Implementation and Evaluation of Weather-Responsive Traffic Management Strategies

Insight from Different Networks

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This study presents the development and application of methodologies to support weather-responsive traffic management (WRTM) strategies by building on traffic estimation and prediction system models. First, a systematic framework for implementing and evaluating WRTM strategies under severe weather conditions is developed. This framework includes activities for planning, preparing, and deploying WRTM strategies in three different time frames: long-term strategic planning, short-term tactical planning, and real-time traffic management center operations. Next, the evaluation of various strategies is demonstrated with locally calibrated network simulation-assignment model capabilities, and special-purpose key performance indicators are introduced. Three types of WRTM strategies [demand management, advisory and control variable message signs (VMSs), and incident management VMSs] are applied to multiple major U.S. areas, namely, Chicago, Illinois; Salt Lake City, Utah; and the Long Island area in New York. The analysis results illustrate the benefits of WRTM under inclement weather conditions and emphasize the importance of incorporating a predictive capability into selecting and deploying WRTM strategies.

The disruptive effect of inclement weather on traffic results in considerable congestion and delay, because of reduced service capacity, diminished reliability of travel, and greater risk of accident involvement. To mitigate the impacts of adverse weather on highway travel, the FHWA Road Weather Management Program 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 (TMCs) 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 TMCs have integrated weather information into their operations to support the operational decisions about 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 Gopalakrishna et al. (*5*) and Murphy et al. (*6*), respectively. Also there have been efforts to integrate the weather effects into decision support tools allowing improved traffic state prediction and estimation (*7, 8*).

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 identified levels of weather information integration in TMC operations and found that 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" (*4*).

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 a 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 system (*13*), 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 the traffic system management (*15*).

On the basis of 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

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for anticipated local conditions. It is important to recognize that TMCs differ on the WRTM strategies that they can employ because of different network characteristics and the highly site-specific nature of weather conditions, thus requiring TrEPS models to flexibly adapt to the local needs and interests. Therefore, 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) is identified to enhance the evaluation procedure. Next, local-specific WRTM strategies are tested and evaluated for three major U.S. areas under this framework, and simulation results and their interpretations are discussed. Finally, a summary, lessons learned, and insights from multinetwork experiments are given.

BACKGROUND

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

Modeling Weather Impacts on Supply- and Demand-Side Parameters

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 and saturation flow rates, and operational parameters at junctions, while the demand-side parameters include the dynamic origin–destination (O-D) 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 that describes how much a parameter value under the normal weather condition is reduced in response to a given weather. A WAF is represented by a function of three weather parameters (visibility, rain intensity, and snow intensity) and is calibrated on the basis of historical weather and traffic data (*7, 16*). 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 O-D 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 Samba and Park (*17*). In the online TrEPS framework, however, it is possible to adaptively estimate and predict O-D and associated flow patterns based on real-time traffic observations, capturing changes in dynamic O-D patterns resulting from weather-related adjustments in trip making (*14*).

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 variable message sign (VMS), and so on. Weather warning VMSs have been implemented in the field and shown to be effective in decreasing the average speed as well as the variance in speed and are therefore 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 U.S. 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 establishes guidelines for using VSL systems in wet weather, which include the design, installation, and operation of the system, as well as case studies of agencies that have implemented weather-responsive VSL strategies (*22*). 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.

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

DEVELOPMENT OF TrEPS-SUPPORTED WRTM FRAMEWORK

Framework

A systematic framework for implementing and evaluating WRTM strategies in the event of inclement weather has been 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 h, 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 offline 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 offline simulation.

During the inclement weather event, TMC managers perform real-time TrEPS operations using the online 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

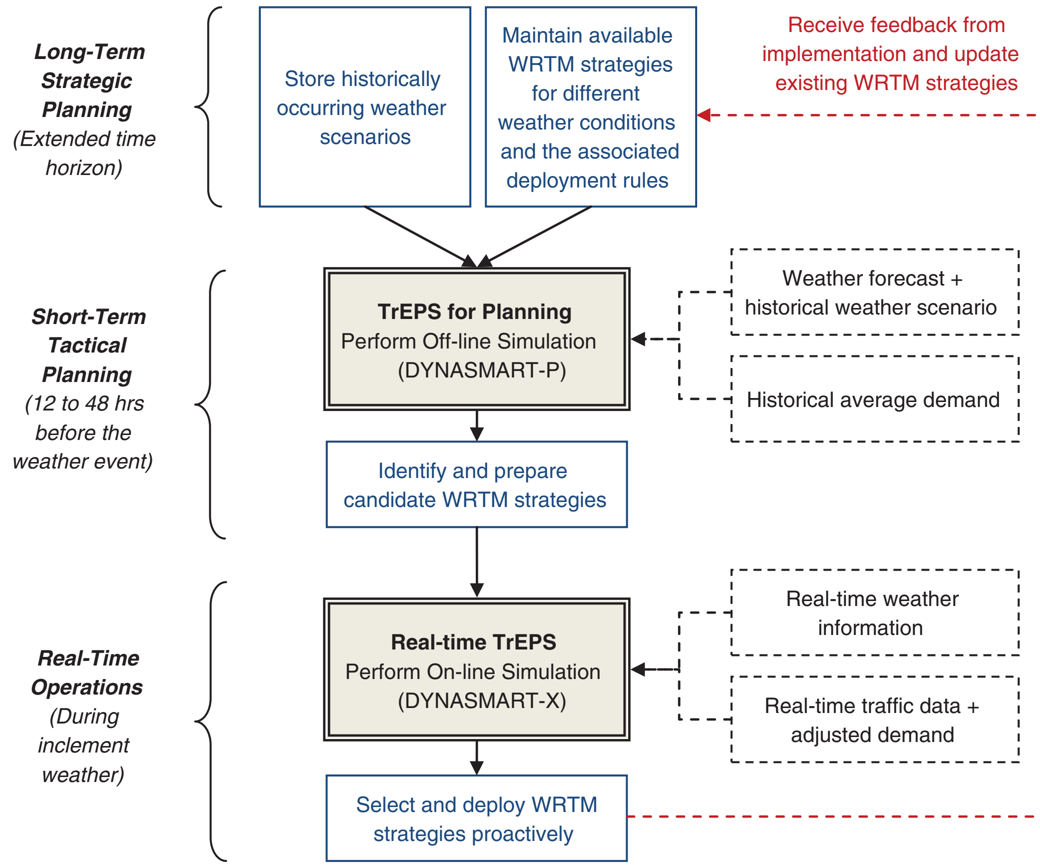


FIGURE 1 TrEPS-supported WRTM framework.

