DEPARTMENT OF TRANSPORTATION

Reducing Winter Maintenance Equipment Fuel Consumption Using Advanced Vehicle Data Analytics

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16. Abstract (Limit: 250 words)

This project analyzes the impact that idling and snowfall have on the fuel consumed by MnDOT's snowplow fleet, with the underlying objective to determine and advise MnDOT on ways to reduce fuel usage of the fleet using vehicle telematics data. This is a significant problem to solve as fuel use reduction contributes to MnDOT's sustainability goals of achieving a 30% reduction in fossil fuel use and greenhouse gas (GHG) emissions from 2005 levels by 2025. Furthermore, rising fuel costs are a future cause for concern due to an increase in business operational costs that increases the burden on taxpayers to keep roads safe in winter. This problem is challenging because existing on-board diagnostics (OBD) data do not contain mass information for the trucks' fuel use, which can fluctuate significantly when they are applying deicing substances to the road. Taking a mean value for the vehicle mass, we observe a clear positive correlation between snowfall and average fuel use. For days with snowfall totaling 4 inches or more, fuel use rises more than 25% on average compared to days without snowfall. In addition, the results from the idling analysis indicate that the idling time associated with the fleet is about 23% of total recorded hours and constitutes about 4.3% of the total fuel used. Daily idling activity reports containing information about idling events and fuel economy are generated for the sampled vehicles and shared with MnDOT.

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Executive Summary

This project investigates the impact of idling and snowfall on the fuel consumption of the Minnesota Department of Transportation (MnDOT) snowplow fleet, with an underlying objective to determine and advise MnDOT on ways to reduce fuel use of the fleet, using vehicle on-board diagnostics (OBD) data.

This work not only quantifies the impact of parameters like idling and snowfall on the fuel consumption of snowplow vehicles, but it also forms a basis for future action to reduce fuel use. For example, efficient auxiliary power units could be used to address long periods of idling. Also, energy use data can be used to strategically place snow fences along Minnesota roads to reduce drifting and blowing snow, thus reducing high fuel consumption due to snowfall events.

The OBD data were obtained from a fleet of 600 MnDOT snowplow vehicles instrumented with AmeriTrak mobile computers integrated into MnDOT's Maintenance Decision and Support System (MDSS). The vehicle computing systems provide high-fidelity vehicle data, which are collected and recorded, on average, every 2 seconds from each active vehicle. The collected data were previously underutilized due to their immense size. The University of Minnesota project team's research efforts were focused on investigating the impact idling and snowfall have on the fuel consumed by MnDOT's snowplow fleet, harnessing large quantities of vehicle data to help improve vehicle fuel economy and lower operating costs.

Fuel use reduction is motivated by both economic and environmental factors. According to the *Inventory of U.S. Greenhouse Gas (GHG) Emissions and Sinks 1990–2019*, the transportation sector accounts for about one-third of total GHG emissions, and medium and heavy-duty trucks are the second highest contributor of GHG emissions within the transportation sector. Plowing operations carried out by MnDOT are a fuel-intensive activity that not only results in GHG emissions but also costs taxpayers a lot of money to keep roads operational in winter. Furthermore, rising fuel costs are a future cause for concern due to the increase in business operational costs increasing the burden on taxpayers to keep roads safe in winter. Efforts to reduce total fuel use would not just result in significant savings in operational costs but would also contribute to MnDOT's sustainability goals of achieving a 30% reduction in fossil fuel use and greenhouse gas (GHG) emissions from 2005 levels by 2025.

Reducing idling is one of the primary ways fuel can be saved in snowplow fleets. Idling refers to situations in which a vehicle's engine is running while the vehicle is stopped. There are a multitude of reasons for vehicle idling in general; for snowplows, some prominent reasons could be to warm up the engine, interim pauses in winter maintenance operations, driver refreshment between trips, loading of chemicals at truck stations, and preventing fuel freezing. In this project, the frequency (number of idle events) and length of idling (minutes/hours) of vehicles across different districts and locations (truck stations, etc.) are analyzed as part of the idling analysis to understand fleet idling behavior. The term *idle event* is defined as three or more minutes during which a plow remains motionless, using the GPS-based speed parameter provided by AmeriTrak as the indicator of movement. Given the definition of idling, frequency (number of idle events) and length of idling (minutes/hours) of vehicles across different districts and locations (truck stations, etc.) are computed for winters from 2018 to 2021. Idling analysisresults show that, from 2018-2021, snowplow fleet idling constitutes about 23% of the total recorded hours, i.e., 52,523 hours, and 4.2% of the total fuel consumed, i.e., 50,343 gallons. In addition, daily idling activity reports containing information about the idle events and sampled fleet fuel economy are generated and shared with MnDOT via email. Some studies indicate that the use of a direct-fire heater reduces fuel consumption by 94-96% and an auxiliary power unit (APU) would reduce fuel consumption by 60-87% in heavy-duty trucks during idling. A recommendation for MnDOT would be to carry out a cost-benefit analysis of using alternative technologies like direct-fire heaters and/or APUs as they would result in a considerable reduction in fuel use and emissions. Another recommendation would be to continue the idling analysis as it would aid in building a framework to systematically address long periods of idling at truck stations and other locations.

In addition to the idling analysis, a more comprehensive energy analysis was performed to determine the impact of snowfall on the fuel economy of the snowplow vehicles. The energy analysis considered 41 snowplows operating in Minnesota that were regularly active over the 2020-2021 winter season (November to March). These vehicles collectively made more than 4300 recorded trips in the winter months, with about 65% of these trips occurring on days with no snowfall as reported by local National Weather Service (NWS) stations. A framework was developed that uses a simplified version of the road load equation to estimate fuel use, with constant vehicle parameters (powertrain efficiency, rolling resistance coefficient, coefficient of drag, and idling fuel rate) determined for each individual vehicle (ESN) using the Levenberg-Marquardt algorithm to solve the least squares problem for all available trips for each vehicle. To account for the change in fuel consumption due to snowfall, the baseline vehicle parameters were fitted using fuel rate OBD data from days without snowfall, i.e., dry days. Because the vehicle mass was unknown for the available data set, a mean value was chosen during the model fitting process, based on the known empty curb weight and the expected maximum gross weight when the vehicle carries a full load of salt. Finally, the dry day model was used to estimate fuel consumption on days with snowfall (snow days), quantifying the gap between expected and observed fuel economy that could be explained by the presence of snow on the road. When estimating fuel use on snow days, the model mass was adjusted to show the impact of salt loading. The results from energy analysis show a significant increase in fuel consumption, over 25, on average when compared to the expected fuel use on dry days, which was observed for days with snowfall totaling 4 inches or more. The results clearly indicated the strong capability of the proposed method for studying the effect of snowfall on energy use. As the available data from snowplows and snowfall was limited in scope, improvements in data collection could lead to more authoritative results in the future. Snow fence and snow trap locations monitored by MnDOT could provide an avenue for interesting future research and were included as parameters in the input data set, but their locations were not up to date with the driving data. A recommendation for MnDOT would be to extend the energy analysis research to identify and mitigate regions of high fuel consumption by snowplow vehicles due to snowfall events by strategically installing snow fences. It would require improving data collection by capturing mass variation of trucks during plowing as it would increase the accuracy of the energy prediction model. Also, updating the snow fence and snow trap locations would aid in validating the energy analysis results.

Chapter 1: Introduction

1.1 Background

Winters in certain sections of the U.S. bring in large amounts of snowfall and severe winter storms and this is particularly evident in states like Minnesota and others in the Upper Midwest. The Minnesota Department of Transportation (MnDOT) deploys winter maintenance vehicles, such as snowplow vehicles and other snow removal equipment, during and before/after snowfall events to ensure that the roads are accessible and safe to travel. Snow plowing involves clearing ice and snow from the roadway using a combination of mechanical (plows) and chemical means (abrasives, salt, brine, etc.). The vehicles used for plowing have different plow configurations such as front-end plow, wing plow, underbody plow, and tow plow. The plow configurations and chemicals used for clearing roadways depend primarily on the pavement type and condition. Although different snowplow vehicles exist, the scope of this project is confined to the analysis of data collected from single-axle and tandem-axle dump trucks.

