Implementation and Evaluation of Weather Responsive Traffic Management Strategies: Insight from Different Networks

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ABSTRACT

The study presents the development and application of methodologies to support Weather Responsive Traffic Management (WRTM) strategies, building on Traffic Estimation and Prediction System (TrEPS) models. First, a systematic framework for implementing and evaluating WTRM strategies under severe weather conditions is developed, where activities for planning, preparing and deploying WRTM strategies are identified in three different time frames: long-term strategic planning, short-term tactical planning and real-time traffic management center (TMC) operations. Next, the evaluation of various strategies is demonstrated using locally calibrated network simulation-assignment model capabilities, and special-purpose key performance indicators (KPIs) are introduced. Three types of WRTM strategies: demand management, advisory and control VMS (variable message signs), and incident management VMS are applied to multiple major US cities, which include Chicago, Salt Lake City and New York’s Long Island. The analysis results illustrate benefits of WRTM under inclement weather conditions and emphasize the importance of incorporating a predictive capability into selecting and deploying WRTM strategies.

KEYWORDS: Advanced network traffic management, Weather-Responsive Traffic Management (WRTM), Traffic Estimation and Prediction, Weather and Traffic Analysis, WRTM Strategies, Dynamic Traffic Assignment, Key Performance Indicators
1. INTRODUCTION

The disruptive effect of inclement weather on traffic results in considerable congestion and delay, due to reduced service capacity, diminished reliability of travel, and greater risk of accident involvement. To mitigate the impacts of adverse weather on highway travel, the Federal Highway Administration (FHWA) Road Weather Management Program (RWMP) has been involved in research, development and deployment of weather responsive traffic management (WRTM) strategies and tools. The most ambitious initiative in this regard is the Clarus weather system, intended to provide traffic management centers with accurate real-time weather information (1-3). Recognizing the importance of tying weather and traffic management together in areas exposed to adverse weather situations, many traffic management centers (TMC) have integrated weather information into their operations to support the operational decisions regarding various WRTM strategies (4). There have been active efforts in states around the country to develop and implement a wide range of advisory, control and treatment strategies under the framework of WRTM. A comprehensive overview of WRTM practices and a collection of case studies from municipal and state transportation agencies can be found in (5) and (6), respectively. There have been also efforts to integrate the weather effects into decision support tools allowing improved traffic state prediction and estimation (7, 8).

In order to reduce the impacts of inclement weather events and prevent congestion before it occurs, weather-related advisory and control measures could be determined for predicted traffic conditions consistent with the forecast weather, that is, anticipatory road weather information. A recent study (4) identified levels of weather information integration in TMC operations and found many TMCs viewed the desirable level of decision support strategies as using “response scenarios through software supply potential solutions with projected outcomes” while the current levels were evaluated as “ad-hoc implementation of weather management strategies.”

The goal of this study is to bridge this gap between the state-of-the-practice and state-of-the-art by integrating WRTM and Traffic Estimation and Prediction System (TrEPS). TrEPS models (9-12) are simulation-based decision-support tools that provide predictive information on how traffic behaves in a given network under likely future conditions. In a previous FHWA project (7), a methodology for incorporating weather impacts in TrEPS was developed. The principal supply-side and demand-side elements affected by adverse weather were systematically identified and modeled in the TrEPS framework. The methodology was incorporated and tested in connection with the DYNASMART-P simulation-based dynamic traffic assignment (DTA) system (13), thereby providing a tool for modeling the effect of adverse weather on traffic system properties and performance, and for supporting the analysis and design of traffic management strategies targeted at such conditions. The methodological development conducted to enable weather-responsiveness of the simulation tools was further calibrated and validated, and integrated in a real-time estimation and prediction capability (14) to support the goal of making WRTM an integral part of traffic system management (15).

Based on the weather-sensitive TrEPS developed in the previous studies (7, 15), this paper establishes a general framework for incorporating TrEPS in actual TMC operations to support the design, implementation and evaluation of WRTM strategies suitable for anticipated local conditions. It is important to recognize that TMCs differ on WRTM strategies they can employ due to different network characteristics and the highly site-specific nature of weather conditions, thereby requiring TrEPS models to flexibly adapt to the local needs and interests. Hence, this study also attempts to identify different
WRTM strategies for different sites to investigate the usefulness of the tool in connection with practical problem solving activities.

