclement | F |
|---|---|---|---|
| Free-Speed (km/h): | 106 | 95 | 0.9 |
| Capacity (veh/h): | 1888 | 1550 | 0.82 |
| Speed-at-Capacity (km/h): | 90 | 75 | 0.83 |
| Jam Density (veh/km): | 100 | 90 | 0.9 |
| Wave Speed (wj) (km/h): | -25 | -24.3 | 0.97 |

**Figure 2-3 Impact of Precipitation on Flow-Density-Speed Relationships;**

*Source: Rakha et al., 2007*

The constant form is observed at different intensity levels for different weather conditions (snow versus rain – See Figure 2-4).

As Ibrahim and Hall's study focused on freeway sections, it is reported that the impact of weather conditions on traffic flow relationships and parameters is different depending on the road types. Chin et al. (2004) used loop detector data from different regions of the United States; these data were linked to different weather parameters. Weather conditions were classified into 5 categories: light rain, heavy rain, light snow, heavy snow, fog and ice. The adverse weather conditions impact was translated into loss of capacity and speed and is reported in Table 2-6.

**Table 2-6 Speed and Capacity Reduction based on Road Type**

| Weather Condition | Highway Type | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Urban Freeway | | Rural Freeway | | Urban Arterial | | Rural Arterial | |
| | Capacity | Speed | Capacity | Speed | Capacity | Speed | Capacity | Speed |
| Light Rain | 4% | 10% | 4% | 10% | 6% | 10% | 6% | 10% |
| Heavy Rain | 8% | 16% | 10% | 25% | 6% | 10% | 6% | 10% |
| Light Snow | 7.5% | 15% | 7.5% | 15% | 11% | 13% | 11% | 13% |
| Heavy Snow | 27.5% | 38% | 27.5% | 38% | 18% | 25% | 18% | 25% |
| Fog | 6% | 13% | 6% | 13% | 6% | 13% | 6% | 13% |
| Ice | 27.5% | 38% | 27.5% | 38% | 18% | 25% | 18% | 25% |

*Source: Chin et al., 2004*

The more detailed impact of weather conditions on capacity, delay, volume and speed is reviewed in the following sections.

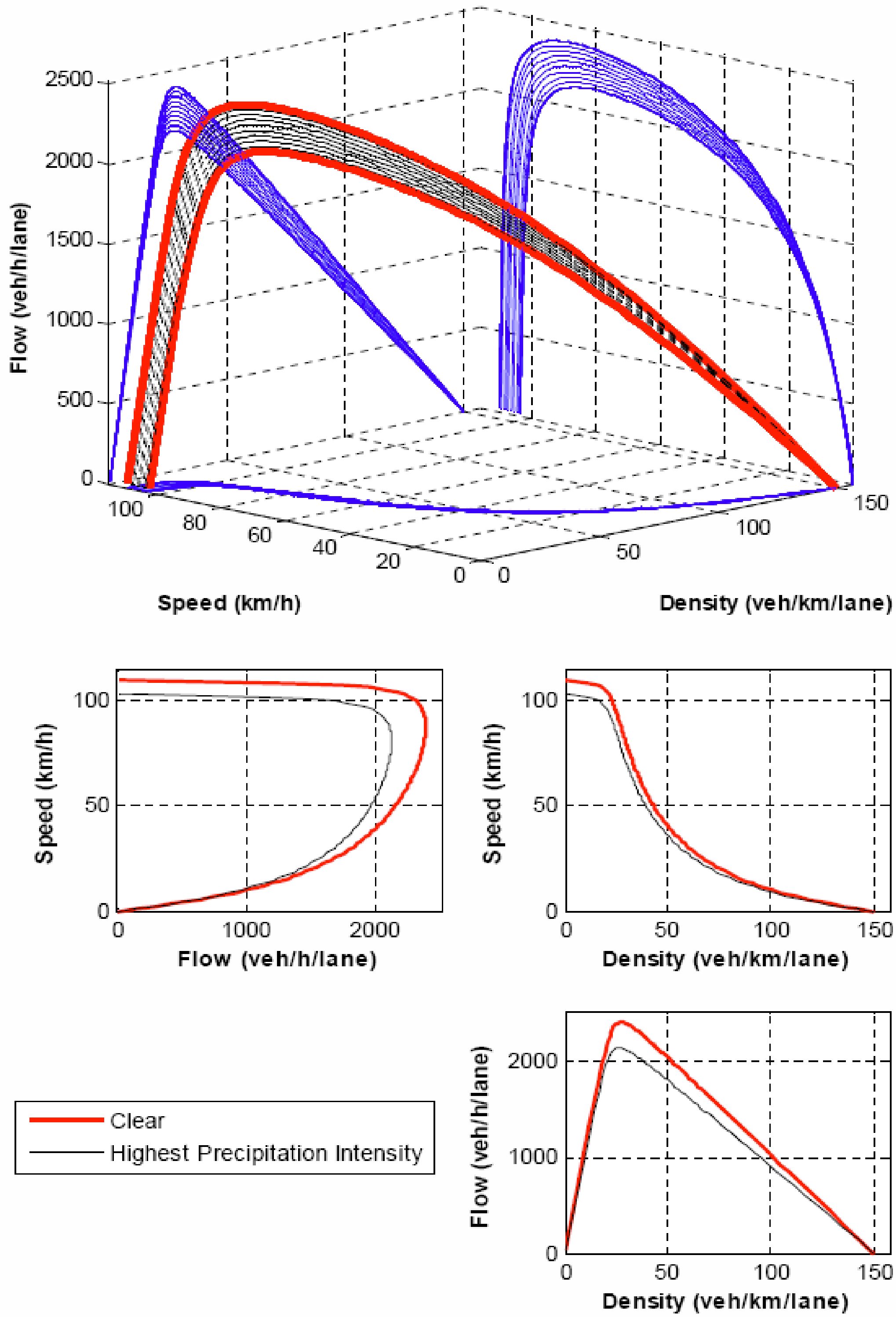



**Figure 2-4 Sample Traffic Stream Model Variation;**

*Source: Rakha et al., 2007*

*Capacity and Saturation Flow Rates*

Adverse weather conditions can significantly reduce the operating speed and thus the capacity in a given road segment (HCM 2000). It is suggested that speeds are not influenced by the presence of wet pavement until visibility is affected (Lamm et al., 1990). Accordingly, light rain does not have noticeable impact on traffic flow compared to heavy rain (10% to 15% reduction in capacity).

Similar to rain, heavy snow is reported to have a potentially large impact on the operating speed (Ibrahim and Hall, 1994). In the corresponding study mentioned earlier, a 30% drop in capacity is attributed to heavy snow compared to a 10% reduction in the case of light snow. The main reason behind such drop is the search for a greater lateral clearance and longer headways since the lane markings are obscured by snow accumulation.

With regard to fog, the HCM noted that a modest amount of research has been performed to quantify the corresponding reduction in capacity. Other research focused on the extent of influence of different environmental conditions on capacity. These environmental conditions were categorized into daylight versus darkness, dry versus wet, and weekend versus weekday conditions; the data were collected on 15 Autobahn sites in Germany (Brilon and Ponzlet, 1995). Table 2-7 illustrates the main findings.

**Table 2-7 Reduction in Capacity from Daylight and Dry Conditions**

| | | Dark and Dry | Daylight and Wet | Dark and Wet |
|---|---|---|---|---|
| Six Lane | Weekday | 13% | 12% | 38% |
| | Weekend | 21% | 27% | - |
| Four Lane | Weekday | 19% | 18% | 47% |
| | Weekend | 25% | 29% | - |

*Source: Brilon and Ponzlet, 1995*

The above results recognize the effect of the reduction in light caused by the dark clouds during winter periods.

Smith et al. (2004) at the University of Virginia studied the impact of different rainfall intensity on freeway capacity and operating speeds. The corresponding traffic (volume, time mean speed and occupancy) and weather (rainfall intensity) data were collected for a one year period between August 1999 and July 2000 on two freeway links in Hampton Roads, Virginia. While the traffic data were collected every 2 minutes using the Smart Travel Laboratory, average speed and flow rates were compiled at 15-minutes intervals. As for the weather data, they were collected by the weather station at Norfolk International Airport (three miles from the study freeway segments) at an hourly rate assuming that the intensity is constant for every 15 minutes in the course of an hour. Based on the guidelines provided by the Swedish Meteorological and Hydrological Institute and the Philippine Atmospheric Services Administration, the rainfall was classified into light rain (0.01 to 0.25 inch per hour) and heavy rain (greater than 0.25 inch per hour). Plotting the speed-flow curves, the maximum throughput observed was estimated to be the capacity. The mean of the highest 5% flow rates was used to determine the change in capacity. It was concluded that light rain decreased capacity by 4 to 10% while heavy rain decreased capacity by 25 to 30%.

Another study by Prevedouros and Chang (2004) used video surveillance data monitoring freeway and arterial roadways in Honolulu between 1996 and 2000. On average, a freeway capacity reduction of 8.3% was observed.

The results of above mentioned studies, regarding the rain effects on capacity, are summarized in Table 2-8.

**Table 2-8 Summary of Rain Effects on Capacity**

| | Capacity Reduction | | | |
|---|---|---|---|---|
| Researcher | Ibrahim and Hall | Brilon and Ponzlet | Smith | Prevedouros and Chang |
| Location | Toronto, Ontario | Germany | Hampton Roads, Virginia | Honolulu, Hawaii |
| Year | 1994 | 1995 | 2004 | 2004 |
| Light Rain | - | 12-47% | 4-10% | 8.3% |
| Heavy Rain | 14-15% | 12-47% | 25-30% | 8.3% |

*Source: Rakha et al., 2007*

<u>*Delay*</u>

Few researchers have been able to quantify the weather impact on the delay experienced by the drivers due to the limitation of data, the inaccuracies involved in travel time estimation and number of explanatory variables involved. Stern et al., (2003) used the metropolitan Washington D.C. network (33 road segments) to collect travel time data for each weekday between December 1999 and May 2001. These data were taken in 5 minute increments between 6:30 am and 6:30 pm. The weather data were collected via Automated Surface Observation System (ASOS) stations at three International Airports in the Washington D.C. area. The travel time was regressed against weather variables for each site using a two-step linear regression process. The final variables kept in the analysis were precipitation type and intensity, wind, visibility distance and pavement conditions.

The study found an average 14% increase in travel time when weather phenomena occur. The pavement condition was the most frequent explanatory variable followed by precipitation.

*Traffic Volume and Demand*

Although traffic volumes reflect the demand side of the problem, it is reviewed in this section as a traffic flow parameter. Adverse weather can reduce demand when drivers cancel or postpone their activities, thus their trips. However, an increase in demand is observed if a good portion of travelers by bicycles or on foot switches to the private vehicle use (short trips). Adverse weather can also shift the peak-hour demand if the drivers choose to leave earlier or later due to unsafe driving conditions.

In 1992, the reduction in traffic volumes during snowstorms in rural areas of Illinois, Minnesota, New York, and Wisconsin (Hanbali and Kuemmel, 1992) was quantified (shown in Table 2-9). The corresponding researchers used automatic vehicle detectors data collected during the first three months of 1991. These data include annual average daily traffic and 24-hour counts. Other data collected include "highway characteristics, level of service (in terms of snow and ice removal), and road treatment. The climate data included storm data (start and end time and date), temperature range, snow depth and type of snow". Comparing hourly traffic volumes during every snowstorm to the "normal" hourly traffic volume, a volume reduction increase with total snowfall was found. However, this reduction is less important during peak-hours and during weekdays. This may be attributed to the non-discretionary type of trips (home to work and work to home trips).

**Table 2-9 Volume Reduction due to Snowstorm**

| Snowfall | Weekdays | Weekends |
|---|---|---|
| < 25 mm | 7-17% | 19-31% |
| 25-75 mm | 11-25% | 30-41% |
| 75-150 mm | 18-34% | 39-47% |

*Source: Hanbali and Kuemmel, 1992*

The winter weather impact on traffic volume and safety was studied by Knapp et al. (2000). Traffic and weather data were collected hourly along interstate highways in Iowa during the years 1995, 1996, 1997 and 1998. The goal is to focus on significant winter storms: precipitation, air temperature below freezing, wet pavement surface and a pavement temperature below freezing for at least 4 hours with an estimated snowfall exceeding 5.1 mm/hr or 0.2 inch/hr.

Covering 64 winter storm events (618 hours), the analysis showed a traffic volume reduction ranging from 16% to 47%. The average reduction was 22.3% where the 95% confidence interval is between 22.3% and 35.8%. Based on a regression analysis, the percent volume reduction had a significant relationship with total snowfall and the square of the maximum wind speed.

*Speed*

The weather conditions increment impact on speed was one of the first aspects of this research to be studied. In 1977, a Federal Highway Administration (FHWA) sponsored study confirmed a decrease in speeds during inclement weather.

In the Highway Capacity Manual, the reported weather impact on speeds is based on Ibrahim and Hall's (1994) study. Conducting a regression analysis on the clear weather data, a quadratic model was found to best fit the flow-occupancy relationship; a simple linear model suited the speed-flow relationship. Moreover, comparing different relationships under different weather conditions, the differences in slope and intercept of the speed-flow function during the rainy (snowy) conditions were more significant that the differences between clear and rainy weather; in light rain, a 1.9 km/hr (1.2 mph) and 6.4 to 12.9 km.hr (4 to 8 mph) reduction in operating speeds is expected during free-flow conditions and at 2400 vehicles/hr flow respectively. In heavy rain, a 4.8 to 6.4 km/hr (3 to 4 mph) reduction in speed can be expected for the free-flow conditions and a 12.9 to 16 km/hr (8 to 10 mph) reduction for the congested conditions. Finally, light snow resulted in a 0.96 km/hr (0.6 mph) drop in free-flow speeds, while heavy snow resulted in a 37.0 to 41.8 km/hr (23 to 26 mph) free-flow speed reduction.

Smith et al. (2004) concluded that although operating speed reductions were not as dramatic as was the case with capacity reductions, statistically significant reduction (3% - 5 %) in operating speed were observed under rainfall conditions compared to no rain at all.

Another related study was conducted by Kyte et al. (2001) on a rural interstate in Idaho. All data were collected from the same four-lane, level grade freeway between 1996 and 2000. High-truck volumes and low flow rates (mostly less than 500 passenger cars per hour per lane – pcphpl) were observed. Collected traffic data include time, speed and vehicle length while weather data contains visibility distance, wind speed and direction, air temperature, relative humidity, roadway surface condition, and type and amount of precipitation. The data were recorded in five-minute intervals. The main results obtained in the study are summarized in Table 2-10.

Padget et al. (2001), investigated whether drivers of SUVs, pickup trucks, and passenger cars choose different vehicle speeds during winter weather at an urban arterial street in Ames, Iowa, between November 1999 and April 2000. The results indicated that winter-weather vehicle speeds for all three vehicle types were significantly less than their normal weather speeds, and that during the day a large percentage of the speed reduction occurs after snow began to accumulate in the gutter pans of the roadway. They also found that speed variability between vehicles types increased during different winter-weather conditions and the magnitude of the speed differences between SUVs, pickup trucks and passenger cars increased with roadway snow cover, but was always less than 5.6 km/h (3.5 mph).

**Table 2-10 Impact of Environment Conditions on Speed**

| Factor | Speed Reduction | |
|---|---|---|
| | km/hr | Mph |
| Wet Pavement | 9.5 | 5.9 |
| Snow Covered Pavement | 16.4 | 10.2 |
| Wind > 24 km/hr | 11.7 (high variation) | 7.3 (high variation) |
| Visibility < 0.28 km (critical) | 0.77 per 0.01 km below critical | 0.48 per 33 ft below critical |

*Source: Kyte et al., 2001*

### 2.1.4 Traffic Control Related Parameters

The changes in traffic related parameters and relationships mentioned above suggest a change in the control scheme applied to manage a transportation system during inclement weather conditions. This section focuses on research performed on the relationships between weather conditions and 1) signalized intersections, 2) unsignalized intersections and 3) variable message signs (including use of the latter as part of road weather management programs).

*Signalized Intersections*

Even though a number of research studies tried to identify the impact of inclement weather on traffic flow parameters at signalized intersections, only a limited effort considered non-standard ways to change signal timing to accommodate such impact. In 1995, Bernardin, Lochmueller and Associates measured saturation flow rates, vehicle speeds, lost time and capacity during summer, winter and severe winter weather conditions (Martin et al., 2000). Summer conditions were defined as temperatures above 14 °F and dry roads or temperatures above 32 °F and wet roads with no ice; winter conditions were defined as temperatures between -22 °F and 14 °F and dry pavement or “well-sanded hard packed snow”; extreme winter conditions were defined as temperature below -22 °F or during snowfall, blizzard, and freezing rain. It was found that summer signal timing is not suitable for winter and extreme winter signal timing. This is mainly due to the slower vehicle speeds and inaccurate measures from detectors covered by snow. Focusing on a 24-signal network in Anchorage, the SIGNAL 85 and TRANSYT-7F signal timing optimization packages were used. SIGNAL 85 determined the final phase sequences and splits based on the chosen cycle lengths and TRANSYT-7F generated offsets giving better arterial progression. The traffic flow parameters input were modified to accommodate the weather changes. Table 2-11 shows the main results. The travel time and the delay measures are provided on an average hourly basis. The results suggest that the improved timing results in a meaningful improvement in delay, accompanied by a slight increase in the percentage of stops.

**Table 2-11 Improvements based on the Winter Signal Timing Modification in Anchorage**

| MOE | Existing Timing (Based on Summer Conditions) | Recommended Timing | Anticipated Improvement |
|---|---|---|---|
| Total Travel Time | 1630 veh-hr/hr | 1416 veh-hr/hr | 13% |
| Total Delay | 930 veh-hr/hr | 716 veh-hr/hr | 23% |
| Average Delay | 49.8 sec/veh | 38.4 sec/veh | 23% |
| Percentage Stops | 64% | 68% | -6% |
| System Speed | 17.1 mph | 19.1 mph | -12% |

*Source: Martin et al., 2000*

It should be mentioned that the study also recommended that no modifications should be made on the all-red (1-3 seconds) and amber (4-5 seconds) times during winter conditions. However, such changes, which are associated with reduced speeds, would also increase the all-red time and decrease the amber time. This topic is still a subject of disagreement between researchers.

A study by Agbolosu-Amison et al. (2004) reveals that inclement weather has a significant impact on saturation headways, particularly once slushy conditions start. The saturation flow rates were found to decrease at 15 ~ 16% under inclement weather conditions (wet & slushy, wheel path slushy and snowy & sticky). However, they concluded that start-up lost time does not appear to be significantly affected by inclement weather.

The Minnesota Department of Transportation conducted a study based on data collected on Hwy 36 between 3-8 pm on several weekdays during different weather conditions (Maki, 1999). Any storm of three inches of snow or more was defined as inclement weather. SYNCHRO III software was used to optimize signal timing during inclement weather conditions by modifying the saturation flow rates, average speeds and lost times. The output data was then compared with those corresponding to the signal timings in use and the existing normal conditions. Based on the simulated scenarios, the small improvement is illustrated in Table 2-12.

Other interesting conclusions were made based on the empirical collected data; during inclement weather conditions, a 15-20% reduction in volumes was reported during the 3-8 pm period and 15-30% reduction during the peak-hour period (5-6pm). Moreover, consistently with the previous study, the speeds decreased from 44 mph to 26 mph (~40%); the saturation flow decreased from 1800 vplph to 1600 vplph (11%); and the start-up delay increased from 2 to 3 seconds.

**Table 2-12 Improvements based on the Winter Signal Timing Modification in Minnesota**

| Scenario | Cycle Length (sec) | Volume on TH 36 (veh/hr) | Percentile Signal Delay/Veh (sec) | Average Number of Stops/Veh | Average Speed (mph) |
|---|---|---|---|---|---|
| "Normal" Weather | 160 | 2513 | 55 | 0.72 | 16 |
| "Adverse" Weather with Existing Timing | 160 | 1912 | 52 | 0.72 | 13 |
| "Adverse Weather" with Optimized Timing | 160 | 1912 | 48 | 0.68 | 13 |

*Source: Martin et al., 2000*

In 1992, Parsonson discussed signal timing in adverse weather conditions by relating it to signal timing during congested conditions. The main recommendation was to have zero offset time (setting all corridor signals to green at the same time) in snowy corridors. This "flushing" is used normally as a management scheme for some heavy congested corridors. Also in 1992, Botha and Kruse studied how the residual ice and snow impacted saturation flow rates and start-up lost times at signalized intersections. The study used data collected at Fairbanks, Alaska. The results are summarized in Table 2-13.

**Table 2-13 Saturation Flow Rates Based on Botha-Kruse Study**

| Category | Winter | Summer | HCM | Winter/Summer Reduction | Winter/HCM Reduction |
|---|---|---|---|---|---|
| Saturation Flow Rate (vplph) | 1463 | 1714 | 1800 | 15% | 19% |

*Source: Botha and Kruse, 1992*

As seen above, the saturation flow rates reported in this study are about 20% less than those calculated using the Highway Capacity Manual (HCM). This indicates the fact that the HCM rates are not reflective of the specific conditions prevailing on the ground.

Gilliam and Withill (1992) used SCOOT adaptive signal control system to reduce the level of congestion at signal networks and that increased due to inclement weather. Wet weather parameters were developed and served as input for the SCOOT system (decreased saturation flow rates and travel times). An important aspect of the study was the method by which a precise traffic monitoring during different weather conditions can be ensured.

One of the most comprehensive studies was performed in 2000 (Martin et al., 2000). During the winter season of 1999-2000, saturation flow rates, start-up-lost times and vehicle speeds were collected for four approaches on two signalized intersections in Salt-Lake City (Intersection 1: 400 E & 900 S; Intersection 2: 1300 E & 500 S). The data was collected during morning and evening peak-hours. The weather data was collected and categorized based on the FHWA 1977 study (Table 2-4). For the saturation flow rate and speed measures, Table 2-14 and Table 2-15 (illustrated by Figure 2-5 and Figure 2-6) show the main results.

**Table 2-14 Saturation Flow Rate (vphpl)**

| Road Surface Condition | Severity | 700 E & 900 S | | 1300 E & 500 S | | Average Percent Reduction |
|---|---|---|---|---|---|---|
| | | AM | PM | AM | PM | |
| Dry | 1 | 1881 | 1736 | 1752 | 1902 | 0 |
| Wet | 2 | 1680 | 1711 | - | - | 6 |
| Wet and Snowing | 3 | 1751 | 1708 | 1491 | 1691 | 11 |
| Wet and Slushy | 4 | - | 1476 | 1321 | 1647 | 18 |
| Slushy in wheel Paths | 5 | - | 1421 | - | - | 18 |
| Snowy and Sticking | 6 | - | - | 1395 | - | 20 |
| Snowing and Packed | 7 | - | - | - | - | - |

*Source: Martin et al., 2000*

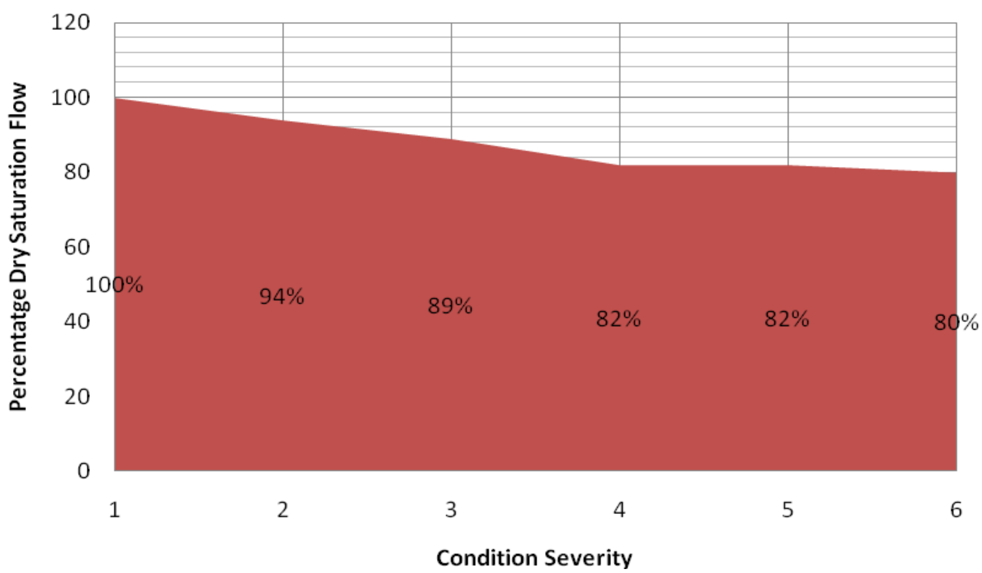



**Figure 2-5 Average Saturation Flow Reductions by Weather Condition;** *Source: Martin et al., 2000*

**Table 2-15 Speed (mph)**

| Road Surface Condition | Severity | 700 E & 900 S | | 1300 E & 500 S | | Average Percent Reduction |
|---|---|---|---|---|---|---|
| | | AM | PM | AM | PM | |
| Dry | 1 | 39 | 31.4 | 28.4 | 27.4 | 0 |
| Wet | 2 | 34.3 | - | - | 25.2 | 10 |
| Wet and Snowing | 3 | 31.4 | 29.4 | - | 23.5 | 13 |
| Wet and Slushy | 4 | - | 22.0 | - | 21.8 | 25 |
| Slushy in wheel Paths | 5 | 25.5 | 23.4 | - | - | 30 |
| Snowy and Sticking | 6 | - | - | - | - | - |
| Snowing and Packed | 7 | - | - | - | - | - |

*Source: Martin et al., 2000*

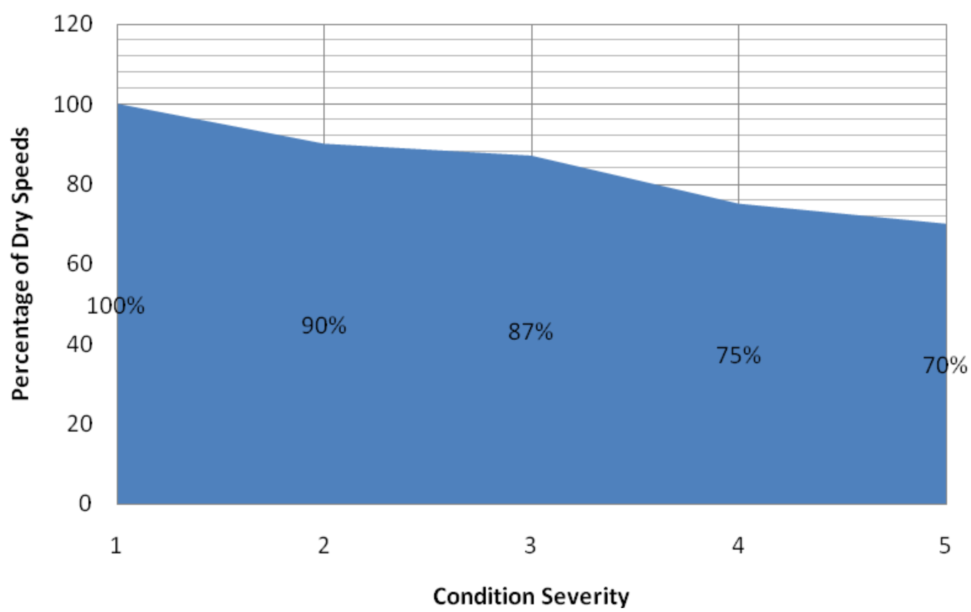



**Figure 2-6 Dry Speed Percentage in Inclement Weather,** *Source: Martin et al., 2000*

As can be seen in Table 2-14, no storm was severe enough to record a severity level of 7. Moreover, no data was available for speeds beyond severity level 5 for both intersections (Table 2-15). Nonetheless, a clear reduction in both saturation flow rate and speed is recorded as the severity level increases. For the speed values, the reductions in this study are almost identical to those reported in the FHWY study in 1977 (Table 2-5 versus Table 2-15). As for saturation flow rates, since no single definition of inclement weather conditions is provided, it is difficult to compare the reductions obtained in the study with those mentioned earlier (Salt-Lake City, Utah; Fairbanks, Alaska; Anchorage, Alaska; and Minneapolis, Minnesota).