On-board diagnostics (OBD) data were obtained from a fleet of 600 MnDOT snowplows that were instrumented with AmeriTrak mobile computers integrated into MnDOT's Maintenance Decision and Support System (MDSS). The vehicle computing systems provide high-fidelity data, which are collected and recorded, on average, every two seconds from each active vehicle. Some delays longer than two seconds exist in the data, which could have been due to communication errors. In addition to the vehicle class, make, model, and year, this data included the following key attributes as time series: speed, GPS position (latitude and longitude), and fuel rate, with elevation information added using a digital elevation model. Other parameters like engine speed, intake manifold pressure and temperature, and exhaust temperature were collected but not used for this study.

Reducing fuel use from winter maintenance vehicles is motivated by both economic and environmental factors. According to the *Inventory of U.S. Greenhouse Gas (GHG) Emissions and Sinks 1990–2019*, the transportation sector accounts for 29% of total GHG emissions. Medium and heavy-duty trucks account for about 24% of GHG emissions within the transportation sector, the second highest after light-duty vehicles, which constitute about 58% of GHG emissions (9). According to data obtained from the MnDOT MDSS, about 1 million gallons of diesel fuel are used in Minnesota each year for plowing operations, resulting in over $2 million in fuel costs (20). While it is well known that fuel use increases for snowplow fleets due to additional miles traveled during snowfall events, the actual impact on vehicle fuel economy in terms of miles per gallon is less understood. It is of critical importance to understand the impact of snowfall on the fuel economy of snow maintenance vehicles to influence operational factors that have the highest influence. For example, detecting high fuel use in areas of high snow accumulation can motivate investment in preventative strategies like snow fences to mitigate blowing and drifting snow on roads. Furthermore, the idling of snowplow vehicles is yet another factor that contributes to fuel consumption and GHG emissions. The OBD data collected from 553 MnDOT Metro District vehicles show that between July 2017 and July 2018, idling vehicles used more than 29,000 gallons of fuel costing

MnDOT more than $85,000 (16). Thus, it is also important to understand idling behavior during winter operations and quantify the impact it has on fuel consumption.

1.2 Project Overview

This project investigated the impact snowfall and idling have on the fuel consumed by MnDOT's snowplow fleet, with an underlying objective to determine and advise MnDOT on ways to reduce the fuel use of the fleet by analyzing vehicle OBD data. Idling refers to situations in which a vehicle's engine is running while the vehicle is stopped. Although there exists a multitude of reasons for vehicle idling in general, when it comes to snowplows, some of the prominent reasons for idling could be due to a cold start, an interim halt in winter maintenance operations, driver refreshment between trips, loading of chemicals at truck stations, prevent freezing of fuel, etc. It is important to analyze the frequency (number of idle events) and length of idling (minutes/hours) across different districts and locations (truck stations etc.) to get a feel for the fleet idling behavior. In 2019, Metro District implemented the idle reduction standards to reduce unnecessary idling. Supervisors receive daily reports when maintenance vehicles idle for 30 minutes or more and when construction vehicles idle for 15 minutes or more at MnDOT facilities. This encourages fleets to reduce unnecessary idling and could become a model for the rest of the agency (16).

It is estimated that a heavy-duty, long-haul truck consumes about 0.8 gallons of fuel per hour while idling and consumes about 1,500 gallons of diesel fuel annually, with an average idling of 1,800 hours per year for rest periods alone (2). Another nationwide survey of long-haul trucks found that idling roughly constitutes 34% of total engine run time, or roughly 1,700 hours per truck annually (15). It is observed that the many hours of idling not only burn up profits but also degrades air quality. These studies also encourage fleet owners to consider investing in idle-reduction technologies like auxiliary power units (APUs), direct-fired heaters, etc. to save fuel, reduce emissions and keep drivers comfortable (2, 19). Fuel cell APUs have the potential to greatly reduce emissions and energy use and save money. A study found that the estimated payback period for fuel cell APUs in a heavy-duty, line- haul truck is about 2.6 - 4.5 years (4).

In addition to the idling analysis, an energy analysis was performed to determine the impact of snowfall on the fuel economy of snowplow vehicles. To isolate the effect of snow, it is important to estimate the fuel consumption of a snowplow vehicle for a given velocity profile and elevation data. However, the problem of using OBD data to determine the fuel economy of snowplow vehicles is challenging primarily because each vehicle can carry a significant amount of salt that is continuously unloaded from the vehicle on a route. Over the course of a route, a given truck can lose between 6 and 12 tons of mass during de-icing operations. In addition, a snowplow can be equipped with different possible plow configurations, including front, side-mounted, underbody, and tow, that can have different effects on truck mass. Winter maintenance trucks also have different uses that influence their fuel economy, including road inspection before major weather events, plowing snow, and salting roads for anti-icing or de-icing. Furthermore, snowfall data obtained from the National Weather Service (NWS) may not represent the actual snow depth on the road. Lack of data regarding truck mass/salting schedules, plow configurations/utility, and on-road snow depth make it difficult to estimate fuel consumption and study its variation across snow days. For simplicity, the de-icing or anti-icing chemicals carried by snowplows are referred to collectively as salt.

Models used to estimate fuel consumption or GHG emissions may be broadly classified as either macroscopic or microscopic models (1). Macroscopic models (21, 22) seek to estimate fuel consumption over an extended period of time (e.g., day, week) and over an extended region (e.g., city, state) while microscopic models estimate instantaneous fuel consumption over a shorter time frame (i.e., seconds) for a given vehicle using instantaneous drive cycle data (i.e., velocity and acceleration profiles).

Microscopic models may be further grouped into three categories as suggested in (6): (i) emission map models (13), (ii) regression models (6), and (iii) load-based models (5, 12). Many disparate models for predicting vehicle GHG emissions are presented by Guo et al. (10).

In works specific to winter maintenance vehicles, some authors have focused on developing more complex dynamic models of snowplows (14, 18). Others have instead prioritized pursuing optimal fleet management using simplified spatial models of vehicle dynamics (11). The fuel efficiency of a road vehicle reduces with an increase in snowfall and density due in large part to an increase in rolling resistance (3, 8). The magnitude of increase in fuel consumption depends not only on the depth and density of snow but also on the amount of snow exposed to the front axle (8). Unlike conventional trucks on the road in winter, snowplows share a unique and dynamic interaction with snow. In general, a snowplow is either driving with its plow down to push snow or not and is dispensing salt or not. When the snow has accumulated over a long period of time and is hard to plow through, de-icing is preferred to prevent damage to plow blades. Because of these dynamic, often unmeasured conditions encountered during regular snowplow operations, the effect of snowfall on the fuel consumption of snowplows is a complex problem in need of further research.

Chapter 2: Snowplow Idling Analysis

2.1 Definitions

2.1.1 Idle Events:

An *idle event* is defined as three or more minutes during which a plow remains motionless, using the GPS-based speed parameter provided by AmeriTrak as the indicator of movement. Data gaps of up to one minute are allowed when determining idling. For instance, if a vehicle appeared idle for 90 seconds, then provided no useful data for one minute, then provided another 30 seconds of data indicating idle, this would be considered an uninterrupted three-minute period at idle.

2.1.2 Useful Data:

The *useful data* is defined as records that suggest the vehicle engine is running and:

- Include coordinates
- Non-null engine RPM greater than zero
- Non-null fuel rate greater than zero

Records that do not meet these criteria are discarded during the database load process.

2.1.3 Winter:

The scope associated with each *winter* considered for idling analysis is as follows:

- Winter one: November 1, 2018 to April 30, 2019
- Winter two: November 1, 2019 to April 30, 2020
- Winter three: November 1, 2020 to March 31, 2021
- Winter four: November 1, 2021 to March 31, 2022

2.2 Data Preprocessing

The data collected over a period of four winters was added to the project database and it consists of hundreds of devices/vehicles offering useful information about their location and fuel consumption. However, some vehicles were excluded from the idling analysis due to quality issues during the data collection process. AmeriTrak devices, which may be associated with more than one vehicle over time, were excluded from consideration when:

- Less than 97.5% of records for a device have a unique timestamp
- The device serial number was paired with more than one vehicle number,
- The device provided fewer than 10 hours of useful data over three winters,
- The vehicle number associated with the device does not appear in the set of vehicle specifications for snowplows provided by MnDOT.