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 according to 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.

Evaluation Approaches for Assessing 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 KPIs 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, O-D or 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., VSL) to improve the overall networkwide 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 caused by 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 critical O-D pairs exist, which account for a majority of overall demand, examining O-D–level KPIs for those critical O-D 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 westbound or north- and southbound), traffic management system 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 KPIs Used to Evaluate WRTM Strategies

Category	KPI	Interpretation
Network level	Accumulated percentage of vehicles that have completed their respective trips: $$\%\text{AccOutVeh}^t = \frac{\text{Out\_Veh}^t}{\text{Tot\_Veh}^t} \times 100 \quad (1)$$ where Out_Veh^t = accumulated number of vehicles arriving at their destinations from time 0 till time t and Tot_Veh^t = accumulated total number of vehicles loaded onto network from time 0 till time t	Time-dependent network throughput
	Percentage change in average travel time: $$\%\text{Change\_AvgTTime}_i = \frac{\text{AvgTTime}_i - \text{AvgTTime}_{\text{base}}}{\text{AvgTTime}_{\text{base}}} \times 100 \quad (2)$$ where AvgTTime_i^t = average travel time of all vehicles in network under scenario i (subscript "base" represents a base-case scenario).	Relative average travel time with respect to given base-case scenario
	Percentage change in average stopped time: $$\%\text{Change\_AvgSTime}_i = \frac{\text{AvgSTime}_i - \text{AvgSTime}_{\text{base}}}{\text{AvgSTime}_{\text{base}}} \times 100 \quad (3)$$ where AvgSTime_i = average stopped time of all vehicles in network under scenario i (subscript "base" represents base-case scenario).	Relative stopped delay with respect to given base-case scenario
	Total travel time	Sum of travel times experienced by all vehicles in network
	Time-dependent average travel time per mile	Average travel time for each departure time interval (normalized)
	Time-dependent standard deviation per mile	Travel time variability for each departure time interval (normalized)
	Time-dependent percentage of lane-miles congested	Temporal evolution of network congestion level
O-D or path level	Descriptive statistics from O-D or path travel time distribution Mean; median; standard deviation; 25th, 75th, or 95th percentiles; etc. Mean of worst (or best) 20% of travel times	Travel time characteristics for given O-D or path
	Reliability measures from O-D or path travel time distribution Buffer index, misery index, planning time index, percent on time, etc. [see SHRP 2 Report (*23*) for comprehensive list and definitions of reliability measures]	Degree of reliability or variability of travel time for given O-D or path
	Time-dependent average O-D or path travel time	Average travel time for each departure time interval for given O-D or path
	Time-dependent standard deviation of O-D or path travel time	Travel time variability for each departure time interval for given O-D or path
	Average link travel time per mile for each link along the path	Link congestion level along given path; can identify bottleneck links
Cross-section level	Cumulative number of vehicles passing through given cross section Cross section vehicle flow rate	Time-dependent cross section throughput
Link level	Time-dependent traffic flow parameters Speed, density, and flow rate	Link performance level characteristics
	Time-dependent average link travel time	Average travel time for each departure time interval for given link
	Time-dependent standard deviation of link travel time	Travel time variability for each departure time interval for given link

APPLICATION TO MAJOR U.S. AREAS

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 offline simulation tools.

Three major U.S. areas were selected for study sites (Chicago, Illinois; Salt Lake City, Utah; and the Long Island area in New York), where weather is one of the major disruptive factors in the local transportation system. Local agencies were contacted: City of Chicago Department of Transportation (DOT), Utah DOT, New York State DOT, and New York City DOT. TMC personnel were surveyed and interviewed to obtain information on existing or recommended WRTM strategies for each site. On the basis of 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,
- Salt Lake City: demand management, and
- Long Island: weather-responsive incident management.

Detailed discussions for each strategy are presented in the next subsections. For each study site, a simulation network was prepared as shown in Figure 2 and supply- and demand-side parameters were calibrated (*15*). The supply-side parameter calibration involves the

