Grip Sensor Technology and Salt Applications

Final Report

CLEAR ROADS

research for winter highway maintenance

Western Transportation Institute

Project CR21-01
August 2025

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16. Abstract (Limit: 250 words)

This project examined roadway grip, or friction, as a viable data source for informing winter maintenance operations, specifically identifying who is using grip data and how it is applied. A literature review, survey, and case studies were developed. Data from two unique case examples, stationary RWIS based grip data and mobile grip data were paired with AVL solid deicer application rate data, and road weather data; and were used to develop models using grip data to support winter maintenance operations in guidance on salt application rates. A long-short term memory (LSTM) neural network model was established to predict the time-dependent evolution of surface grip levels with the inputs of weather parameters, road surface temperature, and salt application rates by considering the sequential effects of road surface grip levels during the winter weather events and make recommendations on salt application rates based on the prediction of road surface grip levels. The random forest model performed the best among different machine learning models. The most important variables identified from the analysis included surface state after application, surface state before application, air temperature after application, water thickness before application, and surface temperature after salt application.

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Grip Sensor Technology and Salt Application

FINAL REPORT

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LIST OF ABBREVIATIONS

AADT –Annual Average Dailly Traffic

AASHTO – America Association of State Highway Transportation Officials

ABS – Anti-Lock Braking System

ADT – Average Daily Traffic

ACRP - Airport Cooperative Research Program

ANN – Artificial Neural Network

APWA - American Public Works Association

AVL – Automatic Vechicle Location

CARS – Condition Aquisition System

CDOT – Colorado Department of Transportation

CNN – Convolution Neural Network

DEA – Data Development Analysis

DOT – Department of Transportation

EMDSS - Enhanced Maintenance Decision Support System

FCD – Floating Car Data

FHWA – Federal Highway Administration

GA – Genetic Algorithm

GIS – Global Information System

GPS – Global Positioning System

GUI – Graphic User Interface

ISU – Iowa State University

ITD – Idaho Transportation Department

KPI – Key Performance Indicator

LSTM – Long-Short Term Memory

MAE – Mean Absolute Error

MAW – Motorists Advisories and Warnings

MCE – Mobility Cost Efficiency

MDSS – Maintenance Decision Support System

ML – Machine Learning

NCAR – National Center for Atmospheric Research

NCHRP - National Cooperative Highway Research Program

NDA – Non-Disclosure Agreement

OEM – Original Equipment Manufacturer

PNS - Pacific Northwest Snowfighters

QA/QC – Quality Assurance/Quality Control

RCM – Road Condition Monitor

RMSE – Root Mean Square Error

RNN – Recurrent Neural Network

RWIS – road weather information system

SHAP - Shapley Additive Explanations

SHRP - Strategic Highway Research Program

SVR – Support Vector Regression

TGI – Tire Grip Indicator

TRB – Transportation Research Board

UDOT – Utah Department of Transportation

UTC - University Transportation Centers

WMO – winter maintenance operations

WSI – Winter Severity Index

EXECUTIVE SUMMARY

The objective of this project was to examine roadway grip, or friction, as a viable data source for informing winter maintenance operations, specifically identifying who is using grip data and how it is applied. Then using grip data, work to develop a methodology to inform material application rates. The end goal is to apply a developed algorithm that can be used as a tool to advise winter maintenance operators on salt application strategies in winter maintenance activities. The following work was completed to achieve the outlined objective.

A literature review was conducted and identified grip sensor technology and other grip data sources such as floating car or crowd sourced data, reviewed the importance of data QA/QC, and sensor calibration to ensure good quality data is available. The literature review found roadway grip data has been used to support real-time decision making, planning, and post storm or post season reviews in winter maintenance operations. Roadway grip was identified as integrally involved in winter maintenance operations Idaho and Utah, and internationally in Finland, Norway, and Sweden. Specific winter maintenance focused decision support tools include the use of grip values to determine when roads are safe or if winter maintenance treatments are needed, identify or forecast roadway conditions, and treatment options.

A survey of state and local transportation agencies was conducted to assess the use of grip data collection and use in winter maintenance operations. Eighteen states indicated they collect and use grip data in winter maintenance operations. The majority of the grip data was collected using stationary mounted non-contact sensors, with many also collecting grip data from mobile non-contact sensors. The collected grip data is being used to make real-time decisions, determine material application strategies, and for planning, and to a lesser extent for training and review of operations and forecasting. Many agencies indicated that the grip data is used in a variety of tools developed to support winter maintenance operations.

Four case studies were developed on Linking Salt Spreader Controller Data with mobile Road Weather Information Sensors, Snow Operations Application Suite, Third-Party Friction Data from Vehicles (Crowd Sourced/Floating Car Data), and Friction Data and Pikealert. Each case study presents an application of grip data in winter maintenance operations.

The algorithms and a decision-making tool were developed using one unique grip dataset collected from stationary RWIS mounted non-contact sensors. An innovative long-short term memory (LSTM) neural network model was established to predict the time-dependent evolution of surface grip levels with the inputs of weather parameters, road surface temperature, and salt application rates. The LSTM model considers the sequential effects of road surface grip levels during the winter weather events and makes recommendations on salt application rates based on the prediction of road surface grip levels until the desired grip level is achieved. In addition, the effects of influencing factors on friction change before and after salt application are analyzed using another dataset of grip collected from mobile non-contact sensors. The random forest model performed the best among different machine learning models. The

most important variables identified from the analysis included surface state after application, surface state before application, air temperature after application, water thickness before application, and surface temperature after salt application.

Recommendations on the use of grip data to support decision making of salt application rates include the importance of using large robust data sets, QA/QC of data, sensor calibration, uniformity of data collection, and the development of guidance for agencies to support these efforts. To advance the use of the developed decision-making tool, agency specific data should be further collected to refine the model.

CHAPTER 1: INTRODUCTION

Measurement and monitoring of roadway friction coefficients are critical components of road safety and maintenance practices. Accurate friction coefficient data plays a crucial role in assessing and improving the safety and performance of roadways, particularly in adverse weather conditions. Traditional methods of measuring friction coefficients often involve manual testing or stationary devices, which may limit the timeliness and efficiency of data collection (Claros et al., 2021). Non-invasive sensors, which can be positioned away from the road surface either overhead, at the roadside, handheld, or on vehicles, employ techniques such as spectroscopy, thermal radiation, or infrared radar to ascertain surface conditions from afar (Fay et al., 2018; Fay et al., 2013). Recent advancements in sensor technology have led to the development of mobile sensors specifically designed for roadway friction coefficient measurement. These sensors offer the ability to collect real-time friction coefficient data while on the move.

Predicting roadway friction coefficients is a growing field that may be able to aid in ensuring safe and efficient transportation systems. Accurate predictions of friction coefficients can help inform decision-making processes related to road maintenance, vehicle design, and overall road safety. Traditional methods of predicting friction coefficients often rely on empirical models or manual testing, which may have limitations in terms of accuracy and efficiency (Juga et al., 2013; Wiener et al., 2022). However, with the advancements in machine learning methods, there is a growing interest in leveraging these techniques to predict roadway friction coefficients with higher precision and reliability. Abohassan et al. (2023) utilized a location-specific and event-based framework to investigate the influence of different weather variables and maintenance operations on the variability of the pavement friction coefficients during snowstorms in urban environments. The results suggested that precipitation, extremely low temperatures, and the potential for black ice formation worsen pavement friction coefficients. Whereas, plowing operations, application of anti-icing chemicals before snowstorms, and frequent deicing operations have a significant impact on improving pavement friction (Abohassan et al., 2023). Novel predictive models were developed to measure road surface friction, using data from a road-based passive sensor system, to provide decision-making support for maintenance operators (Rasol et al., 2023).

Machine learning algorithms have the capability to analyze large datasets and extract valuable insights that can enhance the accuracy of friction coefficient predictions. Deep learning models have been applied to predict the amount of salt applied at the wheel paths using historical data collected by the road mounted sensors and an optical sensor in Sweden (Hatamzad et al., 2022b). By incorporating Shapley Additive Explanations (SHAP) techniques into machine learning models, researchers can gain deeper insight into the factors influencing friction coefficient predictions and understand the contribution of each feature to the model's output. This advanced methodology allows for more transparent and interpretable friction coefficient predictions, enabling stakeholders to make informed decisions regarding road maintenance and safety measures. The integration of SHAP techniques with machine learning methods holds promise for improving the accuracy and reliability of friction coefficient predictions, ultimately leading to more effective strategies for managing road surfaces and ensuring safe driving conditions (Lundberg et al., 2017).

The objective of this project was to examine roadway grip, or friction, as a viable data source for informing winter maintenance operations, specifically identifying who is using grip data and how it is applied. Then using grip data, work to develop a methodology to inform material application rates. The end goal is to apply a developed algorithm that can be used as a tool to advise winter maintenance operators on salt application strategies in winter maintenance activities.

The report presents the work completed as follows.

CHAPTER 2: Methodology

CHAPTER 3: Literature Review

CHAPTER 4: Survey Results

CHAPTER 5: Case Studies

CHAPTER 6: Algorithm and decision-Making Applications

CHAPTER 7: Recommendations

CHAPTER 8: Conclusions

CHAPTER 2: METHODOLOGY

2.1 LITERATURE SEARCH

A literature review was conducted that focused on past and on-going projects, relevant information on grip data use in winter maintenance operations, grip sensor technologies, and tools used to apply grip sensor data to inform winter maintenance operations.

Databases used to gather information included: Transportation Research Information Database, Google Scholar, ISI Web of Science, Montana State University Library, and similar sources. Research conducted in Canada, Europe, and from other available international sources was reviewed, along with the ongoing research and existing documents published by the DOTs, Clear Roads, Pacific Northwest Snowfighters (PNS) Association, University Transportation Centers (UTCs), Strategic Highway Research Program (SHRP), FHWA, National Cooperative Highway Research Program (NCHRP), Airport Cooperative Research Program (ACRP), American Public Works Association (APWA), and AASHTO, and presented at the Winter Maintenance Peer Exchanges.

A summary of the identified relevant literature is provided in Chapter 3: Literature Review.

2.2 SURVEYS

A survey was developed using Qualtrics, a web-based survey tool. The developed survey was distributed on September 21, 2022 to the Clear Roads Technical Panel and Members states, the Snow & Ice List Serv, the Transportation Research Board (TRB) Winter Maintenance Committee and the Road Weather Committee, and relevant transportation agencies involved in a recent Aurora project Roadway Friction Modeling. The survey was closed on October 21, 2022.

A summary of the survey results is provided in Chapter 4: Survey Results. The survey questionnaire is provided in APPENDIX A – Survey Instrument and notes from a follow-up interview are provided Appendix B – Interview with Nira Dynamics.

2.3 CASE STUDIES

Case studies were developed using information gathered from the literature, survey responses, and follow-up interviews. The following case studies were developed on the use of grip data in winter maintenance operations:

- Linking Salt Spreader Controller Data with Mobile Road Weather Information Sensors (Massachusetts Department of Transportation (DOT) and University of Massachusetts, Amherst)
- Snow Operations Application Suite (Idaho Transportation Department)

- Third-Party Friction Data from Vehicles (Crowd Sourced/Floating Car Data) (Iowa DOT), Wejo, and Nira Dynamics)
- Friction Data and Pikalert (Alaska DOT and Public Facilities (DOT&PF) and the National Center for Atmospheric Research (NCAR))

The developed case studies can be found in CHAPTER 5: Case Studies. A list of individuals and organizations in which follow-up interviews conducted to capture additional information for the case studies can be found in APPENDIX C – Case Study Interviewees (Table 9).

2.4 ALGORITHM & DEICSION-MAKING FOR SALT APPLICATION

Friction data from multiple sources was evaluated along with additional road weather variables, from RWIS stations, and AVL data to assess the feasibility of using grip to optimize winter maintenance operations and develop a decision-making tool for salt application rates to achieve the desired friction. Data was used from two states, Iowa DOT and Colorado DOT, and included surface friction levels from grip sensors, air and pavement surface temperatures, precipitation (rate), dew point, and applied winter maintenance treatments (including initial and subsequent operations of deicing, etc.).

Details of how all data sources were processed and models developed can be found in Chapter 6: Algorithm and decision-Making Applications.

CHAPTER 3: LITERATURE REVIEW

3.1 FRICITON MEASUREMENT TECHNOLOGIES

Severe weather-related crashes account for 21% of all vehicle crashes worldwide (Sollen and Casselgren, 2021). Monitoring road weather and road condition can increase the efficiency of winter maintenance activities and reduce weather-related crashes. A factor of considerable interest is road grip or friction, which indicates how slippery the road surface is. There are several instruments which have been utilized to collect roadway grip data.

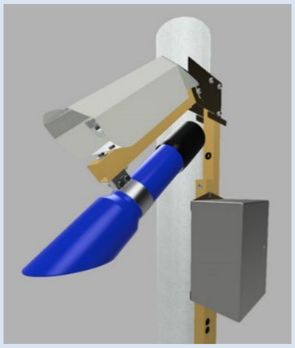
3.1.1 Data Collection Methods

The following general methods are used to collect roadway grip data - stopping distance, deceleration measurements, from calculations using data provided by instrumentation and data acquisition equipment added to/or present on vehicles (Fay et al., 2010), or from non-contact sensors mounted on roadside or on vehicles. While slightly outdated, Fay et al. (2010) provides a summary of many of these friction measuring methods, the functionality, and data quality produced. This report provides discussion of friction wheels or skid trailers. While not the focus of this effort, it is important to note that roadway grip data from other data collection methods is often validated by friction wheels/skid trailers. From a pavement maintenance perspective, locked wheel tests or variable slip devices are commonly used to collect friction data annually or for forensic analysis after accidents. This data can be used to determine baseline pavement friction in non-winter conditions. Due to the lack of winter deployment and limited data collected in US from these devices, this effort will focus on grip data collected from non-contact sensors mounted on roadside or on vehicles, or from data collected by the vehicles themselves and is presented below.

3.1.1.1 Stationary Road Weather Information Systems (RWIS)

Road weather information systems (RWISs) are sensor stations which utilize both in-pavement and non-intrusive sensors to gather real-time atmospheric and pavement surface condition data including grip. An ongoing study, in which this research team is working with Colorado DOT, found that non-contact stationary RWIS-based grip sensors provide consistent and robust roadway grip datasets due to the passive nature of the station (e.g., always on) and their density in the network (e.g., there are a lot of them compared to other grip sensors). However, stationary grip sensors mounted at the RWIS sites provide limited data coverage of an area, because they are only pointing at one location on the pavement, leaving data coverage gaps across a state. Routine maintenance and calibration of these sensors is required annually at a minimum. Table 1 provides information on commonly used stationary non-contact friction sensors currently available.

Table 1. Stationary Sensors

Stationary Sensor Image	Name	Manufacturer	Website
	RWS10	Teconer	https://www.teconer.com/surface-condition-friction-measurements/
	r-condition	Boschung	https://www.boschung.com/en/product/r-condition/
	Remote Road Surface State and Temperature Sensors DST211 and DST111	Vaisala	https://www.vaisala.com/en/products/weather-environmental-sensors/remote-surface-state-sensor-dsc211 https://www.vaisala.com/en/products/weather-environmental-sensors/remote-road-surface-temperature-sensor-dst111
	Stationary Road Weather Information Sensor	Lufft/OTT Hydromet	https://www.lufft.com/products/road-runway-sensors-292/starwis-umb-stationary-road-weather-information-sensor-2317/

Stationary Sensor Image	Name	Manufacturer	Website
	Non-Invasive Road Sensors NIRS31-UMB	Lufft/OTT Hydromet	https://www.lufft.com/products/road-runway-sensors-292/non-invasive-road-sensor-nirs31-umb-2307/
	Ice Sight	HighSierra	No longer available as of March 12, 2024 (Additional information can be found at: https://hsierra.com/?s=IceSight)

3.1.1.2 Mobile Mounted Sensors

Mobile mounted sensors are mounted on vehicles and collect road condition data along the routes the vehicle travels. Generally, these sensors are mounted on supervisors' vehicles, but more recently some sensors can be mounted on plows. Mobile sensors provide grip data for routes and can be used to help fill data gaps between RWIS sites. However, if the vehicle is not routinely driving the routes and collecting grip data on a regular basis, insufficient data will be collected to make informed decisions. It is recommended that mobile sensors are calibrated more regularly (daily, weekly, monthly) for a variety of reasons (hostile environment, cleaning of optics, variation in pavement types, etc.) and the frequency of calibration will be unique to each sensor. See manufacturers' guidelines for calibration frequency and methods. Table 2 provides information on commonly used mobile (vehicle) mounted non-contact friction sensors currently available.

Table 2. Mobile Mounted Sensors

Mobile Sensor Image	Name	Manufacturer	Website
	RCM511	Teconer	https://www.teconer.com/surface-condition-friction-measurements/
	MD30	Vaisala	https://www.vaisala.com/en/products/weather-environmental-sensors/mobile-detector-md30
	MARWIS	Lufft/OTT Hydromet	https://www.lufft.com/products/road-runway-sensors-292/marwis-umb-mobile-advanced-road-weather-information-sensor-2308/
	Mobile IceSight	High Sierra	No longer available as of March 12, 2024 (Additional information can be found at: https://hsierra.com/?s=IceSight)

3.1.1.3 Floating Car Data (FCD) or Crowd Sourced Data

Third parties, like NIRA Dynamics, Volvo Cars, and RoadCloud, have begun utilizing floating car data (FCD), or crowd sourced data, to collect data from vehicle software components. This data can be collected from passenger vehicles or fleet vehicles and can be displayed on a graphic user interface (GUI) which is map-based. NIRA and Volvo Cars estimate roadway grip using a slip-based method which looks at wheel speeds. This method allows for grip data to be collected utilizing existing sensors in the vehicle (Sollen and Casselgren, 2022; Sollen and Casselgren, 2021). This method collects grip data from the wheel track, which represents the closest condition to what a driver experiences on the road. The disadvantage of this data is that is it event-based, meaning deceleration, acceleration, or steering results in more data being captured. If a vehicle is traveling at a constant speed, limited data will be collected (Wallin, 2022; Sollen and Casselgren, 2021). RoadCloud uses optical sensors to estimate roadway grip. While this method can provide continuous grip estimations, it does require extra equipment to be installed on a vehicle (Sollen and Casselgren, 2022; Sollen and Casselgren, 2021).

NIRA Dynamics collects data from vehicles equipped with a tire grip indicator (TGI) which collects road surface grip data (Zachrisson et al., 2022). TGI is a software component within the vehicle which continuously monitors grip between the tire and the roadway. In addition, the TGI collects data on air temperature, relative humidity, and windshield wiper speed. NIRA has collected grip data from fleets of vehicles in Sweden since 2016 and in the Netherlands since 2019. TGI has been integrated into vehicles produced by the Volkswagen Group since 2020, with nearly two million vehicles produced with TGI worldwide each year (Zachrisson et al., 2022). All data is aggregated and anonymized by NIRA. This data can be utilized to adopt performance-based winter maintenance operations. For example, real-time grip data can identify low friction locations which can be used to prioritize winter maintenance activities or collected data can be used to evaluate winter maintenance operations either post-storm or post-season.

The Swedish Transport Administration initiated the Digital Winter Project to examine FCD. FCD was collected from three suppliers, NIRA Dynamics, Volvo Cars, and RoadCloud. This study found that FCD provides similar friction results when compared to a reference method like ViaFrictionm (Sollen and Casselgren, 2022), a tow behind friction wheel, and that FCD coverage made it possible for the Swedish Transport Administration to evaluate the results of maintenance actions during events. The Digital Winter Project found that FCD fleets can provide thousands of grip measurements each minute, particularly during peak traffic time periods, allowing for greater data coverage across the road network (Karim, 2022). The Swedish Transport Administration identified the following benefits of using FCD including better optimization of winter maintenance activities, reductions in negative environmental impacts in winter maintenance activities, reduced traffic crash-related costs, and reduced winter maintenance operations costs (Karim, 2022).

Rijkswaterstaat (RWS), the highway agency of the Netherlands, has been working with NIRA Dynamics FCD since the winter season 2019/2020 to improve their winter maintenance operations. RWS found several uses for FCD, including reducing the number of RWIS sites needed, improving route-based forecasting, and better examination of roadway condition trends which allows for targeted and optimized winter maintenance activities (Donker, 2022).

3.1.1.4 Data QA/QC and Sensor Calibration

Consistent data quality assurance/quality control (QA/QC) ensures that the data collected is of good quality. QA/QC includes consistent periodic examinations of collected data to ensure that the data makes sense. This process can help with early identification of sensors that are down or providing odd readings.

Routine maintenance and calibration of any grip sensors is key to ensuring quality data is being captured. This includes things like periodic cleaning or wiping off the surface of the sensor and ensuring that all sensors are calibrated to the manufacturers' specifications at the recommended frequency.

3.2 USE OF ROADWAY GRIP DATA IN WINTER OPERATIONS

3.2.1 How is grip, friction, data used in WMO?

Roadway grip data has increasingly been of interest to state DOTs and to local and international transportation agencies as it provides a quantitative way to inform and support winter maintenance operations. Roadway grip is of particular interest, because grip values will decrease during winter events as the roadway moves from bare pavement, to wet and or snowy and icy conditions, and this has impacts on mobility and safety. Grip data can be incorporated into winter maintenance operations in many ways including:

Real-Time Decision Making

- Determining when/where roads are no longer safe.
- Determining when/where roads are safe.

Planning

- Determining when to begin winter maintenance operations.
- Determining potential problem areas/hot spots.

Post-Storm/Post-Season Review

- Examine the time period in which the roadway grip was below a defined value or threshold.
- Examine grip recovery time.

- Evaluate performance of winter maintenance activities to determine which techniques are more effective.

3.2.2 Who is using grip data in WMO?

Transportation agencies are increasingly using grip data to inform and support winter maintenance operations. Several agencies have utilized a grip threshold or a defined grip cutoff point between safe and unsafe road conditions to determine when and where to maintain a road or as a method to measure performance.

3.2.2.1 United States

IDAHO DEPARTMENT OF TRANSPORTATION

Idaho Transportation Department (ITD) implemented a number of key performance indicators (KPIs) to evaluate the effectiveness of their winter maintenance program. Using data from their RWIS network, ITD evaluated pattens in grip and adopted a grip level parameter for their winter maintenance operations. When the grip measured by Vaisala's DSC111 sensors was at or below 0.6, then conditions are expected to have an impact on mobility. This threshold of 0.6 is used in ITD's winter mobility index which is a KPI measured for each storm. The mobility index ranges from 0 to 1, representing the amount of time the road conditions did not impact mobility, or the percentage of time the grip value did not fall below 0.6 and with precipitation on a below-freezing roadway. The mobility index is measured as:

$$\text{Mobility Index} = [\text{Grip} \geq 0.6 \text{ duration (hours)/combined events duration (hours)}]\ \%$$

Now maintained by Vaisala, which provides the Mobility Index output on their user interface. ITD's implementation of performance indicators including the mobility index have allowed ITD to assess how well its winter maintenance budget was being utilized (ITS International, 2013). These indicators have allowed the agency to adjust and improve WMO in order to improve efficiency and reduce costs.

Work by Walsh investigated the feasibility of applying ITD Mobility Index in Colorado (Walsh, 2016). Walsh found that the Mobility Index can be applied in Colorado and used as a *performance management tool*-based analysis of CDOTs RWIS data from sections along the I-25 and I-70 corridors. This report assumes that road grip at or below 0.6 indicates the need for treatment or winter operations to be deployed.

UTAH DEPARTMENT OF TRANSPORTATION

The Utah Department of Transportation (UDOT) uses a real-time road weather index to evaluate weather conditions, road conditions, and maintenance performance. The UDOT road weather index quantifies atmospheric conditions and road conditions into a single value; this index accounts for snowfall rate, road temperature, precipitation type, and road grip (Williams, 2022). This index has allowed UDOT to evaluate winter maintenance operations under various conditions, assess resource use, budget and plan for a storm or winter season.

As a part of the road weather index, UDOT has created a performance metric "Rubik's Cube", which is used to determine when road conditions have met an acceptable standard (Figure 1). A grip threshold of 0.50 is used to determine when a road has gone from Red (needs improvement) to Yellow (acceptable).

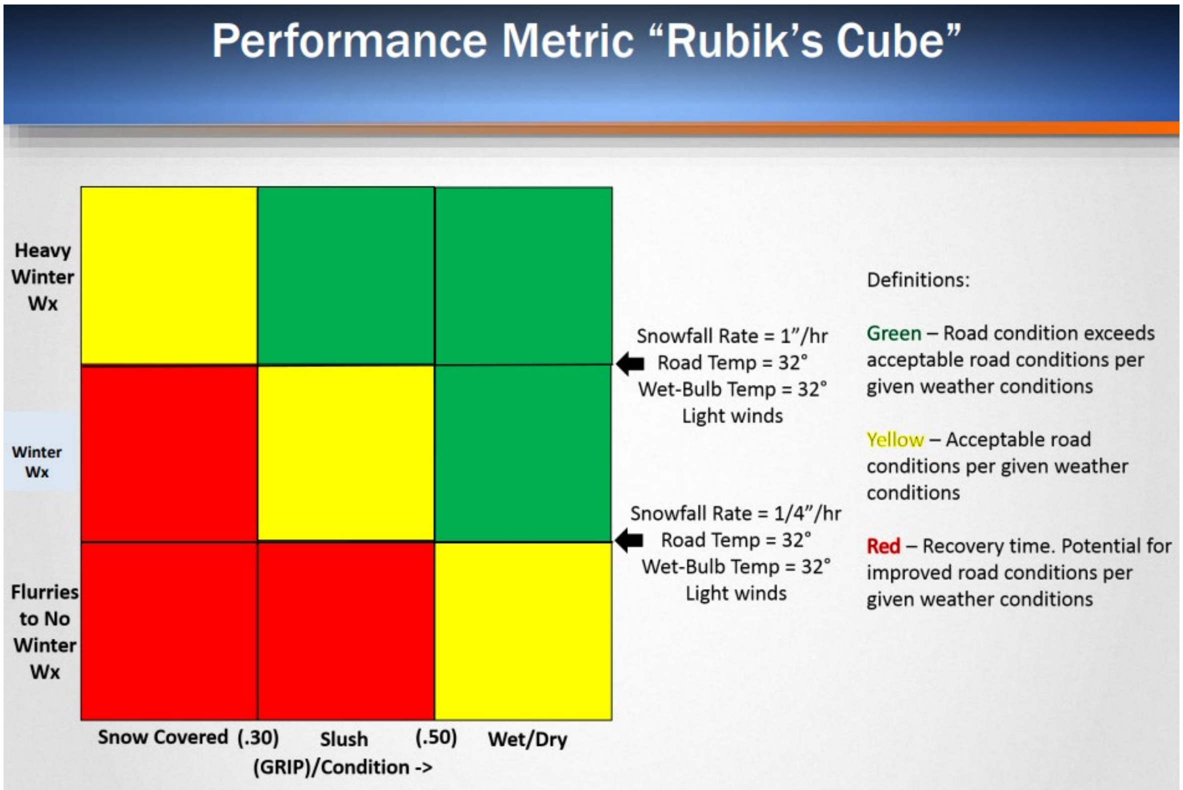


Figure 1. UDOT Performance Metric Rubik's Cube (copied from Williams (2022))

3.2.2.2 International

FINLAND

Finland uses grip measurements to ensure roads remain safe for users. In Finland, they have established road quality standards depending on the road maintenance category (which is based on traffic volume). When a road drops below the set standard grip value (typically around 0.25), it must be returned to that standard within a specific amount of time depending upon the road maintenance class which is based upon average daily traffic (ADT) and classification, see Table 3, Figure 2, and Figure 3.