The paper is structured as follows. First, background information on the weather-sensitive TrEPS is presented. Then, a general framework for implementing and evaluating WRTM strategies using TrEPS is established. A set of key performance indicators (KPIs) are identified to enhance the evaluation procedure. Next, local-specific WRTM strategies are tested and evaluated for three major US cities under this framework; and simulation results and their interpretations are discussed. Finally, summary, lesson learned and insights from multi-network experiments are given.

2. BACKGROUND

This section provides background information on methodologies for capturing weather effects in a DTA model and various traffic advisory/control strategies that are implemented in TrEPS to support WRTM.

2.1 Modeling Weather Impacts on Supply- and Demand-side Parameters.

In order to represent the impacts of weather in a traffic simulation, various supply and demand parameters need to be adjusted. The supply-side parameters include traffic flow model parameters, service/saturation flow rates, and operational parameters at junctions; while the demand-side parameters include the dynamic OD pattern and user responses to information and control measures.

To adjust supply-side parameters, the study uses a weather adjustment factor (WAF), which is a multiplication factor applied to a normal weather parameter to adjust its value in response to a given weather. A WAF is represented by a function of three weather parameters: visibility, rain intensity and snow intensity and calibrated based on historical weather and traffic data (7, 16). In order to implement WAFs in the traffic simulation, a weather scenario needs to be supplied in the form of the three weather parameters.

One way to address changes in demand patterns is to prepare a set of weather-specific OD matrices that are estimated under different weather conditions. Alternatively, a demand reduction factor similar to WAF could be applied to determine the percent average reduction of traffic demand under a given weather condition as proposed in (17). In the on-line TrEPS framework, however, it is possible to adaptively estimate and predict OD and associated flow patterns based on real-time traffic observations, thereby capturing changes in dynamic OD patterns resulting from weather-related adjustments in trip-making (14).

2.2 Weather-responsive Traffic Advisory and Control Strategies

Road weather information, such as en-route weather warning and route guidance, can be disseminated through radio, internet, mobile devices, roadside VMS and so on. Weather warning VMS have been implemented in the field, and shown to be effective in decreasing the average speed as well as the variance in speed, and hence helpful in increasing safety and reliability for the traveling public (18, 19). Weather advisory VMSs, in the form of slippery road condition sign and fog (low visibility) sign, have been implemented and tested in Europe (20, 21). A comprehensive synthesis of recent developments and applications focusing on US practice is presented in the FHWA report (5). Recently, the use of variable speed limit (VSL) systems during inclement weather conditions has received growing attention from local agencies and researchers. A recent report (22) establishes guidelines for using VSL systems in wet weather, which include the design, installation, operation of the system as well as case studies of agencies

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that have implemented weather-responsive VSL strategies. In addition, there are other types of strategies such as demand management and incident management that can be developed or adjusted to address network performance impairment introduced by adverse weather conditions.

In order to evaluate the aforementioned WRTM strategies in TrEPS, DYNASMART had been enhanced to simulate various intervention scenarios under weather such as optional/mandatory detour information via VMS, weather-responsive VSL, demand management via dynamic pricing, etc. For detailed discussion of its modeling capabilities and behavioral rules that govern travelers’ responses to the interventions, readers are referred to (7, 9, 10).

3. DEVELOPMENT OF TrEPS-SUPPORTED WRTM FRAMEWORK

3.1 Framework

A systematic framework for implementing and evaluating WRTM strategies in the event of inclement weather is developed as shown in FIGURE 1. The framework identifies activities in three different time frames: long-term strategic planning, short-term tactical planning and real-time operations. The long-term planning horizon involves establishing and maintaining historical weather scenarios and a library of WRTM strategies, which specifies available WRTM strategies for different weather conditions and the associated deployment rules based on existing guidelines and practices adopted by local operating agencies. Such scenario management schemes allow easy retrieval of any historically occurring weather scenario and the corresponding strategies for simulation analysis using TrEPS as well as systematic feedback loops between planning and operations.

The primary application of the TrEPS capability lies in the short-term planning and real-time operations. Once an inclement weather event is predicted to occur in the next 12 to 48 hours, TMC managers undertake short-term tactical planning, which aims at narrowing down the available WRTM strategies that are right for the expected weather condition and current roadway situations. At this level, the off-line traffic simulation tool is used to perform a wide range of “what-if” analyses to test various WRTM strategies under the weather scenario constructed from the weather forecast and historical weather patterns. Historical average demand is used for running the off-line simulation.