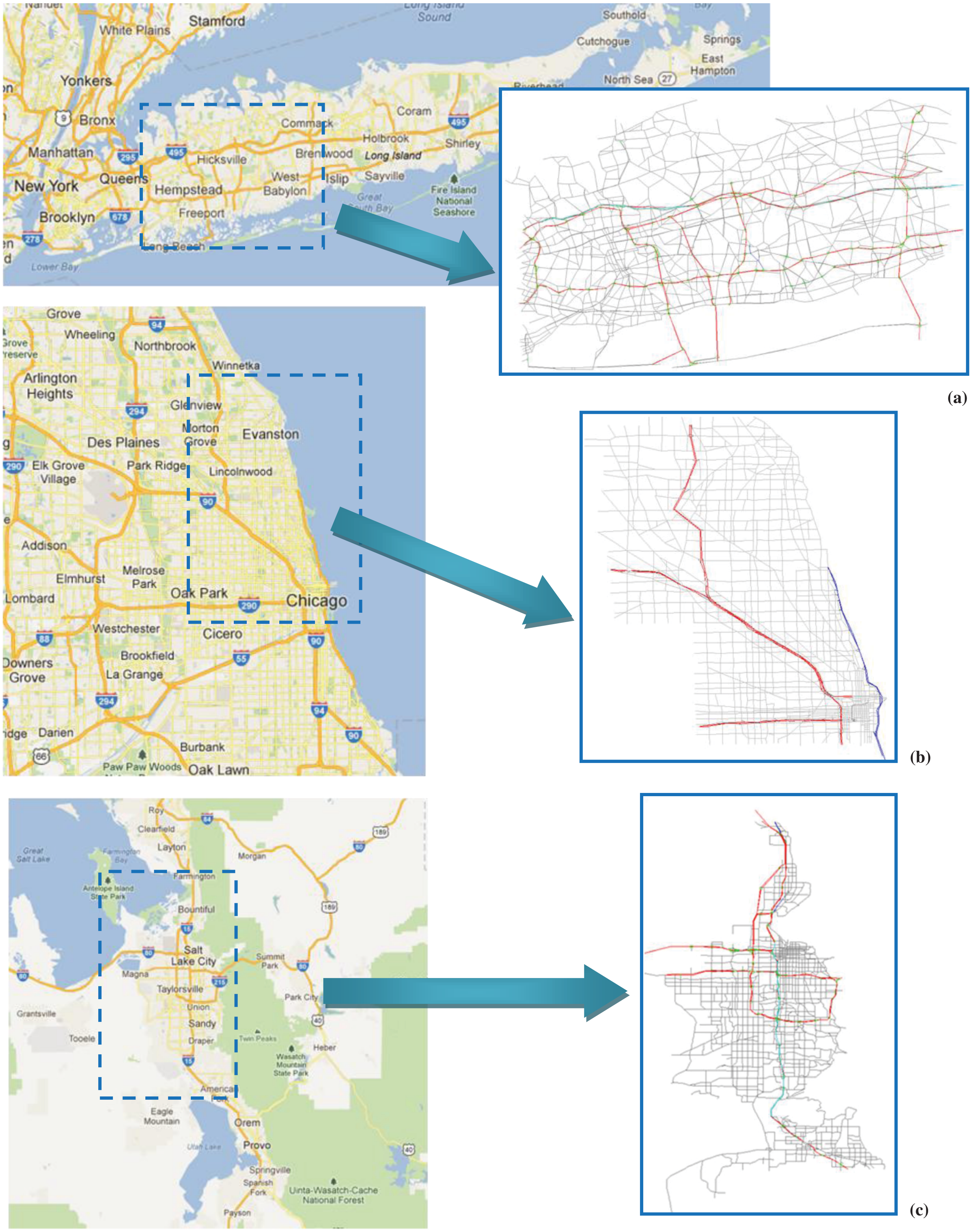


FIGURE 2 Selected networks for the study: (*a*) Long Island, (*b*) Chicago, and (*c*) Salt Lake City.

estimation of parameters in traffic flow models (e.g., speed–density relationship) and the weather adjustment factors (WAFs). The demand-side parameter calibration involves the estimation of dynamic O-D matrices using a simulation-based optimization approach (*24*). The time periods of the estimated demand are 5 to 11 a.m. for Chicago, 6 to 10 a.m. for Salt Lake City, and 6 to 11 a.m. for Long Island.

Advisory and Control Strategies: Chicago

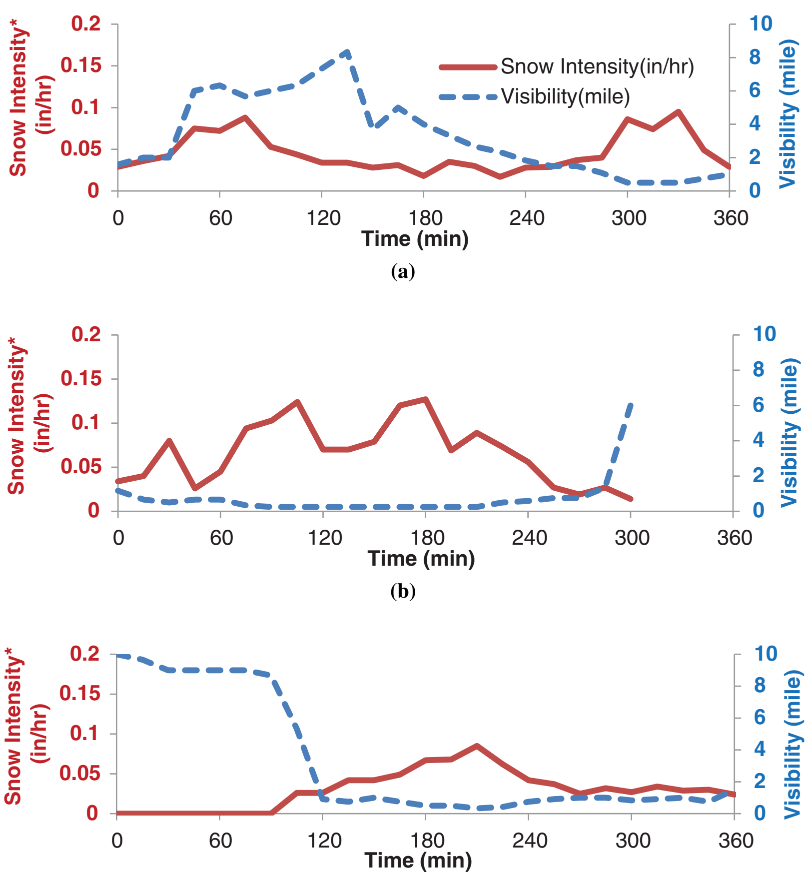
The Chicago network is one of the busiest networks, where flow breakdown and gridlock phenomena are regularly observed during peak hours. TMC managers were interested in performing the what-if analysis with various supply-side WRTM strategies (i.e., testing new strategies that are not currently used). 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 VMS, whereas the latter directly regulates traffic flow or enforces certain rules to improve traffic states under severe weather conditions. In this section, strategies are selected from each type, namely, advisory VMS for the former and VSL for the latter, to evaluate their effectiveness in improving mobility under an inclement weather condition.

Weather Scenario

A moderate snow scenario based on historical data was constructed. The temporal profiles of snow intensity and visibility are presented in Figure 3*a.* This 6-h weather scenario is applied to the simulation horizon covering 5 to 11 a.m.