In addition to the saturation flow rates and speed reductions, Martin et al (2000) reported the following:

1. The start-up loss time increases considerably with the severity of the road conditions, mainly due to the lesser tire traction. The greatest increase is when slush accumulates on the pavement surface.
2. Most of the northern states (cold weather) do not modify their signal timings during inclement weather.
3. A special timing plan is recommended on major corridors in Salt Lake City during inclement weather based on the following:
    a. The modified plan includes new splits and offsets but the same cycle lengths unless inclement weather traffic counts are provided and require a different cycle.
    b. There should be an increase in amber time by 10% to 15% depending on the intersection size. A 10% (0.5 seconds) increase is appropriate for intersections under 50ft wide, and a 15% (1 second) increase is suitable for 100-ft wide intersections.
    c. An increase of all red time by 1 second is recommended to consider the slower clearing at permitted/protected intersections (a 0.75 seconds longer time is needed by the "sneakers").
    d. A decrease in measured (dry) saturation flow rate of 20% is needed.
    e. The average dry speeds are to be reduced by 30%.
    f. As mentioned earlier the start-up loss time should be 23% higher when devising the modified signal timing plan.

*Unsignalized Intersections*

Based on the literature, there appears to be no scientific literature studying the operational aspect of unsignalized intersections during inclement weather. Instead, researchers focused on the gap acceptance and the acceleration (start-up lost time) behavior during different environmental conditions (NCHRP report, 1996).

Based on observations made by Martin et al. (2000), there is an increase of 23% (from 2 to 2.46 seconds) in start-up lost time. This is based on 112 dry weather sample points and 134 snowing weather points (conditions 4-6, See Table 2-14). The decrease of an intersection's efficiency is not solely related to the increase of the start-up lost time. It is also related to the decrease in acceptable gap at unsignalized intersections as well as for permitted left-turn movements at signalized intersections. Martin et al. suggested that the critical gap for severity levels 4 through 6 increased by 25 to 30% on average. This kind of increase is closely related to an intersection width (number of lanes on each approach) and the reduced speeds while accelerating at a slower rate.

*Variable Message Signs (VMS)*

The common approach to managing highway operations under inclement weather has been through the provision of information to travelers, principally through variable message signs. Agencies with more progressive programs also provide speed advisory information, reflecting a control strategy that considers weather in addition to prevailing traffic conditions in setting advisory speeds.

One of the better (and early) examples of this practice in the US is the ATMS program operated by the New Jersey Turnpike Authority (NJTA) to control 148 miles (237.9 kilometers) of their heavily-travelled turnpike. The NJTA system monitors road and weather conditions, and provides speed management and traveler information to motorists accordingly. The system includes 30 environmental sensor stations (ESS) deployed along the turnpike, with pavement temperature and condition data collected at 11 sites. Over 120 Variable Speed Limit (VSL) sign assemblies are positioned along the freeway at two-mile (3.2-kilometer) intervals. Sign assemblies include VSL signs and speed warning signs, which display "REDUCE SPEED AHEAD" messages (in 5-mph increments) and the reason for speed reductions (i.e., "FOG", "SNOW", or "ICE") (Goodwin, 2003).

Other weather-related information provided to motorists tends to address immediate hazardous conditions, such as reduced visibility due to fog or restrictions due to snow. These would impact directly the traffic flow characteristics on the immediately affected section of highway. Other impacts on travel would depend on the manner in which the information is disseminated to the public at large, at their origin location.

The extent of scientific research addressing these impacts is very limited. Very few systematic studies of user responses to this type of information appear to have been conducted. In this section we focus on the more immediate impact of information on the drivers' response during inclement weather conditions. The next section will consider a wider range of traveler responses. Rämä (1999) investigated the drivers' acceptance of weather controlled signs on Finland's south coast. For that purpose, different VMS and variable speed limit signs were adopted and 590 drivers were interviewed. The objective was to assess the reactions at various intervals after the implementation of the signs in question. Although this study is not based on real-time observation, but rather on driver recall (an unreliable approach for this type of application), only a small percentage of drivers said that they modified their behavior based on the posted message or speed limit.

Consistent with the above finding, Andrey et al. (2003) reported that most drivers access weather information prior to their trip and do not change their travel patterns. As for the real-time driving pattern, Boyle and Mannering (2004) used a simulator to assess the impact of "real-time weather/incident hazard information provided by VMS and in-vehicle information system". It was found that drivers reduce their speed under adverse conditions but increase it again downstream trying to make up the lost time. Also using a driving simulator, Ganesh Babu Kolisetty et al. (2006) investigates the effect of variable message signs on driver speed behavior under foggy conditions. Focusing on an 8.5 km stretch of an expressway in Japan, the authors reported that 40% of the subjects were clearly impacted by the VMS, 40% were marginally impacted and 20% were not impacted at all.

## 2.2 User Responses to Weather Events and Weather-Related Information

The performance of networks depends largely on users' response to traffic conditions, which environmental conditions, such as adverse weather, can impact by increasing the variability in performance. Understanding and modeling the relationship between users' behaviors and adverse weather is important for developing strategies that target user behavior. The literature on adverse weather and user behavior has focused on the adjustments users make when faced with these conditions. Although the majority of these studies are based on stated-preference type data that may not accurately reflect users' actual behaviors, some important insights regarding the travel choice adjustments and preferences of users for weather information can be gained. The existing literature on adverse weather and trip-making behavior has examined either the propensity of travelers to change trip-making decisions, or their preferences for supplied weather information. The next section discusses studies on travel decision adjustments with respect to adverse weather, followed by discussion of users' preferences and response to weather information.

### 2.2.1 Adverse Weather and Travel Decision Changes

In addition to driver responses, adverse weather may also impact a host of travel decisions either made pre-trip or en-route. Most of the existing literature examines departure time, mode and route choice adjustments and show that most travelers do make some kind of change in their travel decisions under adverse weather (Khattak and de Palma, 1997; de Palma and Rochat, 1999; Aaheim and Hauge, 2005). In a detailed survey of commuters in Brussels, the results reveal that even travelers with flexible work hours have a regular schedule, and hence do not all make travel choice changes, suggesting that changing departure times, modes or routes in response to bad weather may be governed by habit or inertial effects (Khattak and de Palma, 1997). Among the commuters' whose travel decisions are impacted by weather, a relatively high percentage indicate that departure time would most likely be adjusted relative to route and mode choice (Mannering, Kim, Ng and Barfield, 1995; Khattak and de Palma, 1997; de Palma and Rochat, 1999). One possible explanation for the preference towards departure time adjustment is its relative lower costs in terms of searching for alternatives. Adjusting routes would require users to search for alternatives to the current route, while switching modes require access to alternative modes. Also, although most commuters in the Brussels study had flexible work hours, the higher propensity towards changing departure times may indicate that commuters would most likely use this flexibility in selecting the most convenient starting and stopping times, relative to other alternatives. Similar insights had been obtained by Mahmassani and co-workers in conjunction with laboratory experiments as well as travel diary surveys of commuter behavior dynamics, albeit without explicit consideration of weather (Mahmassani and Stephan, 1988; Caplice and Mahmassani, 1992; Mahmassani et al., 1997).

Mode choice has also received significant attention in regards to adverse weather. In the Brussels commuter study (Khattak and de Palma, 1997), the results show that although a high number of respondents (69%) stated they had access to a secondary mode, only a small fraction (5%) actually switched modes with bad weather, suggesting the low impact of weather patterns on mode choices. Furthermore, since only a small percentage of respondents used bikes for commuting to work, the results suggest that the substitutability between car and transit is limited. One possible explanation is that transit may expose passengers to the elements. In a study of mode choice during winter versus summer months, the authors showed that a decrease in the number of bicycle trips in the winter was accompanied by a large increase in car use for commuting purposes (Bergstrom and Magnusson, 2003). However, these studies are based on stated preference data and may not represent actual behaviors. A revealed preference study on the impact of weather on the travel habits in Bergen, Norway suggests that the impact of weather on the substitution between public and private transport is relatively small (Aaheim and Hauge, 2005). The same study also shows that travel distances decrease under precipitation, except for commute trips where there is little discretion regarding the destination.

Although the previous studies mentioned examine several different travel choices in light of adverse weather, the literature on activity scheduling changes in response to weather is virtually nonexistent. One possible explanation for this is the difficulty in obtaining good quality weather data over space and time for timeframes longer than a day. However, one study on the impact of the perception of weather information on beach trip decisions suggests that depending on the timeframe in which activities were planned, individuals make varying efforts to distort information regarding adverse weather (Adams, 1973). The study was based on interviews of individuals at a popular beach serving the Boston metropolitan region. The results indicated that respondents with a high prior commitment to go to the beach reported a lower likelihood of rain, relative to respondents with lower prior commitments, with all individuals presented the same weather forecast. Furthermore, individuals with a lower prior commitment tend to cancel the trip when given a sixty percent chance of rain. Although the study was not based on revealed behaviors, it suggests that individuals respond to weather forecasts with the commitment of the activity in mind.

Overall, the literature shows that the impact of adverse weather on trip decisions has been examined only to a limited extent, and that almost all of these studies relied on stated preference data. This suggests the difficulty in obtaining revealed travel behavior data under varying weather conditions. Furthermore, these studies seem to have focused more on travel decisions, such as departure time and mode choice, whereas the literature on activity scheduling adjustments to weather has been virtually nonexistent.

### 2.2.2 Adverse Weather Information and User Response

The literature on weather information provision and user response has primarily focused on two issues: (1) the impact of information provision on travel decisions; and (2) the timing of provision. The 2000 Brussels study shows that drivers using secondary sources did not change their travel choices in numbers that were statistically different relative to drivers using their own observations (Khattak and de Palma, 1997). Similarly, de Palma and Rochat (1999) show that, of the respondents who state weather is an important factor in their decisions, only 55% used secondary sources to keep up with weather forecasts, possibly suggesting a low credit given to weather forecasts. A study by Hansen et al (2001) on weather information preferences showed that information about weather-related road conditions is important to all groups including commuters, recreational travelers, and truckers. Also drivers preferred information about road surface conditions and alternative routes above travel time and speeds. Furthermore, the conditions that all groups preferred information on were those that impact vehicle performance and travel speeds, such as accumulation of snow, ice, high winds, and road closures. Although several studies on the impact of information on trip-making behavior have been conducted, few provide any indication of response to weather information specifically. In a study of en-route switching (to switch or not to switch), the choice model estimation results indicated that delays caused by bad weather decrease the propensity to switch (Polydoropoulou et al., 1996). Several studies have examined driver responses to information (Liu and Mahmassani, 1998; Peeta et al., 2000; Peeta and Yu, 2005). However, weather was not explicitly considered in these studies.

A second issue investigated in the literature is the timing of weather information. Hansen et al. (2001) found that truckers preferred information as early as possible, relative to other consumer groups. In a study on in-vehicle information provision, Mannering et al., (1995) found that, in general, the results for weather information mimicked those of other route and road conditions. For example, users driving frequently on major highways with high average commute times have decreased preference for “ahead-distance” information. Users with more flexible work hours and who change residence frequently, with high number of accidents, have higher preference for ahead-distance information. However, some differences were observed. Also, the higher the number of car passengers, the more preference for ahead-distance information. This suggests that carpool vehicles have a higher preference for weather information, possibly due to the increased variability from picking up multiple riders. Furthermore, drivers with a greater number of alternative routes have higher preference for this information. Intuitively, if individuals have little knowledge of alternative routes in a network, information on bad weather may have little impact since they do not know any alternatives.

# 3. Existing Traffic Prediction/Estimation Models and Systems

This section identifies and reviews existing traffic prediction/estimation models and systems that can be used for both planning and real-time traffic management applications at the corridor and network levels.

Since the inception of ITS, traffic estimation and prediction have been considered a core enabling capability for advanced traveler information systems, as well as for advanced transportation management systems, and an integral part of the various architecture documents put forth for ITS through its various stages. However, deployments of traffic management systems (by associated traffic management centers) have proceeded largely without such capability. Similarly, traveler information systems and services with dynamic travel times and/or route recommendations have been very slow in coming to the market. Transportation agencies have generally been reticent to provide predicted travel times to users, partly concerned about public relations in the event of poor prediction or bad recommendations. In addition, for both traffic management and traveler information services, adjustment is still ongoing to use real-time information on prevailing states, and to try and leverage archived information. Hence the ability to make effective use of predictive travel times and traffic conditions often requires a big leap in capabilities and operational culture.

On the other hand, studies have continued to show the value of predictive information when compared to prevailing information—when supplied to travelers to help route choice (Mahmassani and Jayakrishnan 1991; Ben Akiva et al. 1996; Dong et al. 2006), or as a basis for setting prices dynamically (Dong et al. 2007). Systems for traffic estimation and prediction generally fall into two categories depending on the underlying methodology: (1) simulation-based, and (2) statistics-based. The latter uses statistical relations among directly measured quantities (e.g. time series of speeds and volumes) to produce short term predictions of traffic state descriptors for eventual travel time calculation. The former uses a representation of the traffic processes in the system and associated network interactions to project future traffic states. Simulation-based approaches can provide estimates of conditions on parts of the network where sensors are installed, whereas statistics-based approaches can only be applied to links where measurements exist, and does not deal adequately with disruptions in the temporal flow patterns. Hybrid methods that combine simulation-based approaches with advanced statistical techniques for data fusion try to combine the advantages of both approaches.

DYNASMART-P and DynaMIT were conceived as simulation-based approaches to overcome the limitations of “black box” statistical methods which had been used at the link level in the early literature. Both of these tools also incorporate logic that fuses statistical considerations with the structural representations.

While real-time estimation and prediction of traffic, and more important, development of anticipatory strategies have evolved significantly in the past decade, actual applications remain very limited as agencies have shied away from disseminating predictive information and using predictions in generating traffic controls. On the other hand, the past five years have seen the emergence of third parties providing some type of "real-time" traffic information, though most of it is not predictive, and is limited in geographic scope to major facilities with sensors. Often, the third parties are consolidators of information collected by government TMC's. However, a couple of private sector entities are now marketing real-time information that is claimed to be predictive, primarily for handheld GPS-based devices, though (1) the exact basis or method of prediction is not disclosed, though it is not simulation based, and is admittedly (for some) still preliminary; and (2) extensive validation has not been submitted for peer review. The most notable example is INRIX (courtesy of Microsoft corp.), which claims to use Bayesian statistical methods for state estimation. Another is Dash, Inc. a probe-based system where equipped vehicles that receive travel information also act as probes, sending information on their respective locations and times. While the eventual goal is to feature an integrated predictive system, the capabilities available to date are mostly ad hoc.

Because these new systems feature proprietary engines that have not been sufficiently validated within the traffic community, they will not be addressed further in his review. At their current stage of development, these models do not make special provision for weather effects. The discussion will therefore be limited to DYNASMART and DynaMIT as these reflect the state of the art in simulation-based prediction.

## 3.1 Overview of DYNASMART-X

This section presents an overview of DYNASMART-X, which provides state-of-the-art TrEPS functionality, as well as its applicability to support weather-related traffic management.

To place this discussion in context of available simulation-based DTA tools, it is useful to recall the difference between online and offline applications of DTA tools. Online applications are intended for real-time estimation and prediction of traffic conditions over the near-term (typically less than one hour), to be used in conjunction with traffic management activities such as information provision to motorists (via variable message signs or in-vehicle and other portable devices), traffic control via signals or ramp meters, and other traffic management functions such as incident response, traffic diversion and other congestion mitigation functions. DYNASMART-X is such an online traffic estimation and prediction system. On the other hand, offline applications are primarily intended for evaluation and operational planning activities, in conjunction with planned disruptions, scenario planning, contemplated future network and operational improvements, pricing schemes, and so on. DYNASMART-P is intended for such offline planning and evaluation applications.

As an online TrEPS, DYNASMART-X interacts continuously with multiple sources of real-time information, such as loop detectors, roadside sensors, and vehicle probes, which it integrates with its own model-based representation of the network traffic state. The system combines advanced network algorithms and models of trip-maker behavior in response to information in an assignment-simulation-based framework to provide: (1) estimates of current network traffic conditions; (2) predictions of network flow patterns over the near and medium terms, in response to various contemplated traffic control measures and information dissemination strategies; and (3) anticipatory traveler and routing information to guide trip-makers in their travel (Dong et al., 2006). The system includes several functional modules (for OD estimation, OD prediction, real-time network state simulation, consistency checking, updating and resetting functions, and network state prediction), integrated through a flexible distributed design that uses CORBA (Common Object Request Broker Architecture) standards, for real-time operation in a rolling horizon framework with multiple asynchronous horizons for the various modules (Mahmassani et al., 2004).

The functionality of DYNASMART-X is achieved through judicious selection of modeling features that achieve a balance between representational detail, computational efficiency and input data requirements. These features include (Mahmassani et al., 2004):

- A simulation-based dynamic traffic assignment system, with microsimulation of individual user decisions in response to information, and mesoscopic traffic flow simulation approach.
- Multiple user classes in terms of (1) operational performance (e.g. trucks, buses, and passenger cars), (2) information availability and type, and (3) user behavior rules and response to information.
- Representation of traffic processes at signalized junctions, under a variety of operational controls, including real-time adaptive signal policies and coordination schemes.
- Consistency between predicted network states, supplied information, and user decisions.
- State prediction capabilities in a rolling horizon implementation with simultaneous multiple horizons.
- Capability for optimal path assignment and integrated system management.
- Compatibility with different ITS architectures (e.g. centralized vs. distributed)
- Distributed software implementation using CORBA for flexible and scalable execution in a distributed environment.

The TrEPS platform is comprised of four components: (1) the graphical user interface, or GUI, (2) the database, (3) the algorithmic modules that perform the DTA functional capabilities, and (4) the set of CORBA programs used to implement the scheduler and the data broker. The algorithmic component is the main entity in the system in terms of performing the TrEPS functions, and consists of the following modules: (a) state estimation, (b) state prediction, (c) OD estimation, (d) OD prediction, and (e) consistency checking and updating. The purpose of the state estimation module (RT-DYNA) is to estimate the current traffic state in the network. The state prediction module (P-DYNA) on the other hand provides future network traffic states for a pre-defined horizon. The OD estimation module (ODE) is responsible for estimating the coefficients of a time varying polynomial function that describes the OD demand in the current stage. The OD prediction module (ODP) utilizes these to calculate the demand that is generated from each origin to each destination at each departure time interval of the current and future stages. Finally, the consistency checking modules are responsible for minimizing the deviation or discrepancy between what is estimated by the system and what is occurring in the real world, in an effort to control error propagation.

Note that RT-DYNA and P-DYNA are essentially near-identical copies of the same simulation-assignment code, executed in a different manner and with different dynamic inputs. However, the core simulation logic is essentially identical, and is shared with the off-line DYNASMART-P DTA tool used primarily for analysis and evaluation to support operational planning decisions. Accordingly, modifications made in DYNASMART-P to capture the effect of adverse weather would then near-seamlessly be migrated to the on-line DYNASMART-X TrEPS. Hence, the modifications described in the next section are implemented initially in DYNASMART-P.

Capturing the effect of adverse weather on traffic patterns entails both supply side and demand side modifications to the model. As a decision support tool, DYNASMART-X could also help TMC design weather-related management strategies. Figure 3-1 depicts a high-level view of the DYNASMART-X system structure, the interrelationship among the components and modules, and the manner in which capturing weather impacts would affect these modules (Alfelor et al., 2009).

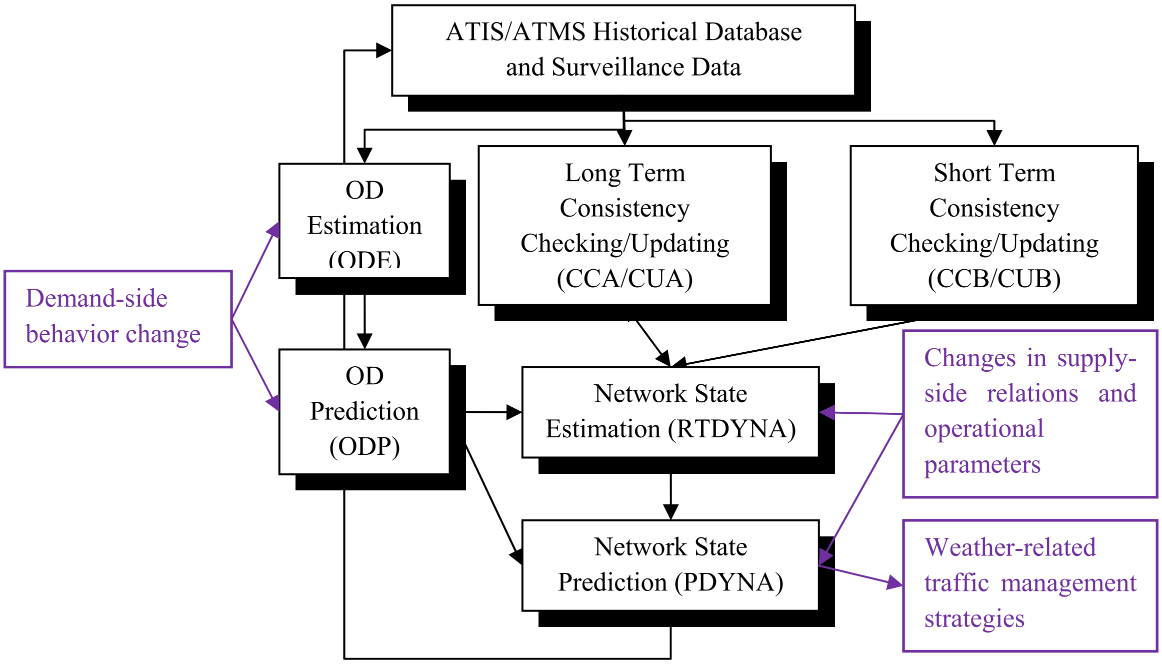



**Figure 3-1 Incorporating Weather Impacts in DYNASMART-X Structure**

## 3.2 Evaluation for Real-time Application of DYNASMART-X

### 3.2.1 Maryland CHART Test Bed

*Data Sources*

This section describes the data available for the Coordinated Highways Action Response Team (CHART) network in Maryland. It also discusses the data quality issues and the data conversion for application of DYNASMART-X to the CHART network. The data includes network geometry data, surveillance system attributes, signal timing data, real-time traffic data, planning data, and other related information. Because the calibration and evaluation plan described later relies on and makes extensive use of these data, it is important to develop a thorough understanding and appreciation of these data elements.

(1) Network geometry and system features

The CHART network was developed using a variety of data sources, including a GIS (geographic information system) file, maps, and field visits. The CHART GIS map file has been provided by the mapping center of the bureau of Transportation Statistics (http://www.bts.gov). Field visits and internet maps (from Mapquest website) were used to modify and fine-tune the network that was produced from the GIS file. In addition to geographic information, zoning and signal information are critical to the network development. The characteristics of the zones have been defined consistent with the traffic analysis zones (TAZs) provided in a transportation planning file from Maryland Department of Transportation (MDOT). The signal locations and signal timing plans were provided by the Maryland State Highway Administration (MDSHA).

The basic input files for DYNASMART include: ***network.dat, xy.dat, linkxy.dat, zone.dat, origin.dat, destination.dat***. They were prepared using TransCAD and converted to DYNASMART using Dynabuilder (developed by the Maryland Transportation Initiative, the University of Maryland).

(2) Signal location and control logic

Information pertaining to signal locations and signal timing plans was provided by the Maryland SHA. The location data consists of a hard-copy inventory of signals by county and location (given by intersecting street names). In addition, signal timing information was provided for some arterials and corridors located in the CHART network. This information was provided in Sychro file format.

The above files are used to set up the input files (***movement.dat, control.dat***) in DYNASMART.

(3) Surveillance system

Real-time traffic data is available from sensors at various locations in the network. Detector information is obtainable from the University of Maryland Center for Advanced Transportation Technology (CATT), Maryland DOT and Maryland SHA. Information describing detector location, as well as detector data is available from the CATT laboratory webpage, http://www.cattlab.umd.edu/cf/index.cfm?js=enabled&bin=trafficData. The detector information is frequently invoked in processing and interpreting the real-time traffic data and the actuated signal data.

(4) Real-time traffic data

Real-time traffic data is available from Center for Advanced Transportation Technology (CATT), Maryland DOT and Maryland SHA. There are 18 detectors located in the network. Two detectors are located on arterials, the rest are on freeways.

Each detector data file contains timestamp information, detector location, traffic direction, vehicle counts, vehicles/hour, speeds, and percent occupancy. Sensors collect 24-hour data in 5 minute intervals. The percent occupancy refers to the percentage of time the detector was occupied during the 5 minute interval. The speed is the average speed recorded over the 5 minute interval. The vehicle count is the number of vehicles observed during the 5 minute interval.

(5) Planning data

There are 111 OD planning zones in the CHART network. Maryland DOT provided a TAZ (traffic analysis zone) file, describing the zonal characteristics of the study area. The OD files contain the static OD matrices for three time periods for the study area corresponding to the following modes: (1) SOV, (2) HOV2, (3) HOV3+, (4) Truck, and (5) Airport passengers. In addition, the three time periods are categorized as follows: (1) AM Peak, (2) PM Peak and (3) Off Peak.

The OD demand files required in DYNASMART include: ***demand.dat*** and ***demand_truck.dat***. The demands were aggregated over all the modes. The static OD matrices can serve as initial values (or targets) when OD demand is calibrated offline or when OD demand estimation/prediction are performed in DYNASMART-X

(6) Other data

Some of the input files for DYNASMART-X are left either empty or with zeroes: ***LinkName.dat***, ***vehicle.dat, incident.dat, workzone.dat, vms.dat, pricing.dat, bus.dat, path.dat, pricing.dat, SuperZone.dat***. The information is either not applicable to the CHART network, or requires more effort to extract appropriately.

Some of the input files kept the default value provided by DYNASMART or offline calibration results: ***TrafficFlowModel.dat, leftcap.dat, yieldcap.dat, StopCap2Way.dat, StopCap4Way.dat, gradelengthPCE.dat, output_option.dat***. Users of course have the opportunity to modify these values if other findings or preferences are available.

Other files such as ***system.dat*** and ***scenario.dat***, as well as DYNASMART-X featured files ***modules.dat*** and ***scheduler.dat*** correspond to advanced settings. The corresponding setting guidance can be found in the DYNASMART-X User Guide.

*Off-line Calibration*

(1) Modified Greenshields model calibration

The traffic flow relations on freeways are specified by a modified Greenshields model in DYNASMART, which can be calibrated against the flow measurements along freeways to determine the possible parameter values at different congestion levels. Special emphasis could be given to freeway segments with on/off ramp weaving movements. Currently DYNASMART does not specifically model these detailed vehicle movements on freeways, but the parameters of the relations can be calibrated to adequately reflect such effects, as DYNASMART allows specification of different parameter values for different physical links. Because of the interruption of traffic flow due to signals, the surface arterials are expected to behave distinctly from freeways. Key parameters in the models, such as the jam density, saturation flow and the model's power parameters need to be estimated using data collected from the arterials of interest. In the current version of DYNASMART, two types of the modified Greenshields model family are available. Type one model is a two-regime model in which constant free-flow speed is specified for the free-flow conditions and a Modified Greenshield model is specified for congested-flow conditions. The second model uses a single regime to model traffic relations for both free- and congested-flow conditions.