During the inclement weather event, TMC managers perform real-time TrEPS operations using the on-line simulation tool (e.g., DYNASMART-X). Real-time TrEPS rely on real-time simulation of the traffic network as the basis of a state prediction capability that fuses historical data with sensor information, and uses a description of how traffic propagates in networks to predict future conditions, and accordingly develop control measures (7-12). The identified strategies are further simulated and evaluated using real-time traffic and weather data in parallel with actual TMC operations to support the decision making process for the strategy deployment. Travel demand for the simulation is constantly adjusted based on the real-time traffic data. Another important activity during this stage is to obtain feedback from the WRTM implementation and update the existing strategy library to achieve optimal performance, improved efficiencies and better preparedness for future WRTM.
3.2 Evaluation Approaches to Assess Effectiveness of WRTM

One of the benefits of using simulation tools is the ability to extract a variety of performance measures from the simulation output in any desirable format. This aspect greatly helps TMC managers analyze the effectiveness of tested WRTM strategies at different angles and levels of detail, which is often not possible from actual data from traffic surveillance systems or loop detectors. Focusing on the traffic efficiency (e.g., mobility and reliability) aspects of the transportation system, this section identifies a set of key performance indicators (KPI’s) to evaluate the effectiveness of particular WRTM strategies, which allow users to compare network performance overall or for particular portions of the network, O-D pairs and segments, with and without WRTM as well as for different WRTM strategies. This provides an understandable method to quantify and characterize the need for and effectiveness of WRTM, and to communicate these impacts to other personnel and decision makers.

TABLE 1 presents a set of KPIs that are categorized into various levels of detail: network-level, OD/Path-level, cross-section level, and link-level. Different KPIs suit different occasions depending on
the purposes of applied WRTM strategies and network characteristics. For example, strategies applied to
the entire network (e.g., demand management) or to major corridors (e.g., variable speed limit) to
improve the overall network-wide performances are best evaluated using the network-level KPIs such as
network throughput, total travel time, percentage of lane-mile congested and so on. Strategies deployed
locally to mitigate congestion due to weather-related events (e.g., flood, snow plowing and weather-
related incidents) would be better assessed using path- or link-level KPIs. The network characteristics
also provide important criteria in choosing proper KPIs. For instance, if there exist critical OD pairs,
which account for a majority of overall demand, examining OD-level KPIs for those critical OD pairs
might provide a more efficient way of evaluating strategies. Another important perspective through which
performance measures may be envisioned is a cross-section of a given network. For networks that have
clear major flow directions (e.g., east- and west-bound or north- and south-bound), TMS operators might
be interested in using cross-section level KPIs, which measure how well the overall traffic flows pass
through a certain cross-section under different weather conditions and WRTM strategies.
### TABLE 1 Key Performance Indicators (KPIs) Used To Evaluate WRTM Strategies