Note that some devices provided data at 1-second intervals instead of the expected two-second interval. Some devices providing data at unexpected frequency were previously identified and handled programmatically. The devices and their associated vehicles considered for idling analysis are listed in Appendix A. Furthermore, there was significant variation in the fuel rate across records, with a long tail on the high end. We retain data contained in a window of 99% of idle period, centered on the median, average fuel rate, keeping data where 0.3039 ≤ gallons per hour < 2.7742.

2.3 Analysis & Observations

Given the exclusion criteria discussed in the previous section, a decent number of vehicles were omitted from being considered for idling analysis. Table 1 consists of the distribution of vehicles included in the analysis, the number of hours of useful data recorded, and fuel consumed across the four winters.

Table 1: Summary of vehicles observed, hours recorded, and fuel consumed during Winters 1-4

	Vehicles Included (By ESN)	Hours Recorded (Useful data)	Fuel Consumption (gallons)
Winter 1	15	4,038	19,457
Winter 2	64	20,623	110,770
Winter 3	440	90,405	477,405
Winter 4	459	116,842	591,271
Total	459 (unique) 978 (total)	231,908	1,198,903

Data from winter one is included in the analysis and should be treated cautiously given both the low number of vehicles and limited activity. The data collection process improved over time and so did the number of vehicles that qualified the analysis criteria. The data used for idling analysis over the course of four winters consist of 978 (total) / 459 (unique) trucks with total recorded hours of 231,908 and total fuel consumption of 1,198,903 gallons of diesel fuel.

Table 2: Summary of idling data Winters 1-4

	Idle Events	Hours at Idle	Fuel Consumed at Idle (gallons)	Median Idle time (seconds)
Winter 1	5,199	916	821	346
Winter 2	27,490	4,675	4,303	358
Winter 3	112,985	21,643	20,526	376
Winter 4	135,759	25,289	24,693	384
Four-year totals and median	279,975	52,523	50,343	376

The idling data such as number of idle events, hours at idle, fuel consumed at idle (gallons), and median idle time (seconds) were computed across winter 1-4 and summarized in Table 2. Over the course of four winters, we observed a total of 279,975 idle events, 52,523 hours at idling, 50,343 gallons of fuel consumed while idling, and a median idle time of 376 seconds. The idling data (idling events, hours recorded & fuel consumption) was further discretized into approximate tertiles of 3–5 minutes, 5–9 minutes, and 9+ minutes, as shown in Table 4. Note that neither overall time-on nor fuel consumption was reduced to account for excluded idle periods. Idling accounts for approximately 4.2% of overall fuel consumption in our fleet, which is about 50,343 gallons of fuel. Idles in the third tertile (9+ minutes) account for 2.9% of overall fuel consumption and 15.6% of the total hours of useful data recorded indicating longer idling times as a significant trend in the fleet's idling behavior.

Table 3: Fleet idling time and fuel consumption for Winters 1-4

	Idle Duration			
	3-5 Minutes	**5-9 Minutes**	**9+ Minutes**	**All**
Idling Events	96,789	91,779	91,407	279,975
Hours Recorded	6,288	10,075	36,160	52,523
% of total time	2.7%	4.3%	15.6%	22.7%
Fuel Consumption (gallons)	6,256	9,442	34,645	50,343
% Overall fuel consumption	0.5%	0.8%	2.9%	4.2%

The median idle time and total idle events were also computed across all the districts for Winters 1-3 and summarized in table 4. Note that all the idling analysis performed beyond this point is confined to Winters 1-3. It is observed that the median idle time by district, 370 seconds (6m10s) across all districts, ranges from 350 seconds (5m50s) to 428 seconds (7m08s).

Table 4: Median idle time by winter and district with n in parentheses for Winters 1-3

	District							
Winter	**1**	**2**	**3**	**4**	**6**	**7**	**8**	**Metro**
1	304 -37	- -	400 -499	- -	399 -380	- -	312 -1,587	358 -2,696
2	364 -5,796	378 -2,195	382 -3,866	430 -1,129	366 -5,059	324 -2,555	326 -2,484	348 -4,406
3	395 -17,241	354 -6,734	374 -12,765	428 -8,717	362 -13,838	366 -8,081	380 -9,180	366 -36,429
Overall	387 -23,074	360 -8,929	376 -17,130	428 -9,846	364 -19,277	350 -10,636	358 -13,251	364 -43,531

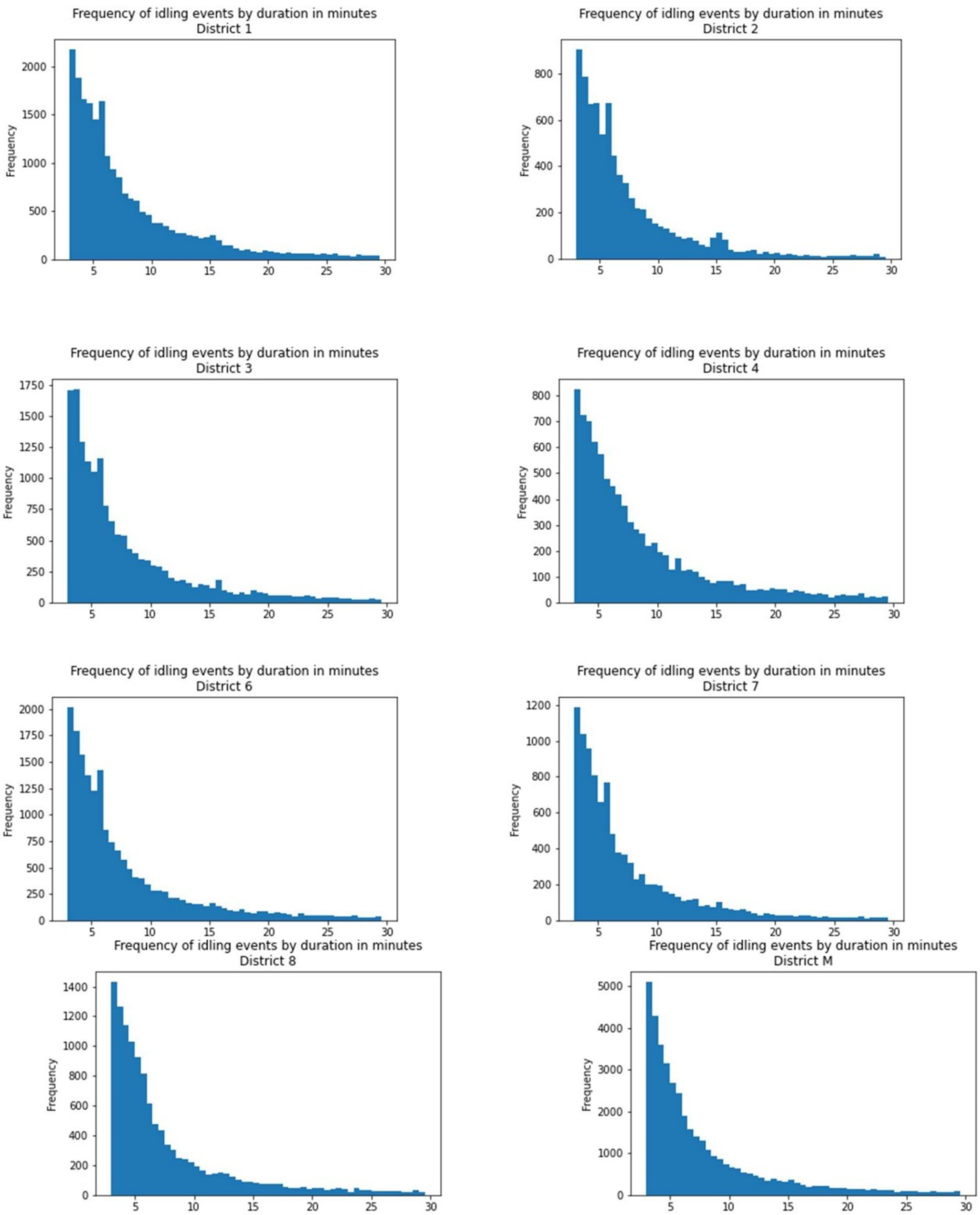
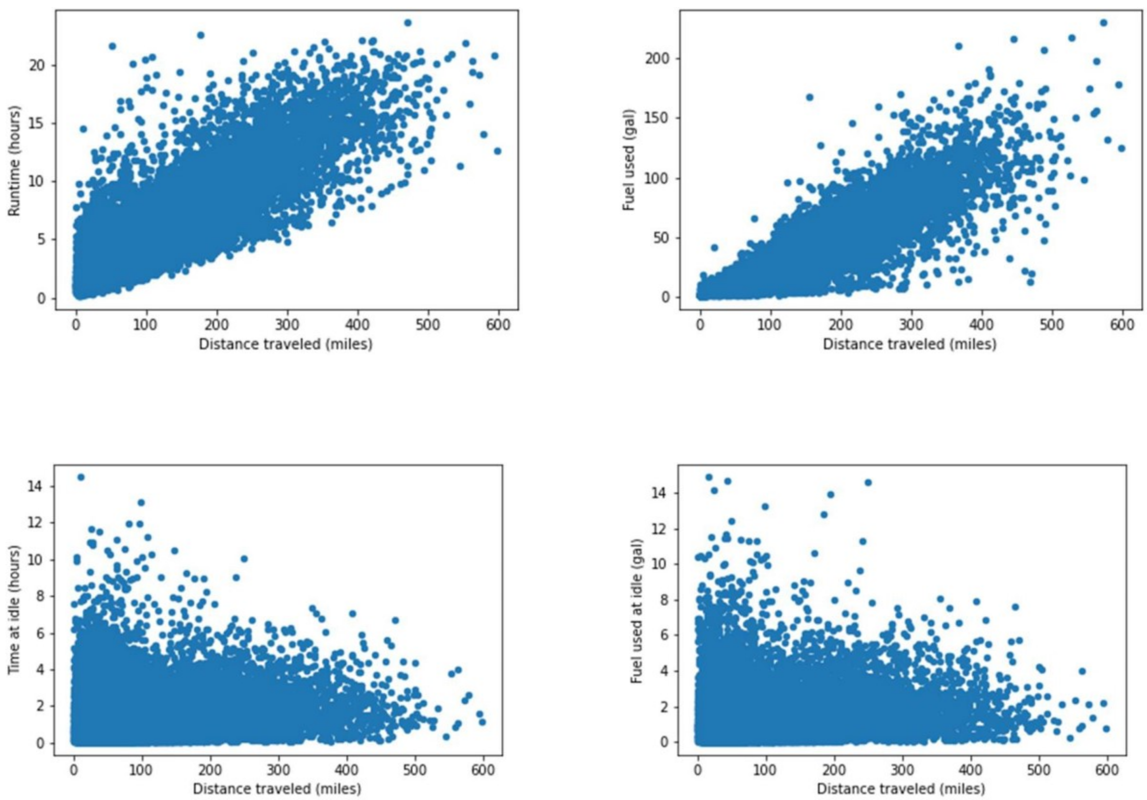