Table 3. Friction (grip) Value and Driving Conditions for Finland (Recreated from Zein (2009))

Friction Value	**0.00 – 0.14**	**0.15 – 0.19**	**0.20 – 0.24**	**0.25 – 0.29**	**0.30 – 0.44**	**0.45 – 1.00**
Driving Condition	Very Slippery	Slippery	Satisfactory Winter Conditions	Good Winter Condition	Not Slippery	Not Slippery

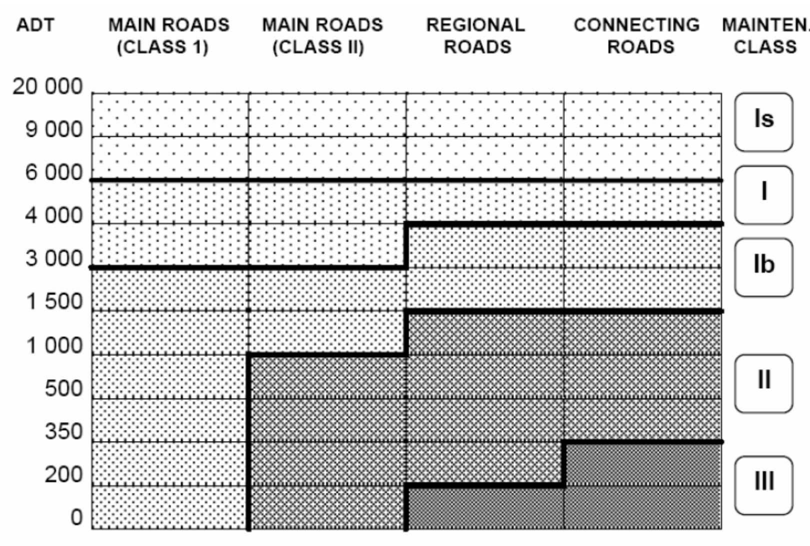


Figure 2. Finland, Road Maintenance Classes (Copied from Zein (2009))

QUALITY STANDARDS OF ANTI-SLIPPING PROCEDURES							
Winter main-tenance class	**Is**	**I**	**Ib and TIb**	**II**	**III**	**K1**	**K2**
Friction requirement — **Normal**	0.30	0.28	0.25	according to traffic de-mands	according to traffic de-mands	according to traffic de-mands	
	road surface below -6 °C **0.25**	Road surface below -4 °C **0.25**	spot sanding **0.25** line treatment **0.20-0.22**				
At night	22 - 05 **0.28**	22 - 05 **0.25**	22 - 05 as needed	22 - 06 as needed	22 - 06 as needed	after 22 K1 by 05 K2 by 06	
Cycle time	**2 h**	**2 h**	**salt 3 h** **sand 4 h**	**6 h** line sanding	**10 h** line sanding	**2 h**	

Figure 3. Finland, Winter Maintenance Quality Standards (Copied from Zein (2009))

SWEDEN

The Swedish Road Administration's current grip thresholds are used as a standard to bring roads back to safe driving conditions within a specified amount of time. This threshold is determined based on the road classification, precipitation type, and road surface temperature. Generally desired grip thresholds range between 0.20 – 0.35, see Figure 4. Generally, a higher-volume road has a higher grip threshold when compared with lower-volume roads.

Standard classes 1–3

Cross-sectional elements	Requirements during precipitation/Action time after precipitation				
	Trigger value		Action time in hours		
	Snowfall	Rain			
	Loose Snow depth cm	Friction μ	Standard class		
			1	2	3
Traffic lane	1	0.30	2	3	4
Side shoulder	1	0.25	4	6	8
Roadside facility	1	0.25	4	6	8

Cross-sectional elements	Dry weather requirements when action time after precipitation has expired			
	Road surface temperature			Evenness cm
	Warmer than -6°C friction coefficient	-6°C to -12°C friction coefficient	colder than -12°C friction coefficient	
Traffic lane	Snow and ice-free	0.35	0.25	1.5
Side shoulder	0,25	0,25	0.25	1.5
Roadside facility	0.25	0.25	0.25	1.5

Standard classes 4–5

Cross-sectional element	Dry weather requirements when action time after precipitation has expired							
	Trigger value				Action Time			
	Loose Snow depth cm		Friction coeff. μ	Eveness cm	Snow depth/friction hours		Evenness hours	
	Standard class				Standard class		Standard class	
	4	5			4	5	4	5
Traffic lane	2	3	0.25	1.5	5	6	48	72
Roadside facility	2	3	0.25	1.5	8	8	48	72

Cross-sectional element	Requirements during precipitation/Action time after precipitation				
	Threshold value			Action time in hours	
	Snowfall		Rain		
	Loose Snow depth cm		Friction coeff. μ		
	Standard class			Standard class	
	4	5		4	5
Traffic lane	2	3	0.25	5	6
Roadside facility	2	4	0.25	8	8

Figure 4. Sweden, Friction (grip) Thresholds (Copied from Zein (2009))

NORWAY

Norway uses grip thresholds as a standard to bring roads back to safe driving conditions in a specified amount of time. This threshold is determined based on the traffic volume, as average annual daily traffic volume (AADT). High-volume roads need to be brought back to a friction coefficient of 0.4, whereas low-volume roads need to be brought back to a friction coefficient range of 0.15 to 0.25 (Figure 5).

Tasks	Triggering criteria and maximum time for action in regard to different AADT		
	< 3000	3001 – 5000	> 5000
Preventive salting	If expected friction value < 0,4	If expected friction value < 0,4	If expected friction value < 0,4
After snowfall: Bare road before	6 hrs.	4 hrs.	2 hrs.

Class of road	AADT	Local sanding		Continuous sanding	
		Start at	Finished within	Start at	Finished within
Trunk Roads		$\mu <$ 0,30	1 hr.	$\mu <$ 0,20	2 hrs.
All other roads	> 1500	$\mu <$ 0,25	1 hr.	$\mu <$ 0,20	2 hrs.
	501 – 1500	$\mu <$ 0,25	2 hrs.	$\mu <$ 0,15	3 hrs.
	0 - 500	$\mu <$ 0,20	2 hrs	$\mu <$ 0,15	4hrs

Figure 5. Norway, Friction Thresholds (Copied from Zein (2009))

Performance metrics utilizing grip data are unique to each transportation agency, depending on the goal of the metric. Example metrics include determining when to treat the roadway or determining the time required to bring a road back to safe driving conditions, etc. Generally, international grip thresholds are lower (around 0.2 to 0.4) when compared with those used in the United States (0.6). Finding the appropriate grip threshold(s) to guide or evaluate winter maintenance activities can be challenging for agencies concerned with driver safety. To determine the most appropriate grip threshold value for your agency consider 1) what grip measurement method best fits your agency and 2) determine the relationship between grip measurements and crash risk in your region (Wallman and Astrom, 2001).

3.3 DECISION SUPPORT TOOLS

Using grip data in winter maintenance operations can be as simple as viewing the data and making an informed decision, such as is done when using grip thresholds. More advanced techniques exist that incorporate road surface condition, temperature, or grip into decision support tools to aid in providing specific guidance for winter maintenance operations, such as deicing products and application rates.

Machine learning based prediction models and decision support tools that apply to the winter maintenance environment or use grip are discussed here.

3.3.1 Machine Learning Based Prediction of Surface Condition and Salt Application

Burris (2018) developed random forest models to predict the observed errors between Road Weather Information Systems (RWISs) and North American Land Data Assimilation System (NLDAS) for the surface and two-meter temperatures. The corrected temperatures were used with different weather variables for the development of the Condition Acquisition Reporting System (CARS) classifier, as shown in Table 4. Decision tree and random forest models were applied to classify the surface condition into Good, Fair, Difficult, and Hazardous. The impacted percentage of road miles was estimated based on the weather feature data using an Artificial Neural Network (ANN) model.

Table 4. Weather Variables for Classification of Road Condition (Burris 2018)

Weather Variable (units)	Source
2m air temperature (K)	NLDAS
10m wind speed (m/s)	NLDAS
Surface temperature (K)	NLDAS
Net surface longwave and shortwave radiation (W/m^2)	NLDAS
Sensible/latent heat fluxes (W/m^2)	NLDAS
Vertical temperature profile (K)	RAP
Categorical precipitation type	RAP
Visibility(m)	RAP
10m wind gusts (m/s)	RAP
Snow depth (m)	SNODAS
Hourly accumulated precipitation (kg/m^2)	Stage IV

Tabrizi et al. (2021) used machine learning techniques to propose an accurate and reliable pavement surface temperature prediction model for road salt management based on the records of hourly temperatures during winter. The proposed methodology was validated using pavement surface temperature data from RWIS and hourly air temperature and solar radiation data from Environment Canada. The deep neural network integrated a Convolutional Neural Network (CNN) with a Long Short-Term Memory (LSTM). LSTM, Convolutional-LSTM (ConvLSTM), Sequence-to-Sequence (Seq2Seq), and Wavelet neural network (Wavenet) models were compared with the proposed model, and the analysis results indicated that the accuracy of proposed model was better than the other models.

Hatamzad et al. (2022a) used four methods to predict road surface temperatures, including linear regression, support vector regression, random forest regression, and artificial neural network. A five-stage framework for intelligent cost-effective WRM prediction was used, including data development analysis (DEA), data acquisition and analysis, feature engineering, feature selection, and cross validation and model evaluation. The results suggested that the proposed methodology could be applied in other prediction applications.

Ahabchane et al. (2019) used machine learning methods to predict the quantity of abrasive and salt required for a specific road segment for each hour based on weather conditions, truck telemetry data, and segment attributes. Geographic information systems (GISs) assisted the researchers to investigate the street-network characteristics. The analysis results indicated that the XGBoost method performs better than other machine learning algorithms. The most important variables were number of passes, segment length, traffic (annual average daily traffic), previous salting quantity, number of passages, truck identity for salt application, roadway width, air pressure, temperature, and elevation. The proposed method could be applied to other regions for different applications of salt and various winter road maintenance practices.

Hatamzad et al. (2022b) developed an ANN model to predict the amount of salt on the wheel track based on the historical data measured by an optical sensor, road mounted sensors, and road condition stations in Sweden. Variables included surface temperature, air temperature, dew point temperature, level of grip, ice layer, precipitation, concentration, conductivity, snow height, freezing temperature, and maximum wind speed. Figure 6 illustrates the relationship between the freezing temperature, amount of chemical, and level of grip. Decreasing freezing temperature and increasing amount of chemical on the wheel track would improve the driving quality on the road surface. The accuracy of the developed ANN model was found as high as 97%.

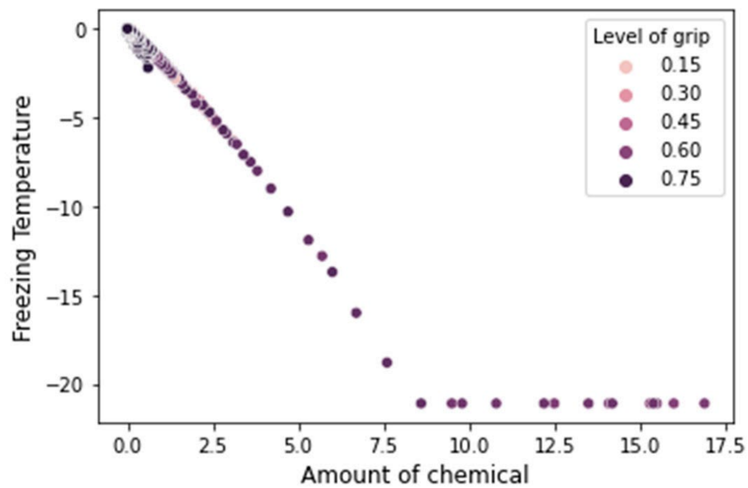


Figure 6. Relationship between the freezing temperature, amount of chemical (g), and level of grip (Hatamzad et al., 2022b)

3.3.2 Machine Learning Based Winter Road Maintenance

Casas et al. (2011) developed a system based on data-mining and multi-agent paradigm to determine the actions to keep the road clean of ice or snow. The data collected at the measurement stations located near the area of interest and stored in the database was used in the multi-agent system, as shown in Figure 7. The multi-agent system consisted of a validation sub-system, prediction sub-system, classification sub-system, and actuation sub-system. The validation sub-system was used to validate the input data to ensure a maximum quality. The prediction sub-system was applied to estimate the meteorological parameters of interest for decision-making, including air temperature, relative humidity, and road surface temperature. The goal of the classification sub-system was to classify the future state of the road surface to decide whether preventive action might be taken. The actuation sub-system was responsible for determining the amount of salt required to maintain clean road surface without ice or snow before a hazardous road situation occurs based on the historical data, numerical prediction, and road state classification.

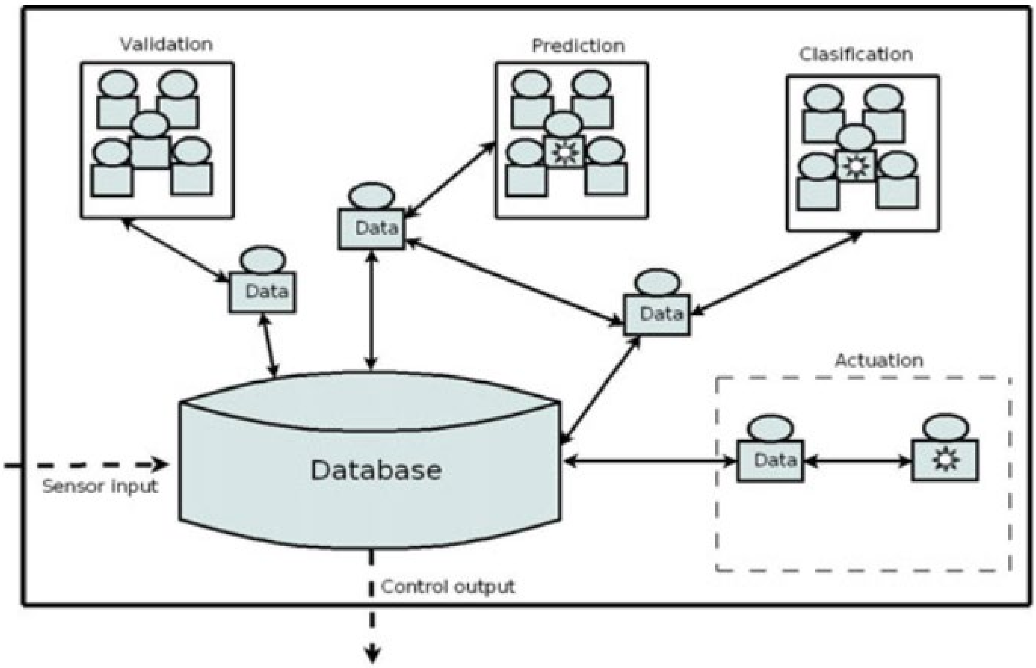


Figure 7. Multi-agent system structure for winter maintenance (Casas et al., 2011)

Hatamzad et al. (2021) developed a classification prediction model for winter road maintenance efficiency by combining DEA and machine learning approaches for the improvement of decision support systems. Road condition data was collected in equivalent time intervals by road weather information systems, optical sensors, and road-mounted sensors. Input of DEA model included surface temperature, base temperature, precipitation, snow height, grip, conductivity, and concentration of chemicals, while output was the amount of chemicals. DEA was applied to calculate efficiency scores according to which efficient and inefficient classes of decision-making units were classified. A series of Machine Learning (ML) approaches were used to classify the labeled efficient and inefficient decision-making units. Support vector machine (SVM) model with optimized parameters by genetic algorithm (GA) was found to perform better than other techniques. As shown in Figure 8, conductivity of salt, base temperature, and level of grip were the top three important input variables for winter road maintenance efficiency. In the proposed approach, inefficient units need to be considered for further assessments.

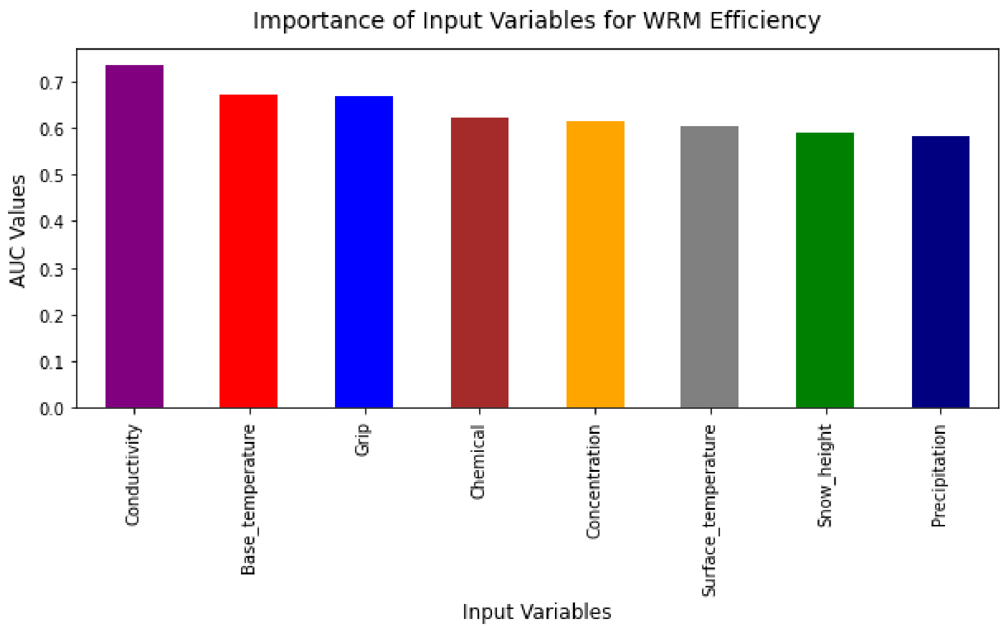


Figure 8. Importance of input variables affecting winter road maintenance efficiency (Hatamzad et al., 2021)

An ongoing project, sponsored by FHWA, is working to develop an AI-based closed-loop approach for winter maintenance decision making (Kessler, 2021). The proposed decision-making framework consists of data, prediction, decision-making, intervention, and feedback, as shown in Figure 9. The research team intend to design the system to collect and process the data through recurrent neural network for deep reinforcement learning to automatically make maintenance decisions. The results from traffic and road conditions will be analyzed using Convolutional Neural Network (CNN) to verify the outcomes and enhance decision-making in the future. The closed-loop approach for winter maintenance activities will start again for another scenario with continuous improvement imbedded in the process as a core principle.

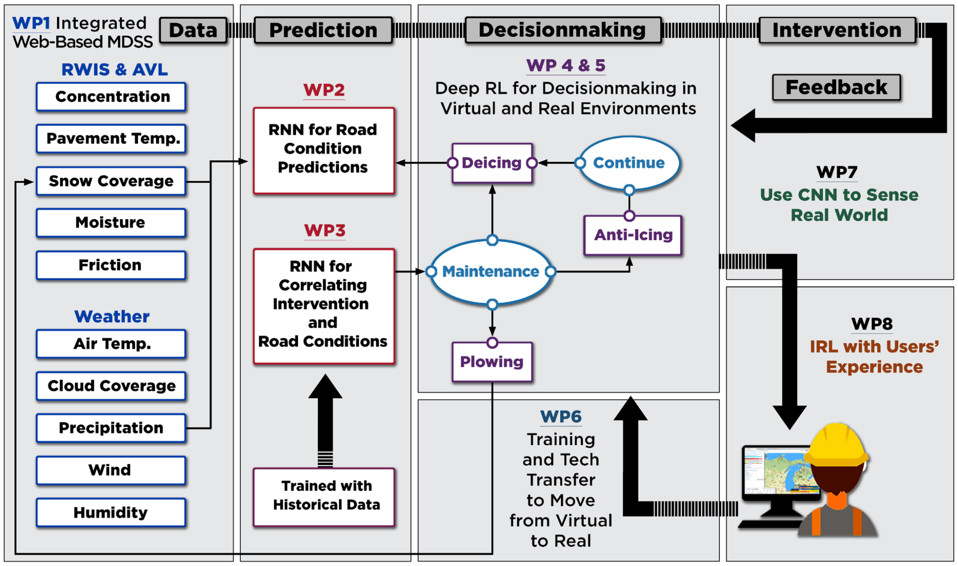


Figure 9. Flowchart of proposed approach for winter maintenance decision making (Kessler, 2021)

CHAPTER 4: SURVEY RESULTS

A total of 41 individuals responded to the survey. Of the 41 responses, 24 respondents (58.5%) indicated that their agency or organization uses roadway grip data in their winter operations, see Figure 10. Those that indicated they do not use roadway grip data in their winter operations were thanked for their time and closed out of the survey.

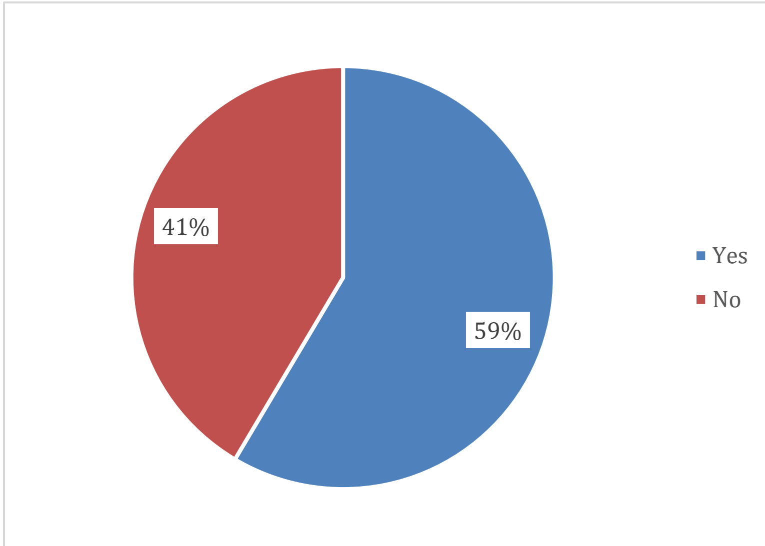


Figure 10. Does your agency use roadway grip data in winter operations?

Respondents came from 18 states across the US, see Figure 11.

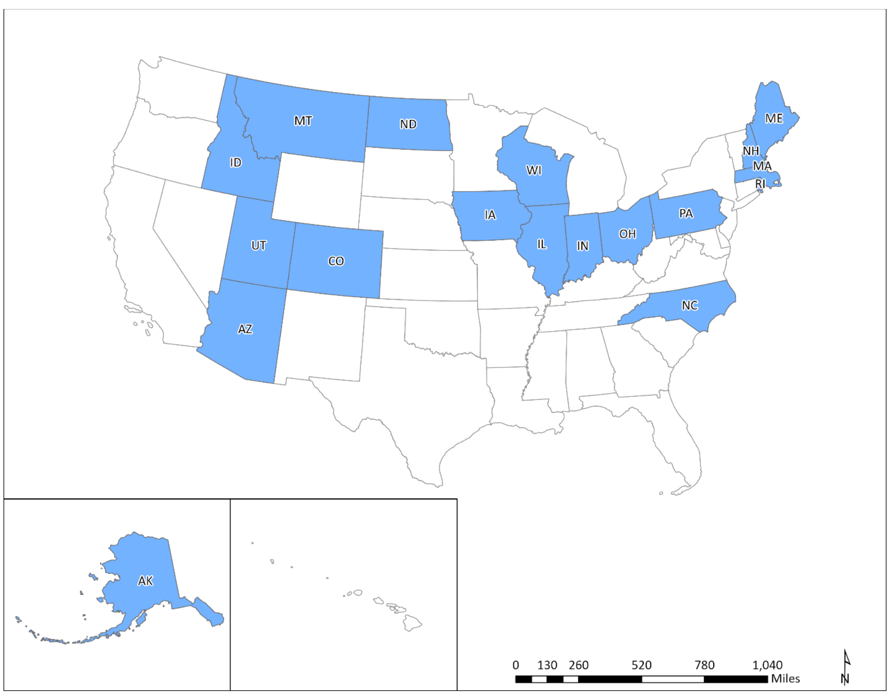


Figure 11. Respondent States that indicated they use roadway grip data in winter operations.

4.1 HOW IS GRIP DATA BEING COLLECTED?

Respondents were asked to share how their agency collects roadway grip data. Twenty-two (22) respondents answered this question (see Table 5 and Figure 12). Stationary road weather information system (RWIS) mounted sensors were the most common grip data collection method being used by 18 respondents (81.8%). Mobile mounted sensors on vehicles are being used by 12 respondents (54.5%). Skid trailers or friction wheels are used by 1 respondent (0.5%). None of the respondents are using floating car data or crowd sourced data to collect grip data. One respondent (0.5%) from Iowa Department of Transportation (DOT) answered other when asked to specify the respondent stated that they recently obtained Wejo data which included grip data however they were currently in the testing and research phase.

Wejo is a third-party data provider powered by Nira Dynamics. Wejo collects data from millions of connected vehicles and provides road network insights like road temperature, slippery road alerts, and live road network updates which can be used to improve winter maintenance operations.[1] The research team conducted a short interview with NIRA Dynamics after they reached out during the surveying process. Notes from that interview are shared in Appendix B – Notes from Interview with NIRA Dynamics.

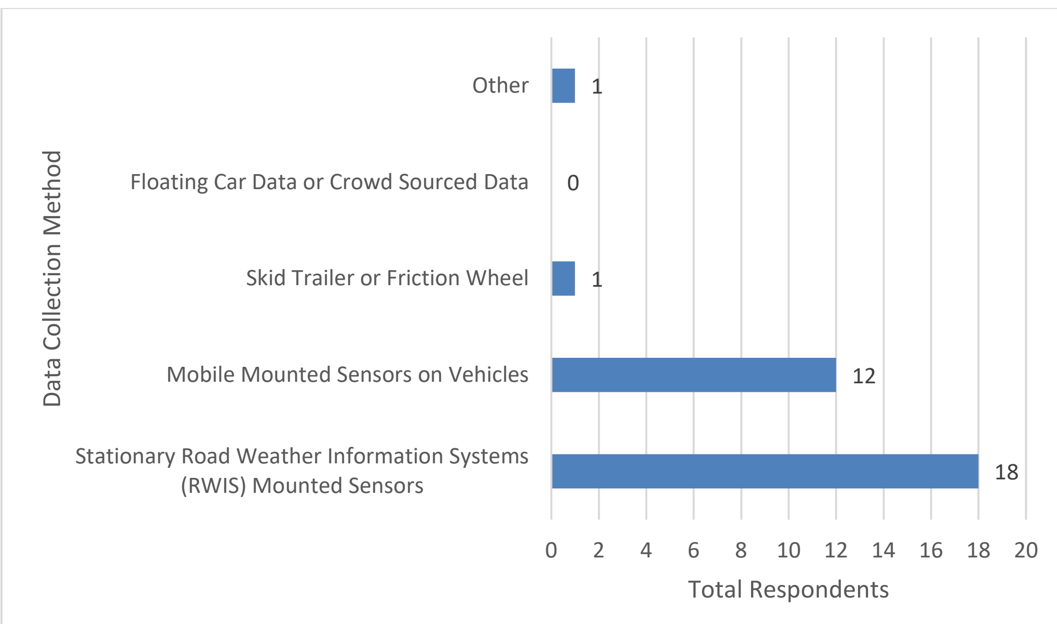


Figure 12. Responses on how agencies collect roadway grip data.