<table>
<thead>
<tr>
<th>Category</th>
<th>Key Performance Indicator (KPI)</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Accumulated Percentage of Completed Vehicles</td>
<td>$% \text{AccOutVeh}^i = \frac{\text{Out} _ \text{Veh}^i}{\text{Tot} _ \text{Veh}^i} \times 100$</td>
<td>Time-dependent network throughput</td>
</tr>
<tr>
<td></td>
<td>where $\text{Out} _ \text{Veh}^i$: Accumulated number of vehicles arriving at their destinations from time $0$ till time $t$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\text{Tot} _ \text{Veh}^i$: Accumulated total number of vehicles loaded onto the network from time $0$ till time $t$</td>
<td></td>
</tr>
<tr>
<td>- Percentage Change in Average Travel Time</td>
<td>$% \text{Change} _ \text{AvgTTime}^i = \frac{\text{AvgTTime}^i - \text{AvgTTime}<em>{\text{base}}}{\text{AvgTTime}</em>{\text{base}}} \times 100$</td>
<td>Relative average travel time with respect to a given base-case scenario</td>
</tr>
<tr>
<td></td>
<td>where $\text{AvgTTime}^i$: Average travel time of all vehicles in the network under scenario $i$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(subscript “base” represents a base-case scenario.)</td>
<td></td>
</tr>
<tr>
<td>- Percentage Change in Average Stopped Time</td>
<td>$% \text{Change} _ \text{AvgSTime}^i = \frac{\text{AvgSTime}^i - \text{AvgSTime}<em>{\text{base}}}{\text{AvgSTime}</em>{\text{base}}} \times 100$</td>
<td>Relative stopped delay with respect to a given base-case scenario</td>
</tr>
<tr>
<td></td>
<td>where $\text{AvgSTime}^i$: Average stopped time of all vehicles in the network under scenario $i$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(subscript “base” represents a base-case scenario.)</td>
<td></td>
</tr>
<tr>
<td>- Total Travel Time</td>
<td>Sum of travel times experienced by all the vehicles in the network</td>
<td></td>
</tr>
<tr>
<td>- Time-dependent Average Travel Time per Mile</td>
<td>Average travel time for each departure time interval (normalized)</td>
<td></td>
</tr>
<tr>
<td>- Time-dependent Standard Deviation per Mile</td>
<td>Travel time variability for each departure time interval (normalized)</td>
<td></td>
</tr>
<tr>
<td>- Time-dependent Percentage of Lane-miles Congested</td>
<td>Temporal evolution of network</td>
<td></td>
</tr>
<tr>
<td><strong>OD/Path-level</strong></td>
<td><strong>Descriptive Statistics from OD/Path Travel Time Distribution</strong></td>
<td>Travel time characteristics for a given OD or path</td>
</tr>
<tr>
<td>---</td>
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</tr>
<tr>
<td></td>
<td>• mean, median, standard deviation, 25th/75th/95th percentiles, etc.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• mean of the worst (or best) 20% of travel times</td>
<td></td>
</tr>
<tr>
<td><strong>- Reliability Measures from OD/Path Travel Time Distribution</strong></td>
<td>How reliable or variable the travel time is for a given OD or path</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Buffer Index, Misery Index, Planning Time Index, Percent On Time, etc.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(see (23) for a comprehensive list and definitions of reliability measures)</td>
<td></td>
</tr>
<tr>
<td><strong>- Time-dependent Average OD/Path Travel Time</strong></td>
<td>Average travel time for each departure time interval for a given OD or path</td>
<td></td>
</tr>
<tr>
<td><strong>- Time-dependent Standard Deviation of OD/Path Travel Time</strong></td>
<td>Travel time variability for each departure time interval for a given OD or path</td>
<td></td>
</tr>
<tr>
<td><strong>- Average Link Travel Time per Mile for Each Link Along the Path</strong></td>
<td>Link congestion level along the given path. Can identify bottleneck links.</td>
<td></td>
</tr>
<tr>
<td><strong>Cross-section level</strong></td>
<td><strong>Cumulative Number of Vehicles Passing through A Given Cross-section</strong></td>
<td>Time-dependent cross-section throughput</td>
</tr>
<tr>
<td></td>
<td><strong>- Cross-section Vehicle Flow Rate</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Link-level</strong></td>
<td><strong>Time-dependent Traffic Flow Parameters</strong></td>
<td>Link performance level characteristics</td>
</tr>
<tr>
<td></td>
<td>• speed, density and flow rate</td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>- Time-dependent Average Link Travel Time</strong></td>
<td>Average travel time for each departure time interval for a given link</td>
</tr>
<tr>
<td></td>
<td><strong>- Time-dependent Standard Deviation of Link Travel Time</strong></td>
<td>Travel time variability for each departure time interval for a given link</td>
</tr>
</tbody>
</table>
4. APPLICATION TO MAJOR US CITIES

This section presents analysis results for testing and evaluating various WRTM strategies using the TrEPS model. The focus of these experiments is to identify local-specific issues and the associated WRTM strategies to address them with help of TrEPS models. This analysis can be viewed as part of the activities under the short-term tactical planning (see FIGURE 1), which intends to prepare a set of appropriate strategies for a given specific weather scenario using off-line simulation tools.

