Calibration of Traffic Flow Models under Adverse Weather and Application in Mesoscopic Network Simulation Procedures

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ABSTRACT

The weather-sensitive Traffic Estimation and Prediction System (TrEPS) aims to accurately estimate and predict traffic state under inclement weather conditions. Successful application of weather-sensitive TrEPS requires detailed calibration of weather effects on traffic flow model. In this paper, systematic procedures of the entire calibration process are developed, from data collection, through model parameter estimation, to model validation. Following the procedures, dual-regime modified Greenshields model and weather adjustment factors are calibrated for four metropolitan areas across the United States (Irvine, Chicago, Salt Lake City, and Baltimore), using freeway loop detector traffic data and weather data obtained from Automated Surface Observing System (ASOS) stations. It is observed that visibility and precipitation (rain/snow) intensity have significant impacts on the value of some traffic flow model parameters, such as free flow speed and maximum flow rate; while these impacts can be included in weather adjustment factors. The calibrated models are fed as input into weather integrated dynamic traffic assignment simulation system. The results show that the calibrated models are capable of capturing the weather effects on traffic flow more realistically than TrEPS without weather integration.

KEYWORDS: Adverse Weather; Weather-Responsive Traffic Management; Traffic Estimation and Prediction System; Traffic Flow Model; Weather Adjustment Factor; Model Calibration.
INTRODUCTION

Driving behaviors and the resulting traffic flow characteristics under inclement weather are different from those observed under so-called “normal” conditions. Based on weather type (rain, snow, frog, wind, etc), duration, and intensity, the impact of weather on traffic network performance may vary under different scenarios.

Maze et al. (1) identified three predominant variable categories that are affected by inclement weather, namely traffic safety, traffic flow relationships, and traffic demand. Andrey et al. (2) found that in Canadian cities, collision rates increase during precipitation by 50-100% relative to normal seasonal conditions. Similar findings are presented in the literature for cities in the United States (3,4), indicating that rainfall and snowfall duration and intensity have a positive and statistically significant relationship to the number of crashes. Maze et al. (1) studied the freeway system in the Minneapolis/St. Paul metropolitan area and showed that adverse weather causes clear reductions in traffic speed, with up to 6% for rain, 13% for snow, 12% for reduced visibility. Ibrahim and Hall (5) analysed the effects of adverse weather on the speed-flow and flow-occupancy relationships for Canadian travellers and found the effects of snow to be much larger than those of rain, causing a reduction in free flow speed of 38-50 km/h. The effects of weather on traffic volume are also evident from empirical data. The research conducted by Datla and Sharma (6) indicates that the impact of cold and snow on traffic volume varies with type of trip and hour of the day. From traffic data collected in Canada, they observed that commute trips experience lowest reductions due to snowy weather with up to 14%, while the recreational trips experience the highest reduction with up to 31%. They also found that reduction of commute trips during off-peak hours (−10% to −15%) was generally greater than those during peak hours (−6% to −10%), however, an opposite pattern was observed for recreational trips. All these studies show that inclement weather may have a significant and comprehensive impact on the transportation system, which cannot be ignored by planners and decision makers.

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. In a project completed in 2006, the Road Weather Management Program used data from Seattle, Minneapolis and Baltimore to develop statistical models and adjustment factors to quantify the impacts of weather on traffic flow (7). One of the challenges remaining is to integrate those models into decision support systems to help improve the performance of the transportation system during inclement weather conditions. Traffic Estimation and Prediction System (TrEPS) is the tool currently available for traffic planners and operators to assist with evaluating and implementing weather-responsive traffic management strategies. Weather-sensitive TrEPS capabilities aim to accurately estimate and predict traffic states under inclement weather conditions.