[1] Wejo no longer exists.

Table 5. How does your agency collect roadway grip data?

Agency	State	Floating Car Data or Crowd Sourced Data	Mobile Mounted Sensors on Vehicles	Skid Trailer or Friction Wheel	Stationary Road Weather Information Systems (RWIS) Mounted Sensors	Other
Alaska DOT&PF	Alaska				x	
Arizona DOT	Arizona				x	
Colorado DOT	Colorado		x		x	
Idaho Transportation Department	Idaho				x	
Illinois Dot	Illinois				x	
Niles Public Works - Illinois	Illinois				x	
Roadway Concessionaire - Indiana	Indiana		x			
City of West Des Moines - Iowa	Iowa		x		x	
Iowa DOT	Iowa				x	x
Maine DOT	Maine		x		x	
Massachusetts DOT	Massachusetts		x	x	x	
Montana DOT	Montana				x	
New Hampshire DOT	New Hampshire				x	
New Hampshire DOT	New Hampshire				x	

Charlotte DOT - North Carolina	North Carolina		x			
North Dakota DOT	North Dakota		x		x	
Ohio DOT	Ohio		x		x	
Pennsylvania DOT	Pennsylvania		x		x	
Rhode Island Airport Corporation	Rhode Island		x		x	
Rhode Island DOT	Rhode Island		x			
Utah DOT	Utah				x	
Jefferson County Highway - Wisconsin	Wisconsin		x			

4.2 HOW IS GRIP DATA BEING USED?

Respondents were asked how their agency uses grip data in their winter operations. Twenty-two (22) respondents answered this question (see Table 6 and Figure 13). The majority of respondents (17 respondents, 77.3%) use grip data for real-time decision making (routing, calling in crews, etc.), material application strategies (15 respondents, 68.2%), and for planning (determining when to begin operations, identifying problem areas, etc.) (12 respondents, 54.5%). Around a third of respondents use grip data for forecasting or for retrospective reviews of winter maintenance operations.

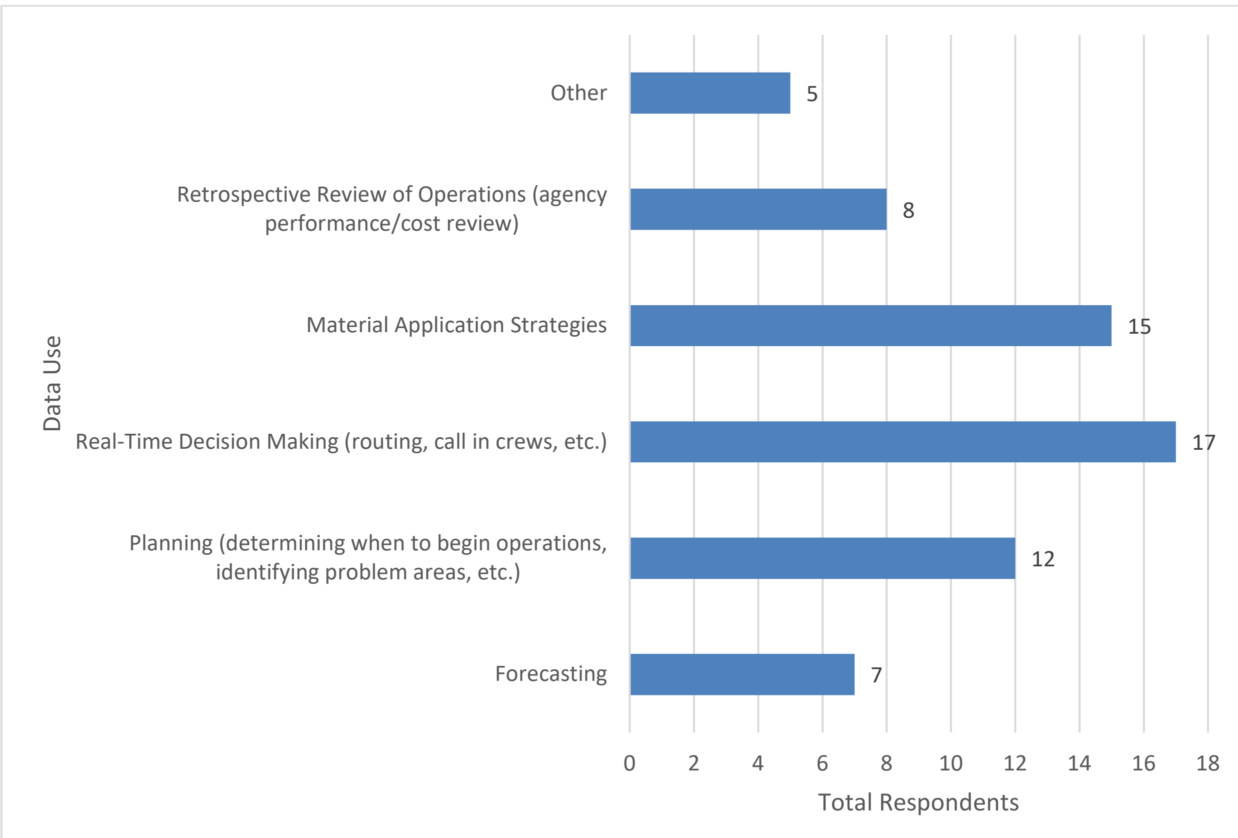


Figure 13. Responses on how agencies use roadway grip data in winter operations.

Table 6. How does your agency use roadway grip data?

Agency	State	Forecasting	Material Application Strategies	Planning (determining when to begin operations, identifying problem areas, etc.)	Real-Time Decision Making (routing, call in crews, etc.)	Retrospective Review of Operations (agency performance/cost review)	Other
Alaska DOT&PF	Alaska	x	x	x	x		
Arizona DOT	Arizona						x
Colorado DOT	Colorado		x	x	x		
Idaho Transportation Department	Idaho		x		x		
Illinois DOT	Illinois			x			x
Niles Public Works - Illinois	Illinois		x	x	x		
Roadway Concessionaire - Indiana	Indiana		x	x	x	x	x
City of West Des Moines - Iowa	Iowa	x	x	x	x	x	
Iowa DOT	Iowa	x	x		x		
Maine DOT	Maine	x			x		
Massachusetts DOT	Massachusetts		x	x	x	x	
Montana DOT	Montana						x
New Hampshire DOT	New Hampshire				x	x	

New Hampshire DOT	New Hampshire					x	
Charlotte DOT - North Carolina	North Carolina		x		x		
North Dakota DOT	North Dakota		x		x	x	
Ohio DOT	Ohio						x
Pennsylvania DOT	Pennsylvania	x	x	x	x	x	
Rhode Island Airport Corporation	Rhode Island		x	x	x		
Rhode Island DOT	Rhode Island	x	x	x	x		
Utah DOT	Utah	x	x	x	x	x	
Jefferson County Highway - Wisconsin	Wisconsin		x	x	x		

Five respondents noted that they are using grip data in another way, see Table 7. These included using grip data to look at bare pavement regain time post-precipitation. Most of these responses noted that grip data is currently being evaluated for use in their agency.

Table 7. Additional explanatory responses on how agencies use grip data in winter operations.

Agency	Response
Illinois DOT	The implementation of the data is being reviewed for potential improvements.
Ohio DOT	They are looking at the data, but we do not have a formal plan on how to use the data.
Roadway Concessionaire - Indiana	Bare pavement regain post precip[itation]
Montana DOT	Informational only at this point, as we have only 1 RWIS station with grip (out of 78 stations), and it has been installed for less than 4 months.
Arizona DOT	Still evaluating.

Last, respondents were then asked whether their agency incorporates roadway grip data into any tools like a maintenance decision support system (MDSS) or a winter severity index (WSI). Out of the 22 responses, 12 respondents (54.5%) indicated they currently incorporate grip data into a tool. Explanatory responses are provided in Table 8. Three agencies noted using grip data for post-storm reporting and evaluation of winter maintenance operations, including the use of grip data in a weather severity index (Maine DOT and Pennsylvania DOT). Several agencies mentioned incorporating grip data into a maintenance decision support systems (MDSS) or other real-time decision-making tools. One agency (Colorado DOT) noted that they have incorporated grip data into public travel notifications.

Table 8. Explanatory responses on how agencies incorporate roadway grip data in any tools.

Response	Agency
Data is ingested into our Pikalert Enhanced Maintenance Decision Support System (EMDSS) and used in forecast models.	Alaska DOT&PF
This is through the third-party AAR.	Arizona DOT
We share our data with our weather service provider to provide more timely and accurate forecasts and treatment recommendation.	City of West Des Moines - Iowa

Mobile sensors [are] mounted on supervisor vehicles to see if there are areas being neglected or inadvertently missed. [Grip data is] incorporated into MDSS and public travel notifications.	Colorado DOT
Forecasters have access to the data. Field staff use as needed for decision making.	Iowa DOT
We have two friction meters. One mounted on a plow and the other on a vehicle. The data is collected and used by WisDOT and the Traffic Operations and Safety (TOPS) Lab at UW Madison. We use the friction recordings to make real time field decisions.	Jefferson County Highway - Wisconsin
It is used in standard post-storm reporting of treatment and WSI.	Maine DOT
We are embarking on a research project that will feed roadway grip levels into a salt spreader controller. Grip levels will be used to control the salt spreader's dispensation rate.	Massachusetts DOT
It is incorporated into the MDSS application to be viewed only. Currently it is not used in the modeling. We have 16 MARWIS [mobile grip sensors] on plow trucks being used in real time decision making.	North Dakota DOT
PennDOT incorporates roadway grip data into the Winter Severity Index for end of the season review.	Pennsylvania DOT
Runway, Taxiway and Apron Snow and Ice Control for both chemical applications and to relay the surface conditions to inbound and outbound air traffic.	Rhode Island Airport Corporation
Road grip is incorporated into our snow and ice performance measure.	Utah DOT

CHAPTER 5: CASE STUDIES

The following four case studies have been developed to highlight the use of grip data in winter operations.

5.1 LINKING SALT SPREADER CONTROLLER DATA WITH MOBILE ROAD WEATHER INFORMATION SENSORS

Massachusetts Department of Transportation/University of Massachusetts Amherst

The Massachusetts Department of Transportation (MassDOT) has partnered with the University of Massachusetts Amherst (UMass Amherst) to develop a salt spreader controller program that will use data from mobile road weather information systems (mobile RWISs, MD30 from Vaisala), which will be installed on MassDOT snowplows.

MassDOT owns over 300 material spreaders and contracts 1,200 additional material spreaders which apply salt, salt/sand, or liquid deicers on Massachusetts roadways. These material spreaders use Certified Cirus (Cirus SpreadSmart system) controllers and Bosch Rexroth (Compu-Spread systems) to control material spread rates. This project will incorporate mobile RWIS data to improve the assessment of roadway conditions and make informed decisions on material application rates in order to maintain the roadway level of service while reducing environmental impacts. The current system requires manual reading of the mobile RWIS data, and this project will look to integrate an automated system that will use an integrated grip value from mobile RWIS data (e.g., grip value, road and ambient temperatures) and an integrated surface state from an external camera system (e.g., roadway surface condition and snow/ice condition) to adjust the spreader controller in order to optimize material use.

This automated system will include three modules: 1) mobile RWIS data collection, which will organize, transfer and store data from the mobile RWIS sensors; 2) treatment decision-making module, which will be an automated decision-making algorithm to determine material application rates necessary; and 3) spreader control module which will implement the decision and provide a user interface.

UMass Amherst worked with MassDOT to install MD30 mobile RWIS on two snowplows. The mobile RWIS data will be used to develop an automated decision-making algorithm for determining material application rates, which will be based on MassDOT's current recommended application rates. This will be used in coordination with automated vehicle location (AVL) and cameras to examine roadway condition and track plow location.

This project is currently in its early phase. Data will be collected, and winter maintenance operation performance will be examined over two winter seasons (2022-2023 and 2023-2024). UMass Amherst will also complete field scenario testing to validate the mobile RWIS sensor-based model for the material spreader controller. If this method is verified, then the project will be expanded, and detailed training tutorials and presentations will be developed.

This project ended in July 2024, after this case study was developed. The following additional information has been provided to support this effort based on information from the final report (Ai et a., 2024). Mobile RWIS and AVL data were used to optimize material application rates. To do this hardware integration, software development, along with a road surface condition deep learning algorithm and salt prediction model were used. Using both winter weather and performance data, and simulations they found the salt rate prediction model performed best showing 34-37% in potential salt saving using the developed system while maintaining similar performance. Ultimately they were able to send grip values from the mobile sensor to the spread controller system on the snowplow to dispense the commensurate amount of salt.

CONTACT INFORMATION

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5.2 SNOW OPERATIONS APPLICATION SUITE

Idaho Transportation Department

Idaho Transportation Department (ITD) partnered with Environmental Systems Research Institute (ESRI) to develop the Snow Operations Application Suite. This application was developed with the goal of providing a way to automate, visualize, and communicate ITD's Mobility Cost Efficiency (MCE) calculations which are used by Idaho's maintenance districts to examine the amount and types of deicing materials used during a storm and make recommendations to reduce the amount of deicing material being used on roadways while maintaining the roadway level of service. The MCE is used to examine performance over storm events and winter seasons and to track resources used including material, labor, and equipment. Previously ITD was completing MCE calculations manually which is time consuming for maintenance district forepersons. The developed application allows these calculations to be completed automatically and provides a geographical view of this data.

The MCE utilizes storm data attributes collected from the state's 130 road weather information system (RWIS) stations and automatic vehicle location (AVL) data from snowplows to determine if the Clear Roads treatment recommendations (material application rates) which are used to compare against the actual material application rate used. For example, ITD costs and salt use versus that recommended by Clear Roads [(ITD costs/Clear Roads)x100]. If the score is 100% than roads were treated "perfectly", less than 100% would indicate that ITD did not treat roadways in the same manner as was recommended by

Clear Roads during that storm event. The MCE is calculated for segments of roadways, which are roughly 2-mile sections of roadway nearest to a RWIS site.

The application was developed over a few years. It originally was tested at four RWIS sites in Northern Idaho and was rolled out by ITD for all RWIS sites in November 2022. The application includes three modules:

1) Live View: The live view includes data on the last three storm events for each RWIS segment, see Figure 14. If a critique is recommended (a critique identifies areas for potential improvement based on pretreatment, response timing, application rates, and resource constraints), then a user can pull up event statistics including MCE, a summary of all data inputs, costs (equipment, driver, material), etc. MCE compares actual treatment data versus the Clear Roads treatment matrix. Data is based on a one-hour lap time. Friction data is reported as a range in Live View, and currently detailed friction data tied to application rates are not provided.

   The live view also provides ITD's mobility score for each RWIS site. ITD's mobility score utilizes a roadway grip threshold of 0.6, as a key performance metric for winter maintenance operations. If roadway grip is at 0.6 or lower, then conditions are expected to have an impact on mobility. The mobility index ranges from 0 to 1, representing the amount of time that road conditions did not impact mobility, or the percentage of time where the grip value did not fall below 0.6.

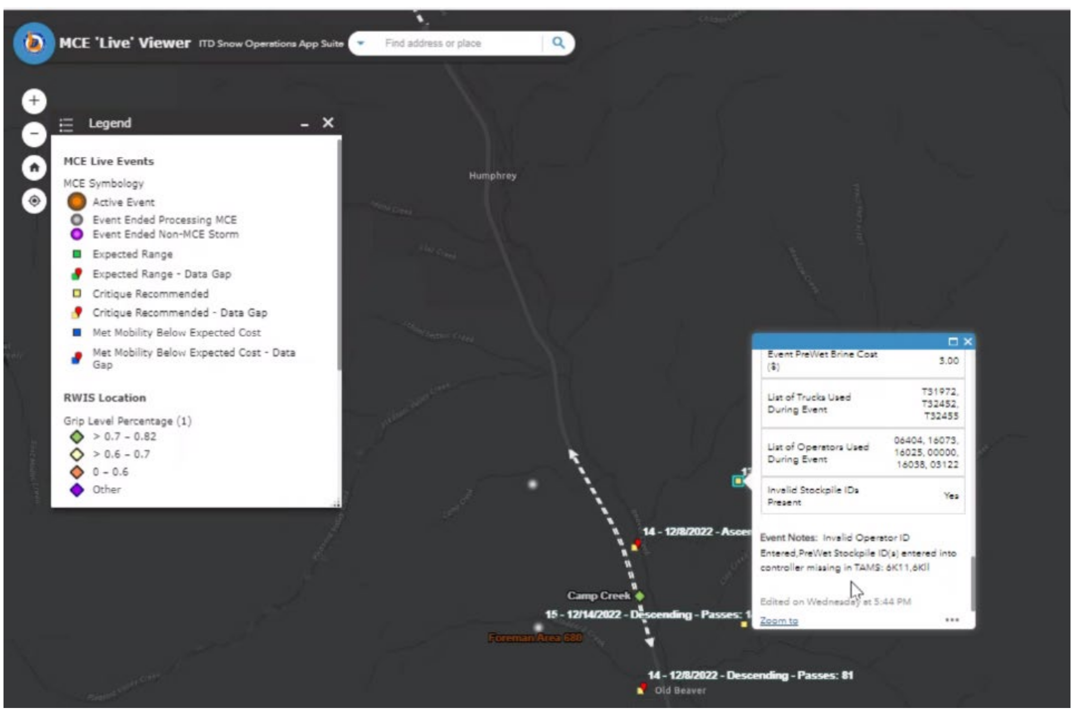

Figure 14. ITD MCE Live View showing a route with grip level percentages.

2) Statewide/Seasonal View: This view provides data for all storms for the season organized by maintenance district, see Figure 15. Data can be viewed by RWIS site or by region. This data includes total storm events/duration, aggregate MCE value, actual and target costs, actual and target equipment miles, average material usage, and mobility scores.

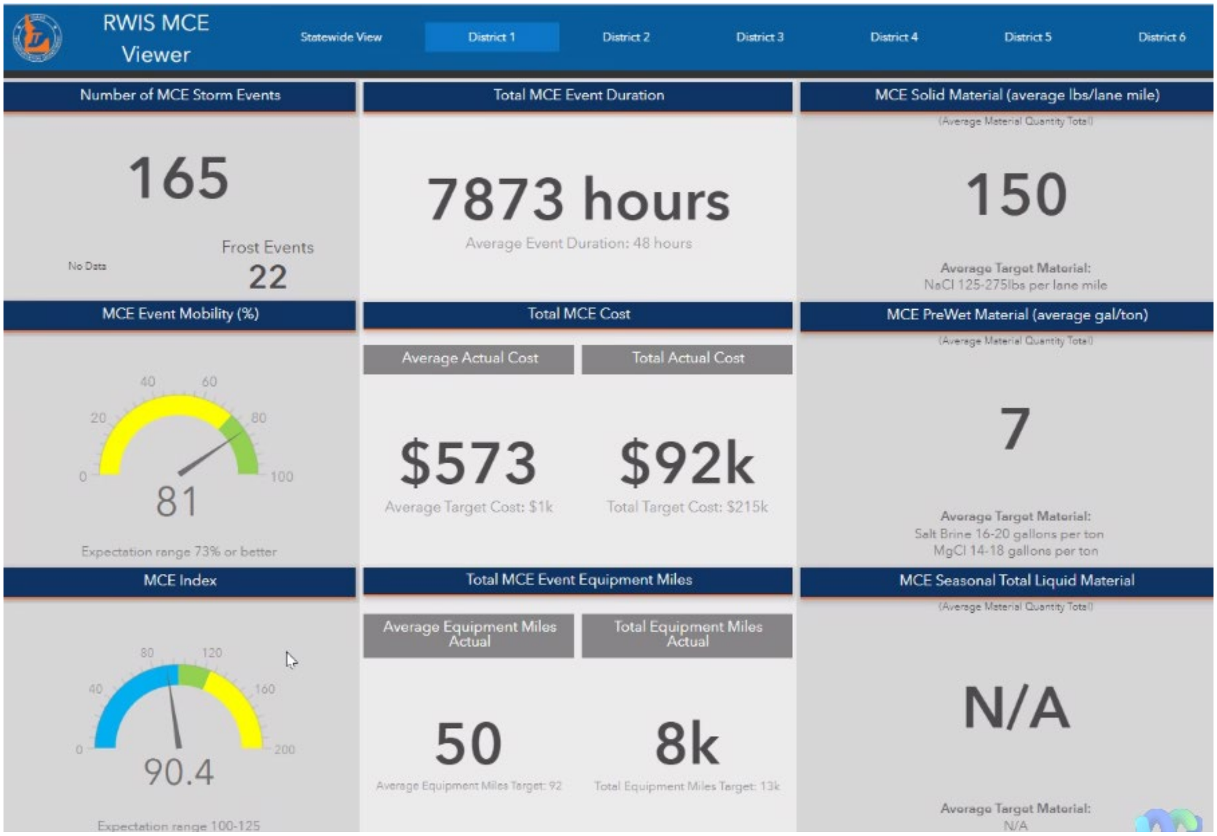

Figure 15. ITD MCE Statewide View

3) Historic View: The historic view displays the same data as the live view but for all storms of a winter season (whereas the live view only provides data on the previous three storms), see Figure 16. This data is organized by maintenance district and can be filtered down to individual RWIS sites.

ITD's overall goal with the snow operations application suite is to assess mobility across the state. In this case, mobility is defined as dry or wet pavement and above freezing (or non-icy pavement). This index improved mobility dramatically over the state from 28% to 80%, but now ITD wants to track how much deicing material (salt) it is taking to maintain this level of mobility and whether the improved mobility is at the expense of over salting or increased costs.

CONTACT INFORMATION

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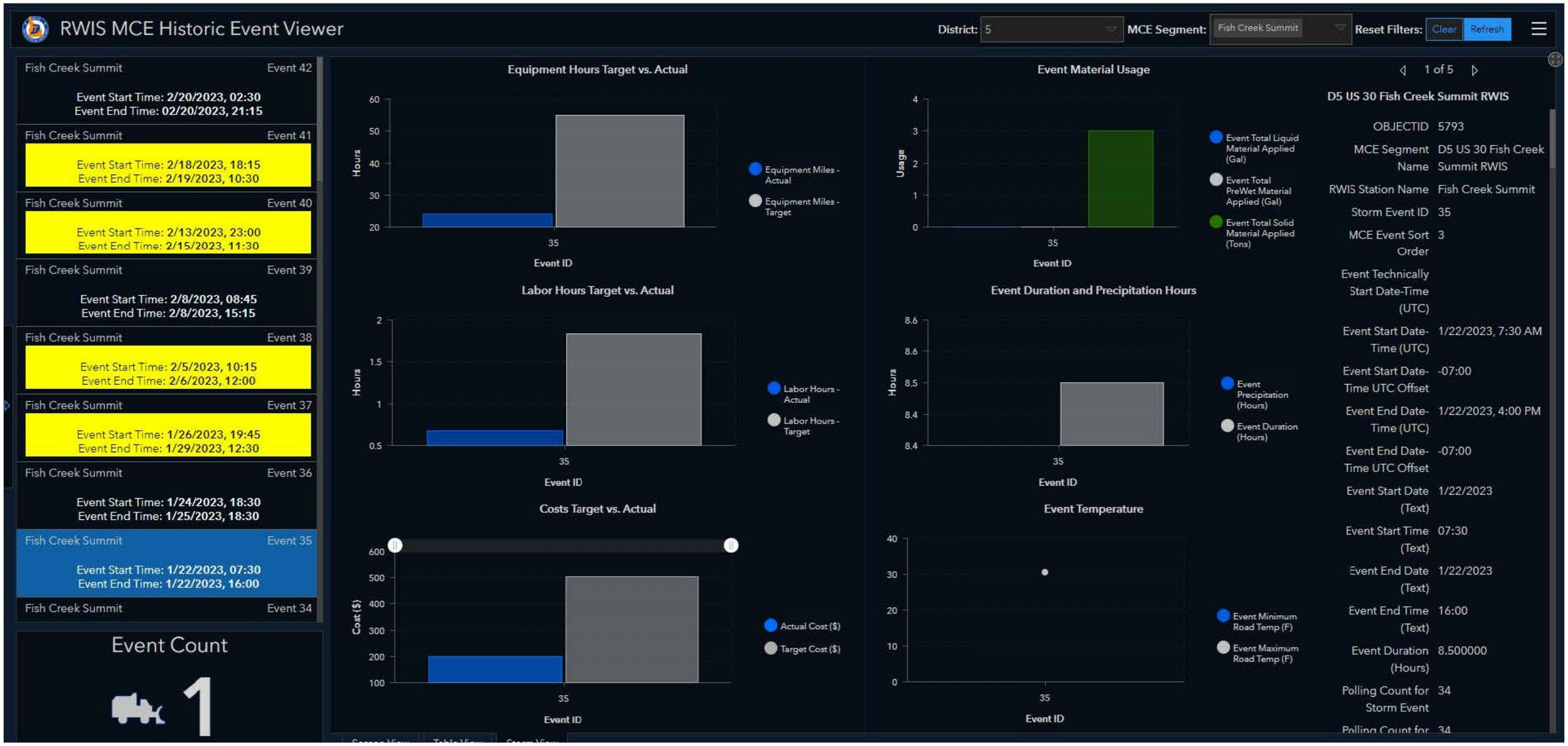

Figure 16. ITD MCE Event Viewer for District 5 Fish Creek Summit showing the event count on the left, and historic viewer summarizing equipment, labor, costs, material use targets versus actual, we well as event duration, precipitation, temperature, etc.

5.3 THIRD-PARTY FRICTION DATA FROM VEHICLES (CROWD SOURCED/FLOATING CAR DATA)

Wejo and Iowa Department of Transportation/Iowa State University

Connected vehicle data or third-party data have entered the US market, providing data to help address mobility challenges. Wejo[2] was a third-party data provider powered by Nira Dynamics. Wejo collected data from 13.7 million connected vehicles. Data is pulled through agreements with vehicle manufacturers (or original equipment manufacturer (OEMS)) from both the United States and Europe. Data is collected using a one-way communication process from in-vehicle sensors. The data was then processed to standardize variables across multiple OEMS and can provide road network insights like road temperature, slippery road alerts, and live road network updates which can be used to improve winter maintenance operations.

