Evaluation of Weather-Related Freeway Car-Following Behavior using the SHRP2 Naturalistic Driving Study

Britton E. Hammit Ph.D. Candidate[1] | Ali Ghasemzadeh, Ph.D.[1] | Rachel M. James Ph.D. Candidate[2] | Mohamed M. Ahmed, P.E. Ph.D.[1] | Rhonda Kae Young, P.E. Ph.D.[3]

[1]University of Wyoming, [2]The University of Texas at Austin, [3]Gonzaga University

UNIVERSITY OF WYOMING

Motivation

Adverse weather conditions **negatively impact the safety, mobility, and reliability of the transportation network**. Weather Responsive Traffic Management (WRTM) strategies have been developed to counteract the hazards and discomforts of adverse weather on the transportation system. In order to secure investments for applications designed to mitigate the negative impacts of adverse weather, explicit evidence of the perceived benefits and challenges are required. Microsimulation modeling is a common tool used to anticipate these impacts and has more recently been introduced in real-time operational strategies. However, for reliable output results, realistic driving behavior must be represented in the models.

The purpose of this paper is to present findings related to intra-driver heterogeneity as a function of weather, or the adjustment in driving behavior to compensate for different adverse weather conditions.

This study provides an evaluation of drivers' car-following behavioral changes in various adverse weather conditions—rain, snow, and fog—and calibrates the Gipps car-following model to identify the transferability of those behavioral nuances.

The results produce conclusive evidence that intra-driver heterogeneity exists in different adverse weather conditions and indicate that this heterogeneity can be captured by calibrated Gipps parameters. **This study supports a greater consideration of weather in current microsimulation modeling practices and contributes a novel trajectory validation methodology that can be used to compare observed and modeled behaviors.**

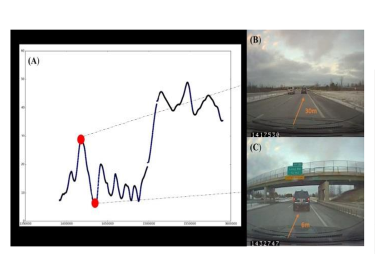
Data

SHRP2 Naturalistic Driving Study (NDS) data were used to conduct this study. As part of the AASHTO Implementation Assistance Program, WYDOT acquired a subset of the NDS database to enable the identification of driving behavior nuances present in adverse weather conditions.

Preliminary data reduction and processing was completed using the **Wyoming NDS Data Analysis Tool**, which is a python-based analytic tool developed by the research team to efficiently process the NDS data.

Automatic Identification of "Car-Following Events", or time frames of data for which the subject vehicle is following a single lead vehicle, was completed when the following criteria were met:

- Minimum of 20 seconds in length
- Maximum of 60 meters apart
- Minimum subject vehicle speed 1 m/s



Trip Sets, which are sets of trips taken by the same driver, on the same route, but in different weather conditions were identified.

Weather Conditions	Count		Average					
	Trip Sets	Trips	Trip Length [min]	Distance Traveled [km]	%Time in car-following	Time in car-following [min]	No. of car-following events	Mean trip velocity [m/s]
All	111	270	26.4	11.4	48%	11.5	6.8	25.9
Fog	2	5	24.2	11.2	60%	14.7	6.6	28.3
Very Light Rain	24	60	26.4	11.2	51%	12.5	7.5	25.6
Light Rain	59	146	25.9	11.2	47%	11.3	6.7	25.9
Moderate Rain	17	40	31.1	13.6	42%	11	6.6	25.4
Heavy Rain	3	7	19.1	9	53%	10.3	6.4	28.4
Snow	4	10	27.5	13.2	38%	8.1	4.1	27.1

Gipps Car-Following Model Calibration

The Gipps car-following model is a safety distance car-following model introduced in 1981, and has been used in many research studies and practical analyses since. The Gipps Model has six input variables:

1. **Reaction Time**
2. **Desired Velocity**
3. **Desired Acceleration Rate**
4. **Desired Deceleration Rate**
5. **Predicted Lead Vehicle's Max Deceleration Rate**
6. **Minimum Separation Gap at a Stop (v=0)**

Model calibration requires the systematic adjustment of input parameters to improve output prediction of car-following behavior. The following calibration procedures were used:

a. <u>Objective Function</u>: RMSE
b. <u>Measure of Performance</u>: Following distance
c. <u>Search Algorithm</u>: Genetic algorithm

The **calibration scores** are shown below. In most conditions a statistically significant difference in calibration score (suggesting the ability of the model to replicate adverse vs. clear conditions) were not identified.