Mahmassani et al. (8) identified several key components within the TrEPS framework where the impact of weather must be incorporated, on both the supply and demand sides. One such element on the supply side consists of well calibrated weather integrated traffic flow...
models. Successful application of weather-sensitive TrEPS requires detailed calibration of weather effects on the underlying traffic flow models. The main objective of this paper is to develop systematic procedures for calibrating traffic flow models under inclement weather, using commonly available freeway loop detector data and weather data collected from Automated Surface Observing System (ASOS) stations, and to apply the calibrated models into a mesoscopic dynamic traffic assignment (DTA) framework. Following the developed procedure, traffic flow models in four U.S. cities (Irvine, Salt Lake City, Chicago, and Baltimore) are calibrated, together with the quantitative weather impact on them. The calibrated models are provided as input into an existing weather integrated dynamic traffic simulation-assignment system, DYNASMART-p. The simulation results show that the calibrated models are capable of capturing the weather effects on traffic flow more realistically than TrEPS without weather integration.

The extensive set of parameter estimates compiled herein, and the range of geographic and network situations considered, forms a rich library that could support future applications of simulation-based dynamic network models to address weather-related scenarios in different locations where local data may not be available, or where the time and/or resources available for the study may not allow full-blown local calibration.

Accordingly, the main contribution of the present work consists of (1) a systematic calibration process for capturing the weather impact on traffic flow relations, (2) an extensive calibration base which confirms that the approach previously presented for one location is applicable in various locations in different regions in the US, (3) a database that serves as a valuable library for application to locations where no local data may be available, (4) full integration of the weather sensitive traffic flow models into mesoscopic DTA framework, and (5) validation and application of the entire simulation-based DTA model under weather conditions.

**MODELING WEATHER IMPACT ON TRAFFIC**

Although the effect of adverse weather on traffic flow may appear evident and easy to perceive, it is still important to develop an accurate quantitative description of the effect for modeling purposes. Hall and Barrow (9) studied the effect of adverse weather conditions on the flow-occupancy relationship using freeway traffic data in Ontario, Canada. They found that adverse weather affects the flow-occupancy function by reducing the slope of the curve corresponding to uncongested traffic state. Similar findings by Ibrahim and Hall (5) indicated that the maximum flow rates of highways are reduced by inclement weather. They also observed that adverse weather causes a downward shift in the speed-flow function. These weather effects are modeled statistically using regression analysis, and the results are quantitatively documented for both rainy and snowy conditions. Rakha et al. (10) studied the impacts of inclement weather on some key traffic stream parameters for several different metropolitan areas in the United States. They calibrated Van Aerde traffic flow model using loop detector data and concluded that the impacts of weather on traffic increases as the rain and snow intensities increase. In their study, they also proposed and developed so-called
weather adjustment factors (WAF), which are used to be multiplied by based clear-condition variables to compute the parameters under weather impact. Parallel efforts have been ongoing in Europe to incorporate the effect of adverse weather in traffic models to support system management actions (11). In addition, some researchers have proposed and developed different methods to incorporate weather effects into the dynamic traffic assignment (DTA) framework. Antoniou (12) identified the different characteristics of traffic flow model under different weather conditions (dry and wet), and proposed on-line calibration procedures for DTA models. Dong et al. (13) recognized the application of DTA simulation tools to support transportation network planning under adverse weather conditions, and developed methodology to incorporate weather impacts into DTA framework. Recently, Mahmassani et al. (14) followed the methodology and demonstrated the use of weather-sensitive DTA models for different road networks.

**Modified Greenshields Traffic Flow Model**

The dynamic traffic assignment system used in this study, DYNASMART, has two types of modified Greenshields models for simulating traffic propagation (15). The first type 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) as shown in FIGURE 1. Dual-regime models are generally used for freeways because freeways have typically more capacity than arterials, and can accommodate dense traffic (up to 2300 pc/hr/ln) at near free-flow speeds (16). On the other hand, arterials have signalized intersections, meaning that a slight increase in traffic would elicit more deterioration in prevailing speeds than in the case of freeways. Therefore, arterial traffic relations are better explained using the other type of modified Greenshields model, the single-regime model. All the traffic data used in this study come from loop detectors installed on highways. Therefore the dual-regime model is chosen to fit the collected historical data.