The two-regime model is generally applicable to freeways, whereas the single-regime model is applied to arterials. Because of their geometric design and controlled access characteristics, freeways can typically accommodate relatively large traffic flow rates (up to 1300vphpl) at near free-flow speeds, hence the applicability of the two-regime model form. Traffic on arterials, on the other hand, experiences greater interference and interaction, resulting in more immediate deterioration in prevailing speeds with increasing density. Therefore, traffic behavior on arterials is better represented using a single-regime model form.

These models can be estimated by conducting a linear regression analysis using time-varying link density and speed data. The parametric analysis procedure is also implemented to help for linear regression analysis. Alternative model forms require variants of this procedure, or the use of other statistical estimation methods.

(2) Time-dependent OD demand calibration

The available OD matrices for the CHART network are intended for planning applications and provide only static OD demand information. Archived real-time link traffic data is combined with the static OD information to perform an offline estimation of time-dependent OD demand. In addition to providing a representation of the structural characteristics of the dynamic OD demand in the CHART network, the resulting offline estimates also serve as a powerful basis and starting point for online OD demand estimation and prediction.

A bi-level optimization method has been developed to estimate the time-varying OD demand flows. In the upper level, the sum of squared deviations of the simulated link flows from the corresponding observed values is minimized; in the lower level a dynamic traffic assignment problem is solved. The process is iterated until convergence in the reduction of root mean square errors (RMSE) of the estimated link-flows is achieved.

In addition, a multi-objective bi-level optimization model is an extension to the iterative bi-level framework proposed above. Specifically, the upper-level problem is a constrained optimization problem, which is to estimate dynamic OD demand matrix, given link flow proportions and/or an initial target OD demand matrix, that will best reproduce the observed link flows. The link flow proportions are generated from the lower-level dynamic traffic network traffic assignment, namely DYNASMART. In this model, two objectives are considered. The first one is to minimize the discrepancy between observed and estimated link flows, and the second is to minimize the deviation between the target and estimated demand.

All entries in the time-dependent demand table, i.e. flows between all origin-destination pairs for all departure intervals during the study period, should be estimated. All other parameters of the procedure are determined internally, given the actual observations and a time-dependent assignment model like DYNASMART. The estimation will be done for a.m. peak hour of the day. The demand flow will be compared across days of the week.

The data required for the calibration is:

- Relatively reliable historical demand matrix (static or time-dependent).
- Real-time traffic data (flow or density) for links with observation.
- Best values for weights on the objectives, obtained by separate approach.
- The pertinent MOEs for testing the OD-estimation module is the root mean square errors (RMSE) in the estimated traffic flow volumes as described.

(3) Effectiveness of off-line calibration

After completion of the speed-density relation calibration and OD demand calibration, an evaluation is needed to assess the effectiveness of the calibration results. The effectiveness is analyzed by comparing the simulated link performance from the DYNASMART simulator with the observed link performance.

Link density and link volumes are outputted as simulation results and can be used for comparison with sensor data. The root mean-squared error (RMSE) is taken as the measure to assess the effectiveness of calibrated speed-density models and time-dependent OD demand matrices which are input to the DYNASMART simulator.

In general, the simulated link performance is less accurate in the peak time (6:00am-9:00am) than the off-peak time (4:00am-6:00am and 9:00am-10:00am). The simulated performance matches the observation data better for the freeway links than for arterial links. In addition, link density exhibits lower error than link volume. The RMSE measure for a certain link performance characteristic varies across links, which indicates that the simulation replicates the actual traffic states quite well for some of the links while for other links it is less accurate.

The discrepancy is likely the result of several sources. First, note that these results are only for an offline application of a priori calibrated models, and do not take advantage of the online calibration and consistency correction functions provide by DYNASMART-X. In fact, these results illustrate the need for an online estimation and prediction capability. One of the sources of discrepancy between simulated and observed data is that the traffic flow model in DYNASMART is currently based on the modified Greenshields model, which is static in nature. However, the collected sensor data reveals that the model does not always provide a very good fit to the observations. Considerable stochastic variation is evident in the field data. In such situations, although the model provides a “best” estimation of link performance under *static* assumptions, its effectiveness in matching sensor data naturally degrades somewhat vis-à-vis actual observations that might exhibit considerable fluctuation. So the more apparent randomness in the observation data, the worse the match is likely to be. Other sources of discrepancy might include the manner in which various traffic controls perform (e.g. fully actuated signal controllers). A third potential source might be that only the discrepancy of link densities is minimized in the objective function formulated in the calibration of OD demand matrices; this might explain the fact that link density exhibits closer match with observed data than the corresponding values of link volume or link speed. Other possible reasons could include limitation of the inherent route choice model, sensitivity of estimation on network configuration and limited quantity and quality of sensor data. Many of these sources suggest that an online approach to calibration, and to estimation and prediction, is likely to considerably improve operational performance of the models. In this case the time-dependent OD demand calibrated off-line can serve as a starting point. It is expected that the estimation errors would become smaller in on-line application since link performance will be updated quasi-continuously to be consistent with real world observations.

In summary, the calibrated speed-density relations and time-dependent OD demand matrices have been successfully implemented in the DYNASMART simulator, and generated reasonable estimation of traffic conditions which replicate actual observations fairly closely. The errors incurred by the simulation have been analyzed; the majority of these would be alleviated in on-line application or provide an important basis for future improvement of the research.

*On-line Calibration*

This section discusses the development of on-line traffic demand estimation and prediction modules, which provide time-dependent traffic demand matrices for dynamic traffic assignment and associated network traffic simulation.

Dynamic origin destination (OD) demand estimation and prediction is an important capability in its own right, and an essential support function for real-time dynamic traffic assignment (DTA) model systems for ITS applications. The dynamic OD demand estimation and prediction problem seeks to estimate time-dependent OD trip demand patterns at the current stage, and predict demand volumes over the near and medium terms in a general network, given historical demand information and real-world traffic measurements from various surveillance devices (e.g. occupancy and volume observations from loop detectors on specific links).

To provide accurate and robust demand estimation and prediction for real-time dynamic traffic assignment in operational settings, the following primary functional requirements need to be satisfied: (1) incorporate regular demand information into the real-time demand prediction process; and (2) recognize and capture possible structural changes in demand patterns under various conditions.

A recursive real-time OD demand estimation and prediction framework (shown in Figure 3-2) is briefly described as follows (Zhou and Mahmassani, 2007).

Step 1: Receive real-time traffic measurements from surveillance system.
Step 2: Fetch link proportion data from the DTA simulator.
Step 3: (OD estimation) Estimate time-varying OD demand matrices involved in the current estimation stage using the Kalman filtering method.
Step 4: (OD prediction) Predict OD demand over next future horizon.
Step 5: Advance estimation stage forward, and then go back to Step 1.

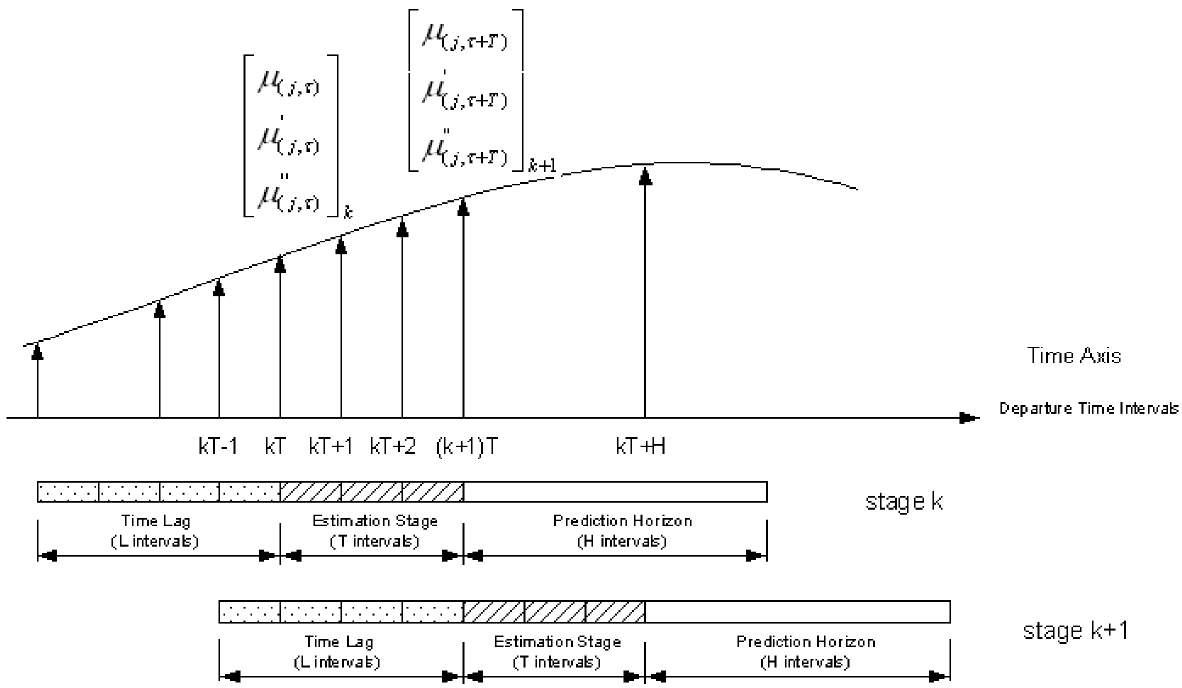



**Figure 3-2 Illustration of Recursive Estimation-Prediction Implementation**

$j$ = index for origin-destination pairs, $j$=1,…, $N_{od}$
$\tau$ = index for aggregated departure time intervals, $\tau$ =1, 2, …
$k$ = index for stage period, $k$ = 1, 2, 3, …
$\mu_{(j,\tau)}$ = structural demand deviation of from a priori estimate for OD pair j with departure time τ

*Evaluation and Applications*

(1) Evaluation of estimation capability

The offline calibrated link-specific speed-density relations are used as traffic flow models for the network. The calibrated time-dependent OD demand matrices are used as the historical demand matrices, which constitute essential input to the on-line OD estimation and prediction. With the adjustments induced by analyzing sensor data using Kalman filter technology, the demand level for each OD pair is estimated. The estimated demand incorporates the historical information and at the same time recognizes the real-time information implied by the incoming sensor data to accommodate the day-to-day changes in traffic demand. It is the estimated demand matrices that load vehicles to the network in traffic estimation.

The RMSEs of density, volume and speed for each of the observed links for different estimation time periods are calculated. Link density and link volume are processed at 5-minute intervals and link volume is obtained from traffic flows mid-block on links instead of link outflows, in order to have meaningful volume values. Compared to the off-line calibration results, the RMSEs for the online estimation are in general lower than those obtained with offline estimation alone, which means that link density and volume could be estimated better in online applications. Whereas the offline simulation would simply load predetermined OD demand tables, the online estimation keeps receiving real-time data, which it uses to update quasi-continuously the internal representation of the system state by means of consistency checking and OD estimation/ prediction.

(2) Evaluation of prediction capability

The traffic prediction in DYNASMART-X is implemented based on a rolling horizon approach. In this framework, the planning horizon is subdivided into several overlapping *stages*. The consecutive stages overlap at fixed intervals, the length of each is referred to as the *roll period*. The *stage length* (or *horizon*) is denoted by $h$ and the *roll period* is denoted by $l$. In the experiment, $h$ is set to 20 minutes and $l$ is set to 5 minutes. The roll period $l$ is the short-term future duration for which the available forecasts of OD desires are considered to be reliable. In the remaining time of the stage, ($h$–$l$), forecasts of OD data are expected to be less reliable. Therefore, the short term prediction should be more reliable and precise than the long term prediction. For a duration A, the traffic status is predicted first time at Stage $m$, second time at Stage $m$+1, third time at Stage $m$+2, and fourth time at Stage $m$+3. It is expected that the prediction is less accurate in Stage $m$ than Stage $m$+3.

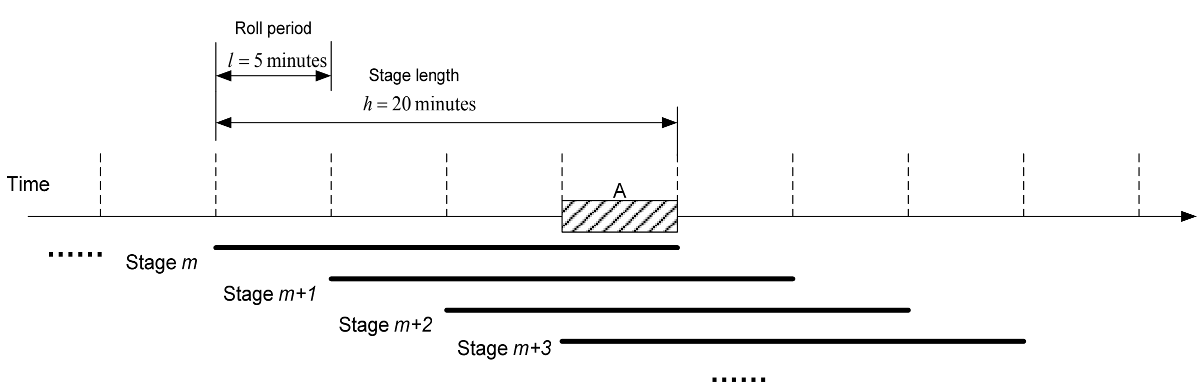



**Figure 3-3 Rolling Horizon Procedure**

To compare the accuracy of predictions, the link performance (density, speed, or volume) is considered through four groups which correspond to prediction obtained at four different times (corresponding to consecutive stages). In other words, the first time prediction indicates the result from the remotest prediction horizon, whereas the fourth time prediction is obtained from the nearest prediction horizon; and so on. The results indicate that the discrepancy of the first time prediction is in general larger than the second, third and fourth times. The fourth time prediction is closest to the actual observed value. This verifies that the short-term predictions in the present rolling horizon procedure are more reliable than the longer-term predictions due to the greater reliability of more recent information.

(3) Travel time information

Pre-trip as well as en-route travel information is an Advanced Traveler Information System (ATIS) user service. Its objective is to inform travelers of traffic and transit conditions, so they can best assess travel options before selecting a route, mode, time-of-day, or deciding whether to make a trip. DYNASMART-X can provide estimations and predictions of network flow patterns and travel times in response to various contemplated traffic control measures and information dissemination strategies.

Based on the predicted OD demand and dynamic assignment simulation result from PDyna, time-dependent link travel times and turning penalties over the prediction horizon can be obtained. If users specified a path, the predictive travel times for different departure time intervals within the prediction horizon are displayed to assist users in making route choice and departure time choice. If users are interested in the travel times between an OD pair, the time-dependent point-to-point travel times as well as the associated shortest paths between the OD pair will be provided.

## 3.3 Overview and Applications of DynaMIT

This section discusses field applications of DynaMIT (Ben-Akiva et al., 2002; Balakrishna et al., 2006), a real time computer system designed to effectively support the operation of Advance Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS) at a Traffic Management Center (TMC). The framework of the system is shown in Figure 3-4. The field implementations made in Hampton Roads, VA and Los Angeles, CA studies are discussed. Note that the DynaMIT networks can be easily converted to DYNASMART and hence be considered in the evaluation of the weather-responsive traffic response models.

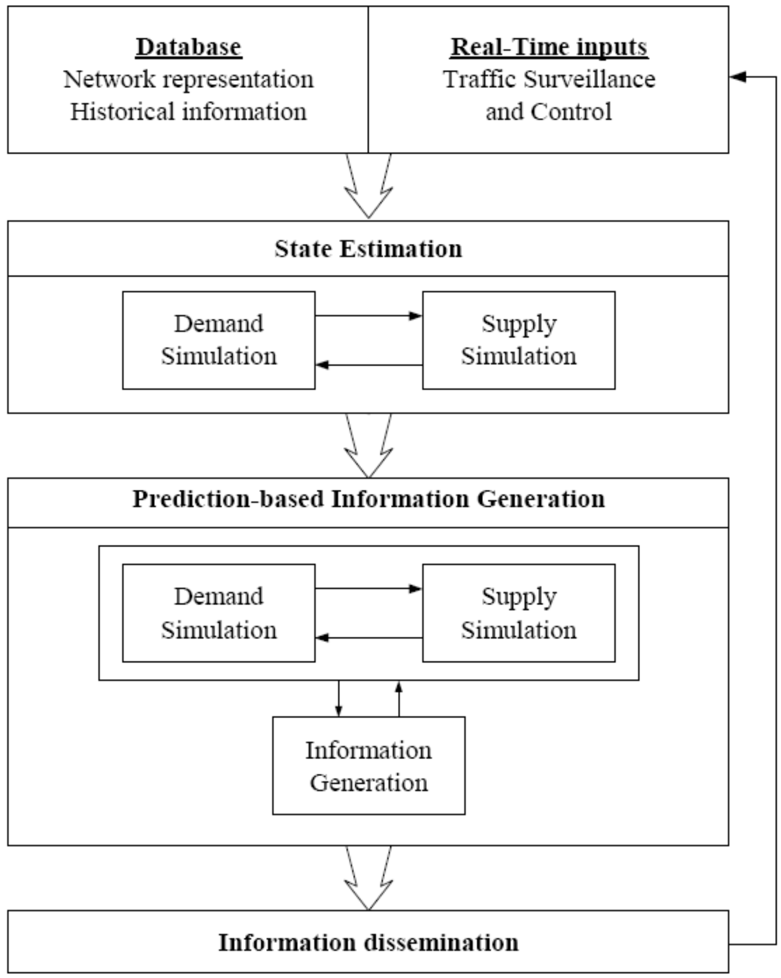



**Figure 3-4** **DynaMIT Framework**

### 3.3.1 Hampton Roads, VA

The University of Virginia (UVA) team evaluated the performance of the DynaMIT-R program in off-line traffic estimation and prediction (Phase I, 2004) and online estimation and prediction capabilities (Phase II, 2006) in Hampton Roads, Virginia (Park et al., 2004; Park et al., 2006).

*Network of Phase I and II*

The Hampton Roads network is composed of three freeways segments: I-64 between Bay Avenue and the Virginia Beach-Chesapeake City Limits, I-64 forming the outer loop, I-564 between Terminal Boulevard and I-64, I-264 between Broad Creek and Rosemont Road, and entire I-664. The same network was used for Phase II.

*Phase I Traffic Data Sources*

Two sets of databases were used for DynaMIT supply parameter calibration and OD demand flow estimation. The first dataset was used for OD estimation and calibration of DynaMIT and the second dataset for both calibration and validation of DynaMIT. For each of years 2001 and 2003 data, two datasets were prepared for supply parameter calibration and historical OD estimation. The dataset for the supply parameter calibration was composed of 10-minute aggregated double-loop detector data with the accuracy of speed and volume data. The dataset for historical OD estimation dealt with volume data from all Smart Travel Laboratory (STL) detectors and Traffic Management System (TMS) stations.

*Datasets of Phase II*

Traffic counts and speed data were obtained from the traffic sensor stations. For the case of supply parameter calibration, only data from the stations configured with double loop detectors was used to ensure accurate speed measures for supply parameter calibration. In addition, traffic data including travel times were used in order to measure the performance of DynaMIT.

Since there existed stations with some missing detector data and inflated by the total number of detectors, and a number of sections where the right most lane or the auxiliary lane carries very low volumes or very high volumes depending on the distance to adjacent interchange and flow characteristics, lane utilization factors were introduced for computing traffic counts of detectors with missing data that could be highly overestimated or underestimated on the basis of equal lane distribution assumption. In the calibration of supply parameters, it was found that they were slightly revised to better represent field traffic conditions by incorporating the lane utilization factors.

*Calibration and Validation of Supply Parameters (Phase I and II)*

The major steps of supply parameter calibration include segment classification, determination of three key parameters (i.e., capacity, free flow speed and maximum density under free flow speed) and curve fittings. First, the segments in the test network were categorized into several homogenous groups according to their characteristics such as corridors and roadway geometric characteristics and number of lanes. A preliminary analysis through the visual inspection of flow and speed data plots was performed to justify the segment classification; and final segment groups were defined with field data availability. Capacity and free flow speed of each segment groups was determined on the basis of field data and recommendations from the Highway Capacity Manual (HCM). The capacities under inclement weather conditions were estimated to be 95% of those under normal conditions and free flow speed was reduced by 2 mph from normal conditions. Maximum densities under free flow conditions were determined using HCM level of service A and B densities.

Since speeds and flows are relatively accurate compared with densities less reliable mainly because they are estimated from occupancies, the UVA team calibrated this two regime flow-speed function instead of speed-density function. Hence, the supply parameters were estimated with traffic sensor data from the first dataset, the estimated parameters were validated with the second dataset. Using the sensor data of double loop detectors from the second dataset, the quality of the supply parameters was visually verified and it was found that the supply parameters fit well.

<u>*Demand Calibration (Phase I and II)*</u>

The objective of demand calibration is to estimate the historical OD flows and the variance-covariance matrix (varcov) for the study network. For the purpose of demand calibration, the planning version of DynaMIT (i.e., DynaMIT-P) was used to compute the assignment matrices during the OD optimization. The historical OD estimations were done for two periods: off-peak (10:30 AM to 12:30 AM) and peak (4:30 PM to 6:30 PM) periods with normal days for the estimation of stable historical OD flows at relatively quick convergence.

Initial OD matrix was obtained by a double-constrained gravity model since the Hampton Roads network is a well-bounded freeway system where the total trips in entering and exiting the freeway system with on ramps as origins and off ramps as destinations should be close. Since the relative reliability of traffic sensor and OD pair demands were not known, calibration process was started by providing higher weights to the OD pairs having low counts and use of the data quality for the stations. Three normal days were used for demand calibration. The following points summarize the procedure followed in the demand calibration process for both Phase I and Phase II.

1. DynaMIT-P program was run with traffic counts from a normal day using the initial OD matrix obtained from a gravity model. Once newly estimated assignment matrices from DynaMIT-P were obtained, the estimated OD matrix was externally optimized via MATLAB software to ensure its convergence.
2. By replacing the initial OD with the OD obtained at the end of step 1, DynaMIT-P was run for the same day again. The estimated OD from DynaMIT-P was again externally optimized via MATLAB.
3. Using the new OD matrix after step 2, DynaMIT-P was run with a second day by following the same procedure as in the above tow steps. An updated OD was obtained.
4. At the end of the second day, varcov matrix was estimated.

5. Using the updated OD matrix obtained at step 3 and varcov matrix at step 4, DynaMIT-P was run for a third day.
6. At the end of third day, the obtained estimated OD was used as historical OD and varcov matrix was computed again.

Both calibration results for off-peak and peak periods showed that the Root Mean Square Normalized (RMSN) errors were decreasing consistently for the last three runs and then showing similar values for the last two runs. Also, high correlation between the simulated and actual sensor counts was observed to show the comparison of counts for the last day of the calibration for both periods. Hence, OD was converged for the off-peak and peak conditions and considered as a reliable historical OD matrix. The same was true to the results of Phase II.

*Evaluation of DynaMIT-R Off-line Performance*

In Phase I, DynaMIT-R (real time version) was implemented with the five different scenarios consisting of two off-peak and two peak periods, and a VMS case. For each of non-peak and peak periods, five normal days were evaluated for the performance of DynaMIT-R under normal conditions, and a mix of normal, bad weather, and incident days were evaluated for such mixed conditions. The VMS scenario evaluated the impact of diversion due to the implementation of VMS display of incident conditions. As a result, it can be concluded that DynaMIT-R fairly well predicts traffic conditions for all the scenarios studied and is also capable of giving guidance to the users of the surface transportation system with the use of VMS functionality.

*Online Evaluation (Phase II)*

Online evaluation for three days was conducted with all required data provided in real-time by various sources such as traffic sensors (e.g., loop detectors), CCTV cameras, Hampton Roads Smart Traffic Center (HRSTC) operators, etc. Through the sources, traffic counts, speed and incident information were fed into the DynaMIT program during online evaluation. In addition, a probe vehicle was employed to obtain field travel times on a few key routes. The other key element was to achieve faster computation on given estimation and prediction intervals. This would help DynaMIT operator have more time to implement various strategies, especially under incident conditions.

With the newly estimated 24-hour historical OD and supply parameters, online evaluation of DynaMIT was implemented. Traffic sensor counts were aggregated into five minute counts and fed into the DynaMIT. The incident management interface provided an incident alert as soon as a new incident is being identified and recorded. With the incident alert and the use of traffic surveillance camera, an operator can assess the condition of incident and enter the incident information to the DynaMIT using the enhanced Java Road Network Editor (jRNE) incident input interface. Since the implementation of DynaMIT was an online-open loop evaluation, there was no feedback from DynaMIT to the field. The performance measures of RMSN errors for volume counts, absolute values of speeds and travel times were considered for comparing the simulated results from DynaMIT with the actual field conditions.

From the online evaluation, the MATLAB enabled DynaMIT, which enhanced OD estimation procedure, significantly improved its computation runtime. Average runtime and maximum runtime were reduced by 44% and 25%, respectively. This would certainly provide more time for an operator at a TMC to better estimate DynaMIT parameters, especially during incidents, and to better evaluate various strategies for proactive control of traffic.

DynaMIT showed good performance with the RMSN errors of 0.15 ~ 0.25 in the estimation of traffic sensor counts, while those of predicted traffic sensor counts ranged from 0.25 and 0.4. These errors were fairly consistent regardless of network congestion levels. The prediction errors were a bit worse than those obtained at the off-line evaluation during the Phase I study. The performance of traffic counts estimation during incidents was as good as those shown during normal conditions, except for a case with sever incident condition where the estimation of incident parameters was not done accurately. As such, it was found that DynaMIT can adequately model incident conditions as long as incident parameters are properly determined.

When speeds and travel times were used in the evaluation of DynaMIT's estimation and prediction capabilities during online evaluation, it was observed that both estimation and prediction show some discrepancies during congested conditions even though traffic counts matched quite well. This clearly indicates traffic count is not a very sensitive measure in the evaluation of DynaMIT's estimation and prediction capabilities. In addition, it suggests that supply parameters may not be optimal for all the segments. Obviously, this was not a limitation of DynaMIT, but it was due to lack of actual field traffic data. Therefore, more efforts in the calibration of supply parameters should be given wherever possible. As traffic data is not available for each segment of the network, supply parameters of those segments were obtained from similar segments.

*Challenges Encountered (Phase I and II)*

The following section includes the challenges that the project teams encountered through both studies and their discussions related with OD estimation and update of varcov matrix.

Phase I:

- Fluctuations in OD flows: The DynaMIT-P (planning version) program estimates OD matrix sequentially, in other words, the ODs for entire 24 hours are not optimized simultaneously. The sequential estimation methodology caused huge fluctuations over time in the estimated OD pairs. Hence, it was observed that for some OD pairs the estimated demand varies unrealistically, resulting in poor estimation of auto regressive parameters.

- Updates on variance-covariance matrix (varcov.dat file): The DynaMIT-R program used in this study used a single value for each sensor or OD demand pair, regardless of the number of time intervals. In reality sensor data could be missing for short-term periods due to malfunction in communication or other errors. Thus, varcov value needs to be updated according to sensor data quality. A solution to this is to update the varcov values according to data quality of a particular day.