Weather Conditions	Average Clear Score (RMSE)	Average Adverse Score (RMSE)	% Score Difference (+, clear is higher)	T-test, P-value, 2side, 1paired
Fog	6.19	5.35	14.60%	0.698
Very Light Rain	5.79	5.44	6.30%	0.224
Light Rain	5.23	5.29	-1.10%	0.773
Moderate Rain	6	4.51	28.30%	***0.005***
Heavy Rain	4.36	4.24	2.70%	0.837
Snow	3.2	3.28	-2.50%	0.927

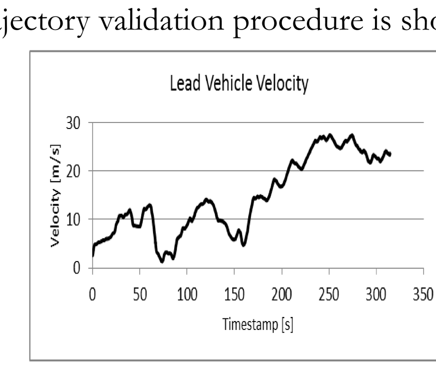
The **average calibrated parameter values** for each condition are shown below. T-test analyses indicate few conclusive trends between calibrated parameter values among clear and adverse weather conditions.

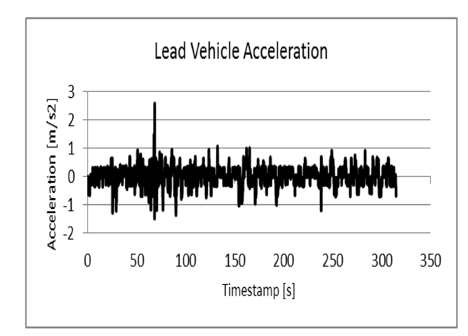
Weather Conditions	Average						
	Reaction Time	Desired Velocity	Desired Acceleration	Desired Deceleration	Predicted Lead Deceleration	Desired Minimum Gap	Deceleration Ratio
Clear	0.8	33.1	1.6	-2.5	-2.4	2.9	1.1
Fog	1.1	32.2	1	-2.9	-2.7	4.4	1.1
Very Light Rain	1.1	33.2	1.6	-2.5	-2.3	3.1	1.1
Light Rain	1	31.1	1.7	-2.5	-2.2	3.2	1.1
Moderate Rain	1	30.2	1.5	-2.5	-2.3	3.6	1.1
Heavy Rain	1.7	34.3	1.3	-2.2	-1.7	3.8	1.2
Snow	1.2	31.8	1.5	-2	-2	3.5	1

Driving Behavior Validation

Car-following model validation is typically performed using one of two primary methods: cross-validation and simulation-validation. **For this study, concepts from the simulation validation methodology are used to inform an alternate method of validation,** such that the intra-driver heterogeneity captured in calibration can be reviewed and quantified. This procedure is called **trajectory validation**, and requires the selection of a realistic car-following event, in which the initialization of the following vehicle and the lead vehicle's trajectory can be used to create following trajectories from each calibrated parameter set. In this manner, **the driver behavior from calibrated model parameters in each adverse condition are compared with the observed behavior differences to determine if the calibrated model is able to replicate driving behavior nuances** (e.g., increased time gap, decreased acceleration).

The selected lead vehicle trajectory (speed and acceleration) used for the trajectory validation procedure is shown below:





Using the calibrated parameters from each trip set, the **root mean square error (RMSE) and Pearson's R correlation coefficient were calculated between each adverse and clear trip** (to identify the magnitude of difference between the predicted behavior).

Weather Conditions	Average RMSE		
	Following Distance	Relative Velocity	Acceleration
Fog	5.7	0.5	0.2
Very Light Rain	5.6	0.3	0.2
Light Rain	5.4	0.3	0.2
Moderate Rain	6.8	0.4	0.2
Heavy Rain	12.4	0.5	0.4
Snow	13.7	0.5	0.3

Weather Conditions	Average R Coefficient		
	Following Distance	Relative Velocity	Acceleration
Fog	0.94	0.78	0.86
Very Light Rain	0.93	0.88	0.89
Light Rain	0.91	0.86	0.88
Moderate Rain	0.79	0.85	0.84
Heavy Rain	0.90	0.82	0.68
Snow	0.87	0.79	0.75

The **RMSE results for following distance** show a clear positive trend indicating that the average difference between Gipps predicted behavior increases with weather intensity. The **Pearson's R correlation coefficient results for following distance** also show greater trend variance as the weather intensity increases. Results for relative velocity and acceleration are similar.

The observed car-following behavior from the original data are compared with the calibrated behavior using the validation trajectory.

Comparison of Following Time Gap

When considering car-following behavior, the intuitive variable to consider is the following gap. In this analysis, the time gap [*g*] is calculated by dividing the following distance [*dX*] (collected from the vehicle's radar unit) by the subject vehicle's velocity [*u*].

A negative value indicates a larger magnitude during the adverse condition, compared with the clear condition (e.g., a negative mean time gap in fog conditions indicates the mean time gap is larger in fog than in the matching clear trips).