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 reevaluate their routes and divert if a better path exists. Two different scenarios were 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

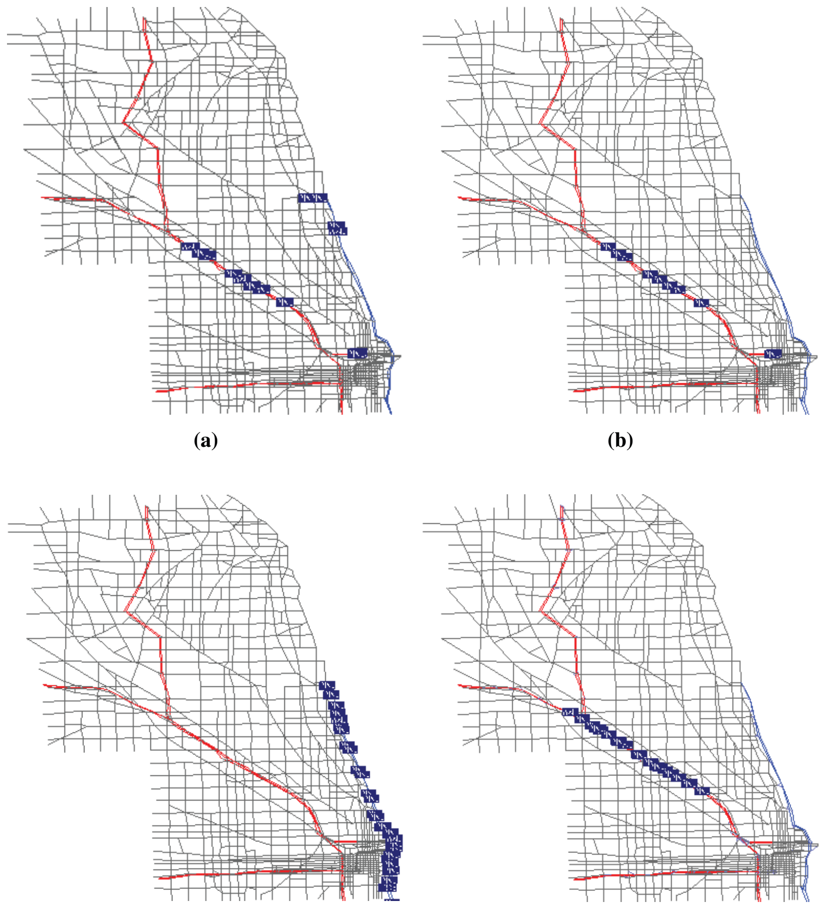


(a)

(b)

(c)

FIGURE 3 Weather scenarios constructed from Automated Surface Observing System data: (*a*) Chicago, December 12, 2010, 10 a.m. to 4 p.m., moderate snow, WRTM strategy tested: VSL and advisory VMS; (*b*) Salt Lake City, December 29, 2010, 3:30 to 8:30 p.m., heavy snow, WRTM strategy tested: demand management; and (*c*) Long Island, January 26, 2011, 6 a.m. to noon, moderate snow, WRTM strategy tested: incident management advisory VMS (* = liquid equivalent precipitation intensity).



(a) (b)

(c) (d)

FIGURE 4 Four scenarios for advisory and control strategies in Chicago: advisory VMS (warning, optional detour) on (*a*) both Kennedy Expressway and Lake Shore Drive (SN_VMS1) and (*b*) Kennedy Expressway only (SN_VMS2), and control VMS (VSL) along (*c*) Lake Shore Drive (SN_VSL1) and (*d*) Kennedy Expressway (SN_VSL2).

on Kennedy Expressway only (Figure 4*b*). The response rate of 50% was 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 according to the 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 5 mph within the range of 35 to 55 mph on the basis of the prevailing visibility and snow intensity. The control rule was constructed on the basis of the guidelines and case studies presented in Katz et al. (*22*). Two different scenarios were 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 were prepared for comparison: a base-case scenario with no snow and no strategy, which was labeled "Base," and a scenario with snow but without strategy, which was labeled "SN."

Analysis Results

Because the objective of the tested strategies is to improve the overall mobility, this paper focuses on networkwide measures for the evaluation. First, travel time–related KPIs were examined. Figure 5*a* presents total travel time for all six scenarios and indicates that the snow effect increased the total travel time by 102,807 h (i.e., 20.4% of the base case) when no strategy was implemented. Compared with SN, all four strategies improved the total travel time, but advisory VMS strategies performed better than VSL strategies in general. Figure 5, *b* and *c*, provides 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 10 a.m., which was caused by an increase in the snow intensity, as shown in Figure 3*a* (Minute 300 corresponds to 10 a.m. in the simulation horizon). All of the tested strategies except SN_VSL1 appeared to mitigate such snow impacts on the TTPM.

Second, a cross-section KPI was observed, which was the cumulative number of vehicles passing through a given cross section. The