Data is collected every 3 seconds along a vehicle's trip. Data on driving events collected includes date, time, location, speed, heading, ignition states, and events including things like harsh braking/harsh acceleration (defined as ±2.67 m/s), wiper status, and anti-lock brake activation. This data is then transmitted from a SIM card over the cellular network. In cases like rural areas where there may be spotty cellular network coverage, the data can be stored and will be transmitted when the vehicle is back in service. No personal information is collected and therefore personal travel information cannot be tied to the data. The GPS location for the data collected is accurate enough to allow lane level analysis, or to about 1-3 meters.

Data could be provided as a raw data file for vehicle trips or as aggregate reports. In addition to providing raw data, other data tools were available, such as the real-time traffic intelligence which allowed a user to look at a road network in real-time including travel time and speed of a road segment and identify slowdowns and incidents. Nira Dynamics, a third-party connected vehicle data provider based in Europe, provides a Road Health tool which examines road degradation and Winter Road Insights which can provide slippery road alerts and real time road condition information. The Winter Road Insight tool is currently not available in the United States due to a lack of vehicle penetration (e.g., limited number of European manufactured vehicles in the U.S.) but could be in the future. The Road Health and Winter Road Insights tools are priced based on the total road miles for a transportation agency. Whereas Wejo's raw data was priced based on the size of the data files (data, time, how many vehicles, etc.).

Iowa State University (ISU) working on behalf of Iowa DOT, has begun to work with raw vehicle data from Wejo. ISU purchased data in October 2022 to examine whether this type of data could be used to

[2] Wejo no longer exists. Data is now being used from Streetlight.

support Iowa DOT and determine how this data could be used. [Note that ISU was not using any of the off-the-shelf tools offered by Wejo.] The raw data included vehicle movement data (which is continuous – described as breadcrumbs every three seconds along a vehicle's journey) and detailed event data (point data) for a vehicle trip. Data elements provided include location, speed, seatbelt on/off, harsh braking/acceleration, anti-lock brake (ABS) engagement, turn signals on/off, stability control, etc. (see Figure 17). This equates to an extremely large volume of data for each day which is provided as a data dump each night.

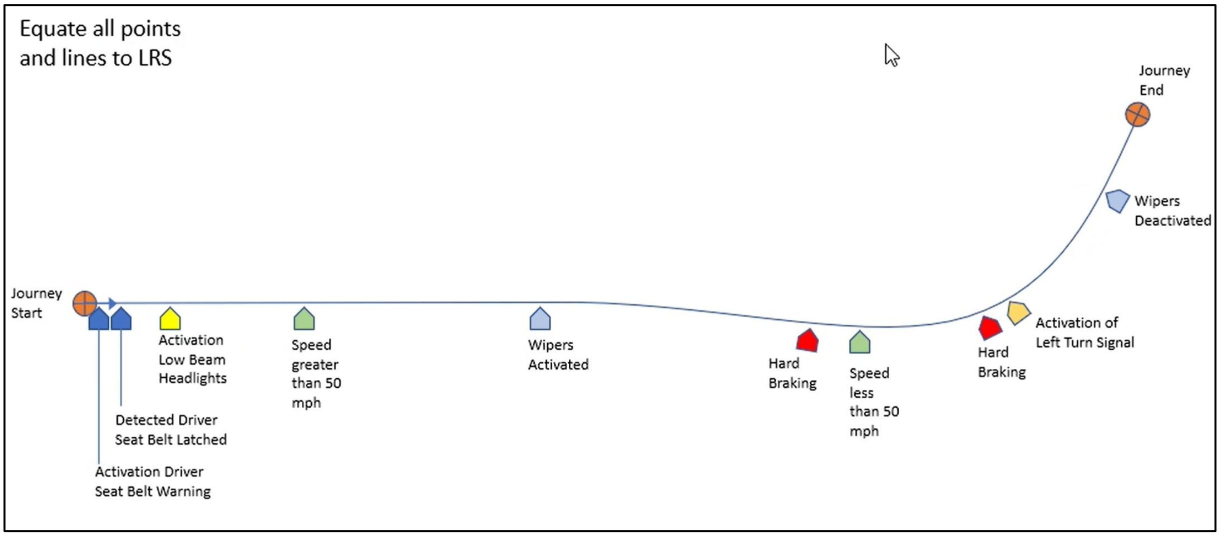

Figure 17. Example of vehicle movement data (continuous) and event data (points). Graphic Credit: Iowa State University, Institute for Transportation

ISU is working to analyze this data set to better understand how representative the data is and what data events it can represent. ISU has recently finished relating the data to Iowa DOT's linear reference system (road network data) which includes data on things like road name, speed limit, road grade, and shoulder width. Data is being collected from vehicles that were manufactured in 2015 or newer, and ISU has found that the data represents around 6 percent of vehicles traveling across the state. Note that ISU also identified a bias in the data towards more affluent areas, which can have up to 10 percent vehicle penetration. They are now working to examine how this data could be used. For example, is a vehicle braking due to slippery conditions or because they saw wildlife on the roadside? Is there a threshold of vehicles slowing down that would indicate one event versus the other? ISU will be working with the data to tease out patterns and develop dashboard tools which can allow for data analysis and application of the information. Additional analysis will include looking at how other data sources, like weather data, can be integrated for a more in-depth analysis. Currently, ISU is working to build confidence in the data and determine how Iowa DOT can best move forward using this data.

ISU has just begun to delve into what the data can do, and it seems like the data possibilities are endless. ISU is continuing to work through ways to streamline processing the raw data and organize it into a usable format. Many offices within Iowa DOT are planning to use this data. The potential applications for data like this make the cost easy to justify because costs can be shared across multiple offices. For winter maintenance operations, Iowa DOT plans to start with looking at traction control and ABS with current weather data in order to detect slippery conditions. The findings could influence how and where to conduct public messaging about wintery conditions.

The ISU and Iowa DOT project is just one that has begun to examine how third-party floating car data could potentially be used to support DOT operations. Several universities across the US have ongoing projects using similar data. Purdue University has two ongoing projects which are examining things like the impact of weather on traffic speeds and leveraging connected vehicle data for winter operations performance measurement.

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5.4 FRICTION DATA AND PIKEALERT

Alaska Department of Transportation & Public Facilities

Pikalert was developed by the National Center for Atmospheric Research (NCAR) to provide data-driven road weather information to both road maintenance agencies and the traveling public in the form of a maintenance decision support system. The Pikalert System provides road weather forecasts for up to 72 hours and treatment recommendations. Pikalert uses connected vehicle data, road weather information systems (RWIS) data, radar, and weather forecast models (FHWA, 2017). Key data elements used in Pikalert include precipitation, road surface condition, visibility data, and blow over risk to assess road segments and determine road segment alerts and appropriate treatment options. These treatment recommendations and alerts can be based on unique user characteristics allowing for tailored recommendations based on the user's environment and maintenance level of service requirements/guidelines. For example at Alaska Department of Transportation and Public Facilities (Alaska DOT & PF) recommendations have been tailored to account for the lack of solar gain as Alaska experiences few daylight hours during the winter season (FHWA, 2017). Data fed into the Pikalert system is run through multiple quality assurance and quality control checks. The system offers three user interfaces; 1) an Enhanced Maintenance Decision Support System (EMDSS) which is geared towards road maintenance agencies and provides segment alerts and treatment recommendations, 2) Motorists Advisories and Warnings (MAW) which is a web-interface that provides road weather information and travel alerts (currently available in participating states), and 3) MAW Mobile App. This is a smartphone application version of the MAW (currently only available for the Denver International Airport)(FHWA, 2017).

Pikalert has recently started to ingest roadway grip data and display this data within the Pikalert dashboard. NCAR's general plan with roadway grip data is to integrate this information into the alerting capacity of the road weather model. Roadway grip is not currently integrated into Pikalert's pavement condition module. Incorporation of roadway grip data would help to improve this algorithm and Pikalert's forecasting, and roadway grip could serve as truthing data for the system. However, roadway grip data is not available from every RWIS site and friction sensor density is variable in each state, with many states having fewer than 50% of RWIS sites collecting this data.

The Alaska Department of Transportation and Public Facilities (Alaska DOT & PF) uses Pikalert to support winter operations by monitoring road conditions, see Figure 18. AKDOT & PF currently have two road weather information systems (RWISs) which also collect roadway grip data, both located in Fairbanks. [AKDOT P&F have public facing RWIS data which can be access at https://roadweather.alaska.gov/gis. This roadway grip data can also be viewed through Vaisala's Wx Horizon platform and through Pikalert's EMDSS display. [Note, AKDOT & PF RWIS uses Vaisala sensors and pay to use the Vaisala dashboard Wx Horizon.] Pikalert provides Alaska DOT & PF with various forecast models from the next 6 hours, 6 hours to 24 hours, and 24 hours to 72 hours to aid in planning of maintenance activities. Alaska DOT & PF's incorporation of roadway grip data is currently limited, however they are considering incorporating roadway grip data from mobile sensors (MD30s, the Vaisala mobile mounted sensor).

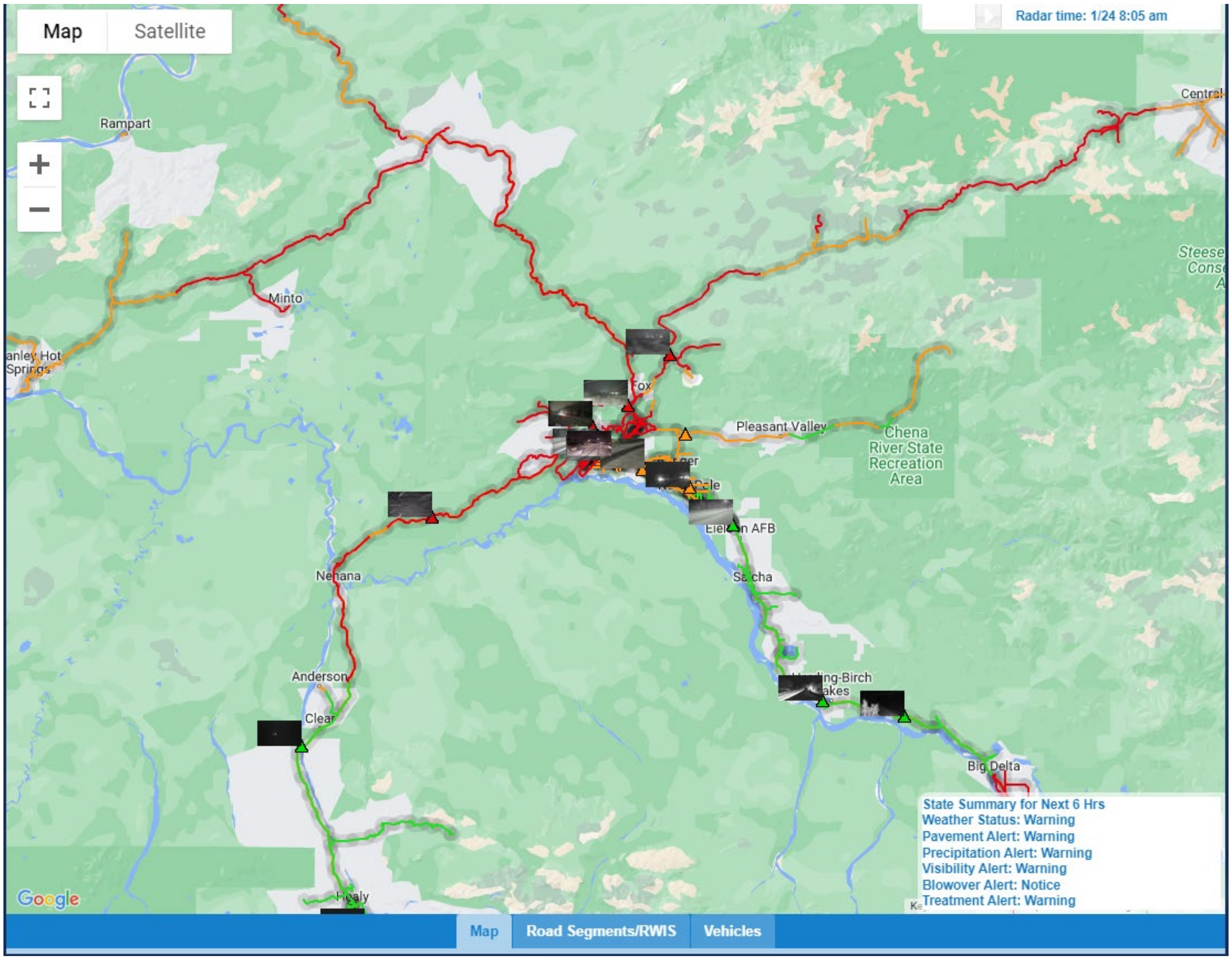

Figure 18. Alaska DOT& PF Pikalert Website

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CHAPTER 6: ALGORITHM AND DECISION-MAKING APPLICATIONS

This chapter is divided into three sections, the first describing the analysis of road weather information system (RWIS) data from Iowa DOT, the second describing the analysis of mobile road condition data from Colorado DOT. The detailed procedure of data processing/integration and model development/application was discussed in each section. Third, a decision-making process for salt application using the developed model is provided with sensitivity analysis. Limitations in data collection and AVL data quality were summarized, and recommendations are made to address these limitations.

6.1 DECISION MAKING OF SALT APPLICATION USING RWIS DATA

6.1.1 Data Collection and Processing

6.1.1.1 Road Weather Information System (RWIS) Data

Many transportation agencies use Road Weather Information System (RWIS) stations to enhance winter roadway maintenance. RWIS stations are installed at fixed locations and provide point-based measurements. The information collected by these stations helps agencies make informed winter maintenance and operational decisions to support mobility and traveler safety. RWIS stations can be a combination of invasive and non-invasive sensors. Non-invasive sensors are located on the roadside away from the road surface, are typically mounted to point down at the roadway, and use spectroscopy, thermal radiation, or infrared radar to ascertain surface conditions (Fay et al., 2013). Non-invasive sensors typically report data on air and pavement temperature, roadway surface condition (dry, damp, wet, icy, etc.), and estimate surface grip (friction) values, but are limited to these data elements (Fay et al., 2014).

The Iowa DOT operates and maintains an extensive RWIS network (62 stations) throughout the state. These stations are strategically placed along highways and roads to gather road weather data and road surface condition information. In this study, the road surface condition and weather data collected during the winter seasons of 2021-2022 (November through March) and 2022-2023 (October through April) were processed and analyzed for the Ankney RWIS station on the bridge deck located on Interstate Highway I-35. Pavement-related data included surface condition, friction (surface grip), road/bridge surface temperature, freezing temperature, conductivity, and salinity. Weather variables included precipitation accumulation, precipitation rate, precipitation intensity, precipitation type, dew point temperature, air temperature, pressure, relative humidity, wet bulb temperature, wind gust speed, wind speed, wind direction, and visibility.

Table 9 summarizes the road surface and weather variables used in the model development in this study. All the RWIS variables were first checked, but only the atmospheric variables showing significant impact on the grip level were used to develop the predictive model. It is noted that the precipitation rate is in liquid rate and thus has a snow-to-liquid ratio of 10:1.

Table 9. Summary of RWIS data used in this study.

Dataset	Description	Symbol	Unit	Range
Road surface - related	Text description of surface grip level	Grip	N/A	low, medium, high
Road surface - related	Road/bridge surface temperature	BridgeTemp	°F	-11-104
Weather	Precipitation rate (liquid)	PrecipitationRate	inch/hour	0.01-0.84
Weather	Air temperature	Temperature	°F	-12-83
Weather	Relative humidity	RelativeHumidity	%	10-99
Weather	Wind speed	WindSpeed	mph	1-41

Figure 19 (a)-(e) illustrates the boxplots of wind speed, precipitation rate, relative humidity, air temperature, and surface temperature. The horizontal line and square point in the middle of box indicate the median and mean values, respectively. These variables were recorded successively at the RWIS station with a time interval of 5 minutes during the entire winter season. Air temperature, relative humidity, and surface temperature in the 2021-2022 winter season were found to be lower than those in the 2022-2023 winter season, while wind speed decreased during 2022-2023. It is noted that the precipitation rate is in liquid rate and thus has a snow-to-liquid ratio of 10:1.

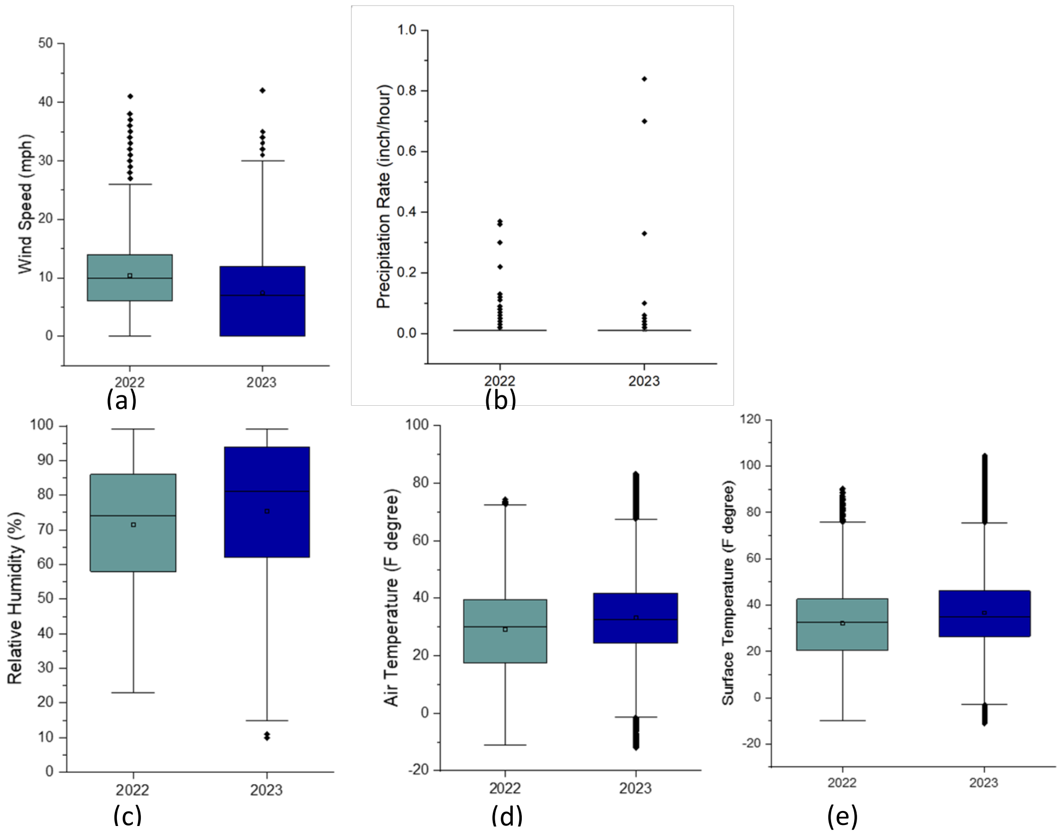
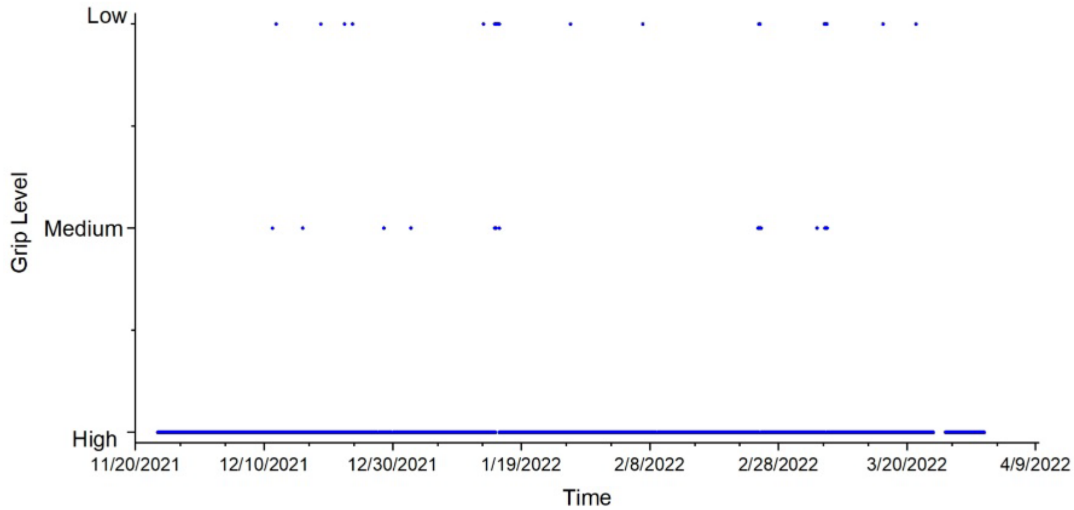
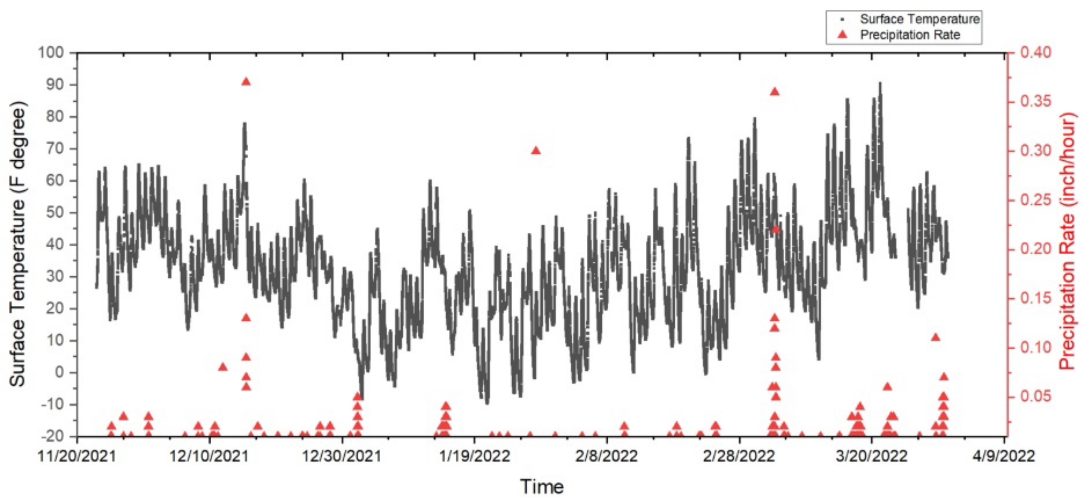


Figure 19. Boxplot of (a) wind speed; (b) precipitation (snow) rate; (c) relative humidity; (d) air temperature; and (e) surface temperature.

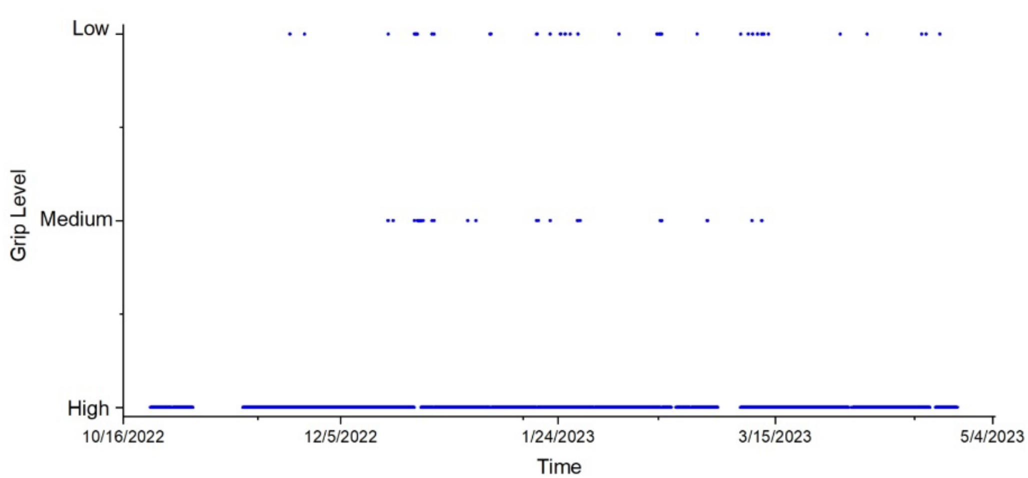
Figure 20 shows the change of grip level (friction coefficient) ((a)(c)) along with the road surface temperatures and precipitation rate (as snow) ((b)(d)) during the two winter seasons. The roadway grip data provided by Iowa DOT are described as low, medium, and high as measured by the sensor from Vaisala and the actual values of grip are not known. Changes in road surface grip are clearly observed to be associated with snowstorms that happen in the winter season. The continuous changing of surface temperature was observed, while the precipitation rate kept at zero except during snow events.


Low
Medium
High
Grip Level
11/20/2021
12/10/2021
12/30/2021
1/19/2022
2/8/2022
2/28/2022
3/20/2022
4/9/2022
Time

(a)


Surface Temperature
Precipitation Rate
Surface Temperature (F degree)
Precipitation Rate (inch/hour)
100
90
80
70
60
50
40
30
20
10
0
-10
-20
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
11/20/2021
12/10/2021
12/30/2021
1/19/2022
2/8/2022
2/28/2022
3/20/2022
4/9/2022
Time

(b)


Low
Medium
High
Grip Level
10/16/2022
12/5/2022
1/24/2023
3/15/2023
5/4/2023
Time

(c)

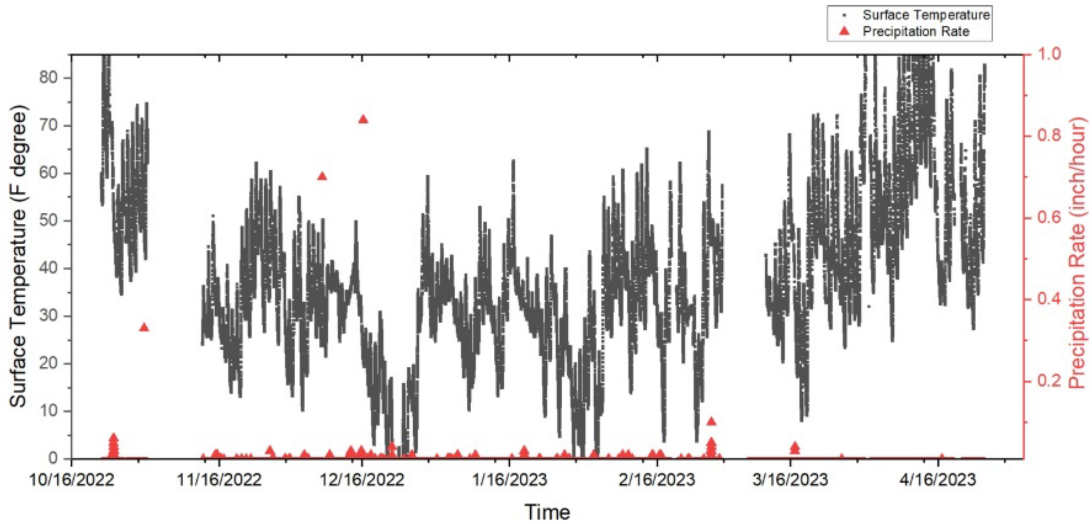


Figure 20. (a) Change of grip level; (b) surface temperature and precipitation rate during the 2021 to 2022 winter season; (c) change of grip level; and (d) surface temperature and precipitation rate during the 2022 to 2023 winter season.