Figure 1 a-h. Frequency of idling events over three winters by district, 3–30 minutes, in 30-second bins

Histograms of idle times, by district, also suggest variation by the district. See figures 1a-h. Note the increase in idle events around 5 and 15 minutes, noticeable for most districts in figure 1. Appendix B includes maps of truck stations and other MnDOT facilities that include clusters of idle events over the three winters, with hours of idling and fuel consumption at the facility, as well as the share of events and values at the facility as a part of the district, and as a share of events at other MnDOT facilities in the district that are included in the appendix. Additionally, idle events are reduced to high-activity days on a district-by-district, winter-by-winter basis. To be considered a high-activity day, the average number of hours per vehicle in the district must be at least seven, regardless of how many vehicles were active that day.



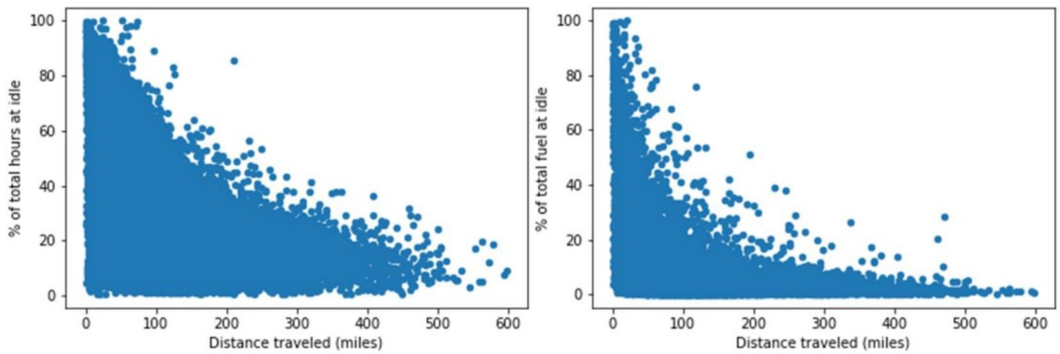
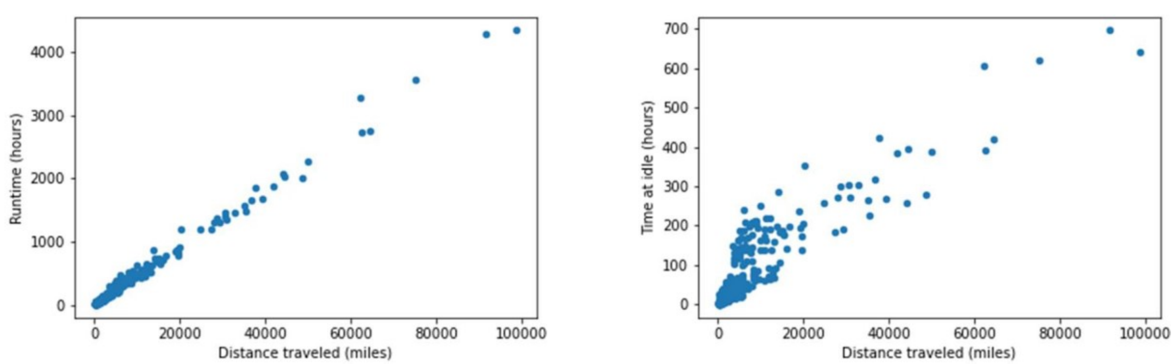


Figure 2a-f. Various measures are plotted according to miles traveled per vehicle per day. Records are limited to records with >1 gallon of fuel consumption and >1 mile traveled.

2.4 Relationship Between Activity and Idling

The distance traveled was compared to overall runtime, fuel consumption, time at idle, fuel consumed at idle, percentage of overall fuel consumed while at idle, and percentage of overall runtime while at idle. Scatter plots of these pairs (figures 2a-f) indicate a decrease in both the rate of idling and the rate of fuel consumed at idle as the distance traveled by a vehicle in a single day increase. As noted in figures 2a-f, vehicle days with either low distance traveled or low fuel consumed is excluded from the plots due to their lower impact and error in the data, which is pronounced for smaller values and may appear as rates greater than 100% for the rates.