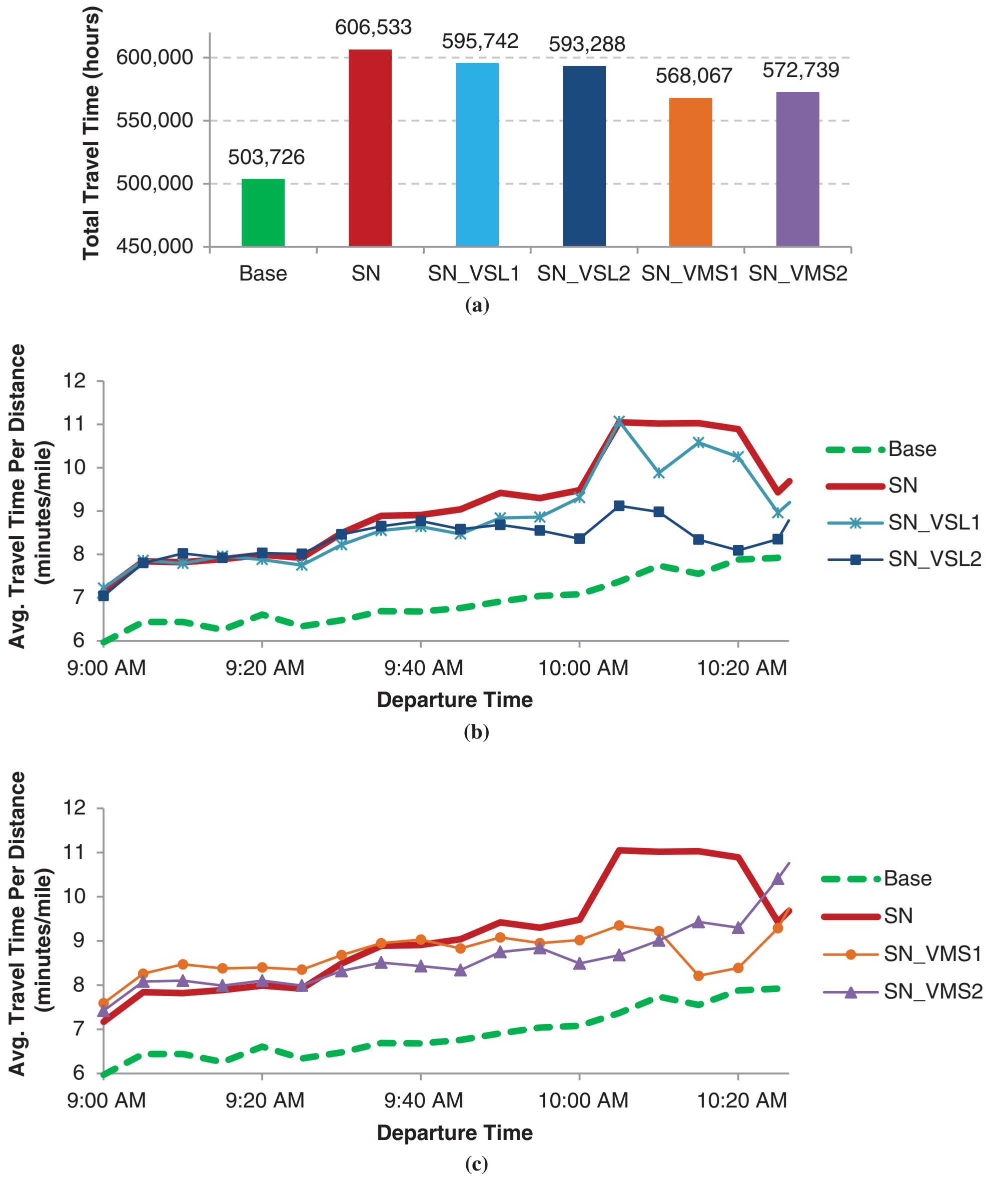


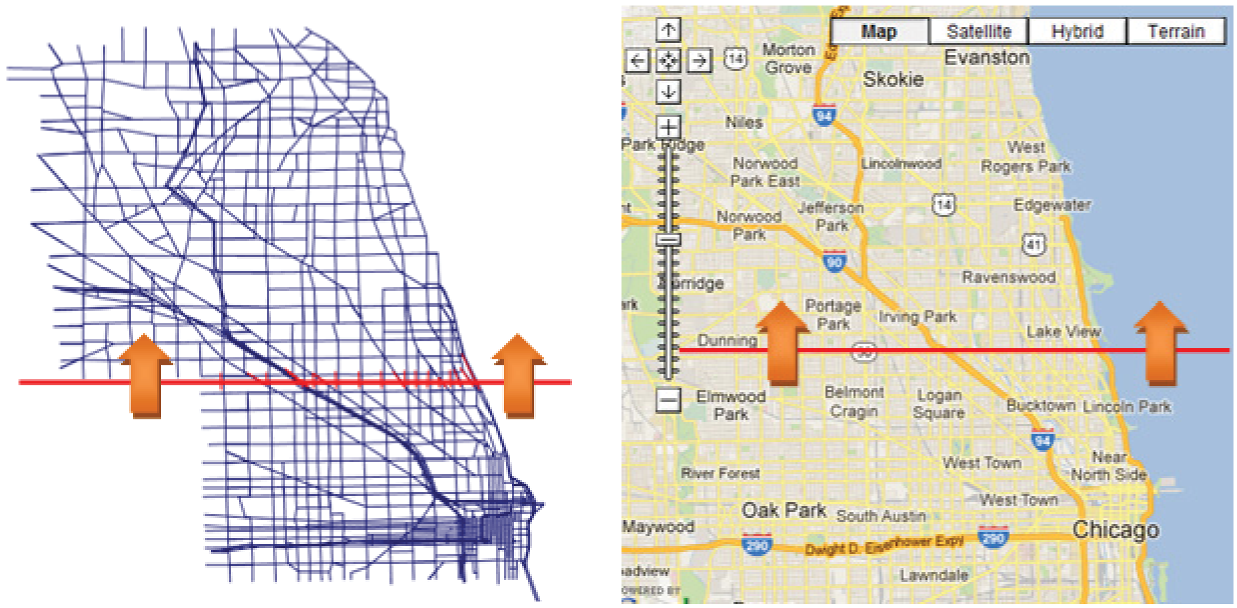
FIGURE 5 Comparison of travel time–related measures for advisory and control strategies in Chicago: (*a*) total travel time for all six scenarios, (*b*) average TTPM for VSL scenarios, and (*c*) average TTPM for VMS scenarios (avg. = average).

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 patterns consistent with the previous analysis results with the travel time KPIs (i.e., SN_VMS1 and SN_VSL1) improved the measure the most and the least, respectively. From both Figure 5 and Figure 7, SN_VMS1 shows varied performance over time: it performs poorly until 9:40 a.m. and becomes the best at the end. One reason for this can be that deploying warning VMSs on more corridors (compared with 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.

This experiment showed that both types of strategies prevented flow breakdown by reducing or slowing down inflows into heavily congested links. Therefore, 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.

Demand Management: Salt Lake City

Cities like Salt Lake City often experience severe winter storms and TMC managers encounter situations where travel demand needs to be managed for the mobility and safety purposes during such



(a) (b)

FIGURE 6 Selected cross section for measuring traffic throughput in Chicago: (a) DYNASMART Chicago network and (b) Google map.