6.1.1.2 Automatic Vehicle Location (AVL) and Salt Application Data

Automatic vehicle location (AVL) is a technology that utilizes a global position system (GPS) to determine the geographic location of a vehicle, and an overview of vehicle travel can be managed by a vehicle tracking system. AVL technology on snowplows can allow for accurate and timely data snowplow location data, plow sensor data (example: salt application rate), and road condition data in real-time.

The salt application rate data collected from plow trucks with the AVL system was provided by the Iowa DOT. The AVL plow truck data provided included the truck location (start/end milepost, longitude, latitude, and altitude), truck speed, solid material application rate, accumulated solid material applied, anti-icing material (liquid) application rate, and accumulated anti-ice material applied. The application rates of solid salt were considered in this study, which ranged from 3 to 436 pounds/lane-mile (lb./ln-mi) across all the data records. Salt data are recorded for solid, prewet, and anti-icing (liquid) in raw data, but the value for anti-icing (liquid) is zero. Pre-wet rates were added to solid materials after unit conversion and considered as total salt application. However, the pre-wet rate is relatively low at the range of 2-12 gallon/ln-mile.

Data from the Ankeny RWIS site and corresponding AVL plow truck were coordinated and located using ArcGIS and Google Earth. Figure 21 shows the location of Ankeny RWIS site on I-35 southbound (SB), in which the red dots show the location data points reported by the AVL for the 23 plow trucks passing the site and applying the salt during the two winter seasons. The AVL plow truck data within 0.4 miles from the RWIS site was extracted, and the plow truck location was estimated to be as close as 50 feet from the RWIS site.

Figure 21. AVL plow truck data around the Ankeny RWIS station on I-35 (Red dots are plow truck location data reported through the AVL system).

6.1.1.3 Integration of RWIS and AVL Plow Truck Data

RWIS and AVL plow truck data were obtained from two separate datasets and were collected over inconsistent observation periods and time intervals. The data was processed to match and integrate the two datasets before further analysis, shown in the flow chart in Figure 22. First, the start and end of snowstorms were identified in the weather data, focusing on storms that lasted more than one day. Then the corresponding road surface grip levels (low, medium, and high) were identified from the pavement observation dataset. Note that Iowa DOT only reports grip categorically as low, medium, and high and does not collect numerical coefficient of friction values. Next, the salt application rates during snowy days surrounding the RWIS station were extracted from the AVL plow truck dataset. Finally, the road surface grip levels were matched with salt application rate data on snowy days for further analysis.

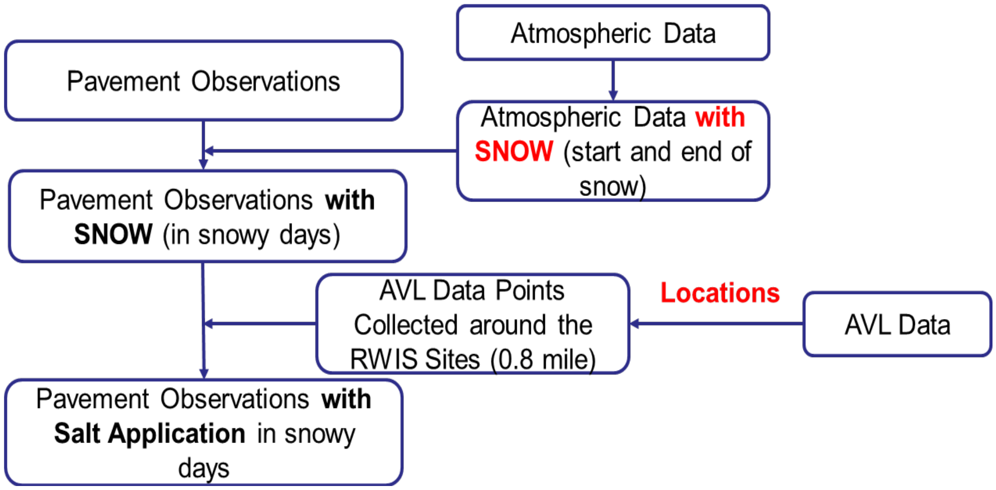
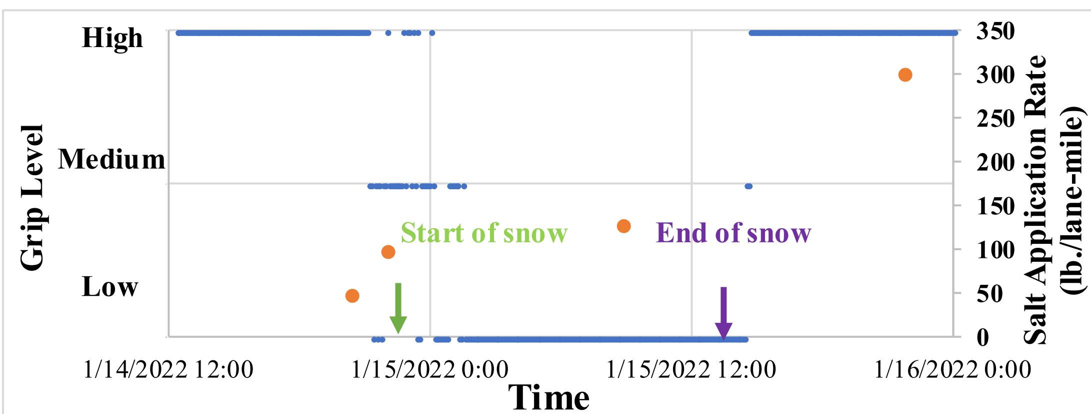
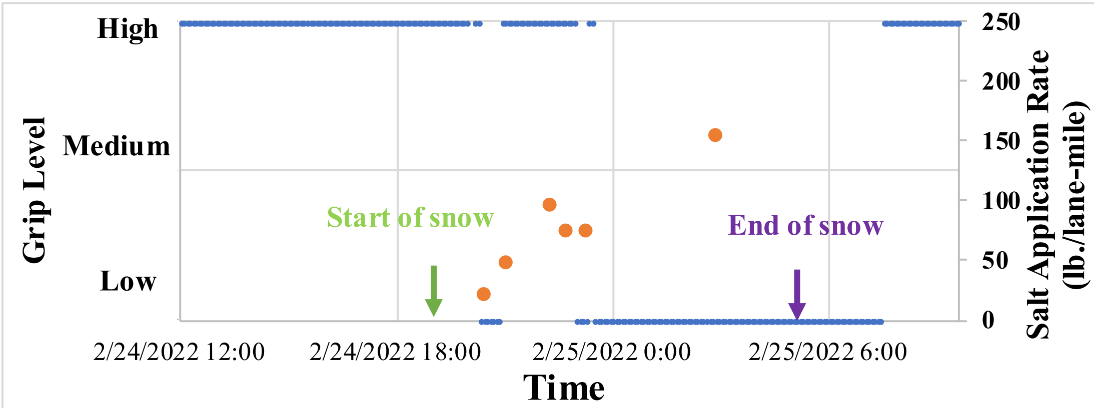


Figure 22. Flowchart of RWIS and AVL data processing.

Figure 23 shows the change in road grip level with salt application during the snowstorms from 1/14/2022 to 1/16/2022 and from 2/24/2022 to 2/25/2022. A high grip level indicates safe road surface condition for driving; a medium grip level means some degradation of grip has occurred; and a low grip level represents obvious and substantial traction loss. The data shows that the road grip level changed from high to medium or low after the storm started, then it was improved to high following salt application and termination of the snowstorm.



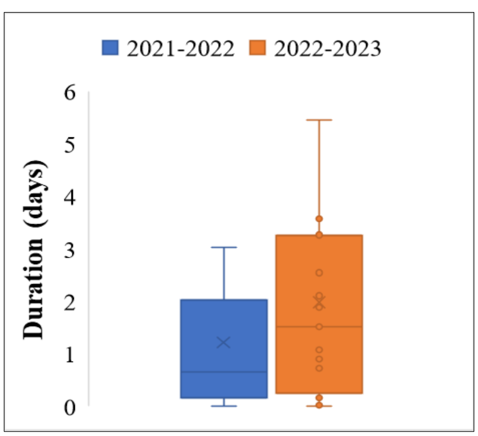
(a)



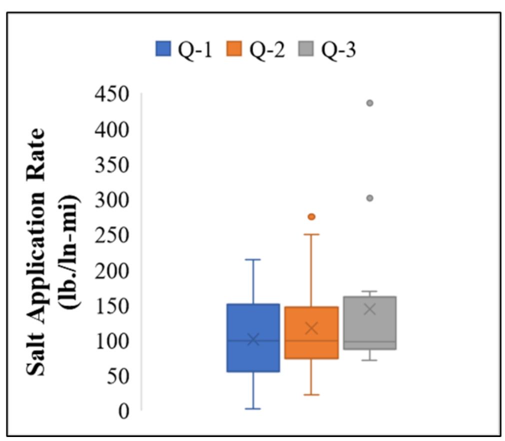
(b)

Figure 23. Road grip level (blue dots) and salt application (orange dots) during the snowstorms: (a) from 1/14/2022 to 1/16/2022; and (b) from 2/24/2022 to 2/25/2022.

The integrated datasets were used to analyze salt application rates and road grip levels during the 2021-2022 and 2022-2023 winter seasons. Figure 24 (a) shows that the duration of snow events ranged in length from hours to days. During each snowstorm, multiple salt applications were applied at the RWIS site, and the time interval between salt applications varied. For each observation of road grip level (blue points in Figure 23), the first three sequential salt applications (orange points in Figure 23) after the snowstorm were extracted and analyzed. The first, second, and third sequential salt application rates are denoted as Q-1, Q-2, and Q-3, and their ranges in two winter seasons are illustrated using boxplot as shown in Figure 24 (b). The horizontal line and cross symbol in the middle of the box indicate the median and average values, respectively. It was found that the average values of three salt application rates were similar. However, the ranges of salt rates for different applications were found varied, and the salt rate of Q-3 was higher than those of Q-1 and Q-2.



(a)



(b)

Figure 24. Boxplots of (a) snowstorm duration and (b) salt application rates Q-1, Q-2, and Q-3 in two winter seasons.

6.1.2 Long Short-Term Memory (LSTM) Model Development

6.1.2.1 RNN for Temporal Pattern of RWIS Data

RWIS stations monitor road surface conditions and weather variables continuously. The time series data of road surface grip level is reported in 5-min. intervals. It is needed to analyze grip levels considering the potential influences of weather variables using a robust machine learning model. While traditional machine learning methods (such as support vector machine, random forest, etc.) are versatile and applicable, these models inherently lack the incorporation of temporal information. In other words, the models operate by treating each data point independently without considering the order or timing of observations.

A recurrent neural network (RNN) can store the patterns of recent input events in the form of activations (short-term memory) using feedback connections. However, time delays between input data and their corresponding response signals are substantial, and the technique of backpropagation in feed backward networks with restricted time windows is implemented in the RNN. Backpropagation, a common algorithm for calculating gradients of the loss function to minimize the error in prediction, accounts for the sequential nature of the data, which adds complexity due to dependencies between time steps. By focusing on a limited number of recent time steps with a restricted time window, the model can avoid the pitfalls of long-term dependencies and reduce computational complexity. Therefore, RNN suffers from short-term memory since it is difficult to extract, carry, and pass patterns from earlier steps to later ones in a long sequence. In the process of backpropagation in RNN, the problem of blowing-up or vanishing gradient, in which a gradient value becomes smaller as it back propagates over time, may exist depending on the size of applied weights and dramatically slows down the learning process. Therefore, the road grip levels in the long term cannot be handled appropriately using an RNN structure, and another deep learning model for long-term time series data is needed to investigate the propagation of road grip levels in the winter season.

6.1.2.2 Principle of LSTM

Long Short-Term Memory (LSTM) is a more advanced RNN architecture that was originally designated to deal with chronological sequences with better long-range dependencies. The standard LSTM structure has been widely used to solve the problem of long-term dependency (Gers et al., 1999). The internal mechanisms named gates in LSTM are capable of regulating the information flow, allowing relevant information to be passed down the long chain of sequences to make predictions (Van Houdt et al., 2020).

The key elements of an LSTM model include cell states and various gates. The cell state is utilized to carry and transfer relative information (including variables related to the weather, pavement, and salt application in this study) down the sequence chain, which works as the "memory" of the network. Data is transferred from preceding temporal stages to subsequent ones, decreasing the influence of short-term memory. In the process of transferring information in a long sequence, gates are applied to keep or discard information. During the training process, the gates, which are diverse neural networks, dictate the information that should be retained or discarded. Figure 25 illustrates the typical LSTM structure with cell state and gates.

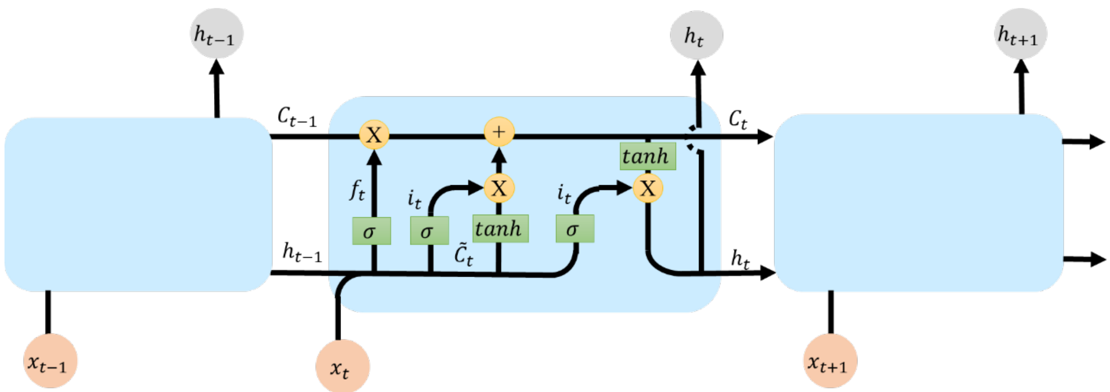


Figure 25. Illustration of LSTM model with layers and cell states.

6.1.2.3 LSTM Model Structure and Development

In the LSTM model, the various values within the internal cell states are updated according to the input data. The time-dependent variables related to road surface temperature, weather conditions, and salt application during the snow events were considered in the model development to predict the temporal evolution of pavement friction (Table 10). This allowed for the periodic change of road surface friction before and after salt application and the effect of time lag with respect to the snow event to be considered. All the RWIS variables were first checked, but only the atmospheric variables showing significant impact on the grip level were used to develop the predictive model.

Table 10. Inputs and output of LSTM model.

Items	Variables
Output	Road surface grip levels from time *t to time t+19*
Inputs	Road surface grip levels from time *t-20 to time t-1*
Inputs	Weather variables *from time t-20 to time t-1*
Inputs	Salt application rates during the snowstorm period (denoted as Q1, Q2, and Q3)

The model was trained with 50% of the field data collected during the snow events of two winter seasons from November 2021 to March 2023. The roadway grip levels during the entire snow season can be automatically predicted using the LSTM model. Due to the limited occurrences of snowstorms, the processed dataset was extremely imbalanced with large amounts of high friction observations, which increased the complexity of data analysis and model development.

During the training and testing processes, the LSTM model assimilated the physical principles from the input and observed data and were fine-tuned to predict the road surface grip levels. Tuning of hyperparameters, including depth of dense layer, learning rate, activation function, batch size, etc., is another critical issue in establishing the structure of a deep neural network like the LSTM model. A dense layer in an LSTM model serves as a crucial component for transforming the output of the LSTM units into the desired format for predictions or further processing. Optimization algorithms, which enable a modeling process to learn from a given data set, were used to find the maximum and minimum of an objective function, or the error or loss. The optimization algorithm used was an extension of the stochastic gradient decent procedure for the iterative updating of network weights based on the training data. It is an efficient method for dealing with a large problem with a lot of data or parameters. This technique is commonly implemented for deep learning applications in natural language processing and computer vision (Kingma & Ba, 2014).

A range of training choices and LSTM model parameters were tweaked to obtain the best results. The parameters of neural network were modified and determined based on a specific loss function of an iterative step. Table 11 summarizes the range of hyperparameters used for optimization. Learning rate is utilized to handle the rate at which an algorithm updates the parameter estimates or learns the values of parameters, and a smaller value of learning rate will make the learning procedure of LSTM model slower and provide a smoother learning curve. Depth of dense layers indicates the number of layers except for the input and output layers, and the number of dense nodes represents the number of nodes in the dense layers. Complicated neutral network with more depth of dense layer, number of dense nodes, will increase the complexity of learning procedure. The batch size is the number of sequences which are forward to the network before the gradients are calculated, and a smaller batch size will increase the learning time.

Table 11. Range of Hyperparameters in Model Optimization

Model Parameters	Range
Learning rate	1e-4~1e-2
Depth of dense layers	0~2
Number of dense nodes	8~512
Batch size	64~128

6.1.3 Analysis of Prediction Results on Surface Grip

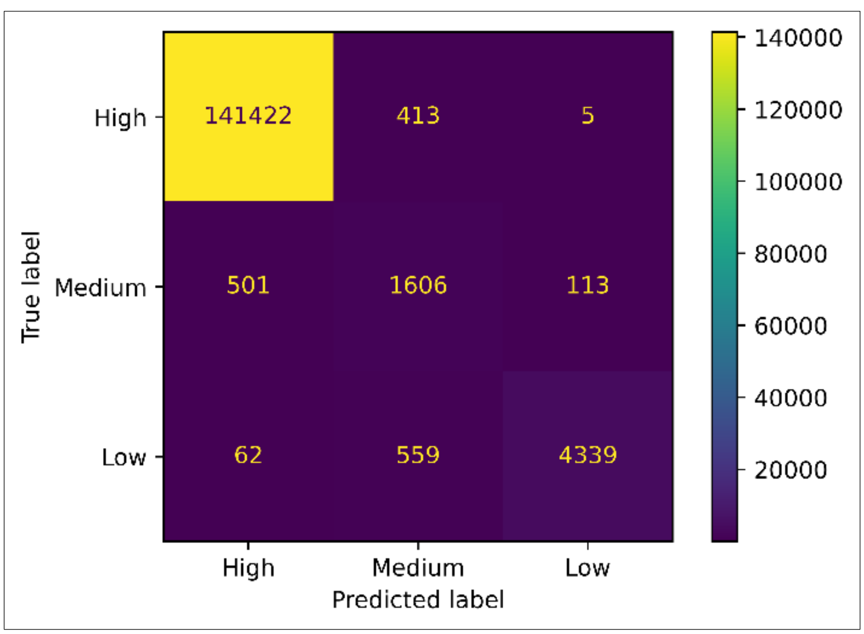
6.1.3.1 Prediction Accuracy of Surface Grip

To validate the model using an independent dataset, the developed LSTM model was implemented to predict road surface friction during the winter season from October 2022 to April 2023. Precision, recall, and F-measure values with corresponding confusion matrix plotted, which work for both binary and multiclass classification issues, were computed to quantify the performance of the trained LSTM model, especially for the imbalance classification. Table 12 presents the precision, recall, and F1-score values of the proposed model for forecasting pavement friction levels. The LSTM model shows good accuracy even with the imbalanced data for grip at high, medium, and low levels.

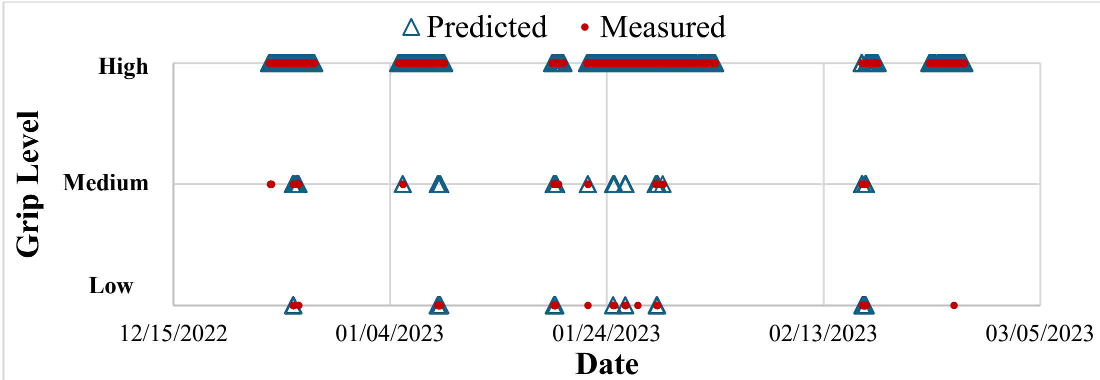
Table 12. Precision, recall, and F1-score values of the LSTM model.

Category	Precision	Recall	F1-Score
High	1	1	1
Medium	0.62	0.72	0.67
Low	0.97	0.87	0.92

Figure 26 (a) illustrates the confusion matrix of the LSTM model to classify road surface grip levels. Figure 26 (b) presents the comparison between the measured and predicted surface grip levels of the independent test dataset. Most of the measured and predicted road surface grip levels were found to overlap, but a few low grip levels were misclassified into medium or high levels.



(a)



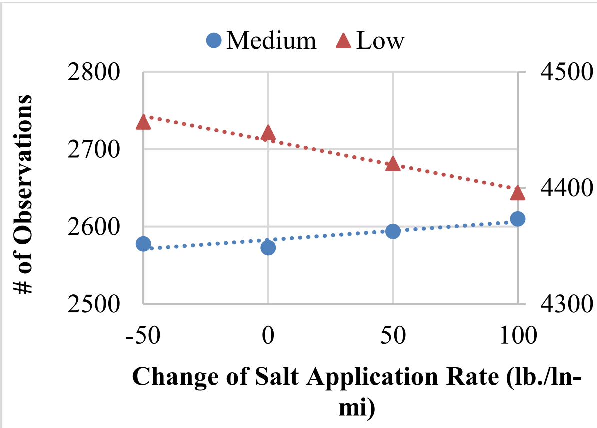
(b)

Figure 26. (a) Confusion matrix of the LSTM model; and (b) Comparison between the measured and predicted values in the testing dataset.

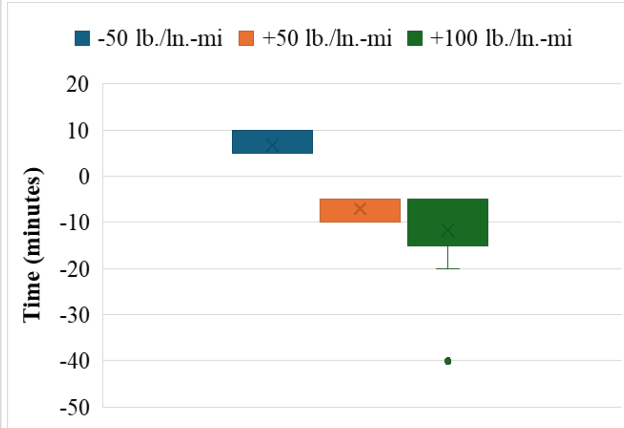
The developed LSTM model was a data-driven model established according to the hidden statistical relationships between road surface grip and various inputs related to atmospheric condition, surface temperature, and salt application during snowstorms. The analysis results above have indicated the ability of the proposed LSTM model to effectively learn long dependencies given extremely imbalanced dataset.

6.1.3.2 Effect of Salt Application on Surface Grip

Sensitivity analysis was conducted to investigate the impact of salt application rate on road surface grip level using the developed LSTM model. The current salt application rate was considered as the baseline case in the analysis. The salt application rate was increased or decreased by 50-100 lb./ln-mi as compared to the baseline case, and the corresponding road surface grip level was quantified. Figure 27 (a) shows the linear relationship between change in salt application rate and grip level. Figure 27 (b) shows the change of time periods needed to achieve grip improvement after salt application to the road surface. A negative value means the road grip level will improve more quickly compared to the original salt application rate. The results indicated that the road grip level tends to improve more quickly when a higher salt application rate is applied to the road surface and vice versa.



(a)



(b)

Figure 27. Effect of salt application on (a) grip levels (Medium: left axis; Low: right axis); and (b) timing of grip level improvement.

6.1.4 Decision-Making of Salt Application

The LSTM model can be further used as an event-based decision-making tool for dynamic adjustments of salt application in winter maintenance. A dynamic decision-making process for winter road maintenance operation is proposed to determine the salt rate based on the desired grip level at road surface using the LSTM model, as illustrated in Figure 28. In the first trial, the initial value of the salt application rate is input to the LSTM prediction model given the weather conditions collected at the RWIS station. The predicted road surface grip level after the salt application is derived and compared with the grip levels before salting to evaluate the effectiveness of salt application. If the grip levels are found to improve after salt application, the operation is considered efficient. If the grip levels are found to be unchanged or even reduced, the operation is considered inefficient, and the salt application rate needs to be increased in the second trial. This procedure of trial and adjustment will continue until the achieved surface grip level is considered acceptable from the agency's point of view.

