Decision Support System for Winter Highway Maintenance Management

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in

Construction Engineering and Management

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ABSTRACT

Snow accumulation on roads is a major safety concern during winter. Winter road maintenance is an effective approach to maintain roads in good driving conditions and reduce accidents. A common approach for a winter road maintenance project is to partition the road network into multiple service areas, set one depot in each area, and assign a truck fleet to each depot to clean the roads during snow events. To conduct operations effectively, proper planning in both the long-term and short-term is essential. For planning a project in the long-term, the appropriate fleet size for each depot needs to be determined, taking into account operations under different snow scenarios. For short-term, lookahead project planning, the operation routes, labor working hours, and the required fleet size for the upcoming snow event need to be determined.

For urban areas, roads usually have similar weather conditions as they are close to each other. Thus, the required vehicle fleet sizes are similar between different snow events, and vehicles can follow similar routes every time. However, for maintenance operations on highways, regional weather events must be considered due to the large spatial scale of the highway network. Different snow events can have different impact areas, which can affect the required fleet size and optimal operation routes. Moreover, the exact impact area of a snow event is difficult to forecast and monitor because of the limitations in weather data. Weather observations and forecasts are usually specific to a few locations that have weather stations, so it can be hard to determine the weather situation on a road between weather stations with differing weather conditions. Therefore, a decision support system is needed to assist project planning for winter highway maintenance operations using limited weather data and considering the stochastic nature of weather events.

In this thesis, two simulation models were developed to help in planning winter highway maintenance operations. The first simulation model uses a performance-based approach to help determine the fleet size in the long-term. This model uses road network information, historical weather data, and vehicle speed distribution as inputs. Monte Carlo method is used to sample random snow areas, and the performance of a certain truck fleet is evaluated by calculating its operation time-cost under various snow scenarios. An appropriate fleet size can then be selected based on an acceptable confidence level. The second simulation model is developed for short-term lookahead project planning. Weather forecast and road network information are used as inputs, and the model can provide short-term fleet size forecast, operation schedule, and route suggestions based on the input data. This model can also be updated in near real-time and can generate updated results based on the operation progress using weather observations and vehicle tracking data. Interpolation methods were also used to estimate the detailed weather condition on each road using limited weather data.

PREFACE

This thesis is an original work by Yipeng Li.

A version of Chapter 3 has been published as Li, Y., Xu, S., Lei, Z., Wu, L., AbouRizk, S., & Kwon, T. J. (2019, December). A generic simulation model for selecting fleet size in snow plowing operations. In *Proceedings of the 2019 Winter Simulation Conference* (pp. 2966-2977). Mr. Shuoyan Xu and Dr. Zhen Lei was involved with concept formation and manuscript composition. Ms. Lingzi Wu was involved with manuscript composition. Dr. Simaan AbouRizk and Dr. Tae J. Kwon had a supervisory role and contributed to concept formation. Dr. Simaan AbouRizk also performed manuscript edits.

A version of Chapter 4 has been published as Li, Y., Liu, C., Lei, Z., & AbouRizk, S. (2020, March). A predictive simulation model of regional weather events for winter road maintenance operations. In *Proceedings of Construction Research Congress 2020*. And has been reprinted with permission from the American Society of Civil Engineers (ASCE). Dr. Chang Liu and Dr. Zhen Lei was involved with concept formation and manuscript composition. Dr. Simaan AbouRizk had a supervisory role and contributed to concept formation.

An industry partner provided data used in this research. These data have been normalized to maintain the partner's privacy.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to Dr. Simaan M. AbouRizk for his supervision, guidance, and support during the planning and development of this research.

I would also like to thank my colleagues Dr. Zhen Lei, Dr. SeyedReza RazaviAlavi, Dr. Chang Liu, and Ms. Maria Al-Hussein. Their help and support throughout this research study were greatly appreciated.