Weather Conditions	Average Difference in					
	Actual Trajectories			Validation Trajectories		
	Mean Time Gap [s]	Percentile 85 Time Gap [s]	Time Gap Standard Deviation [s]	Mean Time Gap [s]	Percentile 85 Time Gap [s]	Time Gap Standard Deviation [s]
Fog	-0.07	-0.05	0.11	-0.4	-0.59	-0.17
Very Light Rain	**-0.11**	**-0.1**	**0.02**	**-0.09**	**-0.1**	**-0.02**
Light Rain	**-0.13**	**-0.17**	**-0.04**	**-0.11**	**-0.16**	**-0.05**
Moderate Rain	**-0.24**	**-0.28**	**-0.09**	**-0.14**	**-0.2**	**-0.04**
Heavy Rain	-0.15	-0.25	-0.1	-1.05	-1.55	-0.31
Snow	-1.64	-2.25	-0.58	-0.89	-1.2	-0.22

Weather Conditions	Average Percent Difference in					
	Actual Trajectories			Validation Trajectories		
	Mean Time Gap [s]	Percentile 85 Time Gap [s]	Time Gap Standard Deviation [s]	Mean Time Gap [s]	Percentile 85 Time Gap [s]	Time Gap Standard Deviation [s]
Fog	-10%	-11%	38%	-21%	-24%	-26%
Very Light Rain	**-8%**	**-7%**	**-2%**	**-5%**	**-4%**	**-5%**
Light Rain	**-13%**	**-12%**	**-10%**	**-7%**	**-7%**	**-7%**
Moderate Rain	**-16%**	**-14%**	**-11%**	**-9%**	**-11%**	**-9%**
Heavy Rain	-11%	-16%	-36%	-61%	-73%	-53%
Snow	-64%	-65%	-54%	-49%	-50%	-29%

Both observed and calibrated conditions suggest a greater deviation from clear conditions as weather intensity increases. When comparing actual and calibrated driving behavior, very light, light, and moderate rain conditions follow similar trends in both the actual and validation trajectories, while fog, heavy rain, and snow conditions are less similar. The reason for this difference is likely related to the sample size available for fog, heavy rain, and snow conditions.

Comparison of Time to Collision

From a safety perspective, time-to-collision (TTC) is a common metric used to quantify collision potential. Various forms of TTC are often used in microsimulation model analyses to evaluate the safety of a specific corridor or intersection. In this study, the basic definition of time-to-collision—only accounting for a rear-end collision with the lead vehicle—is considered.

A negative value indicates the TTC for adverse conditions are greater than for clear conditions. TTC is highly subjective to specific scenarios; therefore, it is expected to find large variation in the actual observed car-following events. As shown, few discernable trends are detected for the actual trajectories.

Weather Conditions	Actual Trajectories		Validation Trajectories	
	Average Difference in Median TTC [s]	Average Percent Difference in Median TTC [s]	Average Difference in Median TTC [s]	Average Percent Difference in Median TTC [s]
Fog	8.68	-211%	-5.9	-5%
Very Light Rain	-1.29	-52%	7.2	8%
Light Rain	4.37	-165%	3.8	4%
Moderate Rain	-5.72	931%	4.9	6%
Heavy Rain	14.95	-65%	29.1	33%
Snow	-2.12	-298%	13.3	14%

Conversely, consideration of the validation trajectories (which are comparable because they were all generated from the same car-following event) shows a slight negative trend relating a decreasing TTC (positive values indicate TTC in clear weather is higher than in adverse weather) with increasing weather intensity.

This finding suggests that the modeled vehicle exhibits riskier behavior in higher intensity weather conditions, likely caused by delayed perception-reaction times and less efficient maneuverability.

Discussion & Conclusions

Chapter 11 of **the 2016 Highway Capacity Manual (HCM) provides Weather Adjustment Factors (WAFs)**, which can be used to predict reduced network speeds, freeway capacity, and estimated demand for evaluating travel time reliability. The factors are reported as a function of: (a) weather type and intensity and (b) facility free flow speed (FFS).

From the adjusted freeway capacities, adjusted time gaps between vehicles can be calculated and are shown in Table 10. **In most conditions, the observed average time gap is less than the calculated adjusted time gap from the HCM** (with the exception of medium-heavy snow), **while the calibrated average time gap is higher** (derived from the trajectory validation procedure).

Description of Weather Condition from the HCM	Adjusted Time Gap	Observed Average Time Gap	Calibrated Average Time Gap
Non-Severe Weather	1.40	1.26	1.48
Medium Rain	1.54	1.52	1.64
Heavy Rain	1.66	1.49	2.25
Medium-Heavy Snow	1.58	2.24	1.91
Low Visibility	1.58	1.12	1.72

The differences in headway estimations between the HCM, observed data, and calibrated conditions are not surprising, as there are many factors and assumptions impacting the development of the HCM WAFs, as well as limitations related to using high resolution driving data. A few of these elements are discussed below:

- **Discretization of weather conditions into explicit categories** is extremely challenging due to the number of elements impacting a drivers' perception of and reaction to adverse weather (e.g., visibility, road surface quality, and vehicle performance).
- **Heterogeneity in driver behavior among different geographic locations** is a common assertion (e.g., drivers from X-state are worse than drivers from Y-state). Guidance suggesting different highway capacities and free flow speeds are available from different transportation agencies nationally and internationally.
- The **method of data collection and the sample size** used in this study focus on the behaviors of 32 drivers out of the 210 million licensed drivers in the United States. Nonetheless, these results still contribute to the understanding of how drivers adjust their behaviors in specific weather conditions.

Acknowledgements

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