Phase II:

- Overestimated ODs: Significantly higher demands were assigned to the certain destination links and resulted in vehicle back-ups and huge congestions. Although the MIT team implemented a quick fix, that simply simulated DynaMIT with a newly estimated OD or retained historical OD. Ideally, this challenge should be addressed by considering link capacity during OD estimation.
- Updating Varcov matrix: The Varcov matrix plays a critical role in the OD estimation. Varcov values of certain OD pairs were fixed during historical OD estimation (or demand calibration) to prevent DynaMIT estimating unrealistic demands (i.e., exceeding destination link capacity) for those OD pairs. Obviously, this was not a solution but one of the acceptable remedies available. In addition, due to unrealistic fluctuation of OD flows, they were redistributed.

### 3.3.2 South Park region of Downtown Los Angeles, CA

The study network in South Park region of downtown Los Angeles consists of two major freeways (I-10 and I-110) and a dense network of arterial streets. It is represented in DynaMIT by a set of 243 nodes and interconnected 606 directed links, which are subdivided into 740 segments to model changing section geometry within a link. Half of more than 200 arterial intersections in the network consist of signalized intersections. Signals along the major arterial segments are synchronized (Wen et al., 2006).

*Demand Calibration*

There was ground work before the demand calibration as follows:

- Path choice set generation
- Defining period of study
- Simplifying assumptions

The path generation process attempted to capture all reasonable and feasible paths for each OD pair. To this end, a suitable path set was obtained using 20 random draws to complement link-elimination based shortest paths from every link on the network to every destination node. In the course of this process, a path with a higher freeway percentage among two paths with same travel time was preferred and all paths longer than the shortest path by more than 20% were eliminated between each OD pair to eliminate many redundant and unreasonable paths. Manual inspection of various OD pairs confirmed that nearly all practical paths were included in the path choice set, which finally contained total of 44,224 OD paths for 3745 OD pairs.

Since DynaMIT would be deployed for real-time traffic estimation and prediction-based guidance generation on the site, the period of off-line calibration encompasses entire 24 hour, excluding 3 hours from midnight to 3:00 AM when arterial data was not available. The 21 hour calibration period was divided into 84 intervals of 15 minutes each, which was decided considering computational efficiency and the fact that sensor counts do not exhibit significantly large variations for shorter interval.

Several simplifying assumptions were made in order to accommodate practical considerations and data availability. The covariance matrices of error between the estimated and a-priori OD flows ($W_h$) and error between simulated sensor counts and observed counts ($V_h$) were assumed to possess a diagonal structure implying that the sensor measurement errors and direct OD measurement errors are uncorrelated. The auto-regressive factors were also assumed to be diagonal suggesting that deviation of OD pair from its historical values depends only on the deviation of same OD pair from its historical values in previous intervals.

Since it was observed that availability of many alternative paths between a freeway-to-freeway OD pair were forcing an unreasonably high proportion of drivers to use part-arterial-based path, path-size logit model was applied to calculated the probabilities of selecting various routes with utility of given path. To resolve this issue, optimal route choice parameters were found.

*OD estimation, Calibration, and Validation*

Five days were selected spanning one entire month and all days of week (Monday-Friday) to carry out the sequential calibration process (Figure 3-5). Generalized Least Square Estimation was used to estimate OD matrix interval by interval. Very high weights were applied to sensor counts and very small weights to seed OD flows so that they could extract all possible information from sensor counts instead of meaningless estimate of seed OD flows for the first day of calibration. Once first day was completely estimated, error covariance matrices were obtained. Calibration procedure for the second day was exactly similar to the first day, except the calculated error covariance matrix used in GLS formulation. This approach was repeated in the third day, fourth day and fifth day, every time recalculating the error covariance matrix and updating historical OD matrices and experienced travel times. The performance of calibration was verified with the estimated error statistics and graphical comparisons of simulated and observed counts for the same periods.

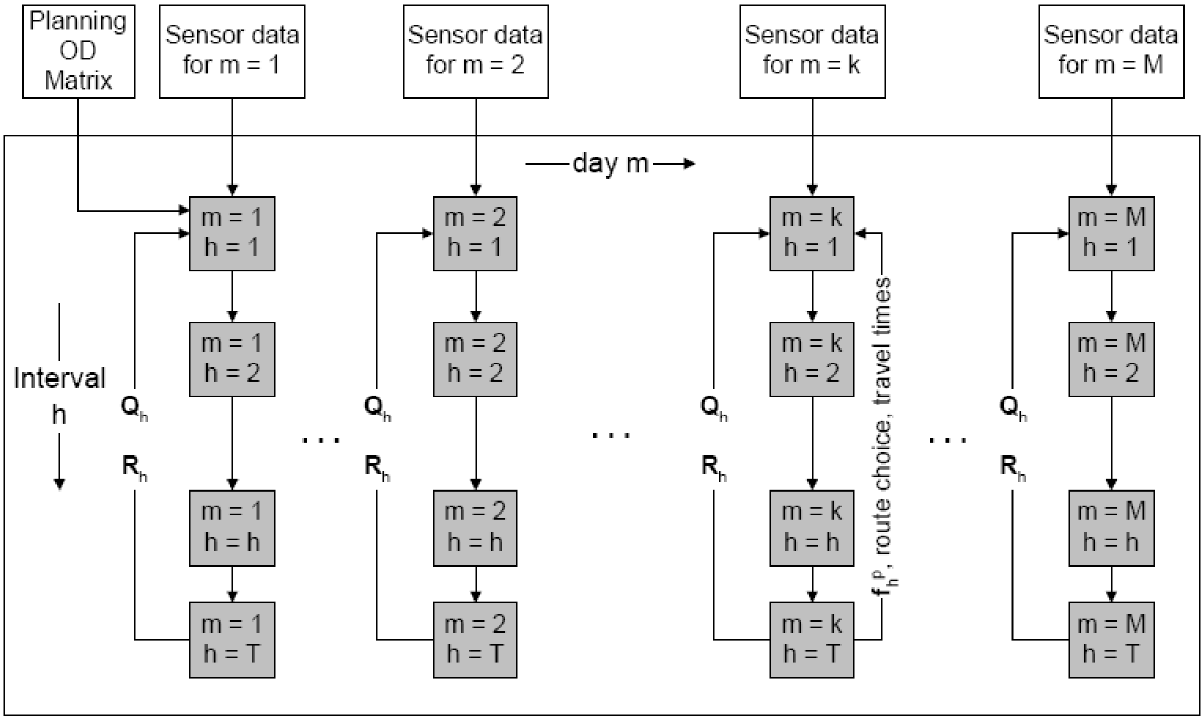



**Figure 3-5** **Within-Day and Day-to-Day Process**

After calibration was done for five days, auto-regressive (AR) factors were calculated for DynaMIT's prediction capabilities. The calibrated AR factors were obtained by regressing the deviations of estimated OD flows for all five days with corresponding historical OD flows with auto-regressive factor equation introduced in the report and presented by the group of OD pairs classified by their size.

Validation were employed to assess whether the calibrated set of historical OD matrices, historical travel times, and variance-covariance matrices continues to perform satisfactorily when supplied with fresh input, as would be the case in an on-site application. For the validation for its estimation and prediction performance, another day of new data which was not used in calibration process was selected. It was observed that errors during validation runs were comparable to those obtained during calibration process within acceptable limit in the validation of its estimation performance.

Prediction tests for calibrated AR parameters were started by estimating OD flows for selected time intervals for both days. Five intervals were picked uniformly during the day to test the effectiveness of the calibrated AR factors. Then, deviations in the OD flows for next fifteen minute period (one-step prediction) were predicted using estimated OD flows for each time period. Similarly, prediction for next fifteen minute (two-step prediction) were performed using a set of estimated OD flows from past intervals, and just predicted OD flow for previous interval was calculated. In the same manner, further step predictions up to next one hour were carried out. It was observed that errors during validation runs were comparable to those obtained during calibration process, and were within acceptable limit. Therefore, it was validated that the historical (calibrated) parameters were able to replicate weekday data. Several variations of the OD prediction method were tested, and one based on moving averages was found to yield the most consistent patterns.

*Off-line Calibration of Speed-density Relationships*

Link performance functions in much of the literature are calibrated by fitting a curve to the observed traffic data. In the previous approaches, the calibration variables were limited to the speed-density function parameters. However, the optimization depends on several other DTA inputs such as OD flows and route choice model parameters. The values selected for these other inputs and parameters thus impact the outcome of the supply calibration. One may thus iterate between demand and supply calibration steps until convergence (as defined by the modeler) is reached. This iterative procedure can be time-consuming and inefficient, as only a subset of the available data is used in either calibration.

Balakrishna et al. (2007) presented a calibration framework that allows the simultaneous calibration of all supply and demand parameters and unknown inputs typical to DTA models (e.g. OD flows, route choice parameters, capacities, speed-density parameters) using any available data (e.g. counts, speeds, densities, queue lengths). Thus all significant DTA inputs and parameters may be estimated simultaneously, providing the most efficient result. The problem is solved with the SPSA algorithm.

This calibration approach provides a unique advantage. Since the parameters of the speed-density functions for all segments are estimated simultaneously, the function parameters for each segment can be calibrated to better fit the traffic data at the network level.

The above method has been applied to the Los Angeles network (Balakrishna et al., 2008), an area of heavy traffic throughout the year owing to commuters and the regularity of sporting and convention special events. The numerical results show that the estimator, denoting supply calibration using count data, results in a significant improvement in replicating the counts and traffic dynamics (speeds) in the area. Further, the increased accuracy is reflected on both freeway and arterial links. In the base case, the speed-density parameters were fitted at individual sensor locations and attributed to all segments in the respective groups.

*On-line Calibration of Speed-density Relationships*

In the current DTA framework, only the OD flows are calibrated on-line. In most cases, the approach to the problem of calibration of the other parameters has been to calibrate the simulation models off-line using a database of historic information. The calibrated parameter values are then used in the on-line simulations. The calibrated model parameters, therefore, represent average conditions over the period represented in the data. Models that were calibrated this way may produce satisfactory results in off-line evaluation studies, which are concerned with the expected performance of various traffic management strategies. However, this may not be the case in real-time applications, which are concerned with the system performance on the given day. If the model that was calibrated off-line is used without adjustment, the system is not sensitive to the variability of the traffic conditions between days, which are the result of variations in the parameters of the system, such as weather and surface conditions. Such variations may cause traffic conditions to differ significantly from the average values. Thus, the predictive power of the simulation model may be reduced. To overcome this problem, real-time data can be used to recalibrate and adjust the model parameters on-line so that prevailing traffic conditions can be captured more accurately. The wealth of information included in the off-line values can be incorporated into this process by using them as a priori estimates.

Tavana and Mahmassani (2000) use transfer function methods (bivariate time-series models) to estimate dynamic speed–density relations from typical detector data. Huynh et al. (2002) extend the work of Tavana and Mahmassani (2000) by incorporating the transfer function model into a simulation-based DTA framework. Qin and Mahmassani (2004) evaluate the same model with actual sensor data from several links of the Irvine, CA network.

Antoniou et al. (2007) formulate the problem of on-line calibration of a DTA model as a nonlinear state-space model that allows for the simultaneous calibration of all model parameters and inputs. The methodology is generic and flexible and does not make any assumptions on the underlying model structure, the parameters to be calibrated or the type of available measurements. Because of its nonlinear nature, the resulting model cannot be solved by the Kalman filter, and therefore, nonlinear extensions are considered: the extended Kalman filter (EKF); the limiting EKF (LimEKF); and the unscented Kalman filter. The solution algorithms are applied to the on-line calibration of the state-of-the-art DynaMIT DTA model, and their use is demonstrated in a freeway network in Southampton, U.K. The LimEKF shows accuracy that is comparable to that of the best algorithm but with vastly superior computational performance. Antoniou et al. (2007) present an application of their on-line DTA calibration methodology using data from a freeway network in Southampton, UK. The study demonstrates the performance gains that can be obtained through the dynamic, simultaneous calibration of the speed-density relationships and other supply-side parameters.

*On-line Evaluation*

For the on-line evaluation, DynaMIT was run in on-line, real-time mode, and the sensor files are used to simulate the surveillance interface setup at LADOT. Through the preliminary studies, a few promising results were achieved. Firstly, estimated counts generally stay close to the actual counts for the entire day. Secondly, predicted counts also follow the same trends and most of them are reasonably accurate. This indicates that estimates reported by DynaMIT through its traffic simulation are likely to reflect the real traffic condition, and the predictions of DynaMIT are likely to foresee the evolving traffic condition. The preliminary evaluation also illustrated that one-step prediction (obtained just one interval ahead of the real-time) is in general better than two-step prediction. It indicated that the accuracy of prediction will deteriorate over time.

Other than the areas introduced above, there are more areas that DynaMIT was tested and applied as a decision-aid tool for traffic diversion particularly in Switzerland. The scope of its application was the development of diversion strategies with a VMS-based system.

# 4. Methodology

This section presents the overall conceptual framework for capturing weather effects in a DTA model, representation of weather data, and the principal supply-side elements that would affect the representation of adverse weather effects on traffic flow propagation and system performance. The demand-side elements that determine user responses to weather and related information and control measures are also presented.

## 4.1 Conceptual Framework

Capturing the effect of adverse weather on traffic patterns entails both supply side and demand side modifications to existing dynamic traffic assignment (DTA) tools. These weather-related elements and their interaction with current DYNASMART functionalities are shown in Figure 4-1 (Dong et al., 2010a). In this study, we mainly focus on two elements, namely, weather impacts on supply-side relations and parameters and user response to weather information and control actions.

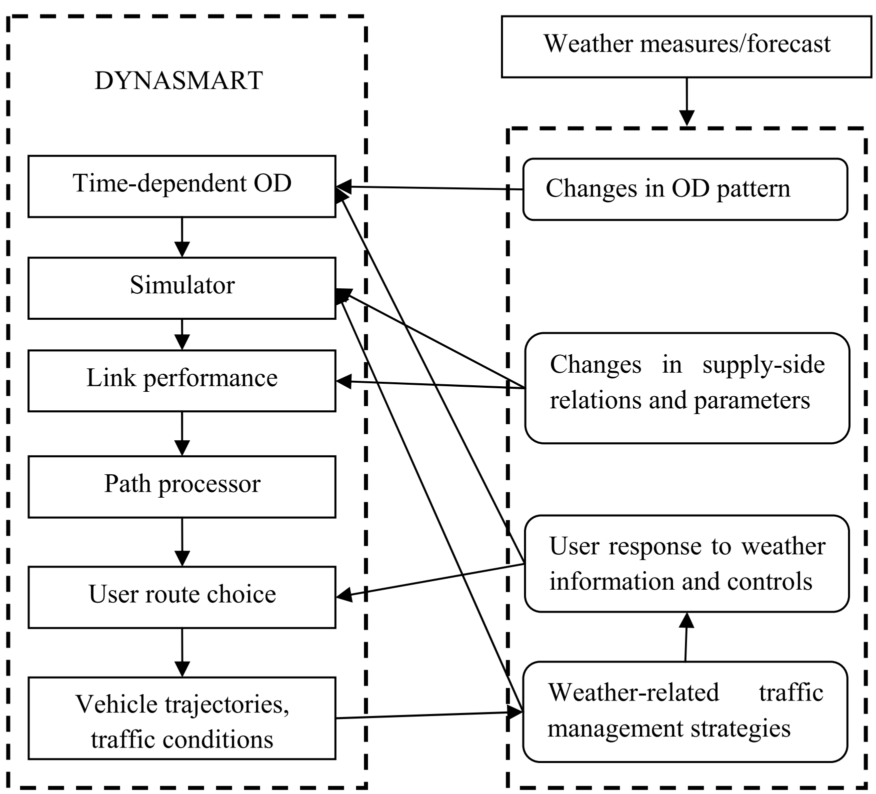



**Figure 4-1 Demand- and Supply- Side Impacts of Adverse Weather**

## 4.2 Weather Data Representation

Several TMC's across the nation, especially in flood-prone areas (e.g. Houston/Harris County's TranStar TMC) are now connected to weather information and forecasting systems. A suitable interface system could help a TMC obtain weather data automatically and simultaneously in real-time from weather stations. The required weather-related inputs for traffic estimation and prediction purposes will be the type, severity and duration of a particular weather condition, and the geographic area influenced by the reported/predicted adverse weather. The specific configuration of the communication architecture and media from weather stations to the TMC is not especially problematic, from the standpoint of real-time performance, because weather data is usually updated only every hour or so, and does not generally fluctuate every minute.

The weather data can be queried from well-established organizations measuring, recording and storing temperature, dew point, wind, altimeter setting, visibility, sky condition, precipitation, and so on. In particular, precipitation type, precipitation intensities (inch/h) and visibility readings (mile) were used in previous studies, including the FHWA Report (Hranac et al., 2006). Therefore, three link-specific weather parameters can be specified through the GUI (Graphical User Interface) or input file, that is, visibility, rain intensity and snow intensity. The default values of these parameters correspond to clear weather conditions. Based on the regional weather conditions, the user could modify all or some of the weather parameters of the links within the impacted area. This will then allow incorporating the effect of the specified inclement weather condition on the estimated/predicted traffic patterns. The procedures devised to capture this impact are discussed next.

## 4.3 Modeling Weather Impacts on Supply Side Relations and Operational Parameters

The principal elements in the simulation that would be affected by adverse weather, and hence may provide a mechanism for capturing weather effects on traffic patterns, include the following:

- <u>Speed-density model for freeway sections (and ramps)</u>

  Both the functional form and the parameter values (free mean speed, jam density, breakpoints for multiple regime models) may be affected by weather, and may be affected differently by the characteristics of different weather instances. The above-mentioned FHWA report (Hranac et al., 2006) summarizes changes in the so-called fundamental diagram observed at a limited number of locations (e.g. Twin Cities, Minnesota).

- <u>Speed-density model for signalized arterials and unsignalized approaches</u>

Empirical evidence collected through the calibration experience with DYNASMART in various cities strongly suggests different functional forms for the speed-density relations for arterials than for freeways. For instance, the latter exhibit distinct multi-regime features that are not present in arterial data. In addition, there is considerably more variation in both functional form and parameter values for arterials than for freeways.

- <u>Service rates and section capacities for freeways and ramps</u>

It is not well understood in the traffic simulation community that service rates and capacities play at least as important a role as the speed-density relation parameters in governing traffic flow under highly congested conditions, when queueing phenomena become critical in determining traffic propagation. Hence specifying these parameters correctly is an essential aspect of calibrating these models. Such parameters will naturally be affected by weather of varying characteristics. Reductions ranging from 5% to 35% have been reported in the literature, and provide a starting point for the modifications addressed in this study.

- <u>Saturation flow rates, section capacities and turning service rates at signalized junctions</u>

Under normal weather condition, the default values of saturation flow rates are consistent with accepted highway capacity manual practices. Yet, these values will be dramatically affected by inclement weather conditions.

- <u>Saturation flow rates and operational parameters at unsignalized junctions</u>

Controls at unsignalized junctions include yield signs, stop signs and roundabouts. Weather effects on these facilities are likely to be of greater magnitude than at signalized intersections given the reliance of unsignalized junctions on human interaction in sharing the right of way, which becomes more difficult under adverse weather.

- <u>Operational characteristics associated with incidents and their impact</u>

Adverse weather magnifies the impact of traffic incidents, increasing their severity and possibly their duration as well. It is suggested that higher severity, longer duration, and possibly greater frequency of occurrence, be used in devising incident scenarios under adverse weather.

- <u>Operational characteristics of work zones and other special events</u>

Work zones typically affect the maximum speed as well as the capacity of the directly affected sections, as well as those that carry traffic in the opposite direction for certain work zone geometries (see DYNASMART-P User's Manual, Mahmassani et al., 2006). Given the significance of weather events that occur in conjunction with work zones in most parts of the country, it would be important to revisit the entire approach to modeling work zones in order to enable better representation of traffic flow in and around work zones under adverse weather conditions.

The inclement weather impact on each of the above-mentioned parameters can be represented by a corresponding weather adjustment factor (WAF), as follows:

$$F_i = \beta_0 + \beta_1 \cdot v + \beta_2 \cdot r + \beta_3 \cdot s + \beta_4 \cdot v \cdot r + \beta_5 \cdot v \cdot s \qquad (4\text{-}1)$$

where

| | |
|---|---|
| $F_i$ | weather adjustment factor for parameter $i$ |
| $v$ | visibility |
| $r$ | precipitation intensity of rain |
| $s$ | precipitation intensity of snow |
| $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ | coefficients |

The parameters are adjusted accordingly if a link is specified as an impacted link. Namely, if link *a* is impacted by inclement weather that is characterized by (*v*, *r*, *s*), a set of WAFs can be calculated for link *a* based on Equations (4-1) and (4-2). Therefore, all the parameters can be adjusted by the corresponding WAFs. For example, the saturation flow rate under inclement weather is represented as follows:

$$f_i' = F_{f_i} \cdot f_i \qquad (4\text{-}2)$$

where

| | |
|---|---|
| $f_i'$ | saturation flow rate under inclement weather |
| $F_{f_i}$ | weather adjustment factor for parameter $f_i$ |
| $f_i$ | saturation flow rate under clear weather |

Therefore, this representation offers a flexible approach to capturing weather effects on traffic flow propagation, allowing sensitivity to a wide range of conditions, and capability to characterize varying types of traffic behaviors under adverse weather conditions.

## 4.4 Modeling Demand Side Behaviors and Parameters

The demand side dimensions and parameters that determine how traffic patterns may be affected by adverse weather consist of two principal categories: (1) those that affect the dynamic OD pattern in the network, and (2) those that affect the distribution of flows in the network, especially in response to information and/or various traffic controls. Hence, changes in destination, departure time or trip cancellation (and, if dealing with a vehicle rather than person OD pattern, changes in mode choice as well) would be reflected in the dynamic OD pattern. On the other hand, route diversions in response to information, route choice decisions based on pre-trip or en-route information, response to various advisory messages and the like would be in the second category. While, of course, we can view the first category as resulting from individual decisions as well, modeling such mechanisms directly would be considerably more complicated (and require a much richer, and unfortunately lacking, empirical survey basis) than trying to capture their net result by inferring the dynamic OD pattern.

(1) Changes in dynamic OD pattern

One of the advantages of an on-line system is its ability to adaptively estimate and predict OD and associated flow patterns as the latter are unfolding. The hybrid Kalman Filter approach with structural temporal effects developed for DYNASMART-X (Mahmassani and Zhou, 2005), along with the consistency checking and updating modules, are intended to capture changes in dynamic OD patterns resulting from weather-related adjustments in tripmaking. As such, both the overall levels of demand, their distribution across OD pairs as well as over time should be captured by the existing system. The main limitation today is that the traffic models may not capture traffic propagation correctly under adverse weather, hence introducing a potentially important source of error in the overall estimation and prediction process (which will affect the OD predictions as well since the latter are linked to the observed measurements through the DTA model and resulting link proportion matrix).

In addition, user response to pre-trip or en route information would also affect dynamic OD pattern, including: (1) Leaving earlier or later; travelers might adjust their departure times due to inclement weather, that is, the decision to leave earlier (e.g. returning home on a day when bad weather is forecast) or later (e.g. waiting out a bad storm). (2) Real-time mode choice; like departure time choice, real-time mode choice is a pre-trip decision that considers weather-related measures in the context of Integrated Corridor Management (ICM) strategies. (3) Trip chaining and tour alteration; adverse weather may lead to changes in the sequence of stops along a tour, or may lead to adding or deleting stops, e.g. when stopping unexpectedly to pick up a child at school early in anticipation of a bad storm.

(2) User responses to information and control measures

This category of demand side phenomena is of critical importance to the ability of DYNASMART-X to serve as an effective decision support tool for traffic management under adverse weather conditions. The principal types of decision situations include the following:

- <u>Response to variable message signs</u>

  New message types and their attributes are introduced in DYNASMART, as well as the behavioral rules that govern the responses to these messages, taking into consideration the attributes of the driver. Note in this regard that the mesoscopic modeling approach adopted in DYNASMART is especially well suited to this type of representation. The fact that individual decision entities are retained in the simulation effectively gives the model the same capabilities as a microsimulation tool from a travel behavior decision standpoint.

- Route choice under adverse weather and related information

A new attribute associated with weather-related risk is included in the generalized cost. Users with varying degrees of risk aversion would choose their routes accordingly. Therefore, the criteria for the driver's route choice include monetary cost, travel time and travel penalty (due to low visibility, or precipitation). Accordingly a generalized cost is specified in Equation (4-3) to reflect these attributes:

$$GC = \beta_0 \cdot c + \beta_1 \cdot t + \beta_2 \cdot p \tag{4-3}$$

where

| | | |
|---|---|---|
| $GC$ | generalized cost | [$] |
| $c$ | monetary cost | [$] |
| $t$ | travel time | [min] |
| $p$ | travel penalty due to adverse weather | [min] |
| $\beta_0, \beta_1, \beta_2$ | coefficients | [-, $/min, $/min] |

The coefficients indicate the relative importance of travel time, cost and weather condition. The value of time is expressed as $\alpha_{VOT} = \dfrac{\beta_1}{\beta_0}$. Similarly, travelers' valuation of weather impact is defined as $\alpha_p = \dfrac{\beta_2}{\beta_1}$ , that is, the traveler's risk taking regarding the adverse weather conditions; by default, $\alpha_p = 1$. Therefore, the generalized travel time can be expressed as follows:

$$GT = c / \alpha_{VOT} + t + \alpha_p \cdot p \tag{4-4}$$

where

| | | |
|---|---|---|
| $GT$ | generalized travel time | [min] |
| $\alpha_{VOT}$ | value of time | [$/min] |
| $\alpha_p$ | risk taking preference | [-] |

## 4.5 Traffic Advisory and Control Strategies

When the estimation and prediction for a given horizon is completed under inclement weather, the predicted information provided by DYNASMART-X can form the basis for intervention by operators at a TMC, in the form of traffic control actions or advisory/mandatory guidance for drivers. If necessary, such actions or strategies can be disseminated to drivers through VMS or other media to alleviate road weather impacts. This section discusses the traffic advisory and control strategy features in the DYNASMART program.

### 4.5.1 Traffic Advisory–ATIS & Variable Message Signs

By use of the predictive travel time provision feature of DYNASMART, the weather/travel information dissemination interface allows selection of one or more paths for specified origin and destination pairs, and provision of predicted travel times for every prediction time interval under inclement weather. Travelers could therefore choose their departure time and/or route based on the predictive information.

In addition, roadside VMS plays an important role in en-route weather warning and route guidance. Field studies (Luoma et al., 2000; Rämä, 2001) have shown that weather advisory VMS can help decrease the average speed as well as the variance in speed so as to increase safety and reliability experienced by the traveling public. Weather VMS also proved most effective when adverse weather and road conditions were not easy to detect. Weather advisory VMS, in the form of slippery road condition signs and fog (low visibility) signs, are in use in various places around the world. For example, in Finland, slippery road condition, implemented in combination with the minimum headway sign, decreased the mean speed by 1.2 km/h with steady display and by 2.1 km/h when the sign was flashing (Rämä, 2001). Hogema and van der Horst (1997) showed that the Dutch fog warning signs, implemented in conjunction with variable speed limits, decreased the mean speed in fog by 8 to 10 km/h (i.e. 5 to 6 mph). Cooper and Sawyer (1993) found that the automatic fog-warning system on the A16 motorway in England reduced the mean vehicle speed by approximately 3 km/h (i.e. 2 mph).

In DYNASMART, two types of weather warning (advisory) VMS are implemented (Dong et al., 2010b): (1) Speed reduction: a VMS warning sign, indicating low visibility (e.g., fog) or slippery road (e.g. rain and snow), would generally reduce the speeds of the traveling public. Therefore a speed reduction value is specified, for this type of weather VMS, to capture travelers' response to the weather warning. The default values, for different types of adverse weather conditions, are set based on the field studies in the literature, discussed earlier. (2) Optional detour: a weather warning sign could also suggest that travelers reevaluate their current route if it passes through a certain area impacted by adverse weather events. Travel penalties, indicating the added delays caused by adverse weather, are specified for the impacted links. Travelers who respond to this type of VMS would take into account the adverse weather penalty in their route choice decision, that is, the penalty will be included in the generalized cost, discussed in the previous section.