![Modified Greenshields Model (dual-regime model)](image)

**FIGURE 1 Modified Greenshields Model (dual-regime model)**
The mathematical expression of the dual-regime modified Greenshields is shown in Equation (1). Six parameters are affecting the shape of the model, namely, breakpoint density ($k_{bp}$), free flow speed ($u_f$), speed-intercept ($v_f$), minimum speed ($v_0$), jam density ($k_{jam}$), and the shape parameter ($\alpha$).

\[
v_i = \begin{cases} 
  u_f & 0 < k_i < k_{bp} \\
  v_0 + (v_f - v_0) \left(1 - \frac{k_i}{k_{jam}}\right)^\alpha & k_{bp} < k_i < k_{jam}
\end{cases}
\]

where

\[
v_i = \text{speed on link } i \\
v_f = \text{speed-intercept} \\
u_f = \text{free-flow speed on link } i \\
v_0 = \text{minimum speed on link } i \\
k_i = \text{density on link } i \\
k_{jam} = \text{jam density on link } i \\
\alpha = \text{power term} \\
k_{bp} = \text{breakpoint density}
\]

Weather Adjustment Factor

Weather Adjustment Factor (WAF), proposed by Rakha (10) to quantify the effect of inclement weather on traffic flow model parameters, is computed as the ratio of the parameter under inclement weather conditions relative to the parameter obtained under normal weather.

\[
WAF_i = \frac{f_i^{\text{Weather Event}}}{f_i^{\text{Normal}}}
\]

where $WAF_i$ is the weather adjustment factor for parameter $i$, $f_i^{\text{Weather Event}}$ denotes the value of parameter $i$ under a certain weather event, and $f_i^{\text{Normal}}$ denotes the value of parameter $i$ under the normal condition.

As many researches have found that the variation in the weather effects on traffic flow is associated with the type of weather condition (5)(7), in this study, we assume that the WAF is closely related to three variables which are representative of severity of weather condition, namely, visibility, rain intensity, and snow intensity. Specifically a linear functional form is used to model WAF as following.

\[
WAF_i = \beta_{i0} + \beta_{i1} \cdot v + \beta_{i2} \cdot r + \beta_{i3} \cdot s + \beta_{i4} \cdot v \cdot r + \beta_{i5} \cdot v \cdot s
\]

where

\[
v = \text{visibility (mile)} \\
r = \text{precipitation intensity of rain (inch/hr)} \\
s = \text{precipitation intensity of snow (inch/hr)} \\
\beta_{i0}, \beta_{i1}, \beta_{i2}, \beta_{i3}, \beta_{i4}, \beta_{i5} = \text{coefficients to be estimated.}
\]

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STUDY AREAS AND DATA DESCRIPTION

The data used in this study are obtained from four metropolitan areas in the United States, Irvine (CA), Chicago (IL), Salt Lake City (UT), and Baltimore (MD). These four areas are chosen because their locations are distributed across the U.S. continent, from west coast to east coast, and are able to represent the weather and traffic conditions in its own territory across the country. Calibration of weather-sensitive TrEPS models requires availability of both weather data and traffic data.

There are two major public sources for archived weather data in the U.S.: the Automated Surface Observing System (ASOS) stations located at airports and the roadside Environmental Sensor Stations (ESS) available from the Clarus initiative. As the historical weather data from ESS have a time resolution of 20 minutes and are only available from 2009, ASOS data with the 5 minute resolution will be used in conjunction with traffic detector data collected and aggregated over a 5-minute interval. ASOS 5-minute weather data are available on the NOAA National Climatic Data Center site (ftp://ftp.ncdc.noaa.gov/pub/data/asos-fivemin). The weather data recorded by ASOS stations are reported in METAR format, a prevailing format used by aviation organizations, which includes various weather information such as visibility, precipitation type and intensity, temperature, dew point, wind direction and speed, etc. TABLE 1 summarizes the airports in which ASOS stations are located for the four study sites, respectively, and time periods for which 5-min ASOS data are available from the above-mentioned website.