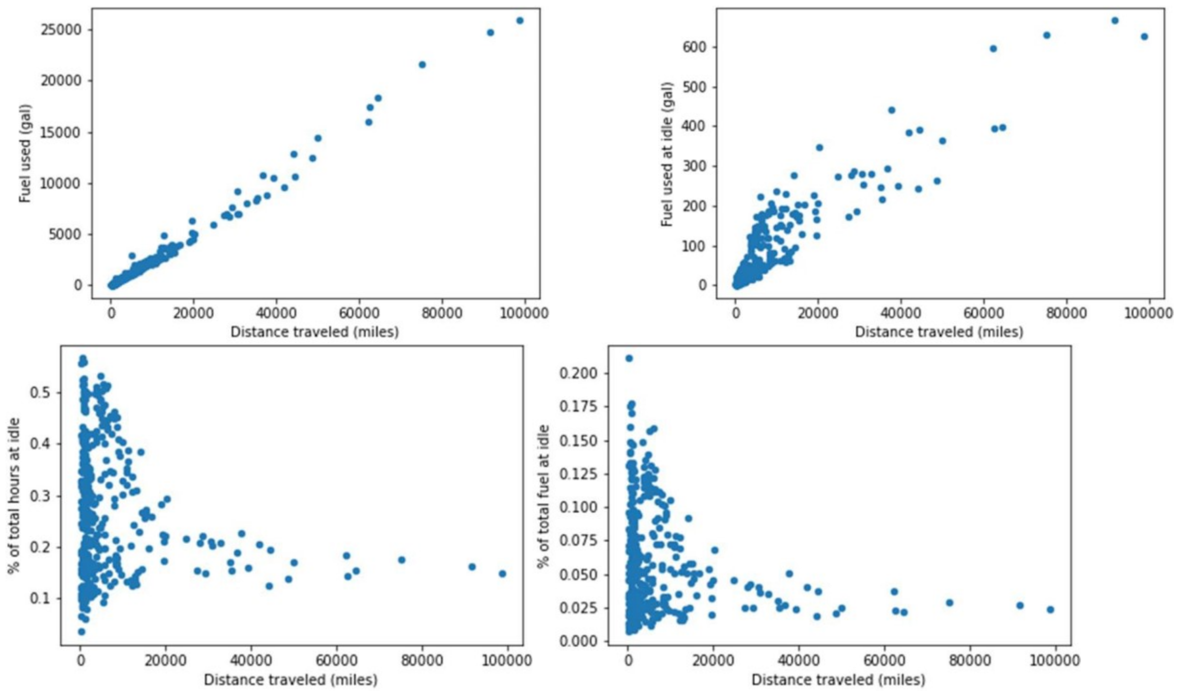


Figure 3a-f. Various measures plotted according to miles traveled in a single day. Records are limited to days with more than 250 miles traveled.

Aggregating by day over three winters, the relationship between miles traveled and other measures are shown in figures 3a-f. In figures 3b and 3d it appears that there may be two or more clusters in the relationship (not verified), with one pattern suggesting a greater increase in idling activity on some days than others, perhaps due to differences in snowplow operations on those days. This pattern is also observed in figures 3e and 3f.

2.5 Fuel Consumption By Location

Polygons representing MnDOT facility locations, linear features representing snow trap areas, and mixed types of geometry representing snow fences are used, with buffers on linear and point features, to flag telemetry by location, e.g. at a truck station, in a snow trap, near a snow fence.

Polygons representing facility locations mix MnDOT-provided locations and locations roughly digitized using aerial imagery. Snow traps are sourced from MnDOT data and include approximately 1,865 miles of linear features. It is important to note that the 1,865 are not lane miles. Snow trap locations are buffered by 10 meters to approximate coverage over the roadway. Snow fence locations are not included at this time as a sample of snow fences suggested significant variation in the distance between roadways and snow fences. The larger buffers required on some snow fence locations would erroneously flag many snowplow records as being within a snow fence area. In future work, a reliable method to identify areas affected by snow fences should be considered.

Table 5: Hours spent, and fuel consumed, by locations, winters 1–3

Location	Hours	% of total hours	Fuel (gal)	% of total gallons
MnDOT facilities	18,377	16	23,134	4
Snow traps	8,775	8	57,344	9
Other	87,915	76	527,163	87
Total	115,067	100	607,641	100

2.6 Conclusions

The results from the idling analysis indicated that the snowplow fleet's idling constituted about 23% of the total recorded hours, i.e., 52,523 hours, and 4.2% of the total fuel consumed, i.e., 50,343 gallons. Daily idling activity reports containing information about the idle events and sampled fleet fuel economy were generated and shared with MnDOT via email. Some studies indicated that the use of a direct-fire heater reduced fuel consumption by 94-96% and an auxiliary power unit (APU) could reduce fuel consumption by 60-87% in heavy-duty trucks during idling. A recommendation for MnDOT would be to carry out a cost-benefit analysis of using alternative technologies like direct-fire heaters and/or APU as they could result in a considerable reduction in fuel use and emissions. Another recommendation would be to continue the idling analysis as it would aid in building a framework to systematically address long periods of idling at truck stations and other locations.

Chapter 3: Snowplow Energy Analysis

3.1 Basic Concepts: Road Load Energy

The energy required for a vehicle to move over a road surface, E_{road} can be estimated using the road load energy equation shown in Equation 1, which is obtained by the summation of components of energy required to overcome the following factors:

- aerodynamic drag E_{aero}
- rolling resistance $E_{\mathrm{rolling\ resistance}}$
- vehicle inertia $E_{\mathrm{veh.\ inertia}}$
- change in elevation $E_{\mathrm{gravitational\ potential}}$.

Equation 1:

$$E_{\mathrm{road}} = E_{\mathrm{aero}} + E_{\mathrm{rolling\ resistance}} + E_{\mathrm{veh.\ inertia}} + E_{\mathrm{gravitational\ potential}}$$

$$E_{\mathrm{road,j,j+1}} = \frac{1}{2}.\rho.C_{\mathrm{D}}.A.v^{3}_{\mathrm{i}}.\Delta t_{\mathrm{i}} + C_{\mathrm{rr}}.M_{\mathrm{veh}}.g.v_{\mathrm{i}}.\Delta t_{\mathrm{i}} + \frac{1}{2}M_{\mathrm{veh}}.a_{\mathrm{i}}.v_{\mathrm{i}} + M_{\mathrm{veh}}.g.\Delta h_{\mathrm{i}}$$

$$v_{\mathrm{i}} = \frac{v_{\mathrm{j+1}} + v_{\mathrm{j}}}{2}, \qquad v^{3}_{\mathrm{i}} = \frac{v^{3}_{\mathrm{j+1}} + v^{2}_{\mathrm{j+1}}.v_{\mathrm{j}} + v_{\mathrm{j+1}}.v^{2}_{\mathrm{j}} + v^{3}_{\mathrm{j}}}{4}, \qquad a_{\mathrm{i}} = \frac{v_{\mathrm{j+1}} - v_{\mathrm{j}}}{\Delta t_{\mathrm{i}}}$$

$$\Delta h_{\mathrm{i}} = h_{\mathrm{j+1}} - h_{\mathrm{j}}, \qquad \Delta t_{\mathrm{i}} = t_{\mathrm{j+1}} - t_{\mathrm{j}}$$

where M_{veh}, A, C_{D}, C_{rr}, v, and a are the vehicle mass, frontal area, coefficient of drag, coefficient of rolling resistance, velocity and acceleration, respectively. Δt and Δh are the elapsed time and change in elevation between samples, and g, ρ are the rate of gravitational acceleration and density of air, respectively.

The energy, measured in volume of diesel fuel in this case, required by a vehicle over a duty cycle is obtained by considering the energy spent on the road as well as that used while idling E_{idling}, as described in Equation 2.

Equation 2:

$$E_{\text{fuel}} \cong \frac{E_{\text{road,pos}}}{{}_{\text{powertrain}}} + E_{\text{idling}}$$

These equations form the basis for the proposed method, which includes dry day model fitting and evaluation, and the application to snow day driving data for analysis as discussed in upcoming framework section.

3.2 Framework

In this work, we investigate the impact of snowfall on the fuel economy of winter maintenance vehicles operating in the state of Minnesota. A framework was developed, depicted in Fig. 4, which uses a simplified version of the road load equation to estimate fuel usage, with constant vehicle parameters determined for each individual vehicle using the Levenberg-Marquardt algorithm (17) to solve the least squares problem for all available trips for each vehicle. To account for the change in fuel consumption due to snowfall, the baseline vehicle parameters were fitted using fuel rate OBD data from days without snowfall, i.e., dry days. Because the vehicle mass is unknown for the available data set, a mean value was chosen during the model fitting process, based on the known empty curb weight and the expected maximum gross weight when the vehicle carries a full load of salt. Finally, the dry day model was used to estimate fuel consumption on days with snowfall (snow days), quantifying the gap between expected and observed fuel economy that could be explained by the presence of snow on the road. When estimating fuel use on snow days, the model mass was adjusted to show the impact of salt loading. The developed methodology is not only useful for explaining fuel economy differences as a function of snowfall for the selected fleet but could also be used by others to determine the snowfall influence of other fleets to influence the placement of snow mitigation infrastructure.