### 4.5.2 Control Strategies

Control strategies include evacuation or diversion under extreme conditions (e.g. severe winter storms, hurricanes and floods), traffic signal control, and Variable Speed Limit displays.

1. Mandatory detour VMS

The mandatory detour VMS advises drivers of lane closures, and mandates all vehicles to follow some user-specified sub-path in the vicinity. This type of VMS is also used to inform drivers of extreme weather conditions and mandate all vehicles to detour, when a certain area or road is closed due to safety concerns. This can be achieved in the DYNASMART program by specifying an incident with 100% capacity reduction on the impacted links. A mandatory detour VMS could be specified upstream of the closed road to advise travelers of a detour path.

2. Weather-responsive signal timing plan

Martin et al. (2000) modified signal timing plans to improve traffic conditions under inclement weather. Several types of events may occur that require changes in prevailing signal times. Weather is such an event; signal timings maintained by traffic controllers in the field, say in a particular weather influence area, may be replaced with a priori prepared adverse weather signal timings. To this end, DYNASMART-X is able to read and implement signal timing plans that are available in real-time.

3. Variable speed limits

VSL utilizes traffic speed and volume detection, weather information, and road surface condition technology to determine appropriate speeds at which drivers should be traveling, given current roadway and traffic conditions. These advisory or regulatory speeds are usually displayed on overhead or roadside variable message signs (VMS). VSL systems are already being used as part of incident management, congestion management, weather advisory, or motorist warning systems to enhance the safety and reliability of roadways (Robinson, 2000). VSL messages are sometimes displayed alongside the weather advisory VMS to inform travelers as well as promote traffic safety, such as on the interurban Highway E18 in Finland (Rämä, 1999).

In DYNASMART, VSL is implemented to regulate the speed of the impacted links/areas under adverse weather conditions (Dong et al., 2010b). The speed limit posted may be adjusted based on prevailing weather conditions and a look-up table. In each look-up table, one or more weather conditions are specified, as well as the corresponding speed limit reductions. For instance, on E18 in Southern Finland between Kotka and Hamina speed limits are set as 120 km/h (74 mph) for good road conditions; 100 km/h (62 mph) for moderate road conditions; and 80 km/h (49 mph) for poor road conditions (Rämä, 1999). Similarly, on the Snoqualmie Pass section of I-90 in Washington State, the speed limit posted is reduced from 65 mph, in ten-mph increments, to 35 mph depending on visibility and weather severity, obtained from multiple weather stations, snow plow operators, and the state patrol (Robinson, 2000). The intent in DYNASMART is to be able to evaluate the response of users to such strategies, and incorporate their effect on predicted conditions.

# 5. Implementation of Weather-Related Features in DYNASMART

This section entails a description of newly added weather related options and associated input files in DYNASMART. The overview of those weather related features is provided in Table 5-1. First, weather conditions can be specified by users for either an entire network or an individual link through "weather.dat". Traffic performance is then simulated in DYNASMART based on the adjusted supply-side parameter relations that are provided through a user-specified input file, "WAF.dat". In addition to the simulation of the weather effect on traffic performance, users can also simulate traffic advisory and control strategies by using various VMS options. Along with existing four types of VMS in DYNASMART, another three weather-related VMS options are developed and implemented, namely, speed reduction VMS, travel risk warning, and variable speed limits. Aside from these new VMSs, an existing mandatory detour VMS could also used to inform drivers of extreme weather conditions and mandate all vehicles to detour, when a certain area or road is closed due to safety concerns as discussed in the previous section. The detailed descriptions of data preparation for these features are presented in the remainder of this section.

**Table 5-1 Weather-related Features in DYNASMART**

| Weather-related option | Description | Associated input file |
|---|---|---|
| Weather data representation | Specify various weather scenarios for the study network over time. Allow users to specify either network-wide weather condition or link-specific weather condition. | weather.dat |
| Applying the weather effect to supply-side parameters | Specify change in supply-side relation and operational parameters regarding weather conditions by applying a weather adjustment factor(WAF) | WAF.dat |
| Modeling traffic advisory (speed reduction) via VMS | Simulate the effect of speed reduction advisory through VMS | vms.dat |
| Modeling traffic advisory (travel risk warning) via VMS | Simulate user response to travel time delay information provided by VMS under inclement weather condition | vms.dat |
| Modeling traffic control (Variable Speed Limits) via VMS | Simulate the effect of variable speed limit control through VMS | vms.dat, vsl.dat, weather.dat |

## 5.1 Weather Data (*weather.dat*)

For the weather scenario, three link-specific weather parameters can be specified by users, that is, visibility, rain intensity and snow intensity. The default values of these parameters correspond to clear weather conditions, that is, no precipitation and visibility greater than 10 miles. Based on the regional weather conditions, the user could modify all or some of the weather parameters ($v$, $r$, $s$) of the links within the impacted area. A new input file, namely *weather.dat*, is created to store the adverse weather specifications, described in Table 5-2.

## Table 5-2 Description of the *weather.dat* Input File

| Record Type | Field | Format | Width | Description |
|---|---|---|---|---|
| Network-wide Weather flag | 1 | Integer | Free | 1: A network-wide weather condition exists;<br>0: otherwise |
| Network Weather Information | 1 | Float | Free | Visibility (mile). |
| | 2 | Float | Free | Rain intensity (inch per hour) |
| | 3 | Float | Free | Snow intensity (inch per hour) |
| | 4 | Float | Free | Start time of the across-the-board weather condition (minutes) |
| | 5 | Float | Free | End time for the across-the-board weather condition (minutes) |
| Number of links | 1 | Integer | Free | Number of links with link-specific weather condition |
| Link Information | 1 | Integer | Free | Link counter (1st link with inclement weather condition) |
| | 2 | Integer | Free | From node |
| | 3 | Integer | Free | To node |
| | 4 | Integer | Free | Number of time periods |
| Weather Information | 1 | Float | Free | Start time for the 1st weather condition (minutes) |
| | 2 | Float | Free | End time for the 1st weather condition (minutes) |
| | 3 | Float | Free | Visibility (mile) |
| | 4 | Float | Free | Rain intensity (inch per hour) |
| | 5 | Float | Free | Snow intensity (inch per hour) |
| ..... | ..... | ..... | ..... | ..... |
| Weather Information | 1 | Float | Free | Start time for the Nth weather condition (minutes) |
| | 2 | Float | Free | End time for the Nth weather condition (minutes) |
| | 3 | Float | Free | Visibility (mile) |
| | 4 | Float | Free | Rain intensity (inch per hour) |
| | 5 | Float | Free | Snow intensity (inch per hour) |
| ..... | ..... | ..... | ..... | ..... |
| Link Information | 1 | Integer | Free | Link counter (last link with inclement weather condition) |
| | 2 | Integer | Free | From node |
| | 3 | Integer | Free | To node |
| | 4 | Integer | Free | Number of time periods |
| Weather Information | 1 | Float | Free | Start time for the 1st weather condition (minutes) |
| | 2 | Float | Free | End time for the 1st weather condition (minutes) |
| | 3 | Float | Free | Visibility (mile) |
| | 4 | Float | Free | Rain intensity (inch per hour) |
| | 5 | Float | Free | Snow intensity (inch per hour) |
| ..... | ..... | ..... | ..... | ..... |
| Weather Information | 1 | Float | Free | Start time for the Nth weather condition (minutes) |
| | 2 | Float | Free | End time for the Nth weather condition (minutes) |
| | 3 | Float | Free | Visibility (mile) |
| | 4 | Float | Free | Rain intensity (inch per hour) |
| | 5 | Float | Free | Snow intensity (inch per hour) |

If both across-the-board network weather condition and link-specific weather condition are defined, link-specific weather information dominates, namely, link-specific weather information applies regardless of the network weather condition; while network weather condition applies for all the links without the link-specific weather condition.

An example *weather.dat* file is shown in Figure 5-1. Particularly, a network-wide weather condition is specified on the first line, namely, low visibility of 0.5 mile and rainfall at the rate of 0.1 inch/hour during the first 2 hours (0 to 120 minutes). In addition, three (i.e. the number on the second line) link-specific weather conditions are defined in the rest of the file. The first link is from node 4042 to 4087 and has two weather events: during 10-40 minutes, the visibility is 1.0 mile with rainfall intensity of 0.1 inch/hour; and during 41-60 minutes, the visibility decreased to 0.5 mile and rainfall intensity increased to 0.2 inch/hour. The second (on the link of 4084 to 4042) and the third (on the link of 3826 to 581) link-specific weather events are defined in the same fashion.

```
1
0.5    0.1   0      0    120
3
1    4042  4087     2
       10    40     1.0    0.1   0
       41    60     0.5    0.2   0
2    4084  4042     1
       10    80     0.5    0     0.1
3    3826   581     1
        0    20     1.0    0     0
```

**Figure 5-1 General Format of the *weather.dat* input file**

Once the weather input file is created, the DYNASMART-P program will return to estimate and predict traffic conditions through the procedure designed to incorporate traffic impact by inclement weather condition. This procedure requires additional components for the entire system to support the efficient and reliable estimation and prediction of traffic impact due to weather changes, discussed next.

## 5.2 Weather Adjustment Factor Data (*WAF.dat*)

When DYNASMART-P receives inclement weather input, a model is needed to simulate traffic conditions affected by inclement weather within DYNASMART-P. For example, an adjustment factor for capacity, free-flow speed, and saturation flow can be applied in the simulator, which is obtained based on the inclement weather parameters (visibility, rain intensity and snow intensity) and the calibrated weather-traffic flow relation. This section describes the impact of weather on the relationships between traffic speed, flow, and density, and other macroscopic measurements.

Both the functional form and the parameter values (free mean speed, jam density, breakpoints for multiple regime models) may be affected by weather, and may be affected differently by the characteristics of different weather instances. The FHWA (2006) report by Cambridge Systematics summarizes changes in the so-called fundamental diagram observed at a limited number of locations (e.g. Twin Cities, Minnesota, shown below). These results suggest a relatively simple-to-apply modification to the existing model underlying traffic propagation on freeways in DYNASMART-P (and –X). Although the applicability of this modification to other environments, or to more extreme conditions in the same environment is not evident, it provides a good starting point for the modification to be implemented. Parameters that are relevant to inclement weather impacts in the supply side of DYNASMART-P are listed by the type of input data in the following table.

**Table 5-3 Supply Side Properties related with Weather Impact in DYNASMART-P**

| Input data | Traffic properties | Note |
|---|---|---|
| Traffic flow model | 1. *Speed-intercept* , (mph)<br>2. Minimal speed , (mph)<br>3. *Density break point* , (pcpmpl)<br>4. Jam density , (pcpmpl)<br>5. Shape term alpha | *The italic styled properties are only available in dual-regime model* |
| Link | 6. Maximum service flow rate, (pcphpl or vphpl)[1]<br>7. Saturation flow rate , (vphpl)<br>8. Posted speed limit adjustment margin, (mph) | |
| Signal control | Cycle length, offset, green, amber, max green, min green | All same units, (seconds) |
| Left-turn capacity | 9. g/c ratio | |
| 2-way stop sign capacity | 10. Saturation flow rate for left-turn vehicles<br>11. Saturation flow rate for through vehicles<br>12. Saturation flow rate for right-turn vehicles | All same units, (vphpl) |
| 4-way stop sign capacity | 13. Discharge rate for left-turn vehicles<br>14. Discharge rate for through vehicles<br>15. Discharge rate for right-turn vehicles | All same units, (vphpl) |
| Yield sign capacity | 16. Saturation flow rate for left-turn vehicles<br>17. Saturation flow rate for through vehicles<br>18. Saturation flow rate for right-turn vehicles | All same units, (vphpl) |

The inclement weather impact on each parameter listed in Table 5-3 can be represented by a corresponding weather adjustment factor (WAF).

$$F_i = \beta_0 + \beta_1 \cdot v + \beta_2 \cdot r + \beta_3 \cdot s + \beta_4 \cdot v \cdot r + \beta_5 \cdot v \cdot s \qquad (5\text{-}1)$$

where

| | |
|---|---|
| $F_i$ | weather adjustment factor for parameter $i$ |
| $v$ | visibility |
| $r$ | precipitation intensity of rain |
| $s$ | precipitation intensity of snow |
| $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ | coefficients |

the new input file, namely *WAF.dat*, is created to store the specifications of above mentioned coefficients, described in Table 5-4.

**Table 5-4 Description of the *WAF.dat* Input File**

| Record Type | Field | Format | Width | Description |
|---|---|---|---|---|
| Weather | 1 | Integer | Free | Parameter index (as shown in Table 2) |
| Adjustment | 2 | Float | Free | Constant term for 1st parameter |
| Factor | 3 | Float | Free | Coefficient of visibility term for 1st parameter |
| | 4 | Float | Free | Coefficient of rain intensity term for 1st parameter |
| | 5 | Float | Free | Coefficient of snow intensity term for 1st parameter |
| | 6 | Float | Free | Coefficient of interaction term of visibility and rain intensity for 1st parameter |
| | 7 | Float | Free | Coefficient of interaction term of visibility and snow intensity for 1st parameter |
| ..... | ..... | ..... | ..... | ..... |
| Weather | 1 | Integer | Free | Parameter index (as shown in Table 2) |
| Adjustment | 2 | Float | Free | Constant term for the last parameter |
| Factor | 3 | Float | Free | Coefficient of visibility term for the last parameter |
| | 4 | Float | Free | Coefficient of rain intensity term for the last parameter |
| | 5 | Float | Free | Coefficient of snow intensity term for the last parameter |
| | 6 | Float | Free | Coefficient of interaction term of visibility and rain intensity for the last parameter |
| | 7 | Float | Free | Coefficient of interaction term of visibility and snow intensity for the last parameter |

An example *WAF.dat* file is shown in Figure 5-2. The first line corresponds to the *Speed-intercept* parameter listed in Table 5-3. The constant term in Equation (5-1) is 0.91 for this parameter; and the coefficients for visibility, rain and snow precipitation are 0.009, -0.404 and -1.455 respectively. Thus the weather adjustment factor for *Speed-intercept* can be calculated as follows.

$$F_1 = 0.91 + 0.009 \cdot v - 0.404 \cdot r - 1.455 \cdot s \qquad (5\text{-}2)$$

The rest of file specifies coefficients for the other 17 parameters listed in Table 5-3.

DYNASMART-P provides the capability of allowing multiple signal timing plans, each of which corresponds to a certain time period (defined by a start time and an end time). Therefore, these times and associated signal controls could be defined to correspond to the weather event(s) of interest.

| Parameter | $\beta_0$ | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ | $\beta_5$ |
|---|---|---|---|---|---|---|
| 1 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 2 | 1 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0.83 | 0.017 | -0.555 | -3.785 | 0 | 0 |
| 4 | 1 | 0 | 0 | 0 | 0 | 0 |
| 5 | 1 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0.85 | 0.015 | -0.505 | -3.932 | 0 | 0 |
| 7 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 8 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 9 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 10 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 11 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 12 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 13 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 14 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 15 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 16 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 17 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 18 | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |

**Figure 5-2 General Format of the *WAF.dat* Input File**

## 5.3 Variable Message Signs (*vms.dat*)

As three types of new VMS are introduced, currently seven types of VMS are supported by DYNASMART-P. Type 1 VMS is the speed advisory VMS that allows users to increase/decrease speed by a certain percentage below/above a certain threshold. Type 2 VMS is the mandatory detour VMS that advises drivers of lane closures, and mandates all vehicles to follow some user-specified sub-path in the vicinity. Type 3 VMS is the congestion warning VMS, which allows users to specify percentages of VMS-responsive vehicles (user class 5) to evaluate the VMS information and divert if a better path exists. Therefore, the user is advised to select VMS type 3 on links that would provide diversion points. Type 4 VMS is the optional detour VMS. Similar to type 2, it also advises drivers with lane closure information. However, type 4 gives drivers the option to follow the detour path or keep their original path, based on the boundedly rational decision rule. Type 5 VMS is the speed reduction (weather) VMS, which suggests a speed reduction due to adverse weather conditions. Type 6 VMS is the travel risk (weather) VMS, which suggests all VMS-responsive and en-route info vehicles to reevaluate their current route and divert to a better route, if exists, considering the weather-related travel penalty associated with the link. Type 7 VMS is the variable speed limits (weather) VMS, which adjusts speed limits according to the weather condition and a look-up table (defined in a separate file vsl.dat). The vsl.dat file allows users to specify multiple variable speed limits (VSL) look-up tables, each of which could define different weather conditions and the corresponding speed limits. Detailed description of this file and its format are provided in Table 5-5 and Figure 5-3, respectively.

**Table 5-5 Description of the *vms.dat* Input File**

| Record Type | Field | Format | Width | Description |
|---|---|---|---|---|
| Number of signs | 1 | Integer | Free | Number of Variable Message Signs |
| Sign description | 1 | Integer | Free | Type of VMS according to the following description<br>1: speed advisory; 2: mandatory detour;<br>3: congestion warning; 4: optional detour;<br>5: speed reduction (weather); 6: travel risk; 7: variable speed limits |
| | 2 | Integer | Free | Upstream node of the 1st VMS link |
| | 3 | Integer | Free | Downstream node of the 1st VMS link |
| | 4 | Integer | Free | Type 1: speed threshold (+ or -) (mph)[1]<br>Type 2: 100[2]<br>Type 3: percentage of user class 5[3] who will actually evaluate and respond to the VMS information<br>Type 4: 100[2]<br>Type 5: 100[2]<br>Type 6: value of risk (default value is 1)<br>Type 7: 100[2] |
| | 5 | Integer | Free | Type 1: percentage reduction or increase in VMS link speed<br>Type 2: number of nodes in detour sub-path<br>Type 3: path preference (0 or 1) for diversion<br>1: current best path; 0: a random path among K-paths<br>Type 4: number of nodes in detour sub-path<br>Type 5: speed reduction on the VMS link<br>Type 6: travel penalty (percentage of link travel time)<br>Type 7: look-up table number |
| | 6 | Float | Free | Start time for the 1st VMS (minutes) |
| | 7 | Float | Free | End time for the 1st VMS (minutes) |
| Subpath[4] | 1 | Float | Free | 1st node in the detour sequence for the 1st VMS (if applicable) |
| ..... | ..... | ..... | ..... | ..... |
| | N | | | Last node in the detour sequence for the 1st VMS (if applicable) |
| ..... | ..... | ..... | ..... | ..... |
| Sign description | 1 | Integer | Free | Type of VMS according to the following description<br>1: speed advisory; 2: mandatory detour;<br>3: congestion warning; 4: optional detour;<br>5: speed reduction (weather); 6: travel risk; 7: variable speed limit |
| | 2 | Integer | Free | Upstream node of the last VMS link |
| | 3 | Integer | Free | Downstream node of the last VMS link |
| | 4 | Integer | Free | Type 1: speed threshold (+ or -) (mph)[1]<br>Type 2: 100[2]<br>Type 3: percentage of user class 5[3] who will actually evaluate and respond to the VMS information<br>Type 4: 100[2] |

| Record Type | Field | Format | Width | Description |
|---|---|---|---|---|
| | | | | Type 5: 100[2] |
| | | | | Type 6: value of risk (default value is 1) |
| | | | | Type 7: 100[2] |
| | 5 | Integer | Free | Type 1: percentage reduction or increase in VMS link speed |
| | | | | Type 2: number of nodes in detour sub-path |
| | | | | Type 3: path preference (0 or 1) for diversion<br>1: current best path; 0: a random path among K-paths |
| | | | | Type 4: number of nodes in detour sub-path |
| | | | | Type 5: speed reduction in the VMS link |
| | | | | Type 6: travel penalty (percentage of link travel time) |
| | | | | Type 7: look-up table number |
| | 6 | Float | Free | Start time for the last VMS (minutes) |
| | 7 | Float | Free | End time for the last VMS (minutes) |
| Subpath[4] | 1 | Float | Free | 1st node in the detour sequence for the last VMS |
| ..... | ..... | ..... | ..... | ..... |
| | N | | | Last node in the detour sequence for the last VMS |

[1] *If positive (+), link speed will be increased (if link speed is lower than the threshold). If negative (-), link speed will be decreased (if actual link speed is higher than the threshold).*

[2] *This entry is read but ignored by DYNASMART-P. It is used to keep the same number of fields for VMS types.*

[3] *If the VMS preemption mode is set to 1 (in scenario.dat), then this fraction applies to user classes 2-5.*

[4] *For VMS types 2, 4 only.*

An example vms.dat is shown in Figure 5-3. The first record indicates that there are 7 VMS locations or sites. The second record states that a type 1 (speed advisory) VMS (field 1) is located between upstream node 1 (field 2) and downstream node 20 (field 3). A +40 mph threshold is given (field 4). The positive sign indicates that if the link speed is less than 40 mph, VMS-responsive vehicles will attempt to increase their speed to reach this speed. If their speed is already above 40 mph, then no action is taken. The next field indicates that VMS responsive vehicles (user class 5) will increase their speed by 10 percent to achieve the recommended speed threshold. The VMS is activated from time 10.0 (field 6) until time 30.0 minutes (field 7).

The third record (2$^{nd}$ VMS link in network) shows that there is a detour type VMS (type 2) (field 2) located between upstream node 53 and downstream node 52. All vehicles need to divert (100%) and there are three nodes in the specified sub-path for detouring. This VMS is activated between minutes 10.0 (field 6) and 80.0 (field 7) of simulation. The next immediate record specifies the node sequence of the sub-path for detouring. The first node is 52, which is required to be the downstream node of the VMS (there is no requirement for the last node on detour sub-path); the remaining two nodes on sub-path are 51 and 14. The mandatory detour-type VMS is of particular importance for work zone and incident operational management strategies, and extreme weather events.

The fourth record (3rd VMS link in network) shows that there is a congestion warning VMS (type 3) (field 1) located between upstream node 48 (field 2) and downstream node 41 (field 3), and a response rate of 15 percent (field 4) is specified. After diversion, vehicles will be assigned the current best (1) path (field 5) starting from the downstream node of the VMS link. The VMS will be activated from minute 0.0 (field 6) until minute 20.0 (field 7).

The fifth record (4th VMS link in network) shows that there is a weather advisory VMS (type 5) (field 1) located between upstream node 53 (field 2) and downstream node 52 (field 3). The VMS suggests a speed reduction (field 4) due to adverse weather conditions. In particular, 5 mph reduction (field 5) in speed is specified for the vehicles traveling on the link during minute 0.0 (field 6) until minute 20.0 (field 7).

The sixth record (5th VMS link in network) shows that there is a weather advisory VMS (type 6) (field 1) located between upstream node 53 (field 2) and downstream node 52 (field 3). The VMS suggests all VMS-responsive vehicles to reevaluate their currents route and divert to a better route, if exists, considering the travel risk associated with the link (field 4 indicates the value of risk). A weather-related travel penalty, 10% extra travel time (field 5) is included in the generalized cost. This VMS is activated between minutes 20.0 (field 6) and 40.0 of simulation (field 7).

The seventh record (6th VMS link in network) shows that there is a weather-responsive variable speed limits (type 7) (field 1) located between upstream node 48 (field 2) and downstream node 41 (field 3). The speed limits are determined based on look-up table 1 (field 5) in vsl.dat. This VSL is activated between minutes 10.0 (field 6) and 20.0 of simulation (field 7).

```
7
      1      1     20     40      10  10.0  30.0
      2     53     52    100       3  10.0  80.0
        52     51     14
      3     48     41     15       1   0.0  20.0
      5     53     52    100       5   0.0  20.0
      6     53     52      1      10  20.0  40.0
      7     48     41    100       1  10.0  20.0
```

**Figure 5-3 General Format of the *vms.dat* Input File**

## 5.4 Variable Speed Limits via VMS (*vsl.dat*)

In order to implement type 7 VMS (Variable Speed Limits) in DYNASMART, an additional file *vsl.dat* needs to be prepared to specify speed limit regulation through one or more look-up tables. In each look-up table, one or more weather conditions are specified, as well as the corresponding speed limit reductions. For example, if there are links whose posted speed limit is 65 mph and variable speed limits under rain and snow are 55 mph and 45 mph respectively, the look-up table has two lines that state the speed reduction of 10 mph (65-55mph) for rain and 20 mph (65-45 mph) for snow. The posted speed limit for all the links in the network is specified in a separate input file (*network.dat*) and these values are used when calculating actual speed limit for certain links in DYNASMART.

**Table 5-6 Description of the *vsl.dat* Input File**

| Record Type | Field | Format | Width | Description |
|---|---|---|---|---|
| Number of tables | 1 | Integer | Free | Number of look-up tables for VSL |
| Table description | 1 | Integer | Free | Look-up table counter |
| | 2 | Integer | Free | Number of lines in the table |
| The 1st line of | 1 | Float | Free | Visibility upper bound (miles) |
| the look-up table | 2 | Float | Free | Visibility lower bound (miles) |
| | 3 | Float | Free | Rain intensity lower bound (inch/hour) |
| | 4 | Float | Free | Rain intensity upper bound (inch/hour) |
| | 5 | Float | Free | Snow intensity lower bound (inch/hour) |
| | 6 | Float | Free | Snow intensity upper bound (inch/hour) |
| | 7 | Float | Free | Speed limit reduction (mph) |
| ..... | ..... | ..... | ..... | ..... |
| The last line of | 1 | Float | Free | Visibility upper bound (miles) |
| the look-up table | 2 | Float | Free | Visibility lower bound (miles) |
| | 3 | Float | Free | Rain intensity lower bound (inch/hour) |
| | 4 | Float | Free | Rain intensity upper bound (inch/hour) |
| | 5 | Float | Free | Snow intensity lower bound (inch/hour) |
| | 6 | Float | Free | Snow intensity upper bound (inch/hour) |
| | 7 | Float | Free | Speed limit reduction (mph) |

An example *vsl.dat* file is shown in Figure 5-4. The first line indicates that there is only one look-up table in the file. The second line shows that the first (and the only one in this example) look-up has four rows. The third line (i.e. the first row of the look-up table) suggests that when visibility is in the range of 1 – 3 miles and there is no precipitation (e.g. fog) the speed limit should be lowered by 5 mph. The rest of the file specifies the other three rows (i.e. weather conditions and the corresponding speed limit reduction) of the look-up table.

```
1
1      4
3      1      0      0      0      0       5
10     2      0      0.25   0      0      10
10     2      0.25   0.9    0      0      15
10     2      0      0      0      0.2    20
```

**Figure 5-4 General Format of the *vsl.dat* Input File**

# 6. Calibration and Evaluation

This section describes a calibration procedure for the speed-density relationship and preparation of WAF.dat file discussed in the previous section. WAF.dat file contains information about changes in traffic parameters according to visibility and precipitation intensity such that weather impact can be reflected in a simulation process in DYNASMART. The weather and traffic data used for calibration are obtained from Archived Data Management System (ADMS) in Virginia.

## 6.1 Data for Calibration

The Archived Data Management System (ADMS) Virginia archives both traffic data and weather data for selected locations in Virginia. Weather data consists of visibility (1-10 mile), precipitation (inch/hour) and weather type. Collection times are not at a fixed interval. Usually there are 1-5 observations for one hour. Traffic data consists of vehicle count, occupancy and speed at 5-minute aggregation interval. The study site is the Hampton Roads network, composed of three freeways segments: (1) I-64 between Bay Avenue and the Virginia Beach-Chesapeake City Limits, I-64 forming the outer loop, (2) I-564 between Terminal Boulevard and I-64, I-264 between Broad Creek and Rosemont Road, and (3) entire I-664.