Three major US cities were selected for study sites: Chicago, IL; Salt Lake City (SLC), UT; and Long Island, NY, where weather is one of the major disruptive factors in the local transportation system. Local agencies were contacted: City of Chicago DOT, Utah DOT, New York State DOT and New York City DOT; and TMC personnel were surveyed and interviewed to obtain information on existing or recommended WRTM strategies for each site. Based on the discussion results, the study found that the following strategies were suitable for assessing their effectiveness under local weather conditions and enhancing TMC managers’ understanding on the proposed framework.

- Chicago : advisory and control strategies
- SLC : demand management
- Long Island : weather-responsive incident management

Detailed discussions for each strategy are presented in the next sub-sections.

For each study site, a simulation network was prepared as shown in FIGURE 2 and supply- and demand-side parameters are calibrated (15). The supply-side parameter calibration involves the estimation of parameters in traffic flow models (e.g., speed-density relation) and the weather adjustment factors (WAF). The demand-side parameter calibration involves the estimation of dynamic OD matrices using a simulation-based optimization approach (24). The time periods of the estimated demand are 5AM – 11AM for Chicago, 6AM – 10AM for Salt Lake City, and 6AM – 11AM for Long Island, respectively.
FIGURE 2 Selected networks for the study: (a) Long Island, NY, (b) Chicago, IL, and (c) Salt Lake City, UT.
Network | Weather Scenario | Related strategies in Sec.3.2
---|---|---
Chicago | **Moderate Snow** | VSL / Advisory VMS
(a) Source: ASOS data (extracted from 2010-12-12 10:00AM – 4:00PM)
Salt Lake City | **Heavy Snow** | Demand Mgmt.
(b) Source: ASOS data (extracted from 2010-12-29 3:30PM – 8:30PM)
Long Island | **Moderate Snow** | Incident Management Advisory VMS
(c) Source: ASOS data (extracted from 2011-01-26 6:00AM – 12:00PM)

**FIGURE 3** Weather scenarios (*liquid equivalent precipitation intensity*)
4.1 Selected WRTM Strategies

4.1.1 Advisory and Control Strategies (Chicago)

The Chicago network is one of the busiest networks, where flow breakdown and gridlock phenomena are regularly observed during peak hours. TMC managers were interested in performing the what-if analysis with various supply-side WRTM strategies, i.e., testing new strategies that are not currently used. Supply-side WRTM strategies deployed to road traffic can be categorized into two types: advisory and control strategies. The former provides travelers with warning and route guidance through radio, internet, mobile devices and roadside variable message sign (VMS), whereas the latter directly regulates traffic flow or enforces certain rules to improve traffic states under severe weather conditions. In this sub-section, we select strategies from each type, namely, advisory VMS for the former and variable speed limit (VSL) for the latter to evaluate their effectiveness in improving mobility under an inclement weather condition.

Weather Scenario We constructed a moderate snow scenario based on historical data. The temporal profiles of snow intensity and visibility are presented in FIGURE 3(a). This 6-hour weather scenario is applied to the simulation horizon covering 5AM to 11AM.

Advisory VMS Scenarios Advisory VMS strategy represents activating VMSs that display the roadway information (e.g., traffic congestion ahead) as well as possible detour paths under the given snow event so that drivers could re-evaluate their routes and divert if a better path exists. Two different scenarios are prepared: SN_VMS1, where advisory VMSs are deployed along the sections on Kennedy Expressway and Lake Shore Drive (FIGURE 4(a)), and SN_VMS2, where advisory VMSs are deployed on Kennedy Expressway only (FIGURE 4(b)). The response rate of 50% is assumed indicating that 50% of all vehicles in the network will respond to a sign if they observe it along their respective paths.

VSL Scenarios VSL strategy represents changing speed limits based on prevailing weather conditions aiming at improving both safety and mobility by reducing the speed and speed variance. The speed limits are changed in increments of 5mph within the range of 35 to 55 mph based on the prevailing visibility and snow intensity. The control rule was constructed based on the guidelines and case studies presented in (22). Two different scenarios are tested: SN_VSL1, where VSL is applied to Lake Shore Drive (FIGURE 4(c)); and SN_VSL2, where VSL is applied to Kennedy Expressway (FIGURE 4(d)).

Other Scenarios In addition to the four advisory and control strategy scenarios, two more scenarios are prepared for comparison: a base-case scenario with no snow and no strategy, which is labeled “Base,” and a scenario with snow but without strategy, which is labeled “SN.”