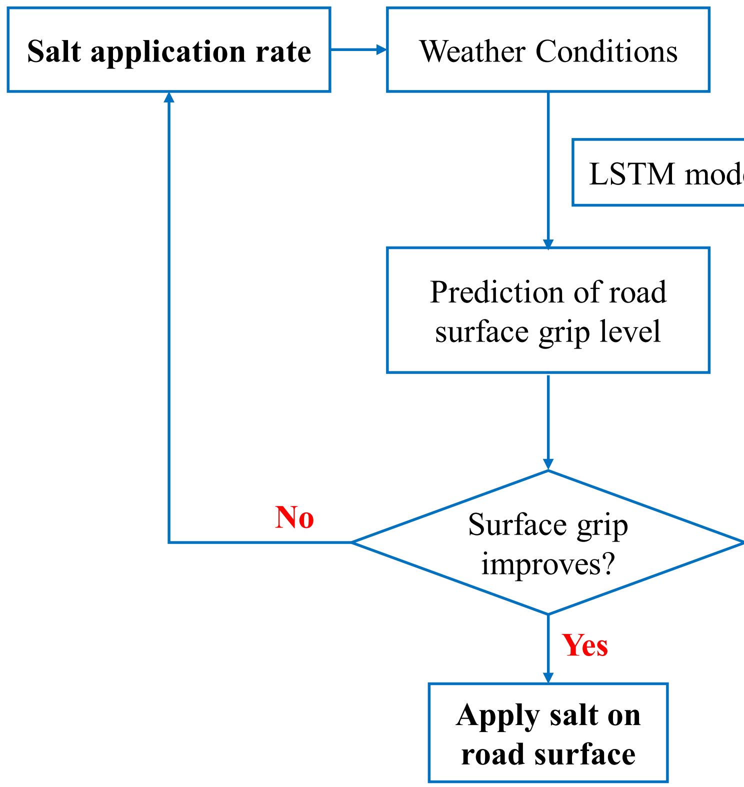
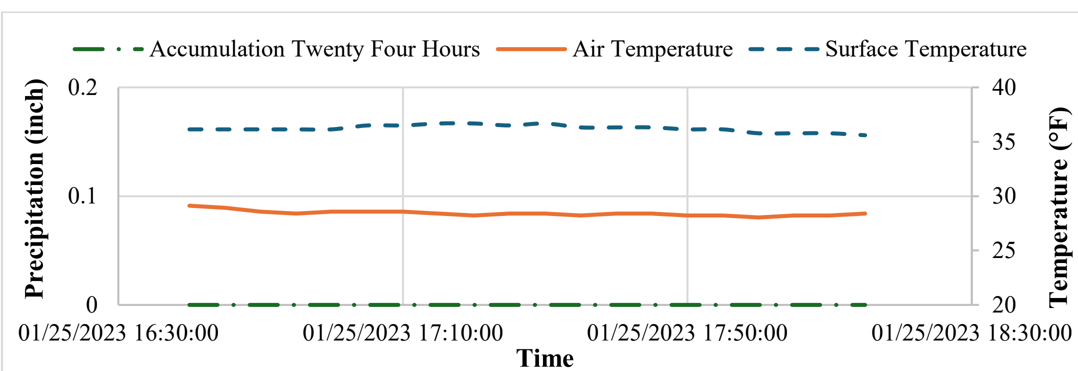
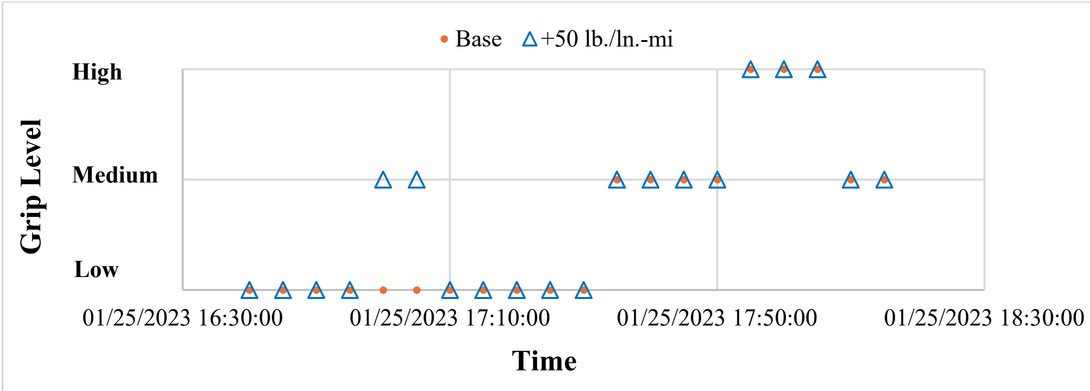


Figure 28. Flowchart of decision-making process using the developed LSTM model and RWIS data.

The effect of salt application on surface grip is further analyzed for individual snow events. Figure 29 shows example results for the snow event on 1/25/2022. The road surface grip levels with the higher (increase by 50 lb./ln-mi in Figure 29 (b) and 100 lb./ln-mi in Figure 29 (c)) or lower (decrease by 50 lb./ln-mi in Figure 29 (d)) salt application rates in the snow event were predicted and compared with the baseline case with the original application rate (113 lb./ln-mi) applied in the field. The results indicate that the influence of salt application rate on road grip levels can be analyzed case-by-case at different snow events for winter roadway maintenance.



(a)



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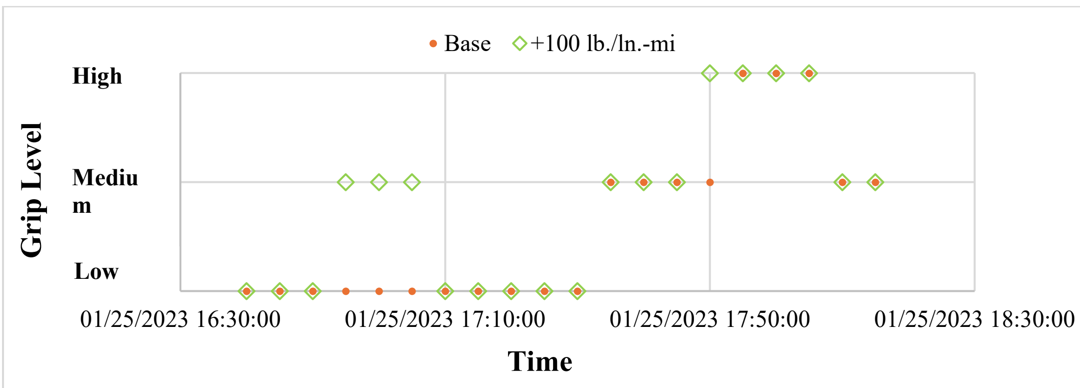

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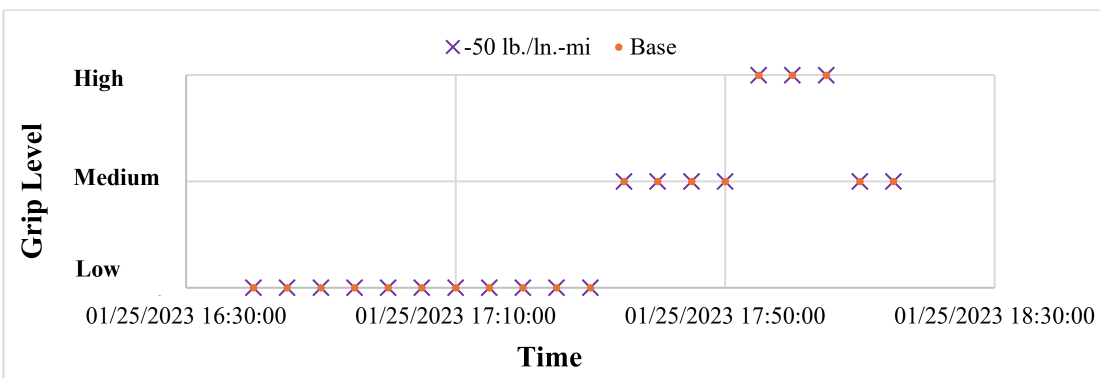
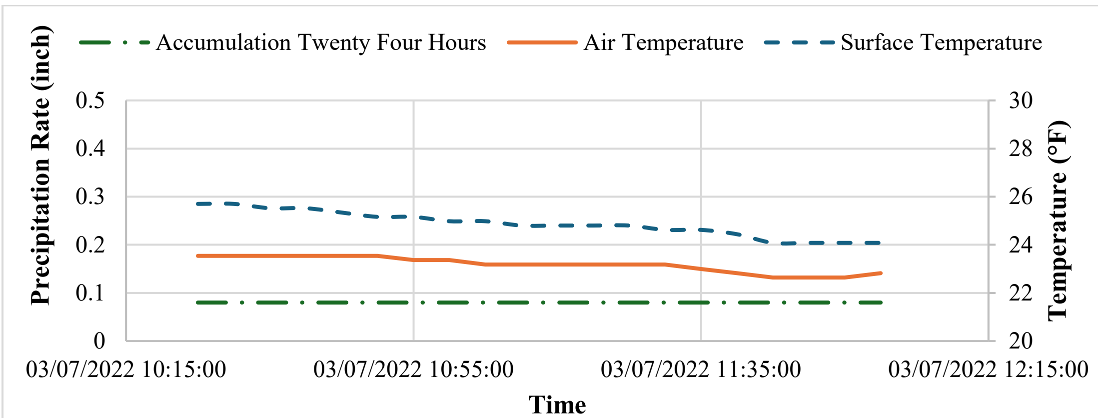


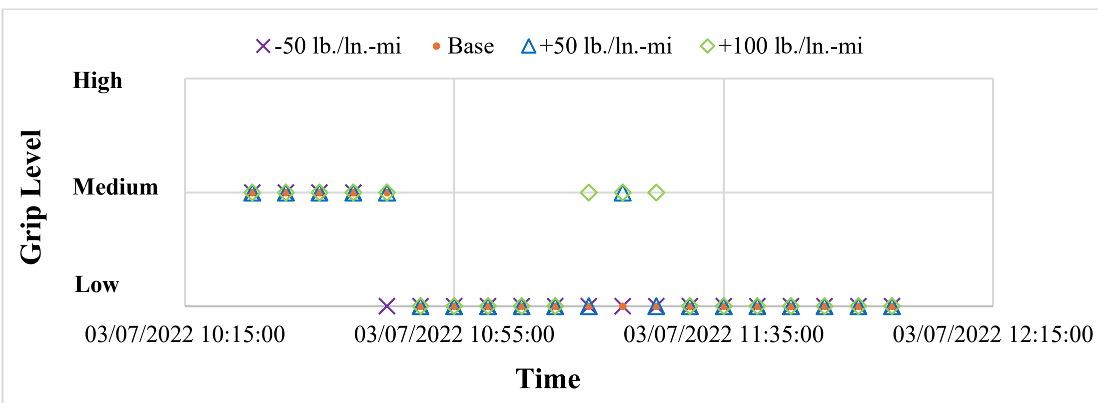
(d)

Figure 29. (a) Weather variables during the snowstorm on 1/25/2022 (salt application rate: 113 lb./ln-mi); Effect of salt application on roadway grip level during the snowstorm: (b) increase of 50 lb./ln-mi; (c) increase of 100 lb./ln-mi; and (d) decrease of 50 lb./ln-mi.

The interaction effects of climate conditions and salt application on roadway friction were analyzed by observing the improvement of grip level in two different snow events, as the same change of salt application rate is applied. Figure 30 shows the climate variables during the snowstorms on 3/7/2022 and 12/15/2022 and the effects of salt application on roadway grip level. Figure 30 (a) and (c) show that the road surface temperature changes continuously, while the precipitation (snow) changes with the snowstorms. The salt application rates were 275 and 245 lb./ln-mi, respectively. The change of road surface grip level due to snow is clearly observed, as shown in Figure 30 (b) and (d). It was found that the predicted roadway grip level was more sensitive to the change of salt application rate on 3/7/2022 during the snowstorm with the colder temperature. This indicates that roadway grip levels tend to be impacted by salt application rate when the temperature is lower.



(a)



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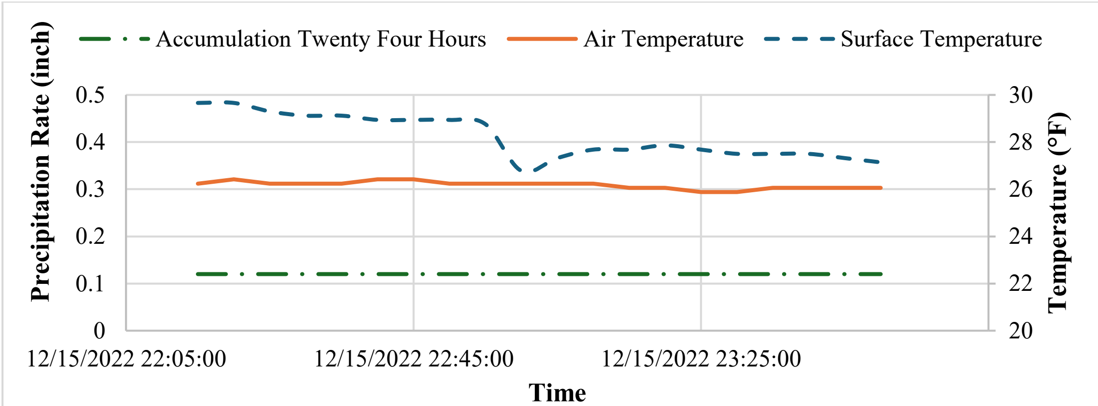

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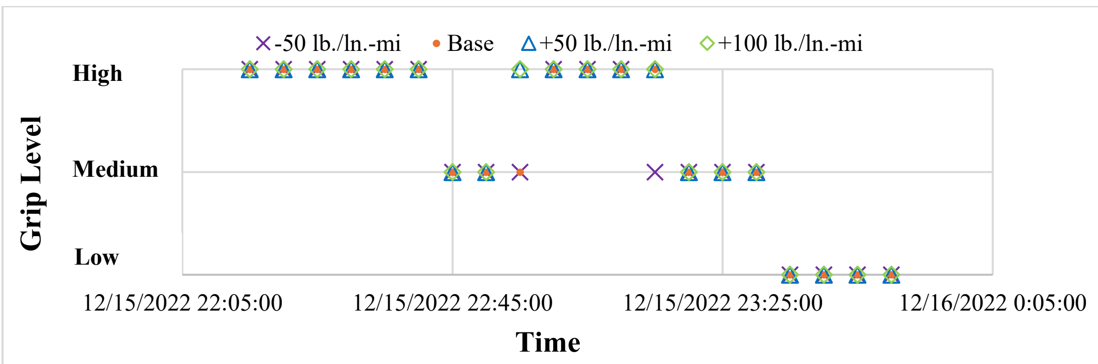
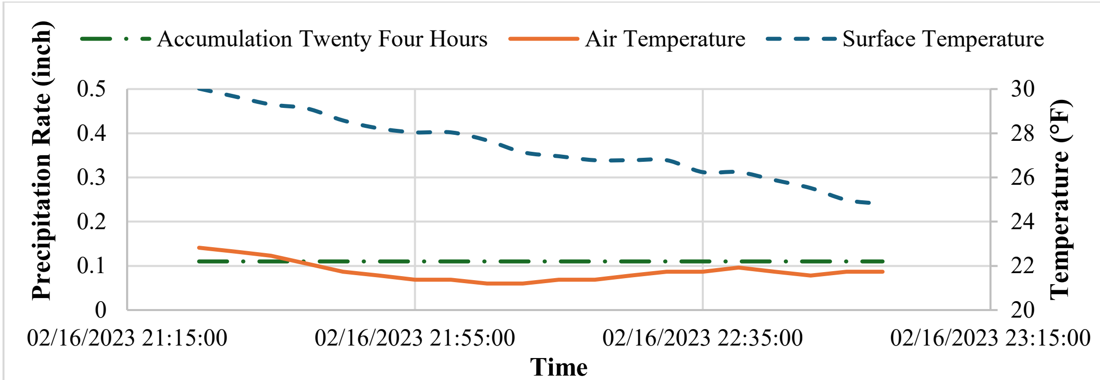


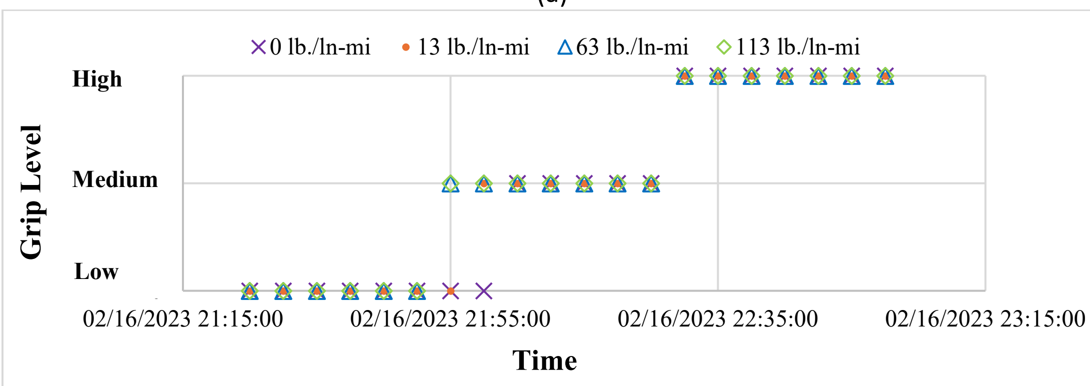
(d)

Figure 30. (a) Climate variables on 3/7/2022 (salt application rate 275 lb./ln-mi); (b) Effect of salt application on road surface grip level on 3/7/2022 ; (c) Climate variables on 12/25/2022 (salt application rate 245 lb./ln-mi); and (d) Effect of salt application rate on road surface grip level.

A hypothetical case was analyzed to see the change of road surface grip with and without salt application. The comparison results using the storm event on 2/16/2023 are shown in Figure 31. The salt application rates were 0, 13, 63, and 113 lb./ln-mi, respectively. Compared to the scenario of no salt, the roadway surface grip improved earlier by 5-10 minutes with salt applications and more salt improved grip faster.



(a)



(b)

Figure 31. (a) Climate variables on 2/16/2023; and (b) Effect of salt application on road surface grip level.

In the common guideline of winter maintenance used by state agencies, the salt application rate is in the range of 100-300 lb./ln-mi and determined based on surface temperature and snow intensity (Du et al., 2019). More salt is suggested for lower temperatures and higher storm intensity, but the salt rate is usually kept constant in the storm event. This method is simple to be implemented but cannot consider the state of roadway friction after change in the decision making of salt application. On the other hand, the LSTM model can be used to predict the time-dependent evolution of surface grip levels with the inputs of weather parameters, road surface temperature, and salt application rates. The sequential effects of input features on the evolution of surface grip levels in the snow events are considered here. This allows real-time decision making of salt application based on grip status and environmental variables but has high requirement on the reliability of prediction model.

6.2 PRELIMINARY ANALYSIS WITH LIMITED MOBILE SENSOR DATA

6.2.1 Data Collection and Processing

6.2.1.1 Road Weather Information System (RWIS) Data

Road weather data were collected from four RWIS stations located on the I-25 corridor in Colorado during February 2023. These include road surface temperature, air temperature (maximum and minimum), dew point, water thickness, road surface state, humidity, visibility, barometric pressure, wet bulb temperature, precipitation rate, precipitation intensity, precipitation accumulation, road surface type, road surface sensor type, road surface friction index, road surface freezing point, road surface salinity, road subsurface temperature, average wind speed, average wind direction, gust wind speed, gust wind direction, spot wind speed, spot wind direction. Figure 32 illustrates the change in snow intensity over time at one of the RWIS stations. Two snow events from 2/14/23 to 2/15/23 and from 2/22/23 to 2/24/23 were observed, and the snow intensity was mostly light. The snow intensity data was processed for further analysis to determine the timing of snow events when road salt was applied during winter maintenance operations using multiple data sources, including road surface condition data and salt application data from AVL on plow trucks.

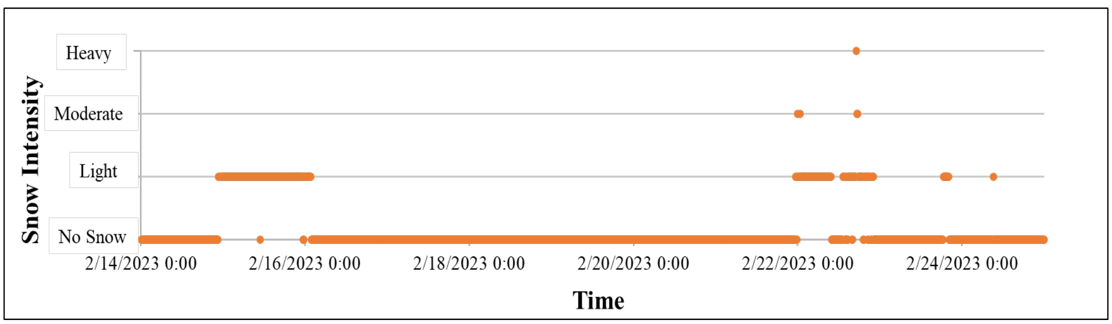


Figure 32. Snow intensity over time in February 14-24, 2023, from RWIS stations along I-25 in Colorado.

6.2.1.2 Road Surface Condition Data

Teconer Road Condition Monitor (RCM) is a non-contact sensor that uses a model-based friction meter, in this case installed on snowplow trucks. The measurement system detects the presence and amount of ice and/or water on a road surface. From this and other data measurements, the built-in model determines the coefficient of friction, which corresponds to the friction between the road surface and the vehicle's tires. The model was developed using braking deceleration measurements as a reference, which indicates fair agreement with some variation. The output data of the mobile sensor is updated approximately once per second (Teconer, 2021).

Two snowplow trucks with both RCM mobile sensors and AVL data actively being collected simultaneously were selected along the Interstate Highway I-25 corridor in Colorado[3]. Figure 33 shows movement of the two plow trucks (dots in different colors) on the I-25 corridor. The RCM mobile sensor data collected during the snow events in February 2023 was extracted for analysis**.** To investigate the influence of road weather variables, air temperature, road surface temperature, surface state, and water thickness before and after salt applications were considered. Friction coefficient values ranged from 0.20 (hard ice) to 0.81 (dry surface).

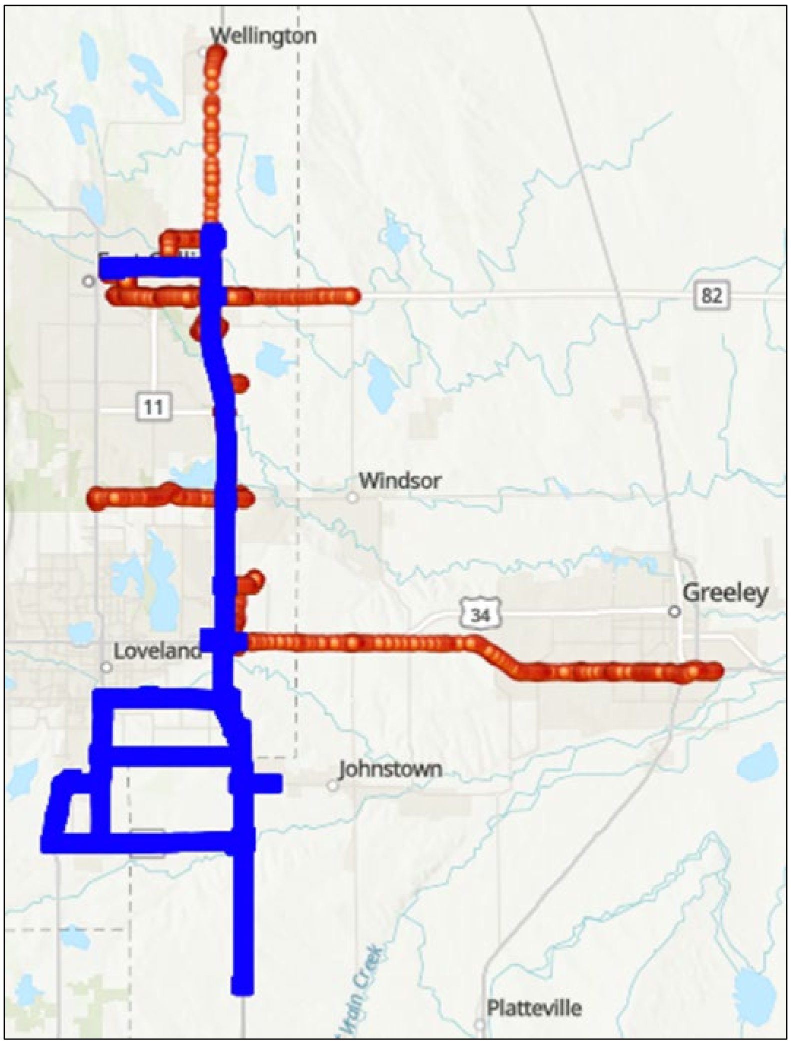
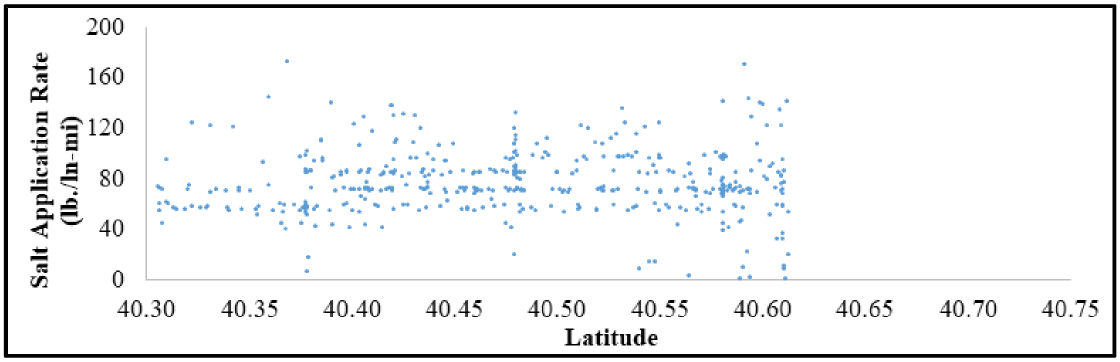


Figure 33. Map of AVL location data from two plow trucks on the I-25 corridor.

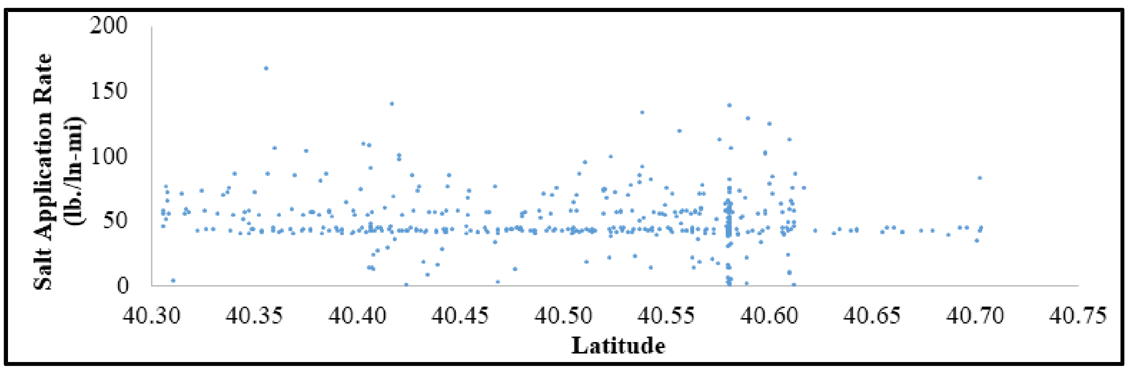
[3] At the outset of this project two snowplow trucks were actively collecting both RCM and AVL data. Later in the project additional snowplow trucks had the capability to collect both RCM and AVL data but one or both data elements were not available for various reasons.

6.2.1.3 Salt Application Data from AVL on Plow Trucks

AVL data from the snowplow trucks allowed for real-time salt application rate data to be collected, along with friction data from RCM sensors installed at the same plow truck. The salt application data from the I-25 corridor during the snow events in February 2023 was extracted, as shown in Figure 34. Friction measurement data collection timing was considered relative to the timing of salt application.



(a)



(b)

Figure 34. Salt application rate from one plow truck during the snowstorm: (a) February 15-16, 2023, and (b) February 22-23, 2023.

6.2.1.4 Data Integration

The timestamps of observations were different among the Teconer RCM sensor (friction) and GeoTab sensor (AVL and salt application) on the snowplow truck, and the sensors at the RWIS station. The coordinates from AVL data were provided to locate the snowplow trucks on the map. Integrating and preprocessing datasets was challenging due to the variable start and end times of snow events, road surface conditions, and salt application along the route. The information on friction, salt applications, and RWIS data were integrated based on the coordinates of observations during snow events.