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 was to study how much demand should be reduced under different weather conditions to maintain a certain level of network performance. Therefore, the goal in using TrEPS here was to provide TMC managers with the information on the optimal level of demand that can improve network performance without negatively affecting productivity under a given weather condition. To achieve this goal, the concept of equivalent demand reduction was employed; equivalent demand reduction is the amount of demand reduction needed to offset network performance impairment introduced by particular inclement weather conditions and to maintain the level of service expected in normal weather conditions.

Weather Scenario

In Salt Lake City, severe winter storms in the recent past motivated local agencies to consider the demand management strategy. Therefore, the weather scenarios were constructed on the basis of

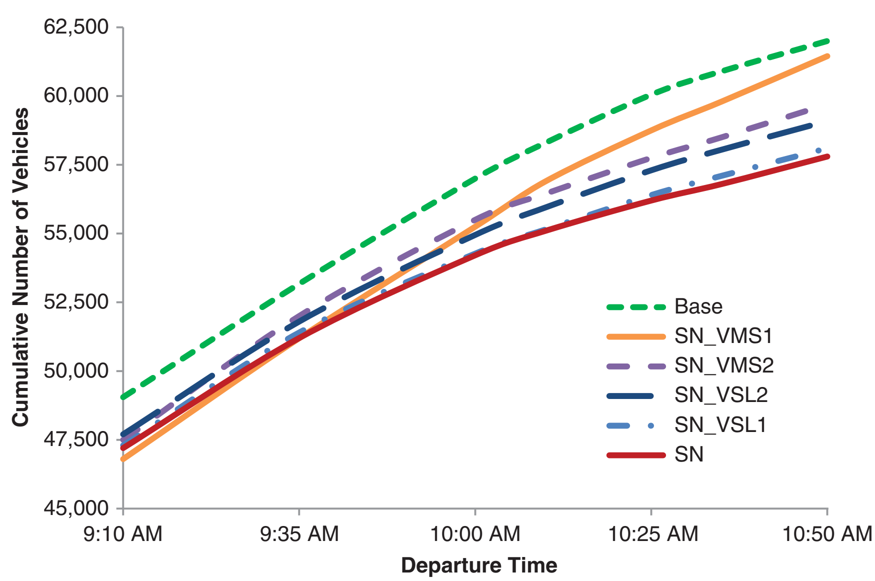


FIGURE 7 Cumulative cross-section throughput over time in Chicago.

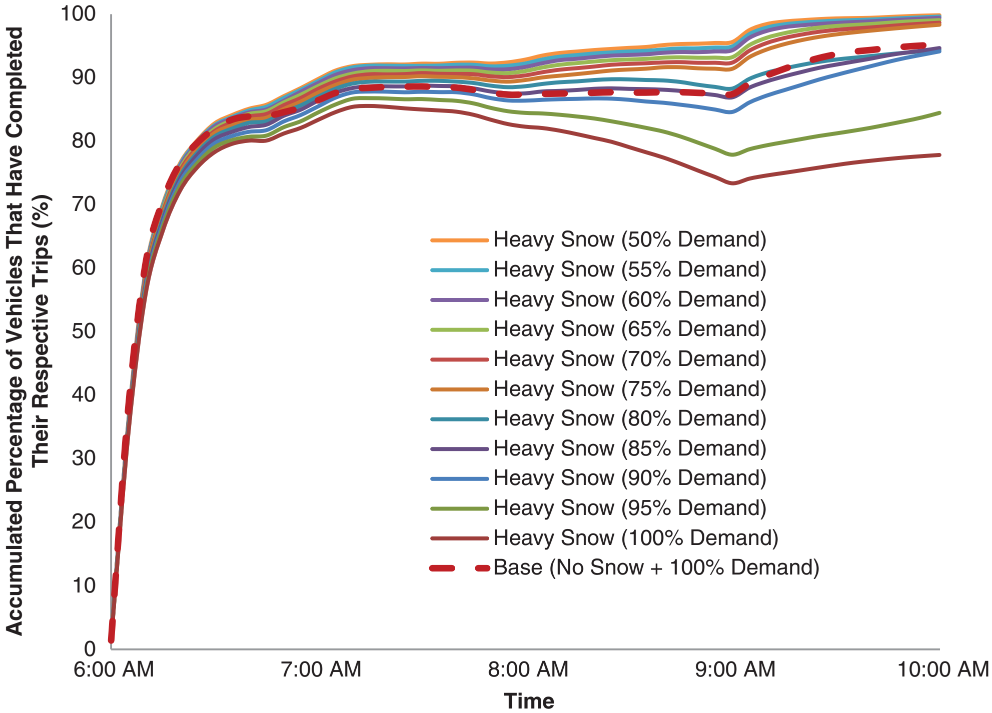
the historical data representing heavy snow conditions. Figure 3*b* shows the temporal profiles of snow intensity and visibility for the heavy snow scenario used for demand management strategies.

Demand Scenario

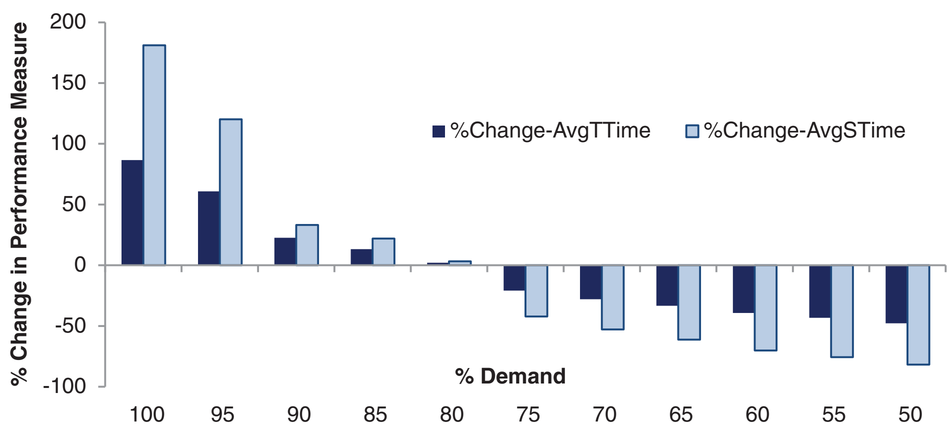
Twelve demand scenarios were prepared: one for the benchmark case, which was 100% of the demand under the normal weather condition (i.e., no snow), and 11 scenarios with different demand levels under the heavy snow condition. The generation of the 11 scenarios started with the full demand (100%) and reduced the total demand by 5% until the reduction percentage reached 50%.