Google Map DYNASMART Network

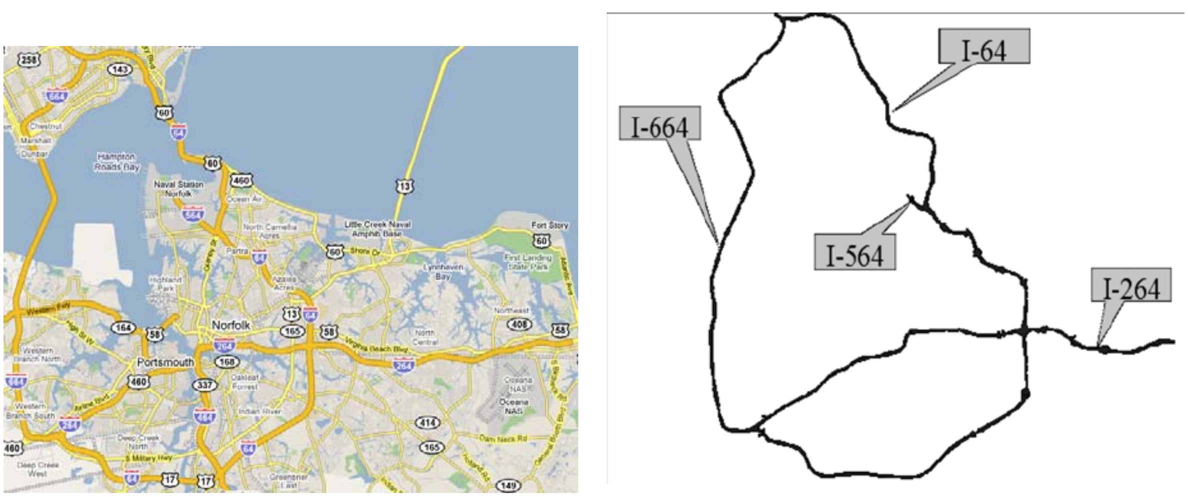



**Figure 6-1 The Hampton Roads Network**

The densities could be converted from the occupancy data using the following relationship:

$$k = \frac{52.8}{L_v + L_s} \cdot occ \qquad (6\text{-}1)$$

where

| | | |
|---|---|---|
| $k$ | density | [veh/mi/ln] |
| $L_v$ | average vehicle length | [feet] |
| $L_s$ | average sensor length | [feet] |
| $occ$ | occupancy | [%] |

$L_v$ is assumed to be 5 meters (approximately 16.4 feet); and $L_s$ is set to 2 meters (approximately 6.5 feet).

## 6.2 Calibration of Speed-Density Function

DYNASMART uses a modified Greenshields model for traffic propagation. In the current version, two types of the modified Greenshields family models are available. Type one is a dual-regime model in which constant free-flow speed is specified for the free-flow conditions (1st regime) and a modified Greenshields model is specified for congested-flow conditions (2nd regime). Dual-regime model is generally applicable to freeways. The reason why a two-regime model is applicable for freeways in particular is that freeways have typically more capacity than arterials and can accommodate dense traffic (up to 2300 pc/hr/ln) at near free-flow speeds. Hence, a slight increase in traffic would not significantly deteriorate prevailing speeds in the 1st regime.

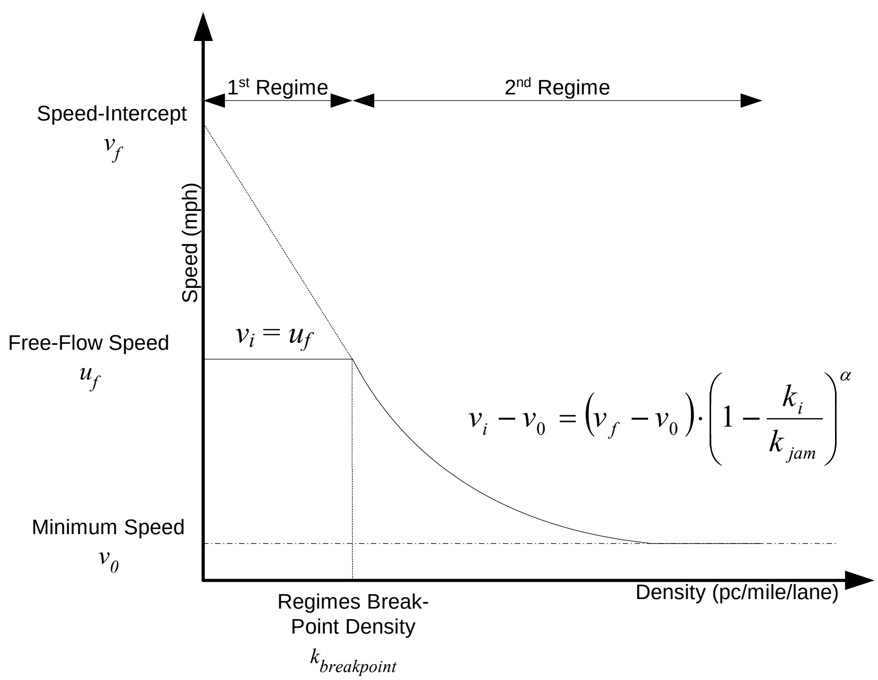



**Figure 6-2 A Dual-Regime Modified Greenshields Model**

In mathematical terms, the dual-regime modified Greenshields is expressed as follows:

$$
\begin{aligned}
&v_i = u_f\,, && 0 \le k_i \le k_{bp} \\
&v_i - v_0 = \left(v_f - v_0\right)\cdot\left(1 - \frac{k_i}{k_{jam}}\right)^{\alpha}, && k_{bp} \le k_i \le k_{jam}
\end{aligned}
\qquad (6\text{-}2)
$$

where

| | |
|---|---|
| $v_i$ | speed on link *i* |
| $v_f$ | speed-intercept |
| $u_f$ | free-flow speed on link *i* |
| $v_0$ | minimum speed on link *i* |
| $k_i$ | density on link *i* |
| $k_{jam}$ | jam density on link *i* |
| $\alpha$ | power term |
| $k_{bp}$ | breakpoint density |

Type two uses a single regime to model traffic relations for both free- and congested-flow conditions, i.e.

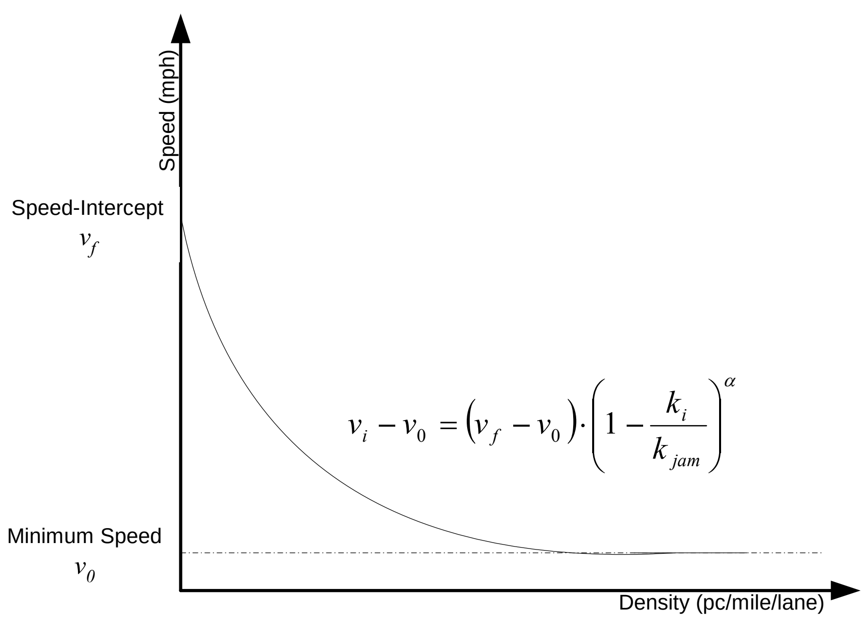



**Figure 6-3 A Single-Regime Greenshields Model**

In mathematical terms, the type 2 modified Greenshields is expressed as follows:

$$
v_i - v_0 = \left(v_f - v_0\right)\cdot\left(1 - \frac{k_i}{k_{jam}}\right)^{\alpha} \qquad (6\text{-}3)
$$

Parameters for the dual-regime Greenshields model (in DYNASMART-P) can be calibrated for the freeways in the Hampton Roads network, that is, I-64, I-264 and I-564, using the time-dependent traffic data from ADMS Virginia. There are six parameters to be calibrated, namely, breakpoint density ($k_{bp}$), free-flow speed ($u_f$), speed-intercept ($v_f$), minimum speed ($v_0$), jam density ($k_{jam}$), and the power term ($\alpha$).

The speed-density relationship could be approximated by two portions, a straight portion and a curvilinear portion. Hence two equations must be estimated to correctly and adequately represent the freeway traffic model structure. The straight portion of the speed-density relationship is represented by the equation:

$$v_i = u_f, \qquad 0 \le k_i \le k_{bp} \tag{6-4}$$

For the straight portion of the model, only one parameter needs to be estimated, namely the mean free speed $u_f$, which reflects the true prevailing freeway speed under uncongested conditions.
On the other hand, the modified Greenshields' model is used to describe the curvilinear portion (second regime) of the speed-density relation, which is expressed by the following equation.

$$v_i - v_0 = \left(v_f - v_0\right)\cdot\left(1 - \frac{k_i}{k_{jam}}\right)^{\alpha}, \qquad k_{bp} \le k_i \le k_{jam} \tag{6-5}$$

Linear regression analysis is the major tool for the calibration of the link traffic flow models. This can be achieved by transforming the modified Greenshields' model into a linear form by taking the natural logarithm on both sides:

$$\ln(v_i - v_0) = \ln(v_f - v_0) + \alpha \ln(1 - \frac{k_i}{k_{jam}}) \tag{6-6}$$

which is in the form of

$$Y = aX + b \tag{6-7}$$

and can be estimated directly by conducting a simple linear regression analysis. The parametric analysis procedure is also implemented to help for linear regression analysis.

The data required to calibrate this component includes:

- Time-varying link density
- Average speed for the corresponding time intervals

The MOE for this task include:

- Goodness of fit - R-squared value in the linear regression;
- Root mean squared error for speed.

The procedures of calibrating speed-density function are as follows.

**Step 1.** Process observation data

**Step 1.1.** Categorized the traffic data (speed and occupancy), for each location, into five data sets according to the weather condition (i.e., precipitation intensity), namely, normal, light rain (less than 0.1 in./hr), moderate rain (0.1 to 0.3 in./hr), heavy rain (greater than 0.3 in./hr), and light snow (less than 0.1 in./hr). Since there have been not much data available for heavier snow, only one category is used for snow.

**Step 1.2.**Convert occupancy into density using Equation (6-1).

**Step 1.3.** For each location and each weather condition, perform Step 2 to 5.

**Step 2.** Fit the data into a dual-regime model. For initial $k_{bp}$ of 10 vpmpl, do the followings.

**Step 2.1** Divide the data set into to subsets based on the initial $k_{bp}$, that is, the first and second regime observations.

**Step 2.2.** For the first regime, the free-flow speed, $u_f$, is estimated as the mean of the speeds. Root mean squared error for speeds is also calculated.

**Step 2.3.** For the second regime, set $v_0$ and $k_{jam}$ based on the observations, that is, the minimum speed observed and maximum density observed.

**Step 2.4.** Transform the second regime data, speed and density, as follows: $Y = \ln(v_i - v_0)$, $X = \ln(1 - \frac{k_i}{k_{jam}})$. Let $b = \ln(v_f - v_0)$.

**Step 2.5.** Perform linear regression of the function $Y = \alpha X + b$ to estimate $\alpha$ and $b$.

**Step 2.6.** Recover $v_f$ from the estimated $b$, that is, $v_f = e^b + v_0$.

**Step 2.7.** Calculate R-squared value for the second regime.

**Step 2.8.** Calculate difference in estimated speeds at the joint of two regimes by comparing $u_f$ in the first regime and the modeled speed value at $k_{bp}$ in the second regime.

**Step 3.** Increase $k_{bp}$ by 1 vpmpl and repeat Step 2.1 to 2.8 until $k_{bp}$ becomes 30 vpmpl.

**Step 4.** Find the optimal value of $k_{bp}$ based on MOEs of the fitted models for each regime and joint fit observations for the entire models.

**Step 5.** Choose the function that fits best to the data set for each weather condition.

The calibration result for one freeway section of I-64 is presented in Figure 6-4. It shows the weather effect on speed-density relation and flow-density relation due to reductions in speed for both 1st and 2nd regime under rain and snow events. Detailed calibration results for all study sections are presented in Appendix A.

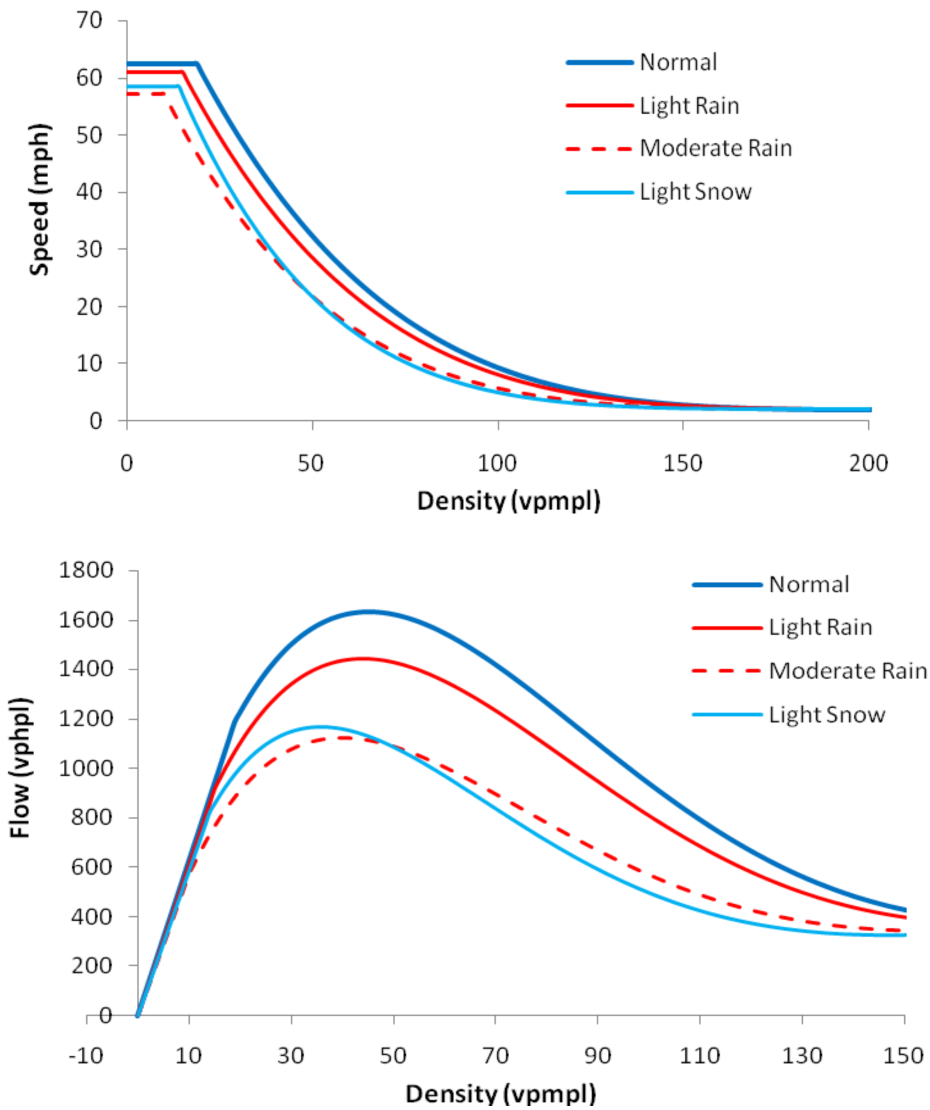



**Figure 6-4 Calibrated Speed-Density and Flow-Density Curves for a Freeway Section I-64**

(Data source: The Archived Data Management System Virginia)

## 6.3 Calibration of Weather Adjustment Factors

Once speed-density functions for different weather conditions (i.e., normal, light rain, moderate rain, and light snow) are obtained for each location, another linear regression is conducted to estimate weather adjustment factor coefficients in Equation (5-1) for the *WAF.dat* file.

The procedures for preparing *WAF.dat* are as follows.

**Step 1.** Calculate the WAFs for each parameter using the relation $F_u = \frac{u'}{u}$, where $u$ and $u'$ represent the parameters under the normal condition and the rain (or snow) condition respectively.
**Step 2.** Conduct linear regression for each parameter using the WAF for a dependent variable and visibility and categorized precipitation intensity of each data point for independent variables.
**Step 3.** Prepare WAF.dat file using calibrated coefficients for each parameter from Step 2.

Note that not all of the parameters listed in Table 5-3 can be calibrated using the observation data. Some parameters could be inferred from other calibrated parameters.
(1) Traffic flow model related parameters, that is, speed-intercept ($v_f$), minimum speed($v_0$), density break point($k_{bp}$), jam density($k_{jam}$), shape term alpha($\alpha$) and maximum service flow rate ($f_{max}$) can be calibrated from the traffic data. However, as minimum speed, jam density and shape term alpha turn out to be insensitive to weather conditions from the calibration results, WAF for those parameters are assumed as 1, which indicates these are not affected by weather conditions.
(2) Link characteristics: saturation flow rate, and posted speed limit adjustment could be inferred from the calibrated traffic flow model.
(3) Signal control: the adjustments in cycle length, offset, green, amber, maximum green, and minimum green could be inferred from the saturation flow rate.
(4) Left turn/stop sign/yield sign capacities could be calibrated using the traffic data, for example, maximum observed flow rate could be used as a surrogate of capacity.

The detailed calibration results of WAF are provided in Table 6-1.

**Table 6-1 Coefficients of Weather Adjustment Factor**

| Input data | Traffic properties | β0 | β1 | β2 | β3 | β4 | β5 |
|---|---|---|---|---|---|---|---|
| Traffic flow model | 1. *Speed-intercept* , (mph) | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| | 2. Minimal speed , (mph) | 1 | 0 | 0 | 0 | 0 | 0 |
| | 3. *Density break point* , (pcpmpl) | 0.83 | 0.017 | -0.555 | -3.785 | 0 | 0 |
| | 4. Jam density , (pcpmpl) | 1 | 0 | 0 | 0 | 0 | 0 |
| | 5. Shape term alpha | 1 | 0 | 0 | 0 | 0 | 0 |
| Link | 6. Maximum service flow rate, (pcphpl or vphpl) | 0.85 | 0.015 | -0.505 | -3.932 | 0 | 0 |
| | 7. Saturation flow rate , (vphpl) | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| | 8. Posted speed limit adjustment margin, (mph) | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| Left-turn capacity | 9. g/c ratio | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 2-way stop sign capacity | 10. Saturation flow rate for left-turn vehicles | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| | 11. Saturation flow rate for through vehicles | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| | 12. Saturation flow rate for right-turn vehicles | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| 4-way stop sign capacity | 13. Discharge rate for left-turn vehicles | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| | 14. Discharge rate for through vehicles | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| | 15. Discharge rate for right-turn vehicles | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| Yield sign capacity | 16. Saturation flow rate for left-turn vehicles | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| | 17. Saturation flow rate for through vehicles | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |
| | 18. Saturation flow rate for right-turn vehicles | 0.91 | 0.009 | -0.404 | -1.455 | 0 | 0 |

# 7. Application

This section demonstrates the application of the resulting weather-sensitive DTA model to an actual network, with particular focus on two aspects: (1) assess the impacts of adverse weather on transportation network; and (2) evaluate effectiveness of weather-related variable message signs in alleviating traffic congestion caused by adverse weather conditions.

## 7.1 Test bed Network and Simulation Settings

Figure 7-1 shows the test network, namely the CHART (Maryland, United States) network (Mahmassani et al., 2005). The network consists, primarily, of the I-95 corridor between Washington, DC and Baltimore, MD, and is bounded by two beltways (I-695 Baltimore Beltway to the north and I-495 Capital Beltway to the south). The network has 2182 nodes, 3387 links and 111 traffic analysis zones (TAZ). A two-hour morning peak (i.e. 7-9AM) dynamic OD demand table estimated for the network is used in the experiments. Travelers are assumed to follow their habitual routes, which are determined by performing a dynamic user equilibrium assignment, as suggested by Mahmassani and Peeta (1993). When an adverse weather event occurs, travelers will stick to their habitual routes if they do not receive specific road weather information, or are not required to detour by certain control measures. However, if such information or controls are available, for example, a weather VMS indicating extra delay on a certain road due to heavy rain, travelers might change to a better route.

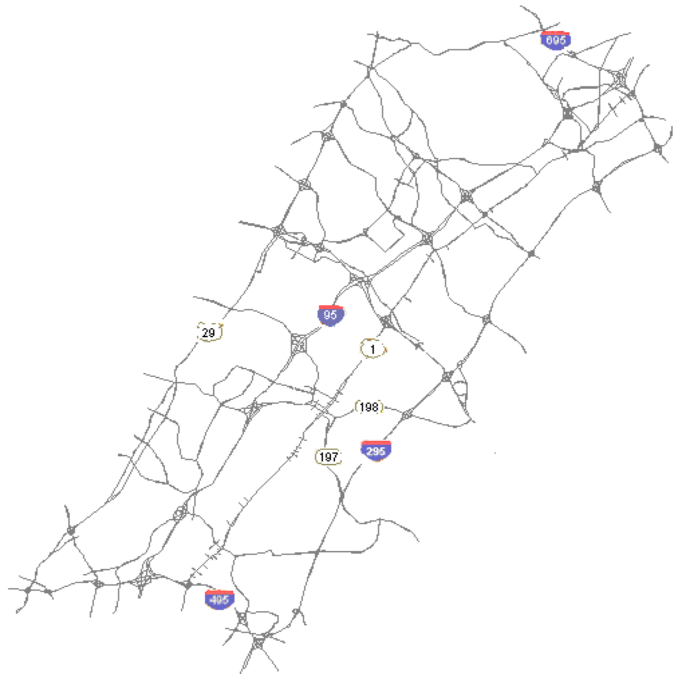



**Figure 7-1 The CHART Network**

## 7.2 Network Performance under Adverse Weather Conditions

To illustrate the effects of network-wide road weather conditions, three scenarios are compared:

1. Scenario 1 ("Clear"): the base case scenario corresponds to clear weather conditions.
2. Scenario 2 ("Moderate rain"): corresponds to a moderate rain day, that is, visibility of 1.0 mile and rain intensity of 0.2 inch/hour.
3. Scenario 3 ("Heavy rain"): corresponds to a heavy rain day, that is, visibility of 0.5 mile and rain intensity of 0.5 inch/hour.

The time-varying network travel times are compared in Figure 7-2 for these three scenarios. Since the rainy weather affects the supply-side parameters, such as lower capacity and saturation flow rate, the network travel times become longer when the weather conditions get more serious.

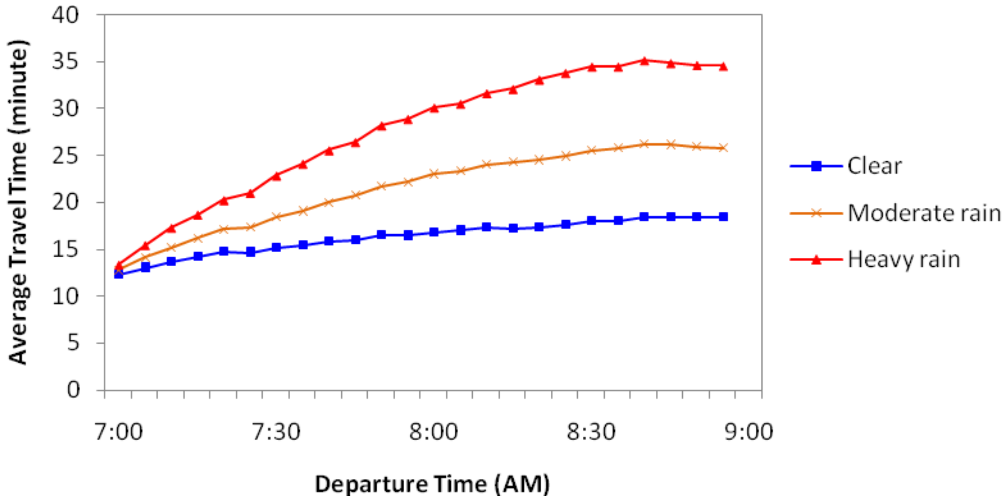



**Figure 7-2 Network Travel Time Comparison**

A similar pattern, namely heavier rain condition resulting in longer travel time, is obtained by examining time-varying travel times between a major OD (origin-destination) pair of the network, as shown in Figure 7-3. Moreover, Figure 7-4 shows the standard deviations of actual travel times at 5-minute intervals. We can see that not only travel time becomes longer when adverse weather occurs, but also the variability of the travel time is greater, making travel less reliable in the network.

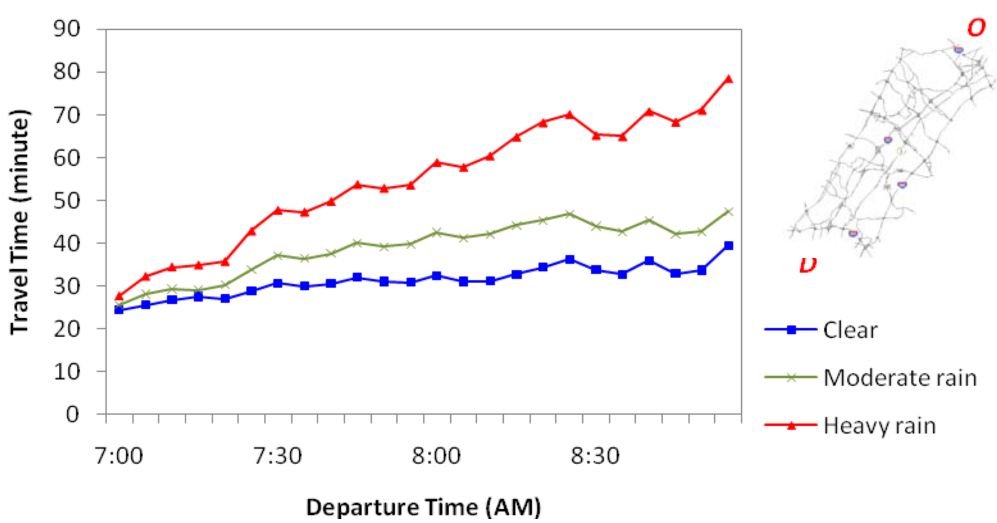



**Figure 7-3 OD Travel Time Comparison**

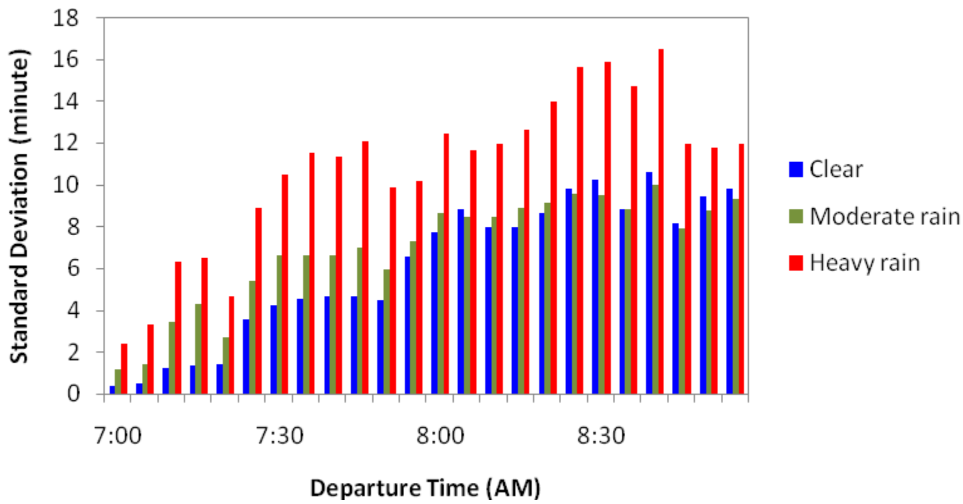



**Figure 7-4 Standard Deviations of OD travel times**

In addition, to examine the impacts of local weather condition (for instance, rain in a certain area of the network) we assume that it rains on a stretch of Freeway I-95, following the pattern shown in Figure 7-5. Namely, the rain starts at 7:10 AM with visibility of 1.0 mile and intensity of 0.2 inch/hour; at 7:40 AM the rain intensity increases to 0.5 inch/hour and the visibility decreases to 0.5 mile, indicating heavier rain situation; then at 8 AM the rain stops.