<table>
<thead>
<tr>
<th>Airport</th>
<th>Location</th>
<th>ASOS data</th>
</tr>
</thead>
<tbody>
<tr>
<td>John Wayne Airport</td>
<td>Irvine, CA</td>
<td>2005 - present</td>
</tr>
<tr>
<td>Midway International Airport</td>
<td>Chicago, IL</td>
<td>2005 - present</td>
</tr>
<tr>
<td>O'Hare International Airport</td>
<td>Chicago, IL</td>
<td>2000 - present</td>
</tr>
<tr>
<td>Salt Lake City International Airport</td>
<td>Salt Lake City, UT</td>
<td>2000 - present</td>
</tr>
<tr>
<td>Baltimore/Washington International Airport</td>
<td>Baltimore, MD</td>
<td>2000 - present</td>
</tr>
</tbody>
</table>
The primary source of traffic data used in this study for traffic flow model calibration is loop detectors installed on freeway lanes. They are available from several web-based data archive systems, like PeMS, GCM, CATT Lab, etc. Historical traffic data with 5 minute aggregation interval through 2005-2009 are used. The distribution of selected loop detector locations in the four study areas are presented in FIGURE 2. In selecting detector locations and collecting data, following criteria are mainly considered.

1. Choose detectors as close as possible to ASOS stations; ideally, no farther than 10 miles from ASOS.

2. Remove the influence of other external events such as incidents/accidents, work zones and special planned events.

3. Include various facility/lane types and calibrate separately for each type. For instance, types can be classified into mainlines, on-ramps, off-ramps and HOV; and the number of lanes could be further distinguished.

4. Find segments that experience a wide range of traffic regimes, i.e., free-flow, stop-and-go and congested states.
Hou, Mahmassani, Alfelor, Kim, and Saberi

Irvine

Chicago

Salt Lake City

Baltimore

FIGURE 2 Maps of Selected Detector Locations in Four Study Areas

CALIBRATION PROCEDURE

Data Preparation

Three major traffic state variables used for TrEPS calibration are link volume (or flow rates), occupancy and speed. To calibrate the modified Greenshields traffic flow model, occupancy data need to be further converted into the density. Cassidy and Coifman (17) have showed that occupancy is linearly related to density by the effective average vehicle length. The exact relationship between these two variables can be expressed as following.
\[ k = \frac{52.8}{L_v + L_s} \cdot o \]  

where

\[ k = \text{density (veh/mi/lane)} \]
\[ L_v = \text{average vehicle length (feet)} \]
\[ L_s = \text{average sensor length (feet)} \]
\[ o = \text{occupancy (\%)} \]

In this study, \( L_v \) is assumed to be 5 meters (approximately 16.4 feet); and \( L_s \) is set to 2 meters (approximately 6.5 feet).

The 5 minute interval traffic and weather data are then matched together according to the timestamps to classify each traffic observation into different weather categories. Weather categories are defined based on the precipitation type and the intensity. With a normal weather as the base case, in which no precipitation is observed, three levels of precipitation intensities (light, moderate and heavy) are used for both rain and snow. **TABLE 2** shows these total number of seven weather categories and the corresponding precipitation intensity ranges: normal (no precipitation), light rain (intensity less than 0.1 in./hr), moderate rain (0.1 to 0.3 in./hr), heavy rain (greater than 0.3 in./hr), light snow (less than 0.05 in./hr), moderate snow (0.05 to 0.1 in./hr), and heavy snow (greater than 0.1 in./hr). The values for the intensity range are based on the literature \((7)(18)\). It happens to Irvine network that no snow precipitations are observed through the years 2005-2009. For the Salt Lake City and Chicago networks, the moderate and heavy categories are merged for both rain and snow since traffic data for heavy rain/snow are not sufficiently covering the whole density range to enable calibration to be carried out. A complete description of weather categorization for different networks is given in **TABLE 2**. A tick is marked in place when the collected data is sufficient to calibrate the traffic flow model for that corresponding weather category.