Analysis Results As the objective of the tested strategies is to improve the overall mobility, we focus on network-wide measures for the evaluation. First, travel-time related KPIs are examined. FIGURE 5(a) presents total travel time for all six scenarios and indicates that the snow effect increases the total travel time by 102,807 hours (i.e., 20.4% of the base-case) when there is no strategy implemented. Compared to SN, all four strategies improve the total travel time while advisory VMS strategies perform better than VSL strategies in general. FIGURE 5(b and c) provide the average travel time per mile (TTPM) for each departure time interval for a selected time period. SN shows a jump in the TTPM at around 10AM, which is due to increase in the snow intensity as shown in FIGURE 3(a) (minute
300 corresponds to 10AM in the simulation horizon). The tested strategies except SN_VSL1 appear to mitigate such snow impacts on the TTPM. Second, we observe a cross-section KPI, which is the cumulative number of vehicles passing through a given cross-section. The selected cross-section is presented in FIGURE 6. The horizontal bar selects all the northbound links including freeways and arterials and the time-dependent traffic flows aggregated over the selected links are measured. FIGURE 7 shows the cumulative cross-section throughputs for the six scenarios. The cumulative throughput performance at the end of the simulation reveals that the pattern consistent with the previous analysis results with the travel time KPIs, i.e., SN_VMS1 and SN_VSL1 improve the measure the most and the least, respectively. From both FIGURE 6 and FIGURE 6, SN_VMS1 shows varied performance over time: performs poorly until 9:40AM and becomes the best at the end. One reason for this can be that deploying warning VMS on more corridors (compared to SN_VMS2) might have invoked unnecessary detours under the light snow condition, while such information became helpful under the heavier snow condition. This suggests that the timing of the strategy deployment is important and the real-time traffic and weather information can improve the effectiveness of the WRTM strategies.

In this experiment, we found that both types of strategies had impacts of preventing flow breakdown by reducing or slowing down inflows into heavily congested links. As such, identifying such breakdown-prone spots is critical in developing effective strategies and TMC managers’ knowledge about local traffic is one of the most important inputs in the TrEPS-supported WRTM framework.
FIGURE 4 Four different scenarios for advisory and control strategies (Chicago).

(a) **SN_VMS1**: Advisory VMS on both Kennedy Expressway and Lake Shore Drive

(b) **SN_VMS2**: Advisory VMS on Kennedy Expressway

(c) **SN_VSL1**: VSL along Lake Shore Drive

(d) **SN_VSL2**: VSL along Kennedy Expressway
FIGURE 5 Comparison of travel time-related measures for advisory and control strategies (Chicago).
FIGURE 6 Selected cross section for measuring traffic throughput (Chicago).

FIGURE 7 Cumulative cross-section throughput over time (Chicago).
4.1.2 Demand Management (Salt Lake City)

Cities like SLC often experience severe winter storms and TMC managers encounter situations where travel demand need to be managed for the mobility and safety purposes during such severe snow events. Managing demand involves providing travelers with information, aiming at a “shift” of their departure times or trip cancelation so that the total travel demand during the peak periods can be reduced. The key research question here is to study how much demand should be reduced under different weather conditions in order to maintain a certain level of network performance. As such, the goal of using TrEPS here is to provide the TMC managers with the information on the optimal level of demand that can improve the network performance but not affect negatively the productivity under a given weather condition. For this, we employ the concept of “equivalent demand reduction,” which is the amount of demand reduction needed to offset network performance impairment introduced by particular inclement weather conditions and maintain level of service expected normal weather conditions.

Weather Scenario In SLC, severe winter storms in the recent past became a strong motivation of the local agencies for the consideration of the demand management strategy. As such, the weather scenarios are constructed based on the historical data representing heavy snow conditions. FIGURE 3 shows all the weather scenarios used for the simulation study throughout this paper and scenarios in FIGURE 3(b) are the one for the demand management strategies for SLC.

Demand Scenario A total of 12 demand scenarios are prepared: one for the benchmark case, which is 100% of the demand under the normal weather condition (i.e., no snow); and the other 11 scenarios with different demand levels under the heavy snow condition. For the generation of the 11 scenarios, we start with the full demand (100%) and reduce the total demand by 5% until the reduction percentage reaches 50%.