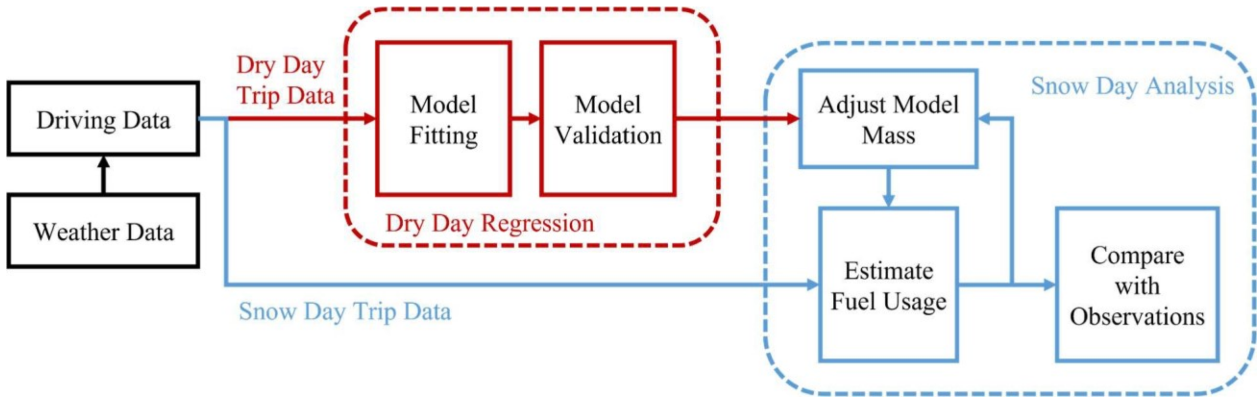


Figure 4: A flow diagram depicting the proposed method for analyzing the variation in fuel consumption with changing snowfall.

3.3 Problem Description

The problem addressed in this energy analysis, estimating the impact of snowfall on snowplow fuel consumption, is at its core a vehicle modeling and energy estimation problem. Given historical OBD data from snowplows driving in a range of winter conditions (dry days and snow days) and relevant historical weather data, the objective is to quantify the impact of snowfall on fuel consumption. A purely empirical solution is somewhat unsatisfactory as it fails to explain the sources of any observed variation in fuel consumption with changing snowfall. A model-based solution should predict vehicle fuel consumption for dry and snow days to isolate the effects of snow from those of changing driving patterns. The information one can glean about the reasons behind changes in fuel usage depends greatly on the scope and quality of available input data. Input data used in this work did not contain some key attributes that might improve the capability of the proposed method, including vehicle mass, plow positioning, trip purpose, on-road snow depth, snow condition, or snow trap and snow fence locations. Under these constraints, the problem requires some additional assumptions to be made to generate results. For example, a mean value or set schedule can be used for the vehicle mass when tuning other model parameters, and trips might be filtered depending on their inferred use case. The method presented in this work may be applied to similar problems in which vehicle energy use or fuel consumption is empirically known to vary with respect to some outside factor (e.g. temperature).

3.4 Data Preprocessing

Because of the variation in the operations and data logging capabilities of each snowplow in the MnDOT fleet, many of the instrumented trucks were not used in this analysis. Due to data quality issues, various filters were applied to the initial input data, removing certain trucks and trips. This preprocessing procedure is depicted in Fig. 5 and described in further detail below. Dry days, on which no snow fell, and snow days, on which some snow fell, were segregated based upon historical National Weather Service (NWS) data from local weather stations.

Four thresholds were used to filter down the original list of logger-vehicle pairs to the 41 used in this study. All input data from a logging device was filtered out if it could not meet the following standards:

- **Unique Records:** More than 97.5% of all the device records have a unique timestamp.
- **No Device Sharing:** The device serial number was paired with only one vehicle number.
- **Driving Time:** The device provided at least 10 hours of driving data over three winters.
- **Frequent Use:** The device recorded 60 or more trips between November 1, 2020 and March 31, 2021.

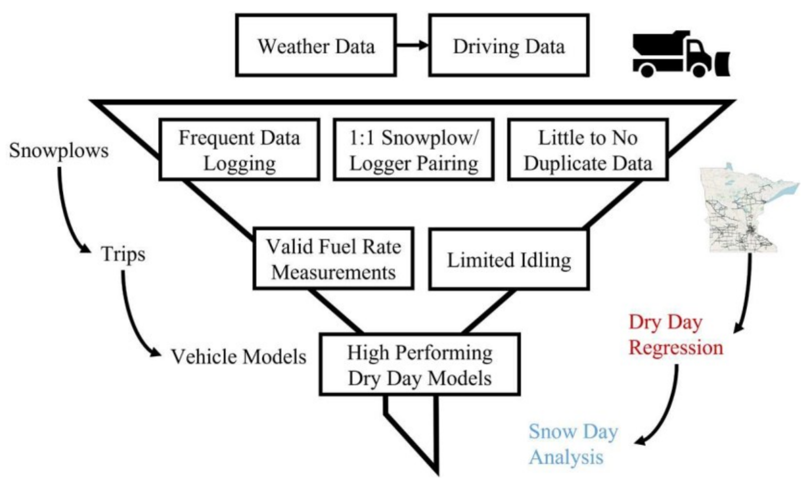


Figure 5: An illustration of the filtering processes utilized to alleviate data quality concerns. The left side shows the sequential progression in terms of what object is being filtered (snowplows, trips, and models). The right side shows the result-generating steps taken after each filtering step.

Two types of trucks exist in the analyzed fleet, in roughly equal numbers, with their separate models designated here as single-axle (SA) or tandem-axle (TA). The slight differences in the two snowplow models are summarized by Table 6.

The analysis presented covers the operations of 41 snowplows operating in the state of Minnesota that were regularly active over the 2020-2021 winter season (November to March). The GPS traces of all 41 vehicles are shown in Fig. 6. These vehicles collectively made over 4300 recorded trips during the winter months, with about 65% of those trips occurring on days with no snowfall reported by local NWS stations.

Table 6: Table 6: Approximately known vehicle model specifications

	Model 1 Single Axle (SA)	**Model 2 Tandem Axle (TA)**
Weight Class	Class 8	Class 8
Curb Weight (kg)	~12,650	~18,200
Salt Capacity (kg)	~6,350	~10,800
GVW (kg)	~19,000	~29,000
Frontal Area (m^2)	8.7	8.7

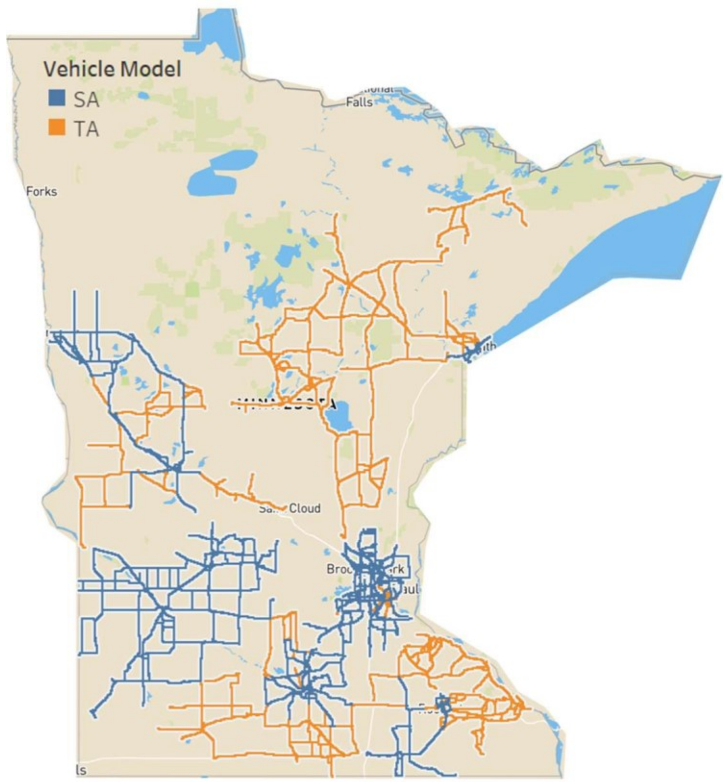


Figure 6: GPS traces of the analyzed trips taken by SA (blue) and TA (orange) snowplows across the state of Minnesota during the 2020-2021 winter season

Even within this group of 41 vehicles, some recorded trips were not considered when fitting the vehicle model parameters, and some trucks were not considered when analyzing snow day fuel usage. First, trips that were not representative of normal snowplow operations were filtered out from the list of dry and snow days. These included trips with any of the following characteristics:

- **Frequent Idling:** The truck was idling for more than 40% of the trip.
- **Fuel Rate Error:** More than 12% of the fuel rate sensor readings were identical.
- **Crawling Trips:** The average trip speed was lower than 15 miles per hour.