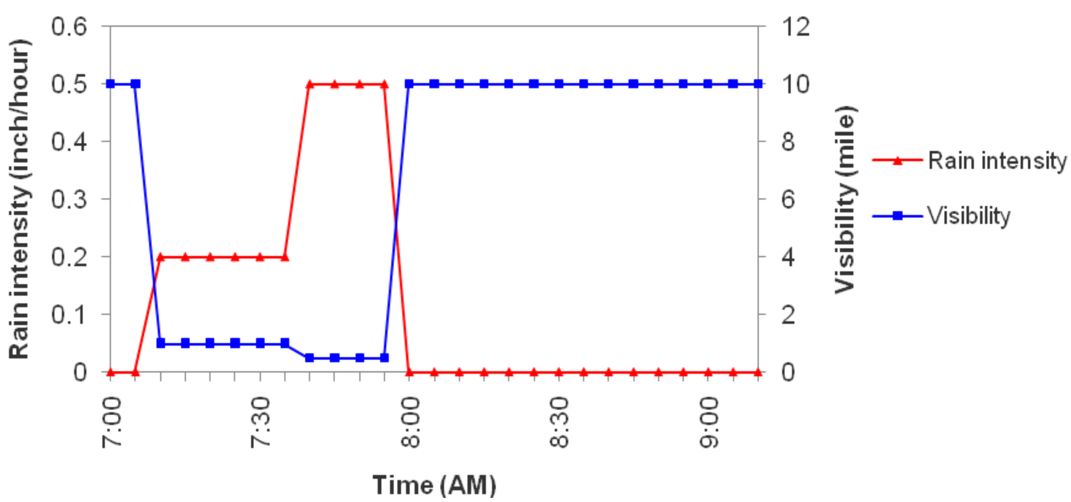



**Figure 7-5 Time-Varying Local Weather Conditions**

A weather-impacted link along I-95 is selected to illustrate local weather impacts on traffic conditions. The speed on the link maintains (nearly) the free flow speed when the weather is clear. With precipitation, however, the speed drops significantly. For the 7:10-7:40 AM time period, when it rains moderately, the speed drops to around 50 mph. This is mainly caused by drivers' speed reduction in response to low visibility and slippery road surface, which could be predicted/calculated using weather adjustment factor shown in Equation (5-1). Nevertheless, in the 7:40-8:00 AM period, when it is raining heavily, the speed drops to as low as 20 mph. This is a combined outcome of drivers' speed reduction response and congestion effects; that is, drivers slow down because of not only the precipitation conditions but also the traffic congestion along the road. Under such circumstances, predicting link performance using the WAF alone, while ignoring the congestion effect caused by the adverse weather conditions, would not be sufficient.

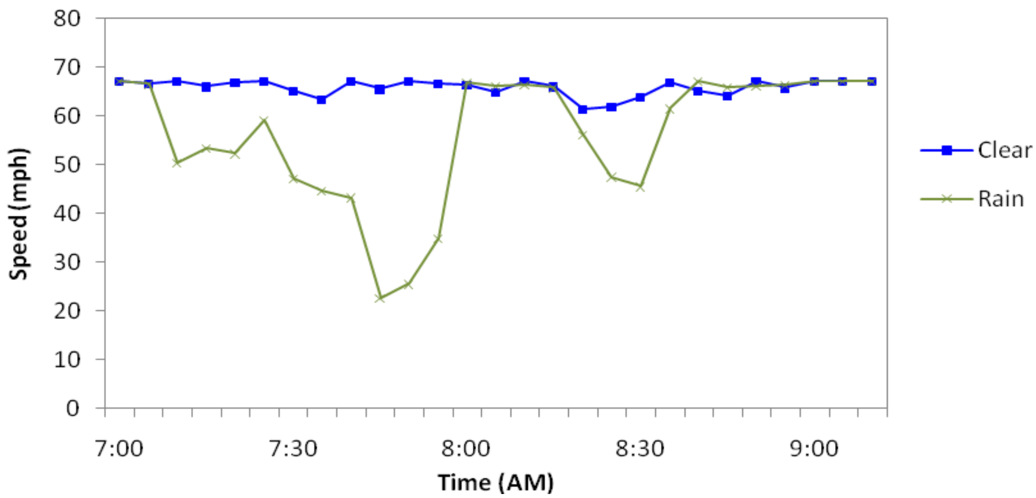



**Figure 7-6 Time-Varying Speeds on a Weather-Impacted Link**

## 7.3 Evaluation of Weather-related Information and Control Strategies

In order to alleviate the impacts of adverse weather, weather-related information and control strategies could be applied. Three scenarios are compared to illustrate the effectiveness of weather detour VMS.

Scenario 1 ("Clear"): the base case scenario corresponds to clear weather conditions. Users are assumed to follow their habitual routes, that is, the user equilibrium.
Scenario 2 ("Rain"): the time-varying weather conditions (Figure 7-6) are applied to a stretch of I-95. Travelers, however, still follow their habitual routes, as there is no road weather information or control measures.
Scenario 3 ("Rain + VMS"): variable message signs are placed upstream of the weather-impacted area, which indicate an extra delay (penalty) on each impacted link due to adverse weather conditions. In particular, the penalty is specified as 50% of link travel time for the moderate rain period (i.e. 7:10 – 7:40AM) and 100% for the heavy rain period (i.e. 7:40-8:00AM).

Figure 7-7 to Figure 7-9 present the link performance under these three scenarios. Weather VMS is able to detour some travelers from the impacted road, reflected in less accumulated flow (as shown in Figure 7-9) on the rain-affected link. As a result, the congestion effect caused by the precipitation condition is eliminated. As shown in Figure 7-7, the speed reductions during the moderate rain period (7:10-7:40AM) are comparable whether VMS is active or not. As explained earlier, this reflects drivers' voluntarily speed reduction to accommodate worse driving conditions for safety concerns. During the heavy rain period, however, weather VMS helps to maintain relatively high speed and relatively low density compared to the no-VMS case. The congestion caused by adverse weather is clearly shown by link density comparison (Figure 7-8). Under clear condition or using weather VMS, the density is kept below 30 vehicles per mile per lane (LOS D or better), indicating relatively uncongested traffic conditions. On the other hand, when there is precipitation on the road but travelers are not informed, heavier congestion is experienced.

In brief, weather detour VMS helps to alleviate traffic congestion by detouring travelers to alternative routes. The voluntary speed reduction due to safety concern is, however, not affected by this type of VMS.

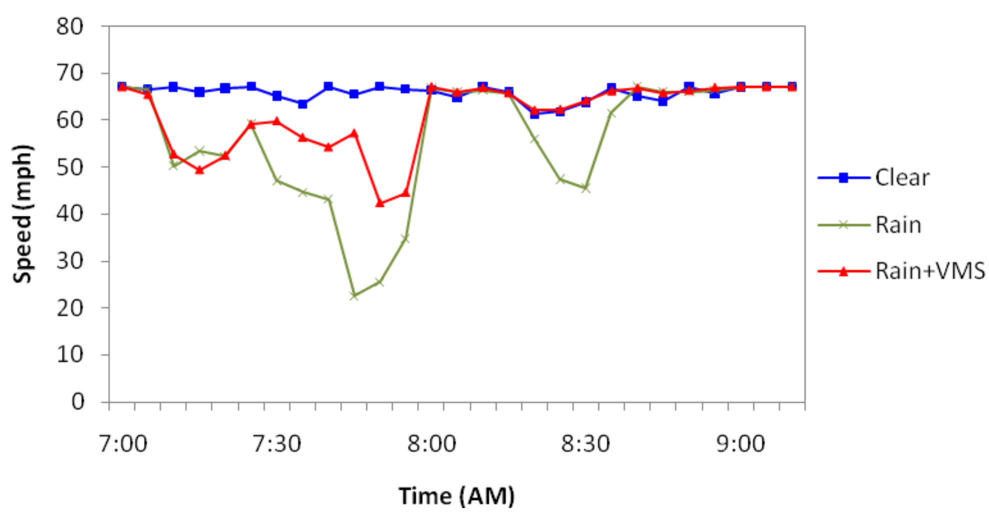



**Figure 7-7 Link Speed Comparison**

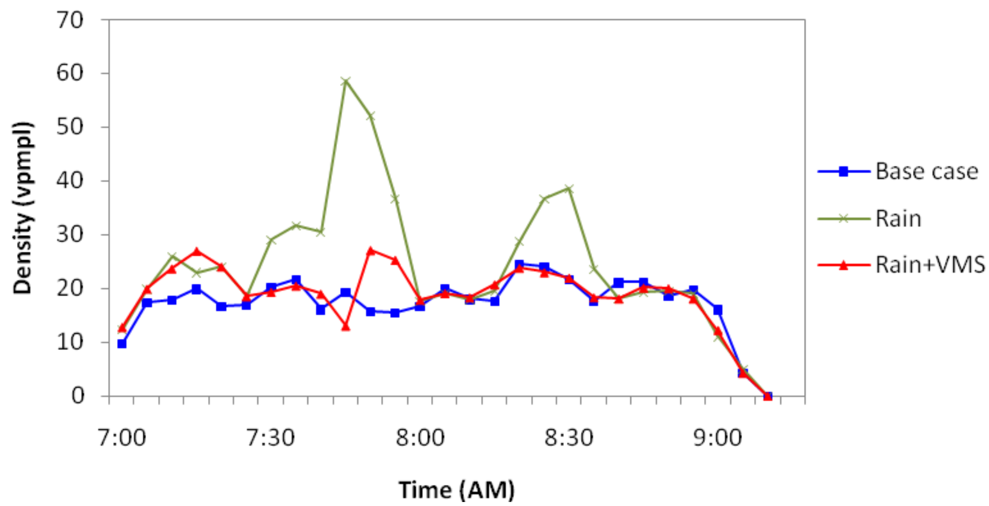



**Figure 7-8 Link Density Comparison**

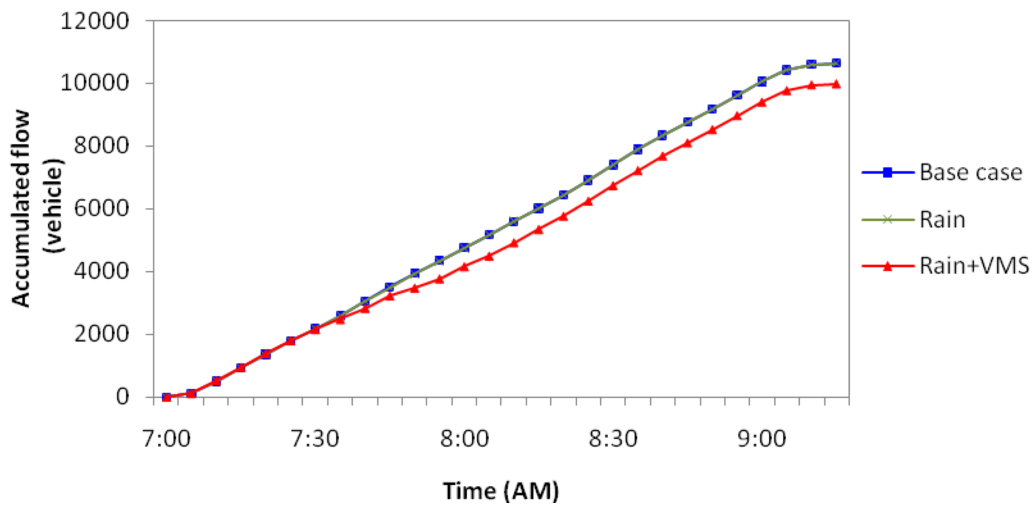



**Figure 7-9 Accumulated Flow Comparison**

In addition, the time-varying travel times of vehicles traveling between an OD pair (affected by the rainfall area) are compared. As shown in Figure 7-10, the precipitation, especially the heavy rain period, affects driving conditions and therefore results in longer travel time. Variable speed limits however help maintain relatively low travel time as the OD flows are distributed more efficiently in response to the speed limit indication. This observation is consistent with Abdel-Aty et al.'s (2006) conclusion that VSL strategies, when properly set, could produce travel time savings, in addition to their potential safety benefit.

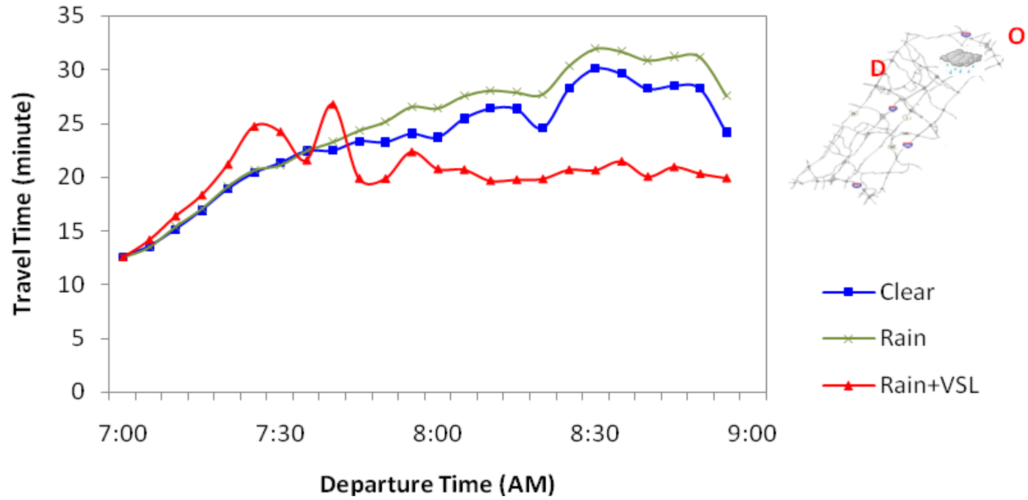



**Figure 7-10 OD Travel Time Comparison**

# 8. Conclusions

The study addresses both supply and demand aspects of the response to adverse weather, including user responses to various weather-specific interventions such as advisory information and control actions. The procedures implemented provide immediately applicable tools that capture knowledge accumulated to date in the growing body of literature regarding weather effects on traffic (especially in an aggregate sense). The application to a real world network shows that the proposed model can be used to evaluate weather impacts on transportation networks and the effectiveness of weather-related VMS.

The high level framework for incorporating weather impacts in TrEPS, presented in this study, provides a direction for future development towards a modern approach to traffic management under adverse weather that recognizes modern technological developments (e.g. weather sensing/forecasting, weather responsive traffic management). In addition, heterogeneous user response to road weather information, reflecting their different risk taking behavior, can also be calibrated and included in a richer router choice model in future study.

While the work accomplished as a result of this research effort advances the state of the art in incorporating weather effects in network analysis tools, additional effort in two main areas is necessary to translate these advances into practice. The first entails actual implementation in the context of a regional planning and/or traffic operations agency to establish the model and calibrate it for application under a variety of local conditions and traffic patterns. While the developments under this project provide all necessary mechanisms as well as default values for most likely situations, only through actual application within a progressive agency committed to providing information to users and to developing measures and plans to deal with weather-related problems will the state of practice fully advance to the desired level.

The second area of development would focus on weather-related traffic management and control measures, and interfacing their actual deployment with the decision-support tools developed in this project. Again, the mechanisms included in this development were in certain cases based on proposed control measures that may have seen no or limited deployment. Actual field testing and monitoring can provide essential data to calibrate and refine these mechanisms. Furthermore, achieving the full benefits of traffic estimation and prediction tools for the intelligent management of traffic systems under weather-related events requires additional development of the real-time components of these tools, and their interface with real-time sensors and weather prediction sources.

## References

Aaheim, H. and K. Hauge (2005) Impacts of Climate Change on Travel Habits: A National Assessment Based on Individual Choices, CICERO Report no. 2005: 07, CICERO.

Abdel-Aty, M., Dilmore, J., Dhindsa, A. (2006). Evaluation of Variable Speed Limits for Real-Time Freeway Safety Improvement. *Accident Analysis and Prevention,* 38, pp. 335–345.

Adams, R. (1973) Uncertainty in Nature, Cognitive Dissonance and the Perceptual Distortion of Environmental Information: Weather Forecasts and New England Beach Trip Decisions. *Economic Geography* Vol 49(4), pp. 287-297.

Agbolosu-Amison, S.J., Sadek, A.W. and El-Dessouki, W. (2004). Inclement Weather and Traffic Flow at Signalized Intersections: Case Study from Northern New England. *Transportation Research Record* 1867, pp. 163-171.

Alfelor, R., Mahmassani, H.S. and Dong, J. (2009). Incorporating Weather Impacts in Traffic Estimation and Prediction Systems. Presented at the Institute of Transportation Engineers (ITE) Annual Meeting and Exhibits, San Antonio.

Andrey, J, Mills, B., and Vandermolen J. (2003). A Temporal Analysis of Weather-Related Collision Risk for Ottawa, Canada: 1990-1998, *Transportation Research Board*, Paper No. 3488, Washington, D. C.

Antoniou, C., Ben-Akiva, M., and H. N. Koutsopoulos (2007). Nonlinear Kalman Filtering Algorithms for On-Line Calibration of Dynamic Traffic Assignment Models. *IEEE Transactions on Intelligent Transportation Systems*. Vol. 8, Issue 4, pp. 661-670.

Balakrishna, R., Antoniou, C., Koutsopoulos, H. N., Wen, Y., and Ben-Akiva, M. (2008). Calibrating Speed-Density Functions for Mesoscopic Traffic Simulation. Greenshields 75 Symposium: TRB Traffic Flow Theory Committee Summer Meeting, July 8-10, 2008, Woods Hole, Massachusetts.

Balakrishna, R., M. Ben-Akiva and H. N. Koutsopoulos (2007) Off-line Calibration of Dynamic Traffic Assignment: Simultaneous Demand-Supply Estimation. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2003, pp. 50-58.

R. Balakrishna, H. N. Koutsopoulos and M. Ben-Akiva (2005) Calibration and Validation of Dynamic Traffic Assignment Systems. H. S. Mahmassani (editor) 16th International Symposium on Transportation and Traffic Theory (ISTTT), Maryland, pp. 407-426.

Ben-Akiva, M., Bierlaire, M., Koutsopoulos, H. N., Mishalani, R., (2002). Real-Time Simulation of Traffic Demand-Supply Interactions within DynaMIT. In M. Gendreau and P. Marcotte (Eds.), Transportation and network analysis: current trends. Miscellenea in Honor of Michael Florian (pp. 19-36). New York: Kluwer Academic Publishers.

Ben-Akiva, M., de Palma, A., and Kaysi, I. (1996). The Impact of Predictive Information on Guidance Efficiency: An Analytical Approach. Advanced Methods in Transportation Analysis, L. Bianco and P. Toth, eds., pp. 413-432, Springer-Verlag.

Bergstrom, A. and R. Magnusson (2003) Potential for Transferring Car Trips to Bicycle during Winter*, Transportation Research A*(37), pp. 649-666.

Bernardin Lochmueller and Associates, Inc. (1995). *Anchorage Signal System Upgrade*. Bernardin Lochmueller and Associates, Inc., Evansville, Indiana.

Botha, J. L. and Kruse, T. L. (1992). Flow Rates at Signalized intersections Under Cold Winter Conditions, *Journal of Transportation Engineering* pp.439-450.

Boyle, L., Mannering, F. (2004). Impact of Traveler Advisory Systems on Driving Speed: Some New Evidence, *Transportation Research Part C*, Issue 12(1), pp. 57-72.

Brilon, W., and Ponzlet, M. (1995). Auswirkungen von zeitlich veraenderlichen leistungsfahigkeiten. Schlussbericht, November 1995

Brilon, W., and Ponzlet, M. (1996). Variability of Speed-Flow Relationships on German Autobahns, *Transportation Research Record* 1555, pp. 91-98.

Caplice, C. and Mahmassani, H.S. (1992). Commuting Behaviour: Preferred Arrival Time, Use of Information, and Switching Propensity. *Transportation Research A*, Vol. 26A, No. 5 pp. 409-418.

Chin, S. M., Franzese, O., Greene, D. L., Hwang, H. L., Gibson, R. C. (2004), Temporary Loss of Highway Capacity and Impact on Performance: Phase 2, Oak Ridge National Laboratory, Report no. ORLNL: TM-2004/209, November 2004.

Cooper, B.R., Sawyer, H. (1993). Assessment of M25 Automatic Fog-warning System. Crowthorne: Transportation Research Laboratory. Final report, Project Report 16.

http://dash.net/product/traffic.php; accessed September 2008.

Dong, J., Mahmassani, H.S., Alfelor, R. (2010a). Incorporating Adverse Weather Impacts in Dynamic Traffic Simulation-assignment Models: Methodology and Application. Submitted to Transportation Research Board Annual Meeting 2010.

Dong, J., Mahmassani, H.S., Alfelor, R. (2010b) Weather Responsive Traffic Management: Deployment of Real-Time Traffic Estimation and Prediction Systems. Submitted to Transportation Research Board Annual Meeting 2010.

Dong, J., Mahmassani, H.S., and Lu, C-C. (2006). How Reliable Is This Route? Predictive Travel Time and Reliability for Anticipatory Traveler Information Systems. *Transportation Research Record: Journal of the Transportation Research Board* 1980, 117-125.

Dong, J., Erdogan, S., Lu C.-C., and Mahmassani, HS. (2007). "State-Dependent Pricing for Real-Time Freeway Management: Static, Reactive, and Anticipatory", National Research Council (U.S.). *Transportation Research Board Meeting* (86th: 2007 : Washington, D.C.). Preprint CD-ROM.

Dynameq - INRO, Simulation for Equilibrium Dynamic Traffic Assignment. Website: http://www.inro.ca/en/products/dynameq/index.php

DYNASMART-P user's guide version 1.3.0. Federal Highway Administration, 2007

FHWA. Clarus web site, at http://www.its.dot.gov/clarus/index.htm

FHWA (1977). Economic Impact of Highway Snow and Ice Control, Final Report, Federal Highway Administration, Report No. FHWA-RD-77-95, Washington, D. C.

FHWA (2004). Identifying and Assessing Key Weather-Related Parameters and Their Impacts on Traffic Operations Using Simulation. Report No. FHWA-HRT-04-131, September 2004.

FHWA (2006). Empirical Studies on Traffic Flow in Inclement Weather. Report No. FHWA-HOP-07-073, October 2006.

Ganesh Babu Kolisetty, V., Iryo, T., Asakura, Y., Kuroda, K. (2006). Effects of Variable Message Signs on Driver Speed Behavior on a Section of Expressway under Adverse Fog Conditions. *Journal of Advanced Transportation*, Vol. 41, No. 1.

Gilliam, W. J., and Withill, R.A. (1992). UTC and Inclement Weather Conditions, IEE Conference, pp. 85-99.

Goodwin, L. (2003). Best Practices for Road Weather Management, Version 2.0. Report No. FHWA-OP-03-081, US. Departmemt of Transportation, available at http://ops.fhwa.dot.gov/Weather/best_practices/CaseStudiesFINALv2-RPT.pdf

Hanabali, R. M., and Kuemmel, D. A. (1992). Traffic Volume Reductions Due to Winter Storm Conditions. *Transportation Research Record* 1387.

Hansen, B., Martin, P., Perrin, J., and D. Meldrum. (2001) Delivering Road Weather Information to the Traveling Public. *Transportation Research Record* 1745, pp. 46-52.

HCM (2000). Highway Capacity Manual, *Transportation Research Board*, United States of America.

Hogema, J.H., van der Horst, R. (1997). Evaluation of A16 Motorway Fog-Signalling System With Respect to Driving Behaviour. *Transportation Research Record*, 1573, pp. 63-67.

Hranac, R., Sterzin, E., Krechmer, D., Rakha, H., Farzaneh, M. (2006) Empirical Studies on Traffic Flow in Inclement Weather, FHWA-HOP-07-073

Huynh, N., H. Mahmassani, and H. Tavana (2002). Adaptive Speed Estimation using Transfer Function Models for Real-Time Dynamic Traffic Assignment Operation. *Proceedings of the 81st Annual Meeting of the Transportation Research Board.*

Ibrahim, A. T. and Hall, F. L. (1994). Effect of Adverse Weather Conditions on Speed-Flow-Occupancy Relationships. *Transportation Research Record* 1427, pp. 184-191.

www.inrix.com, accessed September 2008.

Jayakrishnan, R., Mahmassani, H.S. and Hu, T-Y. (1994) An Evaluation Tool for Advanced Traffic Information and Management Systems in Urban Networks. *Transportation Research Part C*, Vol. 2C, No. 3, pp. 129-147, 1994.

Jones, E. R., and Goolsby, M. E. (1969). Effect of Rain on Freeway Capacity, Research Record, 14-23, Texas Transportation Institute, Texas A&M University, College Station.

Jones, E. R., and Goolsby, M. E. (1970). The Environmental Influence of Rain on Freeway Capacity. *Highway Research Record* 321, National Research Council, Washington, D. C.

Khattak, A. and A. de Palma. (1997) The Impact of Adverse Weather Conditions on the Propensity to Change Travel Decisions: A Survey of Brussels Commuters. *Transportation Research A* 31A(3). pp. 181-203.

Kleitsch and Cleveland (1971). The Effect of Rainfall on Freeway Capacity, Report Number: HSRI TrS-6, Highway Safety Research Institute, University of Michigan, Ann Arbor.

Knapp, K. K., Smithson, L. D., and Khattak, A. J. (2000). The Mobility and Safety Impacts of Winter Storm Events in a Freeway Environment, *Mid-Continent Transportation Symposium Proceedings*.

Kockelman, K. (1998). Changes in the Flow-Density Relation due to Environmental, Vehicle, and Driver Characteristics. *Transportation Research Record*, 1644, 47-56.

Kyte, M., Khatib, Z., Shannon, P., and Kitchener, F. (2001). The Effect of Weather on Free-Flow Speed, Transportation Research Board, Paper No. 01-3280, Washington, D. C.

Lamm, R., E. M. Choueiri, and T. Mailaender (1990). Comparison of Operating Speeds on Dry and Wet Pavements of Two-Lane Rural Highways, *Transportation Research Record* 1280, National Research Council, Washington D.C.

Liu, Y. and H. Mahmassani. (1998). Dynamic Aspects of Departure Time and Route Decision Behavior Under Advanced Traveler Information Systems (ATIS): Modeling Framework and Experimental Results. *Transportation Research Record* 1645:111–119.

Luoma J., Rämä, P., Penttinen, M., Anttila, V. (2000). Effects of Variable Message Signs for Slippery Road Conditions on Reported Driver Behaviour. *Transportation Research Part F*, 3, pp. 75-84.