**TABLE 2 Weather Categorization for the Four Studied Networks**

<table>
<thead>
<tr>
<th>Network</th>
<th>Weather Condition (precipitation intensity (inch/hr))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>normal</td>
</tr>
<tr>
<td></td>
<td>(no precip.)</td>
</tr>
<tr>
<td>Irvine</td>
<td>✓</td>
</tr>
<tr>
<td>Salt Lake City</td>
<td>✓</td>
</tr>
<tr>
<td>Chicago</td>
<td>✓</td>
</tr>
<tr>
<td>Baltimore</td>
<td>✓</td>
</tr>
</tbody>
</table>

* Liquid Equivalent Snowfall Intensity
After traffic data are categorized, parameters in the modified Greenshields model are estimated for each weather condition using a nonlinear regression approach. The following steps describe the procedures for calibrating the dual-regime model, which is used in most cases when traffic data are collected from freeways.

**Procedure for Calibrating Traffic Flow Model**

Step 1. Plot the speed vs. density graph, and set initial values for all the parameters, i.e. breakpoint density ($k_{bp}$), speed-intercept ($v_f$), minimum speed ($v_0$), jam density ($k_{jam}$), and the shape parameter ($\alpha$), based on observations.

Step 2. For each observed density ($k_i$), calculate the predicted speed value ($\hat{v}_i$) using Eq. (1) and the parameters initialized in Step 1.

Step 3. Compute the squared difference between observed speed value ($v_i$) and predicted speed value ($\hat{v}_i$), for each data point, and sum the squared error over the entire data set.

Step 4. Minimize the sum of squared error obtained in Step 3, by changing the values of model parameters.

Previous research conducted by Mahmassani et al. (8) uses an approach that divides the data into two parts (free flow part and congested part) and estimates the two regimes separately. The main advantage of the nonlinear regression method used in this paper is that it estimates the model as a whole, which gives a smooth joint point at the breakpoint density.

Step 4 is implemented by Microsoft Excel Solver which uses the generalized reduced gradient algorithm to find the optimal solution. Based on the observed traffic data, the minimum speed ($v_0$) and jam density ($k_{jam}$) turn out to be insensitive to weather conditions. For Irvine and Baltimore networks, the minimum speed is assumed to be 10 mph, while for Chicago and Salt Lake City, a minimum speed of 2 mph is used. The selection of minimum speed value is based on long-term observations obtained from loop detector data at selected locations. The jam density is assumed to be 225 vpmpl for all the four networks.

**Procedure for Calibrating Weather Adjustment Factor**

Once speed-density functions for different weather conditions (i.e., normal, light rain, moderate rain, heavy rain, light snow, moderate snow and heavy snow) are obtained for each location, linear regression is conducted to estimate the weather adjustment coefficients in Equation (3). The detailed calibration procedures are as following.

Step 1. For each weather condition $c$, calculate the WAF for each parameter $i$ such that

$$ WAF_i^c = f_i^c / f_i^{Normal} \quad \forall c, $$

where $f_i^c$ denotes the value of parameter $i$ under weather condition $c$, $f_i^{Normal}$ denotes the value of parameter $i$ under the normal (no precipitation) condition.

Step 2. Assign $WAF_i$ to corresponding traffic-weather data such that each observation has a
structure similar to the following:
\{time, traffic data (volume, speed, density), weather data(v, r, s), WAF(F_1, \cdots, F_i)\}.

Step 3. For each parameter \(i\), estimate coefficients \(\beta_{i0}, \beta_{i1}, \beta_{i2}, \beta_{i3}, \beta_{i4}, \beta_{i5}\) by conducting the regression analysis using Equation (3) given \(WAF_i\) as a dependent variable and weather data \((v, r, s)\) for all observations as independent variables.

CALIBRATION RESULTS

The procedures developed in the previous section are applied to calibrate the traffic flow model and weather adjustment factors in the four selected study areas. Mahmassani et al. (8) have followed similar steps to calibrated weather sensitive traffic flow models using data collected from Hampton Road network in Virginia. It was observed from their research that different weather conditions do not have significant impact on the magnitude of shape parameter \((\alpha)\). As a result, in this study, the shape parameter is considered as a decision variable only under clear weather condition in the optimization process as described in Step 4 of traffic flow model calibration process; while under other weather conditions (i.e. rainy and snowy) it is set as a constant which is equal to the value obtained under clear weather.