Analysis Results FIGURE 8 shows analysis results from the simulation study. FIGURE 8(a) represents the accumulated percentage of completed vehicles for each time t (i.e., Eq.1 in TABLE 1), which measures the percentage of total vehicles loaded onto the network up to time t that reached their destinations. Compared to the base-case (i.e., 100% demand under no snow), the snow event significantly degrades the network throughput when the full demand is loaded under heavy snow (i.e., Heavy Snow (100% Demand)). The charts suggest approximately 15% drop in throughput at the end of the simulation. As the demand reduction percentage increases, the throughput measure improves. FIGURE 8(b) shows the percentage changes in two selected measures %Change-AvgTTime and %Change-AvgSTime (i.e., Eq.(2) and (3) in TABLE 1), which represent how average travel time and stopped delay worsened (positive changes) or improved (negative changes) relative to the base-case. The snow effect increases the former by 86.5% and the latter by 181.1% when the full demand is loaded. The “equivalent demand reduction” is found to be about 20% (i.e., 80% of original demand), at which the percentage changes become nearly zero in the charts. It is noted that these values depend on the severity and duration of the weather conditions as well as the network demand patterns.

The results provide the TMC managers with insights into the combined effect of demand and weather on traffic. They can be used to identify the equivalent demand reduction, and accordingly set a target that TMC managers can try to achieve through various information dissemination approaches, activity cancellation or rescheduling, and possible incentive schemes.
(a) Time-dependent network throughput measure

(b) %Change in performance measures for different demand levels relative to base-case

FIGURE 8 Analysis results for the demand management (Salt Lake City).
4.1.3 Incident Management VMS (Long Island)
For the Long Island area, we found that TMC managers focused more on preventing and minimizing weather-related disruptions such as incidents rather than trying to manage travel demand due to the limitation on adjustable demand portions. In terms of the incident management in the current framework, the TMC managers can try various strategies dealing with incidents at known black spots under different weather conditions in the off-line simulation environment. A set of selected strategies then can be prepared and considered for the deployment during weather events with the support of the real-time TrEPS. Based on historical incident data, we identified and tested different VMS strategies to investigate their effects on reducing congestion on the incident-impacted area.

Weather Scenario  A moderate snow scenario was constructed based on historical data. The temporal profiles of snow intensity and visibility are presented in FIGURE 3(c). This 6-hour weather scenario is applied to the simulation horizon covering 6AM to 12PM.

Incident Scenario  The incident scenario is constructed based on the actual observations on the snowy day selected for the weather scenario. The historical data show that there were three accidents happened along westbound Long Island Expressway (I-495) between 6AM and 12PM on January 26, 2011 as shown in FIGURE 9(a).

Optional Detour VMS Scenarios  Optional detour VMS is the same type of the advisory VMS tested in the previous sub-section, but deployed only upstream of the incident links during the accident duration to inform drivers of the event and suggest re-evaluating of their routes. Two scenarios are prepared: SN_ACC_VMS1, where VMSs are located at every exit along the adjacent upstream segments (FIGURE 9(a)); and SN_ACC_VMS2, where only selected exits are used for a diversion point (FIGURE 9(b)). The former represents a static type of deployment scheme, which uses the pre-determined VMS locations, while the latter represents a dynamic type of scheme, which determines the locations based on the prevailing traffic conditions. To implement this, we first simulated SN_ACC_VMS1 and examined the traffic conditions on detour routes at each diversion point. If downstream arterials of a particular exit already experience a certain level of congestion and do not have sufficient room for absorbing the diverted traffic, we eliminated VMS from the exit. Consequently, the exits that lead traffic to relatively less congested arterials are only used for the VMS locations for SN_ACC_VMS2.

Other Scenarios  In addition to the two optional detour VMS scenarios, three more scenarios are prepared for comparison: “Base,” a scenario with no snow, no accident and no strategy; “SN,” a scenario with snow only; and “SN_ACC,” a scenario with snow and accidents but with no strategy.