The breakdown of remaining cruising trips after applying these filters is summarized in Table 7. Of the initial 4319 trips, 1454 contained too much idling data, 800 encountered fuel rate errors in which the fuel rate measurement would remain constant after a mid-trip stop, and 331 showed very low average speeds, with many of these trips having more than one issue. After these trips were filtered, the remaining 2622 were classified as cruising trips and used to tune the vehicle models.

Table 7: Accounting of trip data recorded for snowplows of each type

		Winter 2020 Trips		Cruising Trips	
Model	**Truck Count**	Snow Day	Dry Day	Snow Day	Dry Day
SA	22	841	1701	617	831
TA	19	670	1107	525	649

3.5 Dry Day Model

An important parameter necessary for building the dry day model is the mass of truck, M_{veh}. The mass is not included in the available driving data set, and a standard mass schedule is not reasonable to construct as there is no way of determining when a truck is conducting de-icing operations. However, the curb weight, gross vehicle weight (GVW), and salt payload capacity of the trucks are approximately known, as reported in Table 6. This information was used to determine the minimum (unloaded) and maximum (fully loaded) snowplow mass. When fitting the dry day model to available data, the mean mass of the snowplow (half loaded) is assumed to be the representative mass of the vehicle for all the dry trips.

Table 8: Bounds on the possible values for each curve-fit term

Parameter	Variable	Lower Bound	Upper Bound
Powertrain Efficiency	η_{trip}	0.1	0.5
Rolling Resistance Coefficient	C_{rr}	0.004	0.007
Coefficient of Drag	C_{D}	0.5	1.0
Idling Fuel Rate (gal/hr)	f_{ir}	0.05	1.0

As mentioned in Section 3.3, time-series trip data contained measures of the vehicle velocity, elevation, and fuel rate. The fuel rate information was accumulated over time to determine the fuel used over the course of each trip. As indicated by Equation 1, the velocity and elevation data can be used to compute the expected road load energy. However, additional information about the vehicle model besides its mass is required to solve the road load equation - the overall powertrain efficiency for a trip η_{trip}, coefficient of drag C_{D}, rolling resistance coefficient C_{rr} and fuel rate during idling f_{ir}. To estimate these unknown parameters, the curve-fit method in the standard SciPy Python package was used, which implements the Levenberg-Marquardt algorithm for optimization (17). This method solves the least squares problem to find the best parameterization η_{trip}, C_{D}, C_{rr}, f_{ir} for a given function such that the function output (i.e. the fuel usage estimate from Equation 2) is fit optimally to the dependent variable (i.e the observed fuel usage), given some time-series data for the independent variables v, h, t. The unknown parameter values were constrained to keep them within physically reasonable limits. The bounds considered for the unknown parameters are provided in Table 8.

For each vehicle, for each dry day trip, the curve-fit method was used to find the optimal vehicle model parameters (within the given bounds) to provide the best fit between the actual and the estimated fuel usage. A generalized dry day model for each individual snowplow was then obtained by averaging the vehicle parameters across all dry day trips for each truck. The performance of each dry day model was then evaluated for all relevant dry day trips, and the dry day regression results are summarized in Table 9, with measures aggregated for each type of snowplow rather than each individual truck. Full results from the model tuning and evaluation for each individual truck are summarized in Appendix C for each type of snowplow.

Each model was evaluated using multiple test metrics - the coefficient of determination (R2), root-mean-square error (RMSE, reported in gallons), mean absolute error (MAE, reported in gallons), and mean absolute percentage error (MAPE, reported in %). The average vehicle parameters (η_{trip}, C_{D},

C_{rr},f_{ir}) and model performance metrics (R2, RMSE, MAE, MAPE) are shown in Table 9. The dry day models serve as a baseline vehicle model that can then be used to carry out snow day analysis.

3.6 Snow Day Model

To understand the trend between fuel consumption and snowfall, it is important that dry day models predict the fuel consumption accurately for the dry days they were tuned on. In other words, to be useful for further analysis, the tuned vehicle model parameters (η_{trip}, C_{D}, C_{rr}, f_{ir}), must provide estimates that fit closely to the actual observations. Hence, the snow day analysis was only carried out using those trucks which have an average R2 ≥ 0.8 when tested over the dry days. This helps lower the chance of underlying model errors influencing the results, ensuring that the observed trends can be associated with changes in snowfall with greater certainty. Of the original 41 snowplows for which dry day models were developed, 20 showed high enough performance to apply to snow days. Of these 20 snowplows used in the snow day analysis, 14 were SA models, and 6 were TA models. These well-fit SA and TA models accounted for 388 and 177 snow day trips, respectively. The average model parameters and performance metrics (on dry day trips) for the models used to generate the snow day analysis results are reported in Table 9.

When these dry day models are applied to snow day trips, they provide an estimate of the equivalent dry day fuel consumption. The dry day model parameters were fitted assuming that the truck is halffilled with salt, and initially applied to the snow day trips under the same assum ption. However, to assess the impact of truck mass on fuel consumption, the dry day model was also applied to snow day trips with two alternative mass values: Max Mass (i.e., the GVW, when the truck is fully loaded with salt) and Min Mass (i.e., the curb weight, with no payload). Thus, three estimates of fuel consumption were obtained for each trip, one for each mass value, and used to compute the percentage change in fuel consumption relative to the actual fuel used as described in Equation 3.

Equation 3:

$$\Delta f_{\%} = \left(\frac{f_{\mathrm{actual}} - f_{\mathrm{predicted}}}{f_{\mathrm{actual}}}\right) \times 100$$

where f_{actual} and $f_{\mathrm{predicted}}$ represent the final fuel measurement and estimate at the end of a trip, respectively. As the model mass increases, the predicted fuel consumption increases and the $\Delta f_{\%}$ measure decreases, and vice versa.

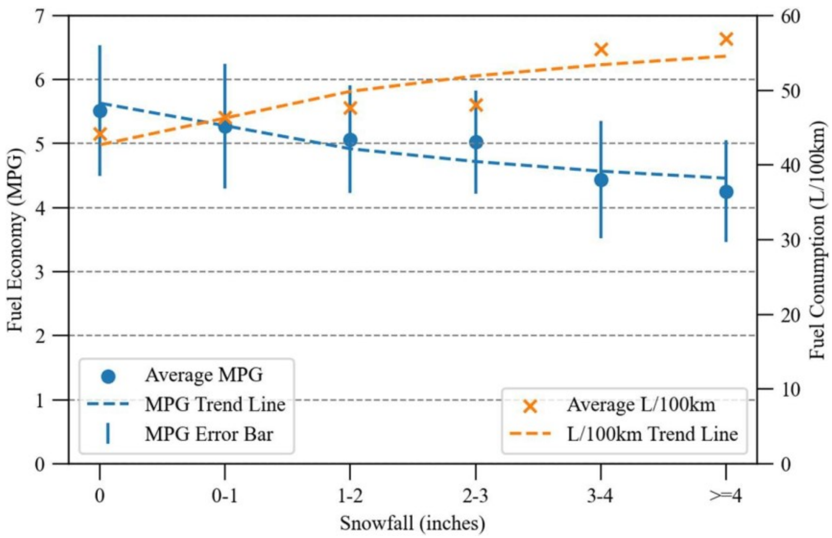
Table 9: Summary of the averaged parameterization and performance metrics for models fitted to dry day trips and for models used to analyze snow day trips.