The goodness-of-fit of the nonlinear regression model, used for evaluating the estimation results, can be measured by the root mean square error (RMSE). The smaller the RMSE is, the better the model represents the data.

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i} (v_i - \hat{v}_i)^2}
\]

where \(v_i\) is observed speed value, \(\hat{v}_i\) is predicted speed value, and \(N\) is number of observations. Another measurement is the R-squared value, which is computed in the same way as in linear regression models. The R-squared value is the ratio of the regression sum of squares to the total sum of squares (Equation (5)), which explains the proportion of variance accounted for in the dependent variable by the model. The closer R-squared value is to 1, the better the model fits the data.

\[
R^2 = 1 - \frac{SSE}{SST} = 1 - \frac{\sum (v_i - \hat{v}_i)^2}{\sum (v_i - \bar{v})^2}
\]

Examples of calibrated speed-density curves for each network are presented in FIGURE 3. It is observed that the overall speed for both uncongested and congested regimes decreases as the weather conditions become severe. The snow event, especially the moderate and heavy snow, causes significant reductions in speed as shown in Chicago, Salt Lake City and Baltimore networks. The quantitative values of the calibrated model parameters are tabulated in TABLE 3, for some selected highway segments.
FIGURE 3 Examples of Raw Traffic Data and Calibrated Speed-density Curves under Different Weather Conditions for Each Network: Irvine (a,b), Salt Lake City (c,d), Chicago (e,f), and Baltimore (g,h).
### TABLE 3 Traffic Flow Model Calibration Results of Selected Highway Segments in Each Network