Mahmassani, H.S. (1998) Dynamic Traffic Simulation and Assignment: Models, Algorithms, and Applications to ATIS/ATMS Evaluation and Operation; in Labbé, Laporte, Tanczos, and Toint (eds.) Operations Research and Decision Aid Methodologies in Traffic and Transportation Management, NATO ASI Series, Springer, pp. 104-132.

Mahmassani, H. S. (2001) Dynamic Network Traffic Assignment and Simulation Methodology for Advanced System Management Applications. *Networks and Spatial Economics*, Vol. 1:2 (3, pp. 267-292.

Mahmassani, H.S., Fei, X., Eisenman, S., Zhou, X. and Qin, X. (2005). DYNASMART-X Evaluation for Real-Time TMC Application: CHART Test Bed, Final Research Report, Maryland Transportation Initiative, University of Maryland.

Mahmassani, H.S., Hatcher, S.C. and Caplice, C.G. (1997). Daily Variation of Trip Chaining, Scheduling and Path Selection Behaviour of Work Commuters. Chapter 15, Part III, *Understanding Travel Behaviour in an Era of Change*, First Edition, pp. 351-379, Pergamon: Elsevier Science Inc., Tarrytown, New York.

Mahmassani, H.S. and Jayakrishnan, R., (1991). System Performance and User Response under Real-Time Information in a Congested Traffic Corridor. *Transportation Research* 25 5, pp. 293–30

Mahmassani, H.S. and Peeta, S. (1993). Network Performance Under System Optimal and User Equilibrium Dynamic Assignments: Implications for ATIS. *Transportation Research Record: Journal of the Transportation Research Board,* 1408, pp. 83-93.

Mahmassani, H.S.; Qin, X.; Zhou, X. (2004) DYNASMART-X Evaluation for Real-Time TMC Application: Irvine Test Bed. US DOT/ FHWATREPS Phase 1.5B Final Report. Maryland Transportation Initiative, University of Maryland.

Mahmassani, H.S.; Sbayti, H.; Erdogan, S.; Lu, C.-C. (2006). DYNASMART-P 1.2 User's Guide and Programmer's Guide. US DOT/ FHWA Final Report. Maryland Transportation Initiative, University of Maryland

Mahmassani, H.S. and Stephan, D.G. (1988). Experimental Investigation of Route and Departure Time Choice Dynamics of Urban Commuters. *Transportation Research Record* 1203, pp. 69-84.

Mahmassani, H. S., and Zhou, X. (2005). Transportation System Intelligence: Performance Measurement and Real-Time Traffic Estimation and Prediction in a Day-To-Day Learning Framework. In E. Abed (Ed.) *Advances in Control, Communication Networks, and Transportation Systems,* In Honor of Pravin Varaiya. Boston: Birkhauser.

Maki, P. J. (1999). Adverse Weather Traffic Signal Timing, *ITE Annual Meeting, Institute of Transportation Engineers*, Washington D. C.

Mannering, F., Kim, S-G., Ng, L., and W. Barfield. (1995) Travelers' Preference for In-Vehicle Information Systems: An Exploratory Analysis. *Transportation Research C*, Vol. 3(6) pp. 339-351.

Martin, P. T., Perrin, J., Hansen, B. and Quintina, I. (2000). Inclement Weather for Signal Timings, MPC Report No. 01-120.

http://mctrans.ce.ufl.edu/featured/dynasmart, accessed July 2008

Mixon-Hill Inc. et al. (2005) Clarus Weather System Design: Detailed System Requirements Specification. Technical Report submitted to FHWA, available at: http://www.clarusinitiative.org/documents/Final_Clarus_System_Detailed_Requirements.pdf

NCHRP Capacity and Level of Service at Unsignalized Intersections, Final Report Volume 2-All Way Stop-Controlled Intersections, April 1996

Padget, E.D, Knapp, K. and Thomas, G.B. (2001). Investigation of Winter-Weather Speed Variability in Sport Utility Vehicles, Pickup Trucks, and Passenger Cars. *Transportation Research Record* 1779.

Park, B., Smith, B. L., Lee, J., Pampati, D., Ben-Akiva, M., and Balakrishnan, R. Evaluation of DynaMIT - A Prototype Traffic Estimation and Prediction System, University of Virginia, Charlottesville, VA. June 2006

Park, B., Smith, B. L., Pampati, D., Cao, J. and Qi, Y. Field Evaluation of DynaMIT in Hampton Road, Virginia, Final Report on Phase I report, University of Virginia, Charlottesville, VA. August 2004

Parsonson, P. S. (1992). Flashing Operation and Signal Timing for Adverse Weather, *NCHRP Synthesis of Highway Practice*, pp. 47-47.

Peeta, S., Ramos, J., and R. Pasupathy. (2000) Content of Variable Message Signs and On-line Driver Behavior. *Transportation Research Record* 1725, pp. 102-108.

Peeta, S. and J-W Yu. (2005) A Hybrid Model for Driver Route Choice Incorporating En-Route Attributes and Real-time Information Effects. *Networks and Spatial Economics* 5, pp. 21-40.

Perrin, J., Martin, P. T., and Hansen, B. J. (2001). Modifying Signal Timing during Inclement weather, *Transportation Research Board*, Paper No. 3233, Washington, D.C.

Pisano, P., Alfelor, R.M. , Pol, J.S., Goodwin, L.C. and Stern, A.D. (2005). Clarus—The Nationwide Surface Transportation Weather Observing and Forecasting System. *Presented at the 21st International Conference on Interactive Information Processing Systems (IIPS) for Meteorology*, Oceanography, and Hydrology http://ams.confex.com/ams/pdfpapers/83961.pdf

Pisano, P. A. and L. C. Goodwin (2002) Surface Transportation Weather Applications. Federal Highway Administration (FHWA) in concert with Mitretek Systems, *presented at the 2002 Institute of Transportation Engineers Annual Meeting*.

Polydoropoulou, A., Ben-Akiva, M., Khattak, A., and G. Lauprete. (1996). Modeling Revealed and Stated En-Route Travel Response to Advanced Traveler Information Systems. *Transportation Research Record* 1537, pp. 38-44.

Prevedouros, P. D. and K. Chang (2004). Potential Effects of Wet Conditions on Signalized Intersection LOS, *ASCE Journal of Transportation Engineering*– Special Issue on Calibration and Validation of HCM Models, Reston, VA.

Qin, X. and H. Mahmassani (2004). Adaptive Calibration of Dynamic Speed–Density Relations for Online Network Traffic Estimation And Prediction Applications. *Proc. 83rd Annual Meeting of the Transportation Research Board,* Washington, D.C.

Rakha, H., Farzaneh, M., Arafeh, M., Hranac, R., Sterzin, E. and Krechmer, D. (2007). Empirical Studies on Traffic Flow in Inclement Weather, Final Report – Phase I.

Rämä, P., and J. Luoma. (1997) Driver Acceptance of Weather-Controlled Road Signs and Displays. *Transportation Research Record* 1573, pp. 72-75.

Rämä, P. (1999). Effects of Weather-Controlled Variable Speed Limits and Warning Signs on Driver Behavior. *Transportation Research Record*, 1689, pp. 53-59.

Rämä, P. (2001). Effects of Weather-Controlled Variable Message Signs on Driver Behavior. Technical Research Centre of Finland, VTT Publications 447.

Robinson, M. (2000) Examples of Variable Speed Limit Applications. Speed Management Workshop. *79rd Annual Meeting of the Transportation Research Board*

Salomen, M., and Puttonen, T. (1982). The Effect of Speed Limits and Weather to the Traffic Flow: Literature Study and Analysis of Traffic Flow on the Western Motorway of Helsinki, Helsinki University, Finland, 1982.

Smith, B. L., K. G. Byrne, R. B. Copperman, S. M. Hennessy, and N. J. Goodall (2004). Investigation into the Impact of Rainfall on Freeway Traffic Flow. (CD-ROM). *83rd Annual Meeting of the Transportation Research Board*. Washington D.C, January 2004.

Snowden, R.J., Stimpson, N. and Ruddle, R.A., (1998). Speed Perception Fogs Up as Visibility Drops. *Nature 392*, p. 450.

Stern, A., Shah, V., Goodwin, L., and Pisano P. (2003). Analysis of Weather Impacts Flow in Metropolitan Washington D.C., Mitretek Systems, Washington, D.C.

Tanner, J. C. (1952). Effect of Weather on Traffic Flow, *Nature*, No. 4290.

Tavana, H. and H. Mahmassani (2000). Estimation and Application of Dynamic Speed-Density Relations by Using Transfer Function Models. *Transportation Research Record*, vol. 1710, pp. 47-57.

Van Aerde, M. (1995). Single Regime Speed-Flow-Density Relationship for Congested and Uncongested Highways, Presented at the 74th TRB Annual Conference, Washington D.C., Paper No. 950802.

Wen, Y., Balakrishna, R. Gupta, A., and Ben-Akiva, M. Deployment of DynaMIT in the City of Los Angeles, Draft of Final Report, Federal Highway Administration, May 2006

Zeitlin, L. R. (1995). Estimates of Driver Mental Workload: A Long-Term field Trial of Two Subsidiary Tasks*, the Journal of Human Factors and Ergonomics Society*, Vol. 37, No. 3, pp. 611-621.

Zhou, X. and Mahmassani, H.S. (2007) A Structural State Space Model for Real-Time Traffic Origin-Destination Demand Estimation and Prediction in a Day-To-Day Learning Framework, *Transportation Research Part B: Methodological*, Vol. 41, No. 8, pp. 823-840.

# Appendix A: Calibration Results for Speed-Density Relation and WAF

| Highway | Milemark | Station ID | Weather condition | $k_{bp}$ (vpmpl) | $u_f$ (mph) | $v_f$ (mph) | $\alpha$ | $v_0$ (mph) | $k_{jam}$ (vpmpl) | RMSE[1] (reg.1) | R-sqrd[2] (reg.2) | # of obs. | | Weather Adjustment Factor (WAF)[3] | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | reg.1 | reg.2 | $F\_k_{bp}$ | $F\_u_f$ | $F\_v_f$ | $F\_f_{max}$ |
| I-64 | 284.2 | 6 | Normal | 16 | 61.5 | 83.4 | 4.2 | 2 | 225 | 4.20 | 0.72 | 296 | 1950 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 16 | 63.0 | 80.4 | 3.4 | 2 | 225 | 5.22 | 0.51 | 84 | 241 | 1.00 | 1.02 | 0.96 | 0.91 |
| | | | Moderate Rain | 15 | 67.0 | 85.3 | 3.6 | 2 | 225 | 4.04 | 0.66 | 13 | 59 | 0.94 | 1.09 | 1.02 | 0.92 |
| | | | Heavy Rain | 16 | 67.4 | 85.0 | 3.2 | 2 | 225 | 3.88 | 0.53 | 7 | 28 | 1.00 | 1.10 | 1.02 | 0.82 |
| I-64 | 284.2 | 8 | Normal | 15 | 63.1 | 85.1 | 4.5 | 2 | 225 | 4.09 | 0.80 | 21710 | 21968 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 10 | 62.9 | 77.0 | 4.6 | 2 | 225 | 6.60 | 0.79 | 1066 | 4043 | 0.67 | 1.00 | 0.91 | 0.91 |
| | | | Moderate Rain | 12 | 51.9 | 63.7 | 3.9 | 2 | 225 | 13.02 | 0.74 | 105 | 299 | 0.80 | 0.82 | 0.75 | 0.74 |
| | | | Heavy Rain | 10 | 57.5 | 70.8 | 4.7 | 2 | 225 | 7.98 | 0.89 | 21 | 85 | 0.67 | 0.91 | 0.83 | 0.71 |
| | | | Light Snow | 10 | 59.9 | 72.4 | 4.3 | 2 | 225 | 7.73 | 0.75 | 107 | 183 | 0.67 | 0.95 | 0.85 | 0.69 |
| I-64 | 286.1 | 23 | Normal | 20 | 50.4 | 64.2 | 2.7 | 2 | 225 | 8.19 | 0.62 | 7160 | 8704 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 15 | 47.8 | 56.6 | 2.5 | 2 | 225 | 7.92 | 0.70 | 372 | 1756 | 0.75 | 0.95 | 0.88 | 0.91 |
| | | | Moderate Rain | 10 | 44.0 | 48.5 | 2.3 | 2 | 225 | 5.48 | 0.65 | 7 | 103 | 0.50 | 0.87 | 0.76 | 0.63 |
| | | | Heavy Rain | 21 | 46.8 | 64.2 | 3.4 | 2 | 225 | 9.28 | 0.94 | 7 | 13 | 1.05 | 0.93 | 1.00 | 0.49 |
| I-64 | 286.1 | 24 | Normal | 12 | 53.2 | 63.6 | 3.4 | 2 | 225 | 9.31 | 0.59 | 7159 | 17859 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 12 | 47.5 | 55.9 | 3.1 | 2 | 225 | 11.85 | 0.53 | 850 | 1871 | 1.00 | 0.89 | 0.88 | 0.89 |
| | | | Light Snow | 12 | 47.8 | 58.0 | 3.7 | 2 | 225 | 15.85 | 0.61 | 53 | 107 | 1.00 | 0.90 | 0.91 | 0.45 |
| I-64 | 286.6 | 27 | Normal | 23 | 33.5 | 41.9 | 2.2 | 2 | 225 | 4.12 | 0.53 | 4058 | 10215 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 28 | 31.6 | 45.4 | 2.9 | 2 | 225 | 4.75 | 0.49 | 523 | 567 | 1.22 | 0.94 | 1.08 | 0.82 |
| I-64 | 286.4 | 28 | Normal | 10 | 52.7 | 58.9 | 2.5 | 2 | 225 | 5.93 | 0.85 | 5536 | 8162 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 11 | 50.8 | 59.2 | 3.2 | 2 | 225 | 6.00 | 0.44 | 483 | 513 | 1.10 | 0.96 | 1.01 | 0.59 |
| | | | Moderate Rain | 12 | 51.6 | 72.4 | 6.4 | 2 | 225 | 9.02 | 0.66 | 35 | 9 | 1.20 | 0.98 | 1.23 | 0.43 |
| I-64 | 282.5 | 37 | Normal | 26 | 65.3 | 195.2 | 9.1 | 2 | 225 | 0.94 | 0.71 | 22113 | 307 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 24 | 65.0 | 118.8 | 5.5 | 2 | 225 | 0.75 | 0.61 | 1533 | 83 | 0.92 | 0.99 | 0.61 | 0.99 |
| I-64 | 283.5 | 47 | Normal | 21 | 64.4 | 128.7 | 7.2 | 2 | 225 | 3.53 | 0.48 | 12376 | 14368 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 14 | 63.7 | 94.4 | 6.3 | 2 | 225 | 4.63 | 0.49 | 569 | 2416 | 0.67 | 0.99 | 0.73 | 0.68 |
| | | | Moderate Rain | 16 | 59.7 | 103.0 | 7.6 | 2 | 225 | 4.95 | 0.78 | 86 | 89 | 0.76 | 0.93 | 0.80 | 0.53 |

| Highway | Milemark | Station ID | Weather condition | $k_{bp}$ (vpmpl) | $u_f$ (mph) | $v_f$ (mph) | $\alpha$ | $v_0$ (mph) | $k_{jam}$ (vpmpl) | RMSE[1] (reg.1) | R-sqrd[2] (reg.2) | # of obs. | | Weather Adjustment Factor (WAF)[3] | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | reg.1 | reg.2 | $F\_k_{bp}$ | $F\_u_f$ | $F\_v_f$ | $F\_f_{max}$ |
| I-64 | 283.5 | 48 | Normal | 25 | 61.2 | 205.4 | 10.5 | 2 | 225 | 7.18 | 0.80 | 23611 | 660 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Moderate Rain | 14 | 54.1 | 72.1 | 4.6 | 2 | 225 | 9.86 | 0.52 | 315 | 64 | 0.56 | 0.88 | 0.35 | 0.74 |
| | | | Heavy Rain | 19 | 56.6 | 118.7 | 8.6 | 2 | 225 | 8.82 | 0.73 | 84 | 13 | 0.76 | 0.93 | 0.58 | 0.72 |
| | | | Light Snow | 11 | 58.1 | 68.1 | 3.3 | 2 | 225 | 8.86 | 0.43 | 116 | 88 | 0.44 | 0.95 | 0.33 | 0.79 |
| I-64 | 282.2 | 50 | Normal | 30 | 65.7 | 87.2 | 2.0 | 2 | 225 | 5.85 | 0.34 | 11257 | 601 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 28 | 63.1 | 99.3 | 3.5 | 2 | 225 | 7.51 | 0.84 | 1349 | 207 | 0.93 | 0.96 | 1.14 | 0.82 |
| | | | Moderate Rain | 21 | 61.9 | 98.2 | 4.8 | 2 | 225 | 5.07 | 0.65 | 224 | 19 | 0.70 | 0.94 | 1.13 | 0.77 |
| | | | Heavy Rain | 11 | 57.6 | 64.8 | 2.4 | 2 | 225 | 12.45 | 0.27 | 36 | 12 | 0.37 | 0.88 | 0.74 | 0.59 |
| I-64 | 282.2 | 51 | Normal | 19 | 62.5 | 89.7 | 4.2 | 2 | 225 | 4.65 | 0.75 | 23153 | 10234 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 15 | 61.0 | 81.8 | 4.4 | 2 | 225 | 6.74 | 0.80 | 1347 | 1968 | 0.79 | 0.98 | 0.91 | 0.87 |
| | | | Moderate Rain | 10 | 57.1 | 71.2 | 5.0 | 2 | 225 | 9.27 | 0.84 | 48 | 252 | 0.53 | 0.91 | 0.79 | 0.89 |
| | | | Heavy Rain | 16 | 61.6 | 85.5 | 4.6 | 2 | 225 | 6.11 | 0.91 | 36 | 49 | 0.84 | 0.99 | 0.95 | 0.72 |
| | | | Light Snow | 14 | 58.5 | 83.2 | 5.6 | 2 | 225 | 6.14 | 0.82 | 127 | 104 | 0.74 | 0.94 | 0.93 | 0.59 |
| I-64 | 282.1 | 52 | Normal | 24 | 38.3 | 47.0 | 1.9 | 2 | 225 | 4.75 | 0.55 | 12660 | 9920 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Moderate Rain | 11 | 38.3 | 47.0 | 4.3 | 2 | 225 | 4.10 | 0.31 | 20 | 59 | 0.46 | 1.00 | 1.00 | 0.41 |
| I-64 | 280.7 | 65 | Normal | 22 | 62.2 | 87.6 | 3.4 | 2 | 225 | 5.47 | 0.59 | 19123 | 21707 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Snow | 27 | 56.7 | 101.9 | 4.7 | 2 | 225 | 9.16 | 0.73 | 250 | 60 | 1.23 | 0.91 | 1.16 | 0.83 |
| I-64 | 280.8 | 66 | Normal | 14 | 65.5 | 112.8 | 8.7 | 2 | 225 | 1.37 | 0.75 | 18478 | 1468 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 16 | 65.1 | 126.5 | 9.2 | 2 | 225 | 1.69 | 0.67 | 1318 | 151 | 1.14 | 0.99 | 1.12 | 1.00 |
| | | | Moderate Rain | 14 | 64.5 | 104.1 | 7.6 | 2 | 225 | 0.74 | 0.98 | 71 | 17 | 1.00 | 0.98 | 0.92 | 0.49 |
| I-64 | 279 | 85 | Normal | 30 | 65.7 | 123.1 | 4.5 | 2 | 225 | 2.87 | 0.73 | 27950 | 1277 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 28 | 63.6 | 110.0 | 4.2 | 2 | 225 | 4.44 | 0.83 | 2284 | 260 | 0.93 | 0.97 | 0.89 | 0.89 |
| | | | Moderate Rain | 28 | 65.3 | 122.8 | 4.9 | 2 | 225 | 9.78 | 0.96 | 79 | 31 | 0.93 | 0.99 | 1.00 | 0.82 |

| Highway | Milemark | Station ID | Weather condition | $k_{bp}$ (vpmpl) | $u_f$ (mph) | $v_f$ (mph) | $\alpha$ | $v_0$ (mph) | $k_{jam}$ (vpmpl) | RMSE[1] (reg.1) | R-sqrd[2] (reg.2) | # of obs. | | Weather Adjustment Factor (WAF)[3] | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | reg.1 | reg.2 | $F\_k_{bp}$ | $F\_u_f$ | $F\_v_f$ | $F\_f_{max}$ |
| I-64 | 279 | 86 | Normal | 12 | 61.1 | 72.6 | 3.2 | 2 | 225 | 4.69 | 0.52 | 17578 | 10478 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 13 | 57.7 | 102.7 | 10.0 | 2 | 225 | 7.38 | 0.27 | 1705 | 567 | 1.08 | 0.94 | 1.42 | 0.67 |
| | | | Moderate Rain | 10 | 42.4 | 65.5 | 10.0 | 2 | 225 | 16.32 | 0.30 | 94 | 55 | 0.83 | 0.69 | 0.90 | 0.43 |
| | | | Light Snow | 14 | 54.0 | 102.7 | 10.3 | 2 | 225 | 8.51 | 0.28 | 84 | 11 | 1.17 | 0.88 | 1.41 | 0.52 |
| I-264 | 13.8 | 148 | Normal | 30 | 68.3 | 147.3 | 5.5 | 2 | 225 | 3.91 | 0.65 | 5538 | 744 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 24 | 64.9 | 94.3 | 3.4 | 2 | 225 | 1.29 | 0.56 | 379 | 246 | 0.80 | 0.95 | 0.64 | 0.85 |
| | | | Moderate Rain | 20 | 64.4 | 100.4 | 4.9 | 2 | 225 | 0.75 | 0.55 | 16 | 19 | 0.67 | 0.94 | 0.68 | 0.59 |
| | | | Light Snow | 16 | 62.5 | 82.4 | 3.9 | 2 | 225 | 1.34 | 0.91 | 14 | 14 | 0.53 | 0.91 | 0.56 | 0.45 |
| I-264 | 14 | 153 | Normal | 14 | 64.9 | 84.0 | 4.1 | 2 | 225 | 1.13 | 0.56 | 5471 | 1366 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 12 | 64.2 | 77.5 | 3.5 | 2 | 225 | 2.34 | 0.85 | 457 | 249 | 0.86 | 0.99 | 0.92 | 0.98 |
| | | | Moderate Rain | 10 | 61.1 | 66.5 | 1.9 | 2 | 225 | 3.82 | 0.98 | 14 | 14 | 0.71 | 0.94 | 0.79 | 0.64 |
| | | | Heavy Rain | 12 | 64.1 | 94.4 | 7.3 | 2 | 225 | 1.07 | 0.76 | 18 | 19 | 0.86 | 0.99 | 1.12 | 0.68 |
| I-264 | 14 | 154 | Normal | 21 | 64.4 | 85.0 | 2.9 | 2 | 225 | 0.64 | 0.82 | 3497 | 1677 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 20 | 63.6 | 85.4 | 3.3 | 2 | 225 | 1.26 | 0.94 | 295 | 148 | 0.95 | 0.99 | 1.00 | 0.88 |
| I-264 | 14.9 | 158 | Normal | 12 | 54.0 | 61.9 | 2.6 | 2 | 225 | 4.64 | 0.62 | 2177 | 28203 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 10 | 53.5 | 61.3 | 3.1 | 2 | 225 | 4.76 | 0.86 | 137 | 2164 | 0.83 | 0.99 | 0.99 | 0.71 |
| | | | Moderate Rain | 11 | 49.3 | 59.1 | 3.7 | 2 | 225 | 3.42 | 0.82 | 10 | 91 | 0.92 | 0.91 | 0.95 | 0.59 |
| | | | Heavy Rain | 17 | 47.2 | 72.6 | 5.7 | 2 | 225 | 4.52 | 0.45 | 17 | 24 | 1.42 | 0.87 | 1.17 | 0.53 |
| I-264 | 16.3 | 168 | Normal | 18 | 51.3 | 61.5 | 2.3 | 2 | 225 | 4.08 | 0.82 | 8566 | 19564 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 12 | 51.4 | 57.8 | 2.2 | 2 | 225 | 6.66 | 0.85 | 172 | 1998 | 0.67 | 1.00 | 0.94 | 0.93 |
| | | | Moderate Rain | 12 | 46.4 | 52.1 | 2.2 | 2 | 225 | 8.53 | 0.82 | 10 | 109 | 0.67 | 0.90 | 0.85 | 0.80 |
| I-264 | 16.3 | 169 | Normal | 10 | 62.3 | 76.5 | 4.7 | 2 | 225 | 2.16 | 0.92 | 19488 | 9717 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 10 | 59.8 | 74.6 | 5.0 | 2 | 225 | 3.73 | 0.91 | 1555 | 645 | 1.00 | 0.96 | 0.97 | 0.89 |
| | | | Moderate Rain | 10 | 54.6 | 65.1 | 4.0 | 2 | 225 | 7.54 | 0.95 | 79 | 18 | 1.00 | 0.88 | 0.85 | 0.78 |
| | | | Light Snow | 16 | 46.2 | 62.2 | 4.2 | 2 | 225 | 11.19 | 0.78 | 89 | 15 | 1.60 | 0.74 | 0.81 | 0.79 |

| Highway | Milemark | Station ID | Weather condition | $k_{bp}$ (vpmpl) | $u_f$ (mph) | $v_f$ (mph) | $\alpha$ | $v_0$ (mph) | $k_{jam}$ (vpmpl) | RMSE[1] (reg.1) | R-sqrd[2] (reg.2) | # of obs. | | Weather Adjustment Factor (WAF)[3] | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | reg.1 | reg.2 | $F\_k_{bp}$ | $F\_u_f$ | $F\_v_f$ | $F\_f_{max}$ |
| I-564 | 50 | 135 | Normal | 16 | 63.4 | 90.8 | 5.0 | 2 | 225 | 7.06 | 0.75 | 38675 | 5125 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Moderate Rain | 10 | 51.7 | 67.1 | 5.9 | 2 | 225 | 13.76 | 0.64 | 253 | 86 | 0.63 | 0.81 | 0.74 | 0.82 |
| | | | Heavy Rain | 11 | 57.9 | 77.3 | 5.9 | 2 | 225 | 9.99 | 0.74 | 53 | 53 | 0.69 | 0.91 | 0.85 | 0.81 |
| | | | Light Snow | 10 | 59.8 | 77.0 | 5.8 | 2 | 225 | 12.14 | 0.79 | 156 | 65 | 0.63 | 0.94 | 0.85 | 0.89 |
| I-564 | 50 | 136 | Normal | 12 | 63.3 | 72.6 | 2.6 | 2 | 225 | 3.49 | 0.67 | 26067 | 2961 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Heavy Rain | 10 | 52.2 | 84.0 | 10.8 | 2 | 225 | 9.60 | 0.64 | 29 | 13 | 0.83 | 0.83 | 1.16 | 0.57 |
| I-564 | 50 | 137 | Normal | 13 | 38.7 | 44.4 | 2.4 | 2 | 225 | 4.30 | 0.49 | 10193 | 7431 | 1.00 | 1.00 | 1.00 | 1.00 |
| | | | Light Rain | 10 | 35.1 | 38.8 | 2.3 | 2 | 225 | 8.94 | 0.25 | 623 | 1053 | 0.77 | 0.91 | 0.87 | 0.80 |

1 Root mean squared error of free-flow speed ($u_f$) for the 1st regime

2 R-squared value of the speed-density curve for the 2nd regime from the linear regression

3 WAF for selected parameters for each location and each weather condition. For normal weather, WAF has the value of 1. These WAF results are used as dependent variables in the linear regression of the WAF calibration process.

# Incorporating Weather Impacts in Traffic Estimation and Prediction Systems

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