Analysis Results  In evaluating the strategies, we focused on investigating how the incident-impacted traffic can benefit from the incident management strategies under snow and used path-level KPIs for the incident-affected corridor, i.e., the travel time distribution between two points (i.e., A and B in FIGURE 9(b)). FIGURE 10 shows a radar chart that compares travel time characteristics under all five scenarios using the six descriptive measures including mean, median, standard deviation, the 95th
percentile, mean of the worst 20% of travel times and mean of the best 20% of travel times. The chart suggests that snow and incident increase the travel time variability rather than the mean travel time as noticeable increases are observed mainly in the average of the worst 20% of travel times and the 95th percentile. In terms of the intervention effect, SN_ACC_VMS2 improves the overall performance as it reduces all six measures compared to SN and SN_ACC. SN_ACC_VMS1, however, performs the poorest among the all five scenarios, i.e., worsens the situation even than do-nothing scenario (i.e., SN_ACC). It implies that statically configured strategies might not work as intended and deployment schemes need to be dynamically determined and modified based on the prevailing traffic conditions. This once again stresses the importance of incorporating the prediction and decision-support capabilities of real-time TrEPS into WRTM.

During this experiment, one important question raised by the TMC managers in the context of weather-responsive incident management was “what is the probability of having incidents under the given weather condition and how much congestion is expected?” This can be effectively addressed by implementing the proposed framework, where historical incident patterns can be maintained as strategic scenarios in connection with weather and other strategies. This will allow quickly producing multiple likely incident scenarios, which can be used to test WRTM strategies to obtain more complete picture of their effectiveness.
FIGURE 9 Incident management VMS strategies (Long Island)
**FIGURE 10** Comparison of path travel time statistics for different scenarios (Long Island)
5. CONCLUSION AND LESSONS LEARNED

The study provides an important milestone in the development and application of methodologies to support WRTM. It brings WRTM applications into the mainstream of network modeling and simulation tools, and demonstrates the potential of both WRTM and TrEPS tools to evaluate and develop strategies on an ongoing basis, as part of the routine functions of planning and operating agencies.

In particular, this paper addresses the following aspects. First, a general framework for implementing and evaluating WTRM strategies under severe weather conditions is developed, where activities for planning, preparing and deploying WRTM strategies are identified in three different time frames. The long-term strategic planning involves establishing and maintaining a library of WRTM strategies, which specifies available WRTM strategies under different weather conditions based on local needs. The short-term tactical planning is to prepare a set of strategies using off-line simulation tools 12 to 24 hours in advance when a severe weather event is predicted. The real-time TrEPS operations then take place during the weather event to support the implementation of the selected WRTM strategies by proving predicted information on traffic states based on real-time traffic and weather data. Next, the framework is applied to three major US cities (Chicago, Salt Lake City, and Long Island) focusing on developing and evaluating local-specific WRTM strategies to investigate the usefulness of the tool in connection with practical problem solving activities. For each network, WRTM strategies are selected based on the local needs and tested using TrEPS model. The analysis results illustrate benefits of WRTM under inclement weather conditions and emphasize the importance of incorporating the predictive capability of TrEPS into selecting and deploying WRTM strategies.

Several important findings were reached through this study regarding the role that network models and simulation methodologies can play in the further development and deployment of WRTM strategies, and the process through which such tools could be most effective in helping agencies attain their objectives within available resources.

1. Most agencies in states and regions that experience severe weather of one type or another believe there is a need for methods to help predict the impact of weather on operations, and develop plans to mitigate the disruptive impact of such weather.

2. Needs vary across different agencies and areas depending on factors that include size of the area and demand pressure on the network, and extent to which the population may be used to inclement weather. Similarly, user responses and levels of acceptability and compliance vary accordingly.

3. In all cases, it was evident that the greatest value of the TrEPS methodologies lies in operations planning and preparedness for weather-related events, rather than in minute-to-minute traffic interventions. Given that most weather forecasts can look ahead from a few hours to a few days, with fairly reliable 12 to 24 hours projections, this gives agencies sufficient time to use the TrEPS methodology off-line to predict the impact of the contemplated weather as well as develop the best strategy to mitigate the negative impact.

4. In all areas, the responses of travelers to information, messages, guidance and controls are an essential ingredient to the overall effectiveness of these measures. While the TrEPS methodology provides the necessary framework and structure to capture these decisions, as well as their evolution, it became clear during the study that a stronger observational basis is needed with regard to what users actually do in bad weather and under different interventions. Nonetheless, the model results exhibit considerable consistency and sufficient robustness in relative terms to
support analysis and implementation of effective weather-related traffic management measures in practice.

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The authors remain solely responsible for all work, findings, conclusions and recommendations presented in this paper.

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