<table>
<thead>
<tr>
<th>Network</th>
<th>Highway</th>
<th>Weather Condition</th>
<th>$q_{\text{max}}$ (veh/5-min)</th>
<th>$v_f$ (mph)</th>
<th>$\alpha$</th>
<th>$k_{\text{bp}}$ (vpmp)</th>
<th>$u_i$ (mph)</th>
<th>$v_0$ (mph)</th>
<th>$k_{\text{jam}}$ (vpmp)</th>
<th># of observations</th>
<th>RMSE</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Irvine</td>
<td>I-405</td>
<td>normal</td>
<td>835</td>
<td>110.75</td>
<td>7.13</td>
<td>16.03</td>
<td>69.45</td>
<td>10</td>
<td>225</td>
<td>513</td>
<td>1775</td>
<td>4.81</td>
</tr>
<tr>
<td></td>
<td></td>
<td>light rain</td>
<td>735</td>
<td>103.96</td>
<td>7.13</td>
<td>15.59</td>
<td>66.30</td>
<td>10</td>
<td>225</td>
<td>163</td>
<td>298</td>
<td>4.67</td>
</tr>
<tr>
<td></td>
<td></td>
<td>moderate rain</td>
<td>647</td>
<td>98.15</td>
<td>7.13</td>
<td>14.89</td>
<td>64.07</td>
<td>10</td>
<td>225</td>
<td>75</td>
<td>46</td>
<td>5.68</td>
</tr>
<tr>
<td></td>
<td></td>
<td>heavy rain</td>
<td>605</td>
<td>90.15</td>
<td>7.13</td>
<td>10.90</td>
<td>66.24</td>
<td>10</td>
<td>225</td>
<td>13</td>
<td>19</td>
<td>5.13</td>
</tr>
<tr>
<td>Chicago</td>
<td>I-94</td>
<td>normal</td>
<td>591</td>
<td>89.15</td>
<td>3.92</td>
<td>20.88</td>
<td>61.48</td>
<td>2</td>
<td>225</td>
<td>654</td>
<td>1074</td>
<td>6.37</td>
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<tr>
<td></td>
<td></td>
<td>light rain</td>
<td>579</td>
<td>90.10</td>
<td>3.92</td>
<td>23.51</td>
<td>57.11</td>
<td>2</td>
<td>225</td>
<td>727</td>
<td>1002</td>
<td>5.79</td>
</tr>
<tr>
<td></td>
<td></td>
<td>moderate rain</td>
<td>486</td>
<td>78.46</td>
<td>3.92</td>
<td>21.43</td>
<td>52.90</td>
<td>2</td>
<td>225</td>
<td>78</td>
<td>166</td>
<td>4.42</td>
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<tr>
<td></td>
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<td>light snow</td>
<td>576</td>
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<td>Salt Lake City</td>
<td>I-15</td>
<td>normal</td>
<td>735</td>
<td>87.24</td>
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<td>19.66</td>
<td>59.14</td>
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<td>light rain</td>
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<td>82.11</td>
<td>4.38</td>
<td>17.53</td>
<td>58.18</td>
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<td>225</td>
<td>622</td>
<td>182</td>
<td>2.91</td>
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<tr>
<td></td>
<td></td>
<td>moderate rain</td>
<td>690</td>
<td>82.84</td>
<td>4.38</td>
<td>19.04</td>
<td>56.90</td>
<td>2</td>
<td>225</td>
<td>368</td>
<td>20</td>
<td>3.09</td>
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<tr>
<td></td>
<td></td>
<td>light snow</td>
<td>565</td>
<td>69.51</td>
<td>4.38</td>
<td>11.92</td>
<td>55.20</td>
<td>2</td>
<td>225</td>
<td>417</td>
<td>721</td>
<td>9.16</td>
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Based on the calibrated traffic model of the four networks, the weather adjustment factors for several key parameters (maximum flow rate ($q_{\text{max}}$), speed intercept ($v_{f}$), breakpoint density ($k_{bp}$), and free flow speed ($u_{f}$)) are computed using Equation (2). It is found that the maximum service flow rate ($q_{\text{max}}$), and free flow speed ($u_{f}$), are sensitive to both rain and snow intensities. As the rain or snow intensity increases, maximum flow rate, speed intercept and free flow speed are reduced. Similar findings are present in the literature (5) (10). It is also found that increasing snow intensity reduces breakpoint density; however, the effect of rain on it is not as clear as that of snow, as in some networks it decreases with rain intensity (e.g., Irvine) while in other cases it increases (e.g., Baltimore). As a summary, the effects of the rain intensity and the snow intensity on different traffic flow model parameters are presented in FIGURE 4 and FIGURE 5, respectively. The calibration results of WAF for the four networks are provided in TABLE 4. The significance of model parameters, p-values, are presented in parentheses under each point estimator in the table. The low R-squared values of breakpoint density ($k_{bp}$) suggest that this parameter is insensitive to visibility and precipitation intensity levels.

FIGURE 4 Effect of Rain Intensity on Weather Adjustment Factors for: (a) maximum flow rate ($q_{\text{max}}$); (b) speed intercept ($v_{f}$); (c) breakpoint density ($k_{bp}$); and (d) free flow speed ($u_{f}$)
FIGURE 5 Effect of Snow Intensity on Weather Adjustment Factors for: (a) maximum flow rate ($q_{max}$); (b) speed intercept ($v_f$); (c) breakpoint density ($k_{bp}$); and (d) free flow speed ($u_f$)
<table>
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VALIDATION

Besides the supply-side traffic flow model and weather adjustment factor calibration, some other components of weather-sensitive TrEPS must be tuned before DTA simulation can be conducted, including demand-side parameter estimation, driver behavior modeling, etc. The detailed implementations of those tasks are beyond the scope of this paper; however, some relevant studies can be found in the literature (19) (20) (21). In this study, the OD matrix is calibrated using a bi-level optimization method (22) (23), based on historical static OD matrix and time-dependent count data on selected links.

After the supply-side and demand-side parameters are obtained, the capability of capturing weather effects on the traffic flows is tested by performing simulations with specific weather scenarios. Given the time required for full-calibration of the network model, the weather-related validation is conducted on one of the networks. The Chicago network is selected for this purpose. First, days with rain or snow events between 5AM and 10AM are identified and the traffic observations are collected for each identified day. Each weather scenario is simulated with the calibrated OD matrix with and without using weather adjustment factors (WAF) in DYNASMART-P. Then the simulated results are compared with the actual observations under the specified weather condition.