Figure 35 shows the salt application data from the two snowplow trucks near the RWIS stations after data integration in February 2023. The locations of four RWIS stations are marked as red stars on the maps. The salt application data is mapped along I-25 from milepost 251.25 (Southbound 1.3 miles south of CO-60) and I-25 milepost 247.6 (Northbound 3.2 miles north of WCR-34). The size and color of the mapped dots indicates the values of salt application rates, and larger and darker dots represented higher salt application rates. Since snowplow trucks were moving along the I-25 corridor during the snow events, the start and end of the snow event for each RCM friction dataset were decided based on the snow intensity data from the nearest RWIS station.

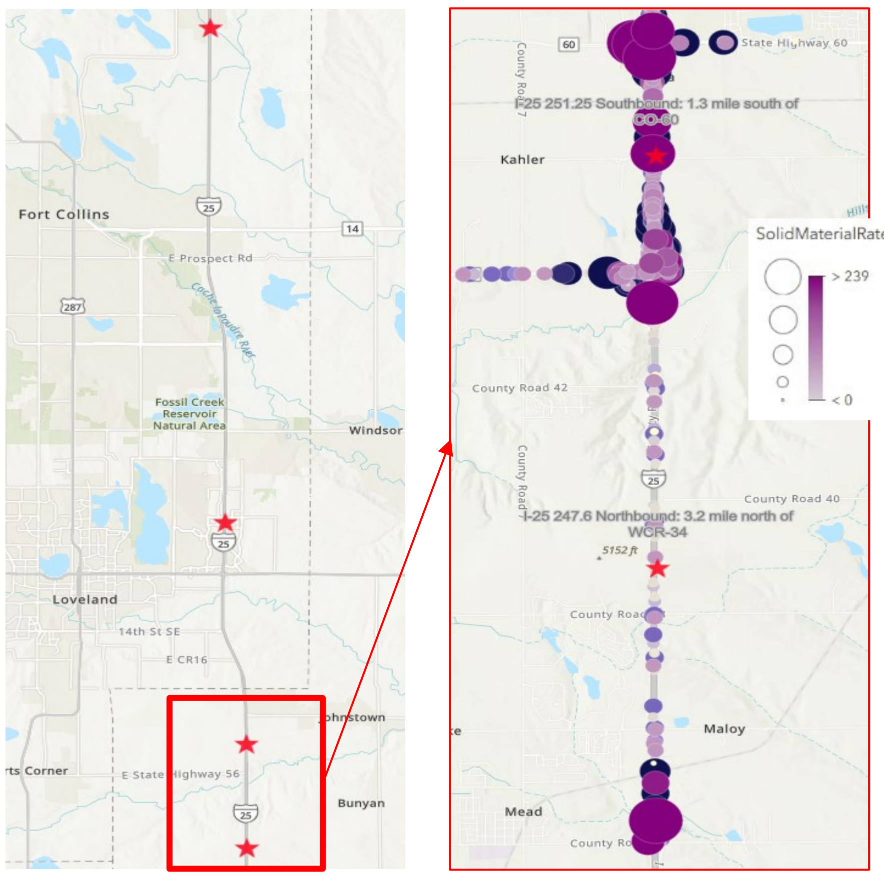


Figure 35. AVL salt application data from spreader sensors on the two plow trucks near the RWIS stations.

The integrated data were used to analyze how road surface friction changes after salt application at different weather conditions. Table 13 shows the selected variables from RWIS, RCM, and AVL data sets. To consider the effect of snow accumulation on surface friction, the time period between the first friction measurement and the start of a snow event and the time period between the second friction measurement and the start of a snow event was determined based on the RWIS, RCM, and AVL data. Additional input variables included road surface state and weather conditions before and after the salt application, such as air temperature, road surface temperature, water film thickness, and dew point temperature, timing of friction measurement after salt application, timing of friction measurements after snow event start, and solid material (salt) application rate. The output was the difference in roadway surface friction coefficients before and after salt applications. The total number of observations was 435 due to limited data availability.

Table 13. Summary of roadway surface grip, weather condition, salt application data.

Data Source	Symbol	Description	Range	Type
RCM411	Delta Friction	Change of Friction coefficient before and after salt applications	0~0.62	Output
RCM 411	Ta_B	Air Temperature before salt application	-23.4~0.6°C	Inputs
RCM 411	Tsur_B	Surface temperature before salt application	-18.7~0.44°C	Inputs
RCM 411	State_B	Road surface state before salt application	N/A	Inputs
RCM 411	Water_B	Water thickness before salt application	0~0.5 mm	Inputs
RCM 411	Tdew_B	Dew point before salt application	-25.2~0°C	Inputs
RCM 411	Ta_A	Air Temperature after salt application	-24.4~4.8°C	Inputs
RCM 411	Tsur_A	Surface temperature after salt application	-20.92~1.09°C	Inputs
RCM 411	State_A	Road surface state after salt application	N/A	Inputs
RCM 411	Water_A	Water thickness after salt application (snow-to-liquid ratio of 10:1)	0~0.509 mm	Inputs
RCM 411	Tdew_A	Dew point after salt application	-26.4~0°C	Inputs
AVL	Solid Material Rate	Salt application rate	0.3~228.3 lb./ln-mi.	Inputs
AVL	AfterT	Timing of friction measurement after salt application	0.001~0.86 hour	Inputs
RWIS	BeforeSnowT	Period between the first friction measurement and snow start	0.002~0.52 hour	Inputs
RWIS	AfterSnowT	Period between the second friction measurements and snow start	-0.5~0.42 hour	Inputs

6.2.2 Machine Learning Model Development

Traditional statistical regression models were first developed to investigate the influence of salt application rate on the change of roadway surface friction coefficients before and after salt applications. The statistical regression model performance was poor due to the variation of weather conditions during snow events. Therefore, machine learning-based regression models were developed using the integrated dataset, including support vector regression, random forest, and gradient boosting regression.

6.2.2.1 Machine Learning Algorithms

Support vector regression (SVR) is a machine learning technique that applies the principles of support vector machine learning to regression issues. The main objective of SVR is to find a function that approximates the relationship between the input features and the target variable while minimizing the error. In SVR, the goal is to find a hyperplane that fits as many data points as possible within a specified margin of tolerance. This is achieved by solving an optimization problem that involves minimizing the loss function, which penalizes errors outside the margin, and maximizing the margin around the predicted values. The formulation of the SVR optimization problem involves the use of a loss function, typically the epsilon-insensitive loss function, and the regularization term to control the complexity of the model (Drucker et al., 1996, Suykens et al., 2002, Smola et al., 2004).

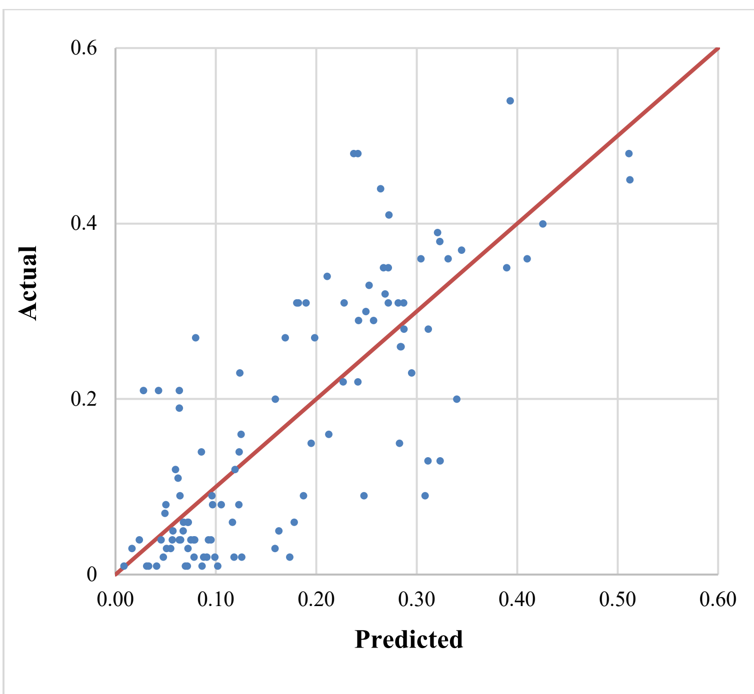
Random Forest is a powerful ensemble learning method that combines the predictions of multiple decision trees to enhance predictive accuracy and generalize well to unseen data. The core principle of Random Forest lies in creating an ensemble of decision trees, where each tree is trained on a random subset of the training data and a random subset of features. This randomness introduces diversity among the trees, leading to a more robust and accurate model. The final prediction of the Random Forest is generated by aggregating the predictions of individual trees, typically through majority voting for classification tasks or averaging for regression tasks. The algorithm is known for its ability to handle high-dimensional data, capture complex interactions, and provide robust predictions. The mathematical formulation of Random Forest involves the construction of multiple decision trees and the aggregation of their predictions using ensemble methods, adding an element of randomness and diversity to the model (Breiman, 2001, Cutler et al., 2007, Liaw & Wiener, 2007).

Gradient Boosting Regression is a popular ensemble learning technique that builds a predictive model by combining multiple weak learners, typically decision trees, in a sequential manner. The principle of Gradient Boosting Regression involves fitting a series of decision trees to the residuals of the previous tree, with each subsequent tree focusing on the errors of the previous ones. The algorithm minimizes a loss function by iteratively adding weak learners to the ensemble, where each learner is trained to correct the errors made by the previous ones. The final prediction is obtained by aggregating the predictions of all the individual trees. The key idea behind Gradient Boosting Regression is the use of gradients of the loss function with respect to the predicted values to update the model parameters in a way that minimizes the loss. The algorithm uses a learning rate parameter to control the contribution of each tree to the overall model (Friedman, 2001, Rosa, 2010, Chen et al., 2016).

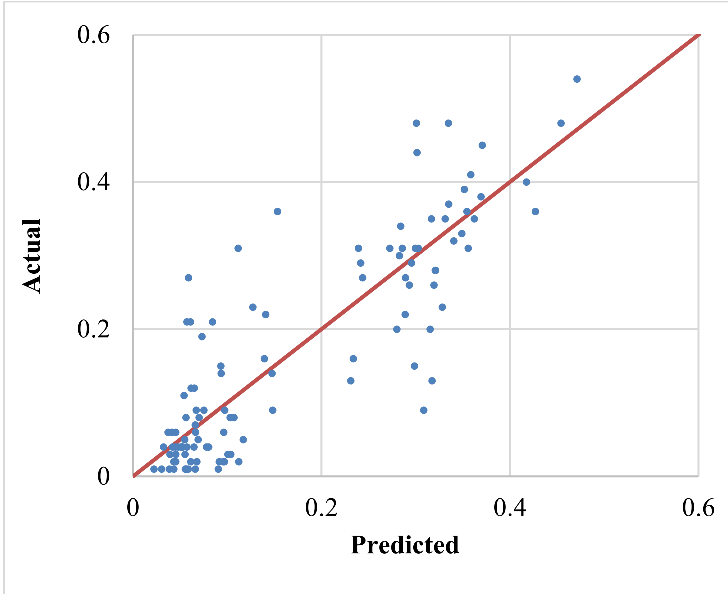
6.2.2.2 Development of Machine Learning Models

The observation dataset was divided into a testing subset (75%) and a training subset (25%) to develop three machine learning models, including support vector regression, random forest, and gradient boosting regression. Tuning of training hyper-parameters was conducted for each regression model. For example, for the random forest model, the number of instances in the ensemble, metric to capture information gain, number of features to evaluate, and whether to use bootstrap sampling were considered in the hyper-parameter tuning. The basic idea behind it is to generate a grid of hyper-parameters and try all the combinations automatically to search for the optimal hyper-parameters to enhance accuracy. The optimized model structure was used to predict the change of friction coefficients and analyze the most important variables according to the SHAP values.

Figure 36 shows the predicted versus actual values of friction coefficient change following salt application for the support vector regression, random forest, and gradient boosting regression models. The plots of random forest and gradient boosting regression models suggest better outcomes compared to that of the support vector regression model.



(a)



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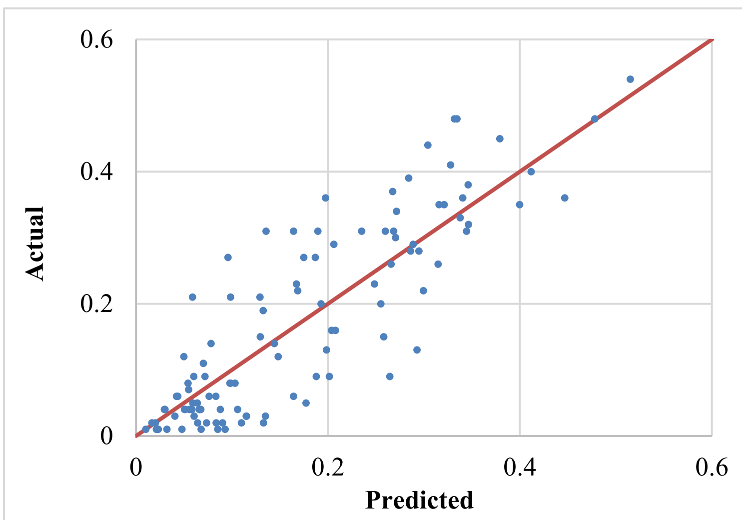


(c)

Figure 36. Predicted versus actual values of friction coefficient changes after salt application using (a) support vector regression, (b) random forest, and (c) gradient boosting regression.

Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared value are common metrics used to evaluate the performance of regression models. RMSE is a measure of the average magnitude of the errors between predicted and actual values, calculated by taking the square root of the average of the squared differences between predicted and actual values. MAE, on the other hand, measures the average magnitude of the errors without squaring them, providing a more straightforward interpretation of the model's performance. R-squared value, also known as the coefficient of determination, quantifies the proportion of the variance in the dependent variable that is predictable from the independent variables. It ranges from 0 to 1, with higher values indicating a better fit of the model to the data.

Table 14 illustrates the metrics of regression models. The results show that the random forest model outperformed according to the R-squared values, and the RMSE values of the random forest and gradient boosting regression models were similar. The fitted regression models were applied to analyze the variable importance and derive the optimal salt application rate using the SHAP technique.

Table 14. Model performance comparison of predicted versus actual change in friction coefficient after salt application.

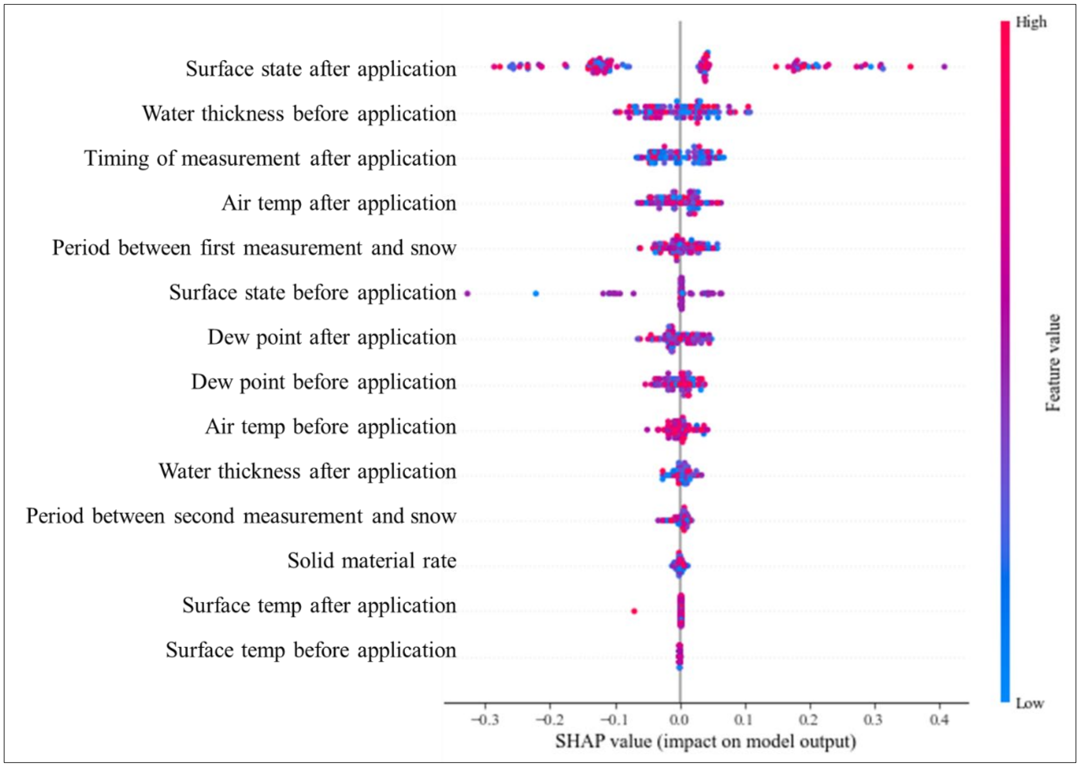
Performance Metrics	Support Vector Regression	Random Forest	Gradient Boosting Regression
R^2 (Train)	0.77	0.90	0.99
R^2 (Test)	0.63	0.74	0.71
RMSE	0.14	0.07	0.08
MAE	0.11	0.05	0.06

6.2.2.3 Analysis of Influential Variables

Sophisticated machine learning algorithms can provide accurate predictions, but it is challenging to interpret the model. Thus, in model interpretation, SHAP is used to measure each feature's contributions to the final prediction of the model by assigning a SHAP value to each feature. A higher average SHAP value indicates a more important parameter. SHAP values interpret the process of deriving the final model output by starting from the base value that would be a prediction if none of the features are known, after which SHAP values are incrementally calculated conditioned on one feature at a time. The feature's contribution is determined by accumulating all the feature combinations. When the addition of a feature increases the output value, it has a positive SHAP value.

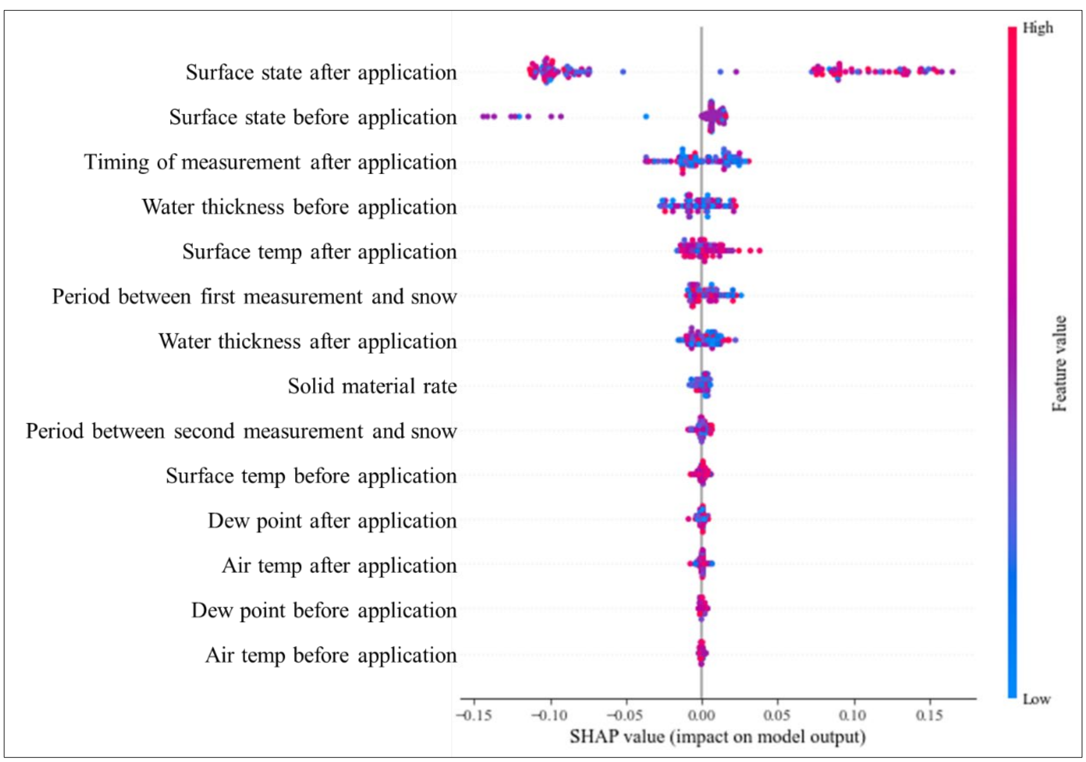
In this study, global interpretation of the derived model was conducted by calculating the SHAP values, and the positive and negative correlations between variables and prediction were illustrated by the SHAP value plots. SHAP (SHapley Additive exPlanations) is a game-theory approach that generates a unified framework to interpret any machine learning models (Shapley, 1988). The principle of SHAP is based on Shapley values, which are obtained from cooperative game theory and allocate the overall contribution of each feature to the prediction outcome. SHAP values offer a fair and consistent way to attribute the impact of individual features on the model's output by considering all possible orderings of feature importance. By calculating SHAP values for each feature, one can gain a comprehensive understanding of how the model arrives at a particular prediction and identify the key factors influencing the outcome. This interpretability aspect of SHAP makes it a powerful tool for explaining complex machine learning models and facilitating informed decision-making in various applications, including predictive modeling, risk assessment, and feature engineering (Lundberg & Lee, 2017). The Shapley kernel is a function that assigns a weight to each subset of features based on their importance in determining the model output. It measures the impact of adding or removing a feature from the subset on the prediction outcome. SHAP uses a weighted average of the Shapley values, known as the Shapley Additive Explanation, to explain the contribution of each feature to a particular prediction. This approach provides a coherent and interpretable way to understand the model's decision-making process (Lundberg et al., 2020).

Figure 37 illustrates the calculated SHAP values for each regression model, including support vector regression, random forest, and gradient boosting regression models. The variables of greatest importance were consistent for different regression models. The features are sorted and plotted by decreasing importance. For example, according to the calculated SHAP feature, for the random forest model in Figure 37 (b), the most important variables included surface state after application, surface state before application, air temperature after application, water thickness before application, and surface temperature after salt application. The most important variables were consistent for three different machine learning models. The road surface states before and after salt applications reflected the change in road surface friction coefficients. Air temperature, road surface temperature, and water thickness indicated the road weather conditions, such as temperature and snow intensity, which were consistent with the determination of salt application rate based on road surface temperature and snow intensity in the winter maintenance guidelines implemented by several state DOTs (Du et al., 2019).



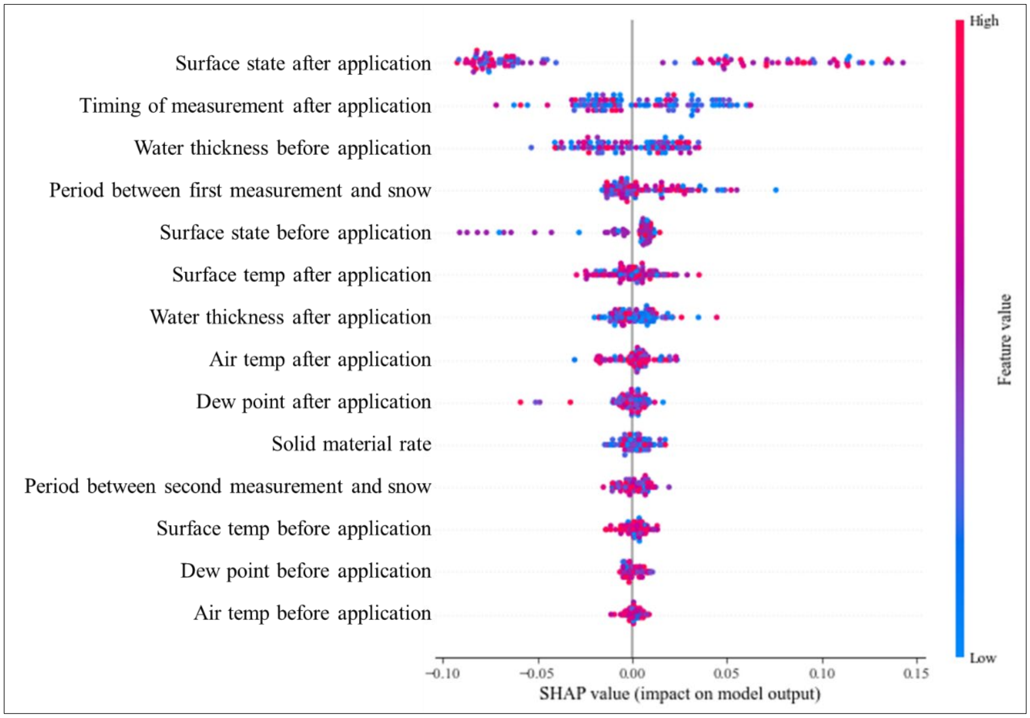
High
Surface state after application
Water thickness before application
Timing of measurement after application
Air temp after application
Period between first measurement and snow
Surface state before application
Dew point after application
Dew point before application
Air temp before application
Water thickness after application
Period between second measurement and snow
Solid material rate
Surface temp after application
Surface temp before application
Feature value
Low
−0.3
−0.2
−0.1
0.0
0.1
0.2
0.3
0.4
SHAP value (impact on model output)

(a)



High
Surface state after application
Surface state before application
Timing of measurement after application
Water thickness before application
Surface temp after application
Period between first measurement and snow
Water thickness after application
Solid material rate
Period between second measurement and snow
Surface temp before application
Dew point after application
Air temp after application
Dew point before application
Air temp before application
Feature value
Low
−0.15
−0.10
−0.05
0.00
0.05
0.10
0.15
SHAP value (impact on model output)

(b)



(c)

Figure 37. SHAP feature importance for machine learning models: (a) support vector regression, (b) random forest, and (c) gradient boosting regression.