	Model	Parameters				Metrics			
		η_{trip}	f_{ir}	C_{rr}	C_{D}	R2	RMSE	MAE	MAPE
Dry Day Regression	SA	0.29	0.53	0.0064	0.73	0.80	1.75	1.47	18.73
	TA	0.32	0.55	0.0064	0.77	0.77	2.8	2.38	21.63
Snow Day Analysis	SA	0.31	0.55	0.0064	0.75	0.86	1.26	1.05	16.41
	TA	0.34	0.58	0.0064	0.78	0.83	2.2	1.86	19.97

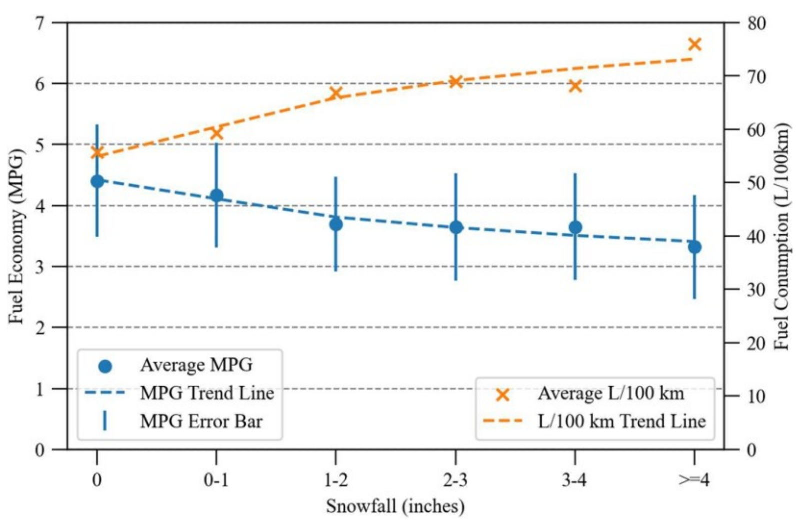
3.7 Results & Discussions

The empirical fuel economy (MPG) and fuel consumption (L/100km) values for SA & TA models in Fig. 7 show decreasing and increasing trends, respectively, as snowfall increases, thus providing strong evidence that supports the inherent positive correlation shared between snowfall and energy consumption.

The baseline-vehicle model that was developed by training over the dry day trips has enabled us to isolate and evaluate the impact of snowfall on fuel consumption by estimating the equivalent dry day fuel consumption for each of the snow day trips. The snow day analysis metric described in Equation 3 captures the difference in fuel usage between a snow day trip and an equivalent dry day trip as a percentage of the actual fuel used. Given the fuel usage trend in Fig. 7, the expectation is that with increasing snowfall, the fuel usage for the trips increases, thus increasing the gap between the baseline-vehicle model fuel usage and actual/empirical fuel usage. Results from the snow day analysis are visualized in Fig. 8 and it can be observed that the results align with the expectations. As the snowfall increases, the change in fuel consumption (%) becomes more evident and the trends are consistent across different mass values (max, avg, min) and also across the vehicle models (SA/TA). It is observed that for days with snowfall totaling 4 inches or more, fuel use increased approximately 29% on average in comparison to days without snowfall for the SA model whereas for the TA model, the fuel increases by about 26%. Thus, it can be inferred that increasing the intensity of snowfall significantly increases fuel usage and in turn reduces the fuel economy of winter maintenance vehicles.



(a) SA Model

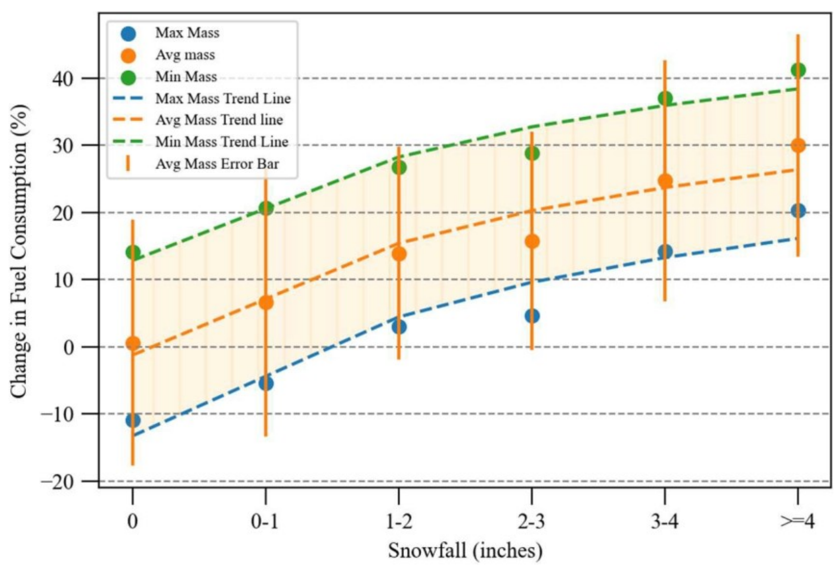


(b) TA Model

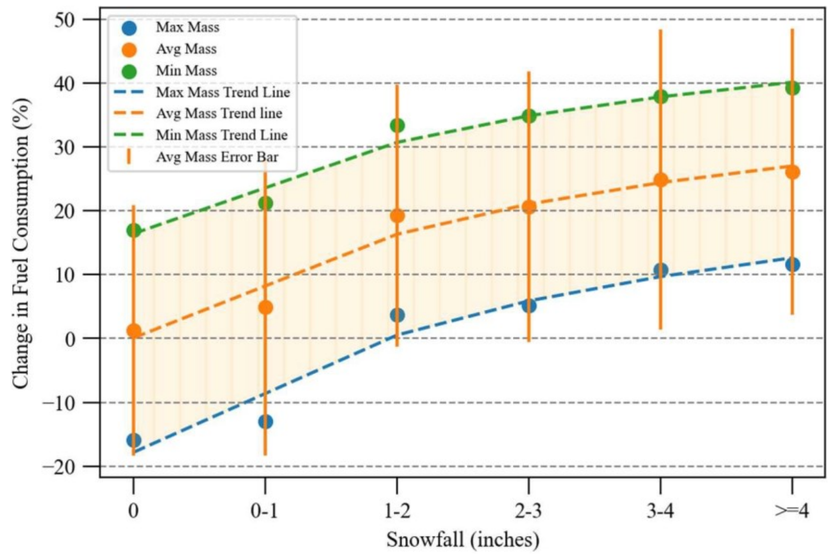
Figure 7: Empirically observed trends in fuel economy as a function of snowfall, averaged across all 41 snowplows, computed separately for snowplows of each type

Although the baseline-vehicle model aided in revealing and quantifying the trends associated with snowfall and fuel economy, it should be noted that the results hold true at a macroscopic level (multiple trips). The error bars on the change in fuel consumption (%) for an average mass scenario for SA & TA models in Fig. 8 show the distribution of values within one standard deviation. Thus, using the baseline-vehicle model for comparing fuel economy trends or determining the increase in fuel consumption at a microscopic level (individual trip) might not always yield the expected results. This drawback faced by the dry day regression model can be mapped to some crucial limitations at the data collection stage.

First, the mass of the vehicle is an important factor that can influence the fuel usage, the diverse utility (salting), and plow configurations (front, side, underbody, tow, etc.) can result in varying mass schedules across each trip. Another limitation with regards to data collection is the frequency at which data is recorded. The instrumentation on the snowplows records data every 2 sec and given the erratic variation of actual fuel rate, the current frequency with which data is being recorded can cause discrepancies when computing the amount of fuel used over a trip. The unavailability of mass data associated with each trip, the assumption of the mean mass of the snowplow as the representative mass figure for winter trips, and the frequency of data collection are the potential reasons for the poor performance of the model at the microscopic level.



(a) SA Models (dry day models with R2 ≥ 0.8)



(b) TA Models (dry day models with R2 ≥ 0.8)

Figure 8: Percent change in fuel consumption, comparing observations from snow day trip data to expected dry day fuel consumption predicted by top-performing dry day models. Trends are shown for dry day model predictions with minimum (unloaded), maximum (fully loaded), and mean mass values.

Error bars are shown for the points obtained using the mean mass value.

3.8 Conclusions

This study sought to address the current lack of data regarding fuel consumption dependence during snowfall days for winter maintenance vehicles. Assuming a constant mass for the two analyzed snowplow models, vehicle parameters were fitted to available OBD data from snowplows driving on dry days, and the resulting models were applied to analyze fuel consumption on days with snowfall.

A significant increase in fuel consumption, over 25% on average when compared to the expected dry day fuel usage, was observed for days with snowfall totaling 4 inches or more. The results clearly indicated the strong capability of the proposed method for studying the effect of snowfall on energy use. As the available data from snowplows and snowfall were limited in scope, improvements in data collection could lead to more authoritative results in the future.

Snow fence and snow trap locations monitored by MnDOT could provide an avenue for interesting future research and were included as parameters in the input data set, but their locations were not up to date with the driving data.

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