Performance measure of simulation is considered at two different levels, aggregated network level and individual link level. At network level, two measures of error are used: \( RMSE_{Flows} \) and \( RMSE_{Speeds} \). \( RMSE_{Flows} \) represents the discrepancy between the observed and simulated link counts for all time periods for all links. Similarly, \( RMSE_{Speeds} \) represents the discrepancy between the observed and simulated link speed for all time periods for all links. These two quantities are calculated using the following equations.

\[
RMSE_{Flows} = \sqrt{\frac{\sum_{l=1}^{L} \sum_{t=1}^{T} (M_{l,t} - O_{l,t})^2}{LT - 1}} \tag{7}
\]

\[
RMSE_{Speeds} = \sqrt{\frac{\sum_{l=1}^{L} \sum_{t=1}^{T} (MS_{l,t} - OS_{l,t})^2}{LT - 1}} \tag{8}
\]

where \( M_{l,t} \) is the simulated link flow, whereas \( O_{l,t} \) is the observed link flow on link \( l \) at time \( t \). Similarly, \( MS_{l,t} \) is the simulated speed, and \( OS_{l,t} \) is observed link speed on link \( l \) at time \( t \).

TABLE 5 shows the results based on the test using a snow scenario observed on January 7, 2010 in Chicago. A lower \( RMSE_{Speeds} \) value for “With Weather Features”, indicates that the discrepancy between the overall simulated and observed link speeds is much smaller when weather specific parameters are used. In other words, the use of the weather adjustment factors captures the weather effect on the road traffic thereby producing more realistic simulation results. Similarly, for the link counts, an equivalent pattern is observed, that is, the counts are matched better in the simulation by using weather features.

The overall experiment results reveal that the weather-sensitive TrEPS indeed has the ability to model the effect of weather conditions.
TABLE 5 RMSE Values for the Selected Snow Scenario

<table>
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<th>SNOW Scenario: 2010-01-07 (Chicago)</th>
<th>RMSE Speeds</th>
<th>RMSE Flows</th>
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<td>Without Weather Features</td>
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Graphical comparison is made at individual link level. FIGURE 6 presents observed and simulated speeds with and without weather specific parameters on a selected link. FIGURE 7 presents observed counts vs. simulated counts with and without weather specific parameters on a selected link. In the link-level comparisons, it is observed that simulation results that consider the snow effects are closer to the actual traffic conditions than those that ignore the weather effects.

![Observed and Simulated Speeds](image-url)

FIGURE 6 Observed and Simulated Speeds on a Selected Link in Chicago Network
FIGURE 7 Observed and Simulated Counts on a Selected Link in Chicago Network

CONCLUSION

Systematic procedures for calibrating weather-sensitive traffic flow models for application in the TrEPS mesoscopic network simulation model are developed in this paper, from data collection, through model parameter estimation, to model validation. The methods are demonstrated and applied in four different networks in the U.S. using publicly available traffic and weather data. The results show that inclement weather can affect traffic flow by changing the values of some model parameters, e.g., heavy snow could reduce free flow speed and the maximum service flow rate on highways by as much as 30-40%. It is observed
that the impact increases with the severity of weather condition (visibility, rain/snow intensity), which is consistent with the findings in the literature. The DTA simulation based model validation results show that when a well-calibrated traffic flow model is integrated in TrEPS, it is able to produce more realistic traffic conditions under weather than when running the simulation without considering any weather effect. The methodology developed in this paper could be incorporated in connection with Weather-Responsive Traffic Management systems, thereby providing a tool to better model 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. Given the diverse range of geographic regions of the site locations considered in this study, the extensive set of parameter estimates compiled herein provides a rich library that could support future applications of simulation-based dynamic network models to address weather-related scenarios in different locations where local data may not be available, or where the time and/or cost available for the study may not allow full-blown local calibration. Additional validation and consideration of more sites would contribute to expanding the database and advancing the state of the art and practice in weather-response network traffic modeling.

ACKNOWLEDGMENT

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