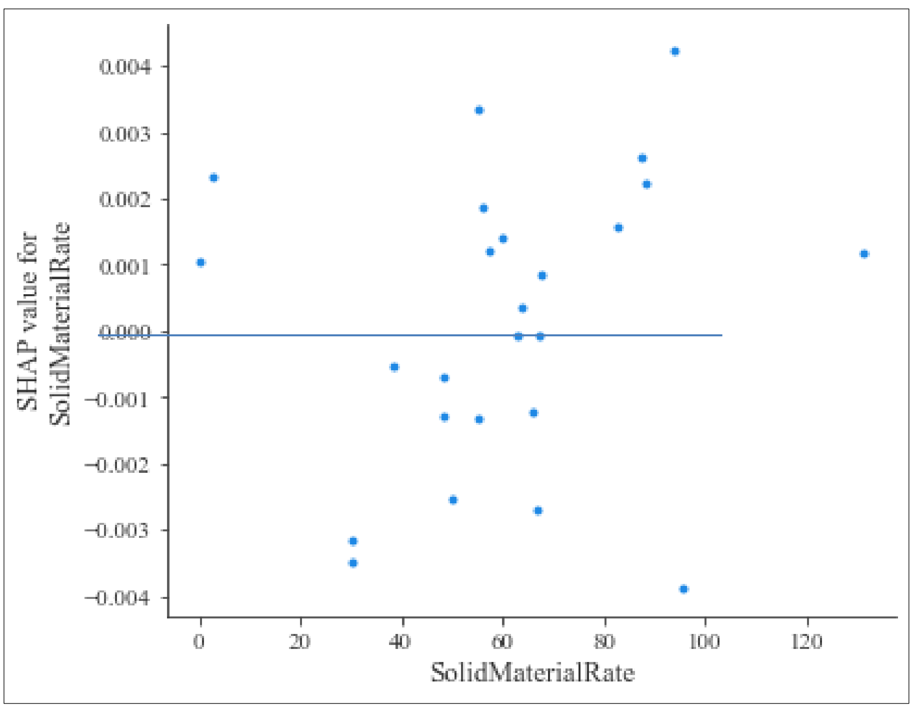
6.2.3 Sensitivity Analysis of Salt Application Rate

To analyze the effect of salt application rate on road surface grip, the SHAP value for solid material application rate was plotted in a dependence plot using the random forest model. A dependence plot is a type of scatter plot that displays how a model's predictions are affected by a specific feature, such as the salt application rate in this case study. SHAP dependence plots are an alternative to partial dependence plots and accumulated local effects. In general, the salt application rate has mostly a positive effect on the model, and the optimal salt application rate is needed to establish an efficient and effective winter roadway maintenance program.

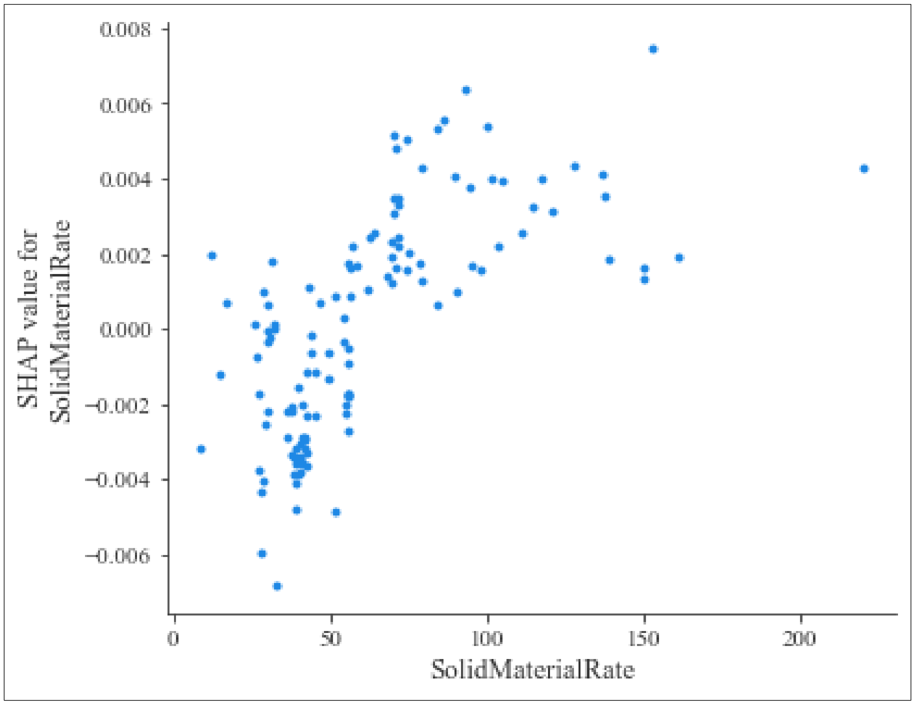
In general, solid material application rate is determined by road surface temperature and snow intensity. However, the recommended salt application rate varied in different states. For example, when road surface temperature was > 26 °F, 20 ~ 26 °F, and < 20 °F, the recommended salt rates were 100, 125, and 150 lb./ln-mi for light snow in Iowa. In Colorado, the weather conditions of snow and freezing rain were considered, and a wide range of salt application rates (like 75~150 lb./ln-mi) was recommended for each temperature range, including > 30 °F, 25~30 °F, 20~25 °F, 15~20 °C, and < 15 °C (Du et al., 2019). Light snow was observed at the RWIS station in February 2023. Therefore, the SHAP values were calculated for the scenarios of road surface temperature > 26 °F, 20~26 °F, and < 20 °F, respectively.

Figure 38 presents the SHAP dependence plot of solid material application rate based on the random forest model. Every dot was a single prediction from the dataset with the specific road surface temperature. The x-axis indicates the value of the selected feature (salt application rate in this example), and the y-axis indicates the calculated SHAP value for the corresponding feature. The changing trend or slope of the SHAP value suggested that the selected feature changed the output of the model for the sample's prediction.

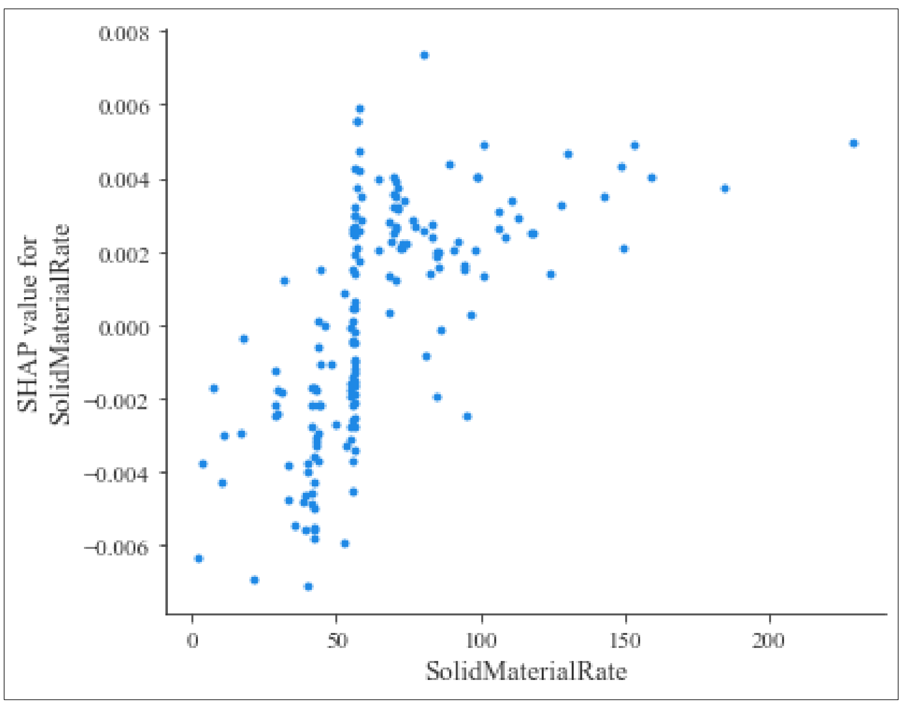
The analysis results indicated that road surface grip improved as the salt application rate increased when the salt application rate was less than 80 lb./ln-mi. The salt application rate has greater influence on road surface grip when it was less than 100 lb./ln-mi. The SHAP value suggests how much the feature contributed to moving the output from the base value (average model output) to the individual prediction. The negative values on the y-axis indicate salt application has negative effect on the friction changes as compared to the average model output. While the positive values suggest salt application has a positive effect on the friction change as compared to the average model output. Thus, the changing trend or slope of predictions is used to indicate the variable's influence, and an increasing trend indicates the positive influence on the output (of salt application on roadway friction).



(a)



(b)



(c)

Figure 38. SHAP dependence plot of solid material application rate during a light snow event based on the random forest model when the road surface temperature is: (a) >26°F; (b) 20~26°F; and (c) < 20°F.

6.3 SUMMARY OF ALGORITHM RESULTS

6.3.1 Iowa DOT Analysis

Data-driven approaches were used to predict road surface grip levels using RWIS and AVL datasets. Data pre-processing was conducted to compile the dataset having continuous records of weather variables, surface temperatures, grip levels with discrete observations of salt application. An innovative LSTM neural network model was established to predict the time-dependent evolution of surface grip levels in winter seasons with the inputs of weather parameters, road surface temperature, and salt application rates. Importantly, the LSTM model considers the sequential effects of input features on the evolution of road surface grip levels in the snow events and thus can be used as a decision-making tool of salt application for winter operation maintenance.

The proposed decision-making tool based on the developed LSTM model is a dynamic process through adjusting the salt application rate based on the prediction of road surface grip levels until the desired grip level is achieved. Given the weather conditions at the RWIS station, the change of road surface grip levels after salt applications can be updated automatically by the LSTM model. However, it is not a straightforward approach compared to a table-based guideline that is currently used by state DOTs. The interaction effects of salt application and weather conditions on the variation of road surface grip with time were analyzed, and the grip was found to be more impacted by salt application rates when temperatures were lower (colder), and snow intensity was greater.

Although the feasibility of dynamic decision making of salt application is proved, the LSTM model is developed with a limited dataset and needs be further refined with more data covering large variations in climate conditions and geographical locations for improved accuracy and reliability.

6.3.2 Colorado DOT

Machine learning regression models were developed to predict the change of roadway surface grip after salt application data considering weather variables during the snow events. The mobile sensor, road weather, and salt application data collected on the I-25 corridor in February 2023 by Colorado DOT were analyzed. Among different machine learning models, random forest was found to fit the integrated dataset with the largest R-squared value and the smallest error value. The impact of each variable on the change of surface grip was investigated. The impact of salt application rate on friction coefficient change was found to be limited. The most important variables included surface state after application, surface state before application, air temperature after application, water thickness before application, and surface temperature after salt application.

There are concerns on road surface friction and weather condition data collected using the mobile sensors installed on the snowplow trucks with AVL data collection. This presents the limitation when applied to winter maintenance operations. Integrating AVL data with other systems, such as snowplow sensors and road weather information from RWIS sites, can be complex due to the difference in timestamp and coordinate system and may not always provide reliable data. Due to the limited data collected in the project period, developing a decision-making tool for salt application was not achieved using mobile sensor data. More data is needed to develop predictive models of friction change due to salt applications at various weather conditions (air temperatures and snow intensity) using mobile sensor data in future studies.

CHAPTER 7: RECOMMENDATIONS

7.1 SUPPORTING THE USE OF GRIP DATA TO INFORM SALT APPLICATION RATES - IMPLEMENTATION OF THE ALGORITHM AND DECISION MATRIX

Maintaining road surface grip during snowstorms is critical for mobility and safety. Measurement and monitoring of roadway surface grip are critical components of road safety and maintenance practices, particularly in adverse weather conditions. Road surface grip can be used as a quantitative indicator for effective winter maintenance and can be used as a decision-making tool. This study used data-driven approaches to predict road surface grip (pavement friction) to inform salt application rates used in winter maintenance operations using RWIS based, mobile sensors, and AVL data.

7.1.1 Iowa DOT RWIS Data

Roadway surface grip and road weather parameters were collected from RWIS sites in Iowa. Traditional machine learning approaches were employed to develop predictive models of grip, which provided robust results and importance ranking of variables but required complex data pre-processing for model development. An advanced recurrent neural network (RNN) model using long short-term memory (LSTM) was developed with Bayesian optimization of model hyperparameters. The LSTM model considers sequential effects of surface temperature, atmospheric condition, and salt application on the time-dependent evolution of road surface grip and was found to effectively predict salt application rates in an event-based scenario. The interaction of salt application rate and weather condition on road surface grip were analyzed, and the grip was found to be more impacted by salt application rates when the air/pavement temperature was lower (colder).

Recommendations based on these findings include.

1. Use of a complex model has pros and cons.
    a. The complex model does a good job of predicting how friction will change with salt applications, but requires knowledge of modeling techniques, data management and QA/QC, and knowledge of how to interpret the results.
2. Based on limited data
    a. This work is based on data from two RWIS sites in Iowa. To further the test this method, it is recommended that data from significantly more RWIS sites be incorporated.
    b. This work is based on categorical friction data. The friction data was provided as high, medium, or low; not the typical 1.0 – 0.0 coefficient of friction (μ) values. This means that the model could only determine if salt application led to a categorical change in friction, for example from high to medium. This limits the understanding of how salt application rate affects roadway friction.
3. Variability of Influence of Salt at Cold Temperatures

    a. The LSTM model showed that roadway grip is influenced by salt application rates when air/pavement temperatures were colder. This could be investigated further using data from storm events with temperatures at the lower working temperatures for salt (15-20°F) to help identify the point of diminishing returns (increase salt application versus improvement in friction).

7.1.2 Colorado DOT AVL and Mobile Sensor Data

Roadway surface grip and road weather condition data were collected via mobile sensors on snowplow trucks in Colorado. The performance of machine learning models, including support vector regression, random forest, gradient boosting regression, artificial neural network, and Bayesian neural network, were compared, and the influence of road weather variables on the change of roadway friction coefficient before and after salt application were investigated using SHAP. The calculated SHAP values were used to develop recommendations for salt application rates. The impact of salt application rate on the friction coefficient was limited when compared to the weather condition variables. The most important variables included surface state after application, surface state before application, air temperature after application, water thickness before application, and surface temperature after salt application. The salt application rate of 100 lb./ln-mi was found to be an important threshold, below which the effect of salt on road surface grip was significant.

Recommendations based on these findings include.

1. Based on limited data
    a. The analysis is based on one month of data from two plow trucks. While additional data was provided (from more trucks and additional months), consistent data was not collected limiting the complete dataset.
2. Communication between DOT, data provider
    a. Establishing an efficient data communication plan between an agency (DOT) and the data provider, and possible the data owner, will allow for easy data requests, open communication, and understanding of expectations about timing and needs.
    b. Data labeling often varies between agencies or sensor vendors. A recommendation is to create a crosswalk file, or file that defines how each agency or organization labels the data, the units of the data, and the source or sensors used to collect the data. This will provide a map for understanding of the data.
3. Data Considerations
    a. For multiple data sources, the timestamp and coordinate system varied, requiring significant effort to match and convert the date, time and location information in pre-processing. For example, to more easily integrate data from multiple sources and companies, it is recommended that the same coordinate system be used.

b. Salt application rates data varied significantly and rarely followed the suggested guidelines. This may be an artifact of how the data was recorded, such that actual salt application rates were not recorded due to the relatively large timestamp interval. Adjusting the timestamp interval to capture the actual salt application rate is recommended.
c. Mobile sensors enable monitoring of road surface friction conditions at multiple locations. The development of data collection and data quality assurance/quality control (QA/QC) requirements is recommended to aid in a more robust data set that can be used to support the modeling of grip and salt application and development of a decision-making tool.

7.1.3 General Recommendations

The proposed machine learning models should be further verified with larger datasets in future studies. Additional considerations for the impact of road salt applications should look at economic cost and environmental impacts to determine the optimum salt application rate for varying winter roadway conditions and maintenance tools.

The use of stationary RWIS based data versus mobile sensor data has pros and cons associated with each. For many states the RWIS system is robust with statewide coverage of the road network, often at specific distance intervals; but this data represents only a point location. Whereas mobile sensor data often has less coverage of a state but provides data wherever the vehicle travels. In the last few studies using both RWIS based and mobile sensor data, RWIS based data has produced the best results in terms of modeling roadway friction because the datasets are often larger and more representative (Weiner et al., 2023). For mobile data to provide similar quality of results, in terms of modeling roadway friction, data from many vehicles, repeated data collected from road segments, and longer-term data sets are required. This will require a concerted effort by an agency to ensure the mobile sensors are turned on, maintained, calibrated, and are reporting good quality data.

Additional data to consider for future analyses includes the use of AVL based data, such as plow up and down and calibration records or certification for spreaders (solid and liquid). This will enhance the accuracy of model prediction on grip changes after winter maintenance treatments.

CHAPTER 8: CONCLUSIONS

From the literature review the following conclusions can be made.

- Use of road weather and road condition data can increase the efficiency of winter maintenance activities and reduce weather-related crashes. Roadway grip is a good indicator of when a road is safe or conversely unsafe.
- There is an increasing interest in utilizing grip data to assess winter maintenance operations. Grip data is being used both internationally and in the United States as a maintenance threshold or performance metric.
- There are several methods used to collect grip data, and each has its own pros and cons. Friction wheels or skid trailers provide high quality pavement friction data, but due to limited winter deployment in the U.S., data availability is limited. Stationary sensors mounted at RWIS sites can provide a robust grip dataset but provide limited spatial coverage. Mobile sensors can provide better data coverage of an area, but mobile devices should be installed on vehicles that travel routes frequently to provide sufficient data. Floating car data, or crowd sourced data, is an emerging data source which has been shown to provide robust grip datasets. Floating car data is being tested at the Swedish Transport Administration and in the Netherlands Highway Agency.
- Machine learning is being used to predict road surface condition, temperature, and recommend salt application rates. Additionally, ML can be used to develop decision support systems for winter maintenance that can provide recommendations of treatment type and material. Grip data appears to be a valid input variable in these prediction models.
- Data-driven winter maintenance operations will only succeed if the data used is of good quality. Conducting QA/QC on any data collected, maintenance of equipment, and calibration of both sensors and salt delivery systems (salt spreaders) is critical to ensure quality data is being collected.

From the Survey the following conclusions can be made.

- Eighteen states across the US indicated they use grip data in winter operations. The majority of the grip data was collected using stationary mounted non-contact sensors, with many also collecting grip data using mobile sensors. The collected grip data is being used to make real-time decisions, determine material application strategies, and for planning, and to a lesser extent for training and review of operations and forecasting. Many agencies indicated that the grip data is used in a variety of tools developed to support winter maintenance operations.

From the Case Studies the following conclusions can be made.

- While several transportation agencies have begun to incorporate roadway grip data into their winter maintenance operations, those highlighted in the case studies are in the early phases of

implementation. The complete picture of the benefits of integrating this data into decision-making is not yet known. This is particularly the case with third-party grip data where this data only recently became available in the United States. However, as grip data becomes more readily available through various sources, the opportunities seem to be endless. Additionally, as programs like ITDs MCE mature, successes and lessons learned can be shared.
- Transportation agencies that have begun to collect and integrate grip data into their winter maintenance practices have been able to optimize resources (e.g., material, labor), measure winter maintenance operations performance, and efficiently treat roadways by providing real-time feedback and automating winter maintenance operations. Specifically, ITD is automating calculations that were previously done manually and MassDOT is working to automate the decision-making process for application rates at the spreader controller.

From the development of the Algorithm the following conclusions can be made.

- An RNN LSTM model can be used to predict friction evolution during the storm event and recommend salt application rates for decision making. Key model variables include roadway surface temperature, air temperature, salt application rate, and roadway grip. This method requires complex modeling and data management. The model found that roadway grip improved more quickly with increased salt application rates, especially at lower temperatures.
- Grip data from both stationary RWIS sensors and mobile sensors were utilized in this effort. In both instances, challenges with the data limited the extent of the analysis. The RWIS based grip data was provided as categories (low, medium, high) and not as coefficient of friction values. The mobile data was very limited in quantity.
- To support a more robust analysis, additional data from a variety of storm events is recommended.

Recommendations based on the review of the literature, developed case studies, and the algorithm development are provided in Chapter 7: Recommendations.

8.1 FUTURE RESEARCH

The following future research or work will help support advancement of this research effort.

- Continue work to test the developed models using more data, from a variety of storm types, salt application methods and strategies, etc. for decision making of salt application rates.
- Identify and develop a data collection plan for mobile sensors where mobile data is routinely collected to create robust data sets to allow for analysis.
- Develop a guidance document to address data needs, data management, coordination and data sharing between DOT and data providers for winter roadway maintenance.

- Develop a data management plan that addresses data sources, calibration required for spreaders and sensors, data collection frequency, data quality control procedures to perform before data is used in any analysis, and a crosswalk file to explain the data.

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APPENDIX A – SURVEY INSTRUMENT

CR 21-01 Grip Sensor Technology and Salt Applications Survey

This survey has been created to help support Clear Roads and its member states in their understanding of how agencies are using roadway grip or friction information, what technology they used to capture this information, and how they are applying this information in winter operations.

Information gathered in the survey will be used to inform other agencies on the prevalence of roadway grip data collection and use. Some of the identified instances will be used to create case studies highlighting various roadway grip data collection networks and how roadway grip has been integrated into operations and decision making.

This research study was reviewed by the Montana State University Institutional Review Board (irb@montana.edu). Participation in this survey is voluntary and you may skip any question you do not want to answer and/or you can stop at any time. Proceeding with the survey indicates your consent to participate. The survey should take about 5 minutes. Any questions or comments can be directed to Karalyn Clouser of WTI/MSU at karalyn.clouser@montana.edu or (406) 529-0654.

Thank you for your time.

1. Does your agency/organization use roadway grip, or friction, data in winter operations?
   - Yes (*If checked, continue to question 2.*)
   - No (*If checked, end the survey.*)

2. How does your agency collect roadway grip data? (Check all that apply.)
   - ☐ Stationary Road Weather Information Systems (RWIS) Mounted Sensors
   - ☐ Mobile Mounted Sensors on Vehicles
   - ☐ Skid Trailer or Friction Wheel
   - ☐ Floating Car Data or Crowd Sourced Data
   - ☐ Other (please specify):

3. How does your agency use roadway grip data in winter operations? (Check all that apply.)
   - ☐ Forecasting
   - ☐ Planning (determining when to begin operations, identifying problem areas, etc.)
   - ☐ Real-Time Decision Making (routing, call in crews, etc.)
   - ☐ Material Application Strategies
   - ☐ Retrospective Review of Operations (Agency performance/cost review)
   - ☐ Other (please specify):

4. Does your agency incorporate roadway grip data in any tools (example: Maintenance Decision Support System (MDSS), Weather or Winer Severity Index (WSI), decision tree, etc.)?
   - Yes (*If checked, continue to question 5.*)
   - No (*If checked, continue to question 6*.)

5. Please explain how your agency incorporates roadway grip data in any tools.

6. Please provide the following information.

   Agency (road/airport):

   Location (country/region/state):

7. May we follow up via email or phone to learn more about your roadway grip data availability, networks, tools used, etc.?
   - Yes (*If checked, continue to question 8*.)
   - No (*If checked, end the survey*.)

8. Contact information

   Name:

   Email Address:

   Phone Number:

We thank you for your time spent taking this survey.

APPENDIX B – INTERVIEW WITH NIRA DYNAMICS

Interview with Björn Zachrisson, Product Strategist at NIRA Dynamics (Currently under review for approval by Bjorn, 10/28/2022)

October 24, 2022

- NIRA Dynamics is a software company only within the automotive industry. Software is within the ABS braking system. In the connected domain have software inside of vehicles and collect wheel speed signals for rotation and relation between the wheels. They derive a lot of information, e.g., friction, slip of wheels on the replica axel and plot the slip of the driving axel versus the torque. Their model calculations are based on experience from extensive tire and tire pressure testing. Can also provide information on "wet state" from windshield wiper blade data.
- An example map displaying NIRA data in the UK was shared. This showed nearly 100,000 vehicles from the full Volkswagen group family (Audi, Volkswagen, Skoda & Seat not available in the US) worth of data including road friction, ambient temperature, wet state, and road surface temperature (estimated – started testing last season). The map displays vehicle data from red to green.
    - Red – very slippery, like driving on ice, no self-driving support allowed from an automaker perspective.
    - Green – good enough to drive on autobahn (German highway system with no speed limit) at full speed, full self-driving support allowed from an automaker perspective.
- Typically, friction data is measured in groups, so friction data may not be reported on all road segments. Their focus is on quality data not quantity.
- Use case study:
    - KPIs – how much time was road slippery when it should not be, or how long was is slippery?
    - Identify trouble spots and treat early to avoid issues.
- Looked at road friction and ambient (air) temperature and there was a strong correlation. Did not even consider treatments. (If they exclude the bridge temperature from the vehicles, then the air temperature is fairly accurate (±0.5 degrees), but RWIS air temperature is more accurate (±0.1 degrees).
- Use friction (KPIs) to assess road condition and flag when sites are slippery when they should not be. Report as percent (%), only on the high-density road network.
- Data delay is 3-10 minutes from collection to display. Data is stored in 10 minute time windows over 75 foot segments. In areas with poor cellular service, the data transmission may be delayed however Europe in general has great cellular coverage.
- Provide alerts for high confidence situations e.g., very slippery, via email or text. 2021 alerts were 100% accurate, according to the Dutch DOT. First full-size fleet up and running in the Netherlands, then in Sweden.
- DOTs in Netherlands/Sweden report accidents real-time on Twitter, so they have access to that data.

- An upcoming project with Aurora, teaming with Purdue will use NIRA data. Last winter was the first year of analysis of data from Indiana. Expecting a report and possibly a TRB presentation in 2024.
    - We will follow up on results from this effort.
    - Here is another related Aurora project by researchers from Utah: Roadway Ice/Snow Detection Using a Novel Infrared Thermography Technology | Institute for Transportation (aurora-program.org)
- Live road Maintenance feature, now for US data as well. The major drawback in the US is low penetration (availability of data from vehicles) of connected vehicles (VW and Audi). Work is ongoing (usually NDA limited) to get one American or multiple Asian original equipment manufacturers (OEM's) to provide data, especially in rural areas.
- Use historical data to see which roads are freezing first and prioritize them higher on the salting routes.
- Use live data to see when the salt has no effect anymore, or for that matter see when it does give the intended effect.
- Salt residue algorithm used by some weather forecasters is being paired with data to develop algorithms by other researchers - VTI (Swedish Federal Research Institute, Anna Arvidsson, TRB WM Committee Chair) and Swedish project. Ongoing project looking at forecast, salt residue, connected vehicles, to develop dynamic routing.
    - We will follow up to learn more about this effort.

APPENDIX C – CASE STUDY INTERVIEWEES

Follow-up interviews were conducted to capture additional information for the case studies. Interviews were conducted with the following individuals and organizations (Table 15).

Table 15. Case Study Interviewees

Interviewee, Organization	Case Study Topic
Mark Goldstein, Massachusetts DOT	Linking Salt Spreader Controller Data with Mobile Road Weather Information Sensors
Dr. Chengbo Ai, University of Massachusetts Amherst	Linking Salt Spreader Controller Data with Mobile Road Weather Information Sensors
Steve Spoor, Idaho Transportation Department	Snow Operations Application Suite
TJ McNeff, Idaho Transportation Department	Snow Operations Application Suite
Tina Greenfield, Iowa Department of Transportation	Third-Party Friction Data from Vehicles
Alex Lee-Warner, Wejo	Third-Party Friction Data from Vehicles
Neal Hawkins, Intrans, Iowa State University	Third-Party Friction Data from Vehicles
Zach Hans, Intrans, Iowa State University	Third-Party Friction Data from Vehicles
Skylar Knickenbocker, Intrans, Iowa State University	Third-Party Friction Data from Vehicles
Dan Schacher, Alaska Department of Transportation and Public Facilities	Friction Data and Pikalert
Gerry Weiner, National Center for Atmospheric Research	Friction Data and Pikalert
Amanda Siems-Anderson, National Center for Atmospheric Research	Friction Data and Pikalert

CLEAR ROADS

research for winter highway maintenance

Lead state:
Minnesota Department of Transportation
Research Services
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