Analysis Results

Figure 8 shows analysis results from the simulation study. Figure 8*a* represents the accumulated percentage of vehicles that had completed their respective trips for each time *t* (i.e., Equation 1 in Table 1), which measures the percentage of total vehicles loaded onto the network up to time *t* that reached their destinations. Compared with the base case (i.e., 100% demand under no snow), the snow event significantly degraded the network throughput when the full demand was loaded under heavy snow [i.e., heavy snow (100% demand)]. The charts suggest an approximately 15% drop in throughput at the end of the simulation. As the demand reduction percentage increased, the throughput measure improved. Figure 8*b* shows the



(a)



(b)

FIGURE 8 Analysis results for demand management in Salt Lake City: (*a*) time-dependent network throughput measure and (*b*) percentage change in performance measures for different demand levels relative to base case.

percentage changes in two selected measures, %Change_AvgTTime and %Change_AvgSTime (i.e., Equations 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 increased the former by 86.5% and the latter by 181.1% when the full demand was loaded. The equivalent demand reduction was found to be about 20% (i.e., 80% of original demand), at which point the percentage changes became nearly zero (Figure 8*b*). These values depend on the severity and duration of the weather conditions as well as the network demand patterns.

The results provide TMC managers with insights into the combined effect of demand and weather on traffic. These results 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 cancelation or rescheduling, and possible incentive schemes.

Incident Management VMS: Long Island

For the Long Island area, it was found that TMC managers focused more on preventing and minimizing weather-related disruptions such as incidents rather than trying to manage travel demand because of the limitation on adjustable demand portions. For 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 offline 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. On the basis of historical incident data, the authors identified and tested different VMS strategies to investigate their effects on reducing congestion on the incident-affected area.

Weather Scenario

A moderate snow scenario was constructed on the basis of the historical data. The temporal profiles of snow intensity and visibility are presented in Figure 3*c*. This 6-h weather scenario was applied to the simulation horizon covering 6 a.m. to noon.

Incident Scenario

The incident scenario was constructed on the basis of the actual observations on the snowy day selected for the weather scenario. The historical data show that there were three accidents that happened along westbound Long Island Expressway (I-495) between 6 a.m. and noon on January 26, 2011, as shown in Figure 9*a*.

Optional Detour VMS Scenarios

Optional detour VMS is the same type of advisory VMS tested in the previous subsection, but deployed only upstream of the incident links during the accident duration to inform drivers of the event and to suggest reevaluating their routes. Two scenarios were prepared: SN_ACC_VMS1, in which the VMSs were located at every exit along the adjacent upstream segments (Figure 9*a*), and SN_ACC_VMS2, in which only selected exits were used for a diversion point (Figure 9*b*). The former represents a static type of deployment scheme that uses the predetermined VMS locations, while the latter represents a dynamic type of scheme that determines the locations on the basis of the prevailing traffic conditions. To implement this dynamic scheme, SN_ACC_VMS1 was simulated and the traffic conditions on detour routes at each diversion point were examined. If downstream arterials of a particular exit were already experiencing a certain level of congestion and did not have sufficient room to absorb the diverted traffic, the VMS was eliminated from the exit. Consequently, only the exits that led traffic to relatively less-congested arterials were used for the VMS locations in SN_ACC_VMS2.

Other Scenarios

In addition to the two optional detour VMS scenarios, three more scenarios were 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.

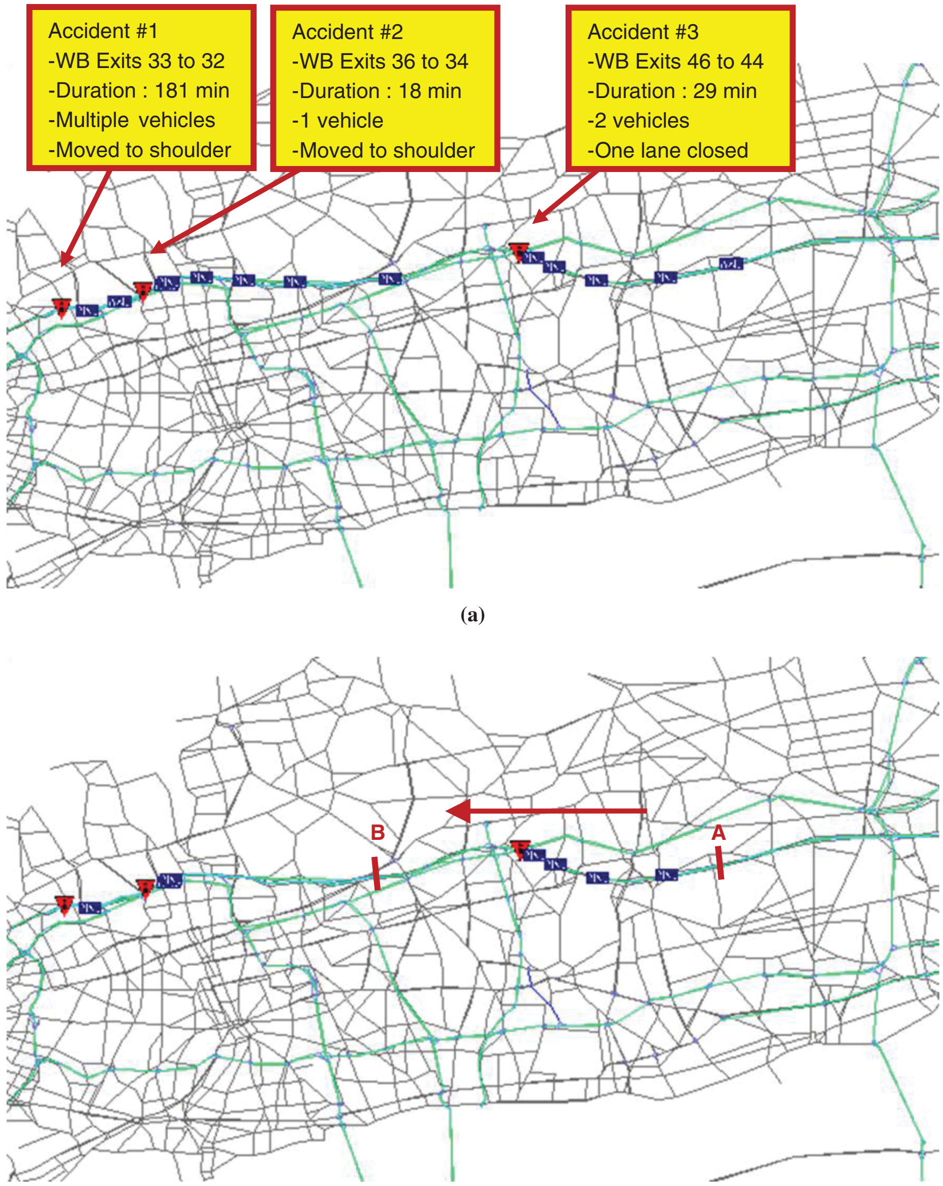
Analysis Results

In evaluating the strategies, this study focused on investigating how incident-affected 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 by using six descriptive measures: the mean, median, and standard deviation of travel times; the 95th percentile travel time; the mean of the worst 20% of travel times; and the mean of the best 20% of travel times. The chart suggests that snow and incidents increased the travel time variability rather than the mean travel time, as noticeable increases were observed mainly in the average of the worst 20% of travel times (i.e., Worst20%) and the 95th percentile. For the intervention effect, SN_ACC_VMS2 improved the overall performance because it reduced all six measures compared with SN and SN_ACC. SN_ACC_VMS1, however, had the poorest performance of all five scenarios [i.e., worsened the situation even more than the do-nothing scenario (i.e., SN_ACC)]. These results imply that statically configured strategies might not work as intended and that deployment schemes need to be dynamically determined and modified on the basis of the prevailing traffic conditions. This conclusion again stresses the importance of incorporating the prediction and decision support capabilities of real-time TrEPS into WRTM.

During this experiment, the TMC managers raised two important questions in the context of weather-responsive incident management: what is the probability of having incidents under the given weather condition, and how much congestion is expected? These questions can be effectively addressed by implementing the proposed framework, in which historical incident patterns can be maintained as strategic scenarios in connection with weather and other strategies. This step will allow the rapid creation of multiple likely incident scenarios that can be used to test WRTM strategies to obtain a more complete picture of their effectiveness.

CONCLUSION AND LESSONS LEARNED

This 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



(a)

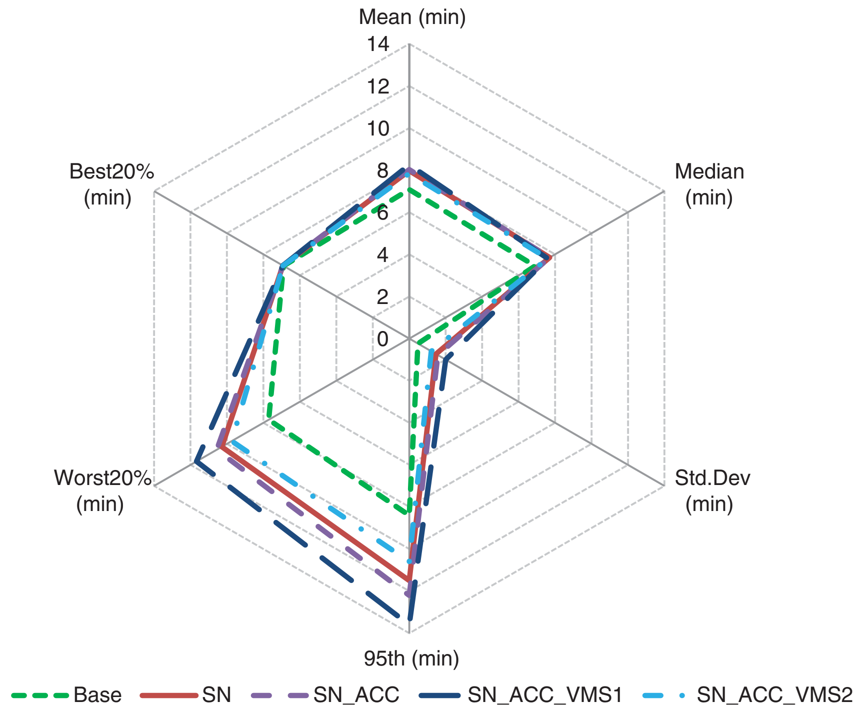
(b)

FIGURE 9 Incident management VMS strategies on Long Island: (*a*) detour option at every exit and (*b*) detour option at selected exits (WB = westbound).

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 WRTM 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 offline simulation tools 12 to 24 h 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 U.S. areas (Chicago, Salt Lake City, and the Long Island area of New York), 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 according to the local needs and tested using the TrEPS model. The analysis results illustrate the 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 about the role that network models and simulation methodologies can play



Scenario	#Obs	Mean	Median	Std.Dev	95th	Worst20%	Best20%
Base	3940	7.08	6.9	0.48	8.4	7.71	6.90
SN	3873	7.97	7.7	1.47	11.5	10.28	6.93
SN_ACC	3872	8.03	7.7	1.57	12.2	10.56	6.93
SN_ACC_VMS1	3727	8.25	7.6	2.00	13.6	11.67	6.93
SN_ACC_VMS2	3740	7.84	7.6	1.21	10.6	9.74	6.92

FIGURE 10 Comparison of path travel time statistics for different scenarios on Long Island (obs. = observations; std. dev = standard deviation).

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 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, according to factors that include the size of the area, demand pressure on the network, and the 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-h projections, agencies have sufficient time to use the TrEPS methodology offline 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. Although 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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