Finally, I wish to thank my parents, Mr. Jiangtao Li and Ms. Changling Zhao, for their support and encouragement throughout my study at the University of Alberta.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 CHAPTER 1: INTRODUCTION

1.1 Background

Road safety is a major concern in many northern countries during winter. Studies have shown that snow precipitation on roads significantly increases accident risk (Andrey, Mills, & Vandermolen, 2001; Eisenberg & Warner, 2005; Mills, Andrey, & Hambly, 2011), and winter road maintenance activities can reduce the accident rate by maintaining safe driving conditions (Usman, Fu, & Miranda-Moreno, 2010; Usman, Fu, Miranda-Moreno, & Perchanok, 2012; Usman, Fu, & Miranda-Moreno, 2012). In Canada, the annual cost of winter road maintenance is about $1 billion (Andrey et al., 2001), and it is over $2 billion in the United States (Transportation Research Board & National Research Council, 2004). Since winter road maintenance activities usually involve a considerable amount of equipment and high costs, operation planning is crucial for successful and efficient operations. According to Perrier, Langevin, and Campbell (2006), decision-making in winter road maintenance can be categorized into four levels: strategic, tactical, operational, and real-time. The strategic and tactical levels involve partitioning service areas, selecting vehicle depot locations, and assigning fleets to depots; these levels are usually updated on a medium-term or long-term basis. The operational and real-time levels involve vehicle routing, scheduling, staffing the vehicles, and response to sudden changes like the weather. These levels usually require day-to-day updates or responses in a short time frame.

Various research has been conducted on related topics to help decision-makers plan winter road maintenance operations. In this thesis, research focused on selecting fleet sizes for long-term planning, as well as routing and scheduling for short-term decision-making. This thesis specifically focused on winter road maintenance operations on highways. Different from the operations in urban areas, highway networks usually have large spatial scales, and regional weather events must be considered. Roads in urban areas are generally close to each other and experience similar weather conditions, so operations in different snow events can follow the same operation routes. However, on highways, a snow event may only affect a part of a service area. Thus, different snow events may require different fleet sizes, and using fixed pre-determined routes can result in low operation efficiency. Additionally, available weather data is usually limited to a few weather station locations, so it is hard to determine the exact impact area of a snow event or the required fleet size.

1.2 Problem statement

In winter highway maintenance operations, the highway network is usually divided into multiple sectors, with one vehicle depot for each sector that houses vehicles when not in use and stores chemicals or abrasives used in sanding operations. One truck fleet is assigned to each depot, and the size of the truck fleet depends on the size of its service area. This truck fleet must be enough to perform the maintenance operation in a worst-case snow scenario, where all the roads in the sector are covered with snow. The fleet must also be able to finish the maintenance work within the level of service (LOS) time requirements for each road. However, most of the time, it is unlikely that all the areas will be experiencing snow simultaneously. It is possible that only part of the service area needs maintenance, and fewer trucks are needed in this case. Therefore, more detailed operation planning before each snow event becomes necessary. Based on short-term weather forecasts, the operation team estimates how many vehicles will be needed for the operation and calls the corresponding operation crew to stand by. The maintenance routes are also planned in this process. Since the weather conditions vary each time and the road network is different for each service sector, this planning process can create a lot of work. Also, during the operation process, the plowing route is continuously adjusted by truck drivers' visually assessing the actual snow accumulation on the road. If the actual accumulation amount on certain roads is higher than expected, the truck will plow these roads to ensure that the road is safe. As for sanding operations, trucks are loaded with chemicals or abrasives to apply. Due to limitations of truck capacity, each truck can only sand a limited length of roads and must return to the depot to reload.

When planning for winter highway maintenance operations, the available weather forecasts and observations are usually limited to the data collected at Road Weather Information System (RWIS) stations. These stations are typically located on the sides of highways, and they can provide weather observations and short-term weather forecasts at their locations. However, due to the limited number of RWIS stations and the large spacing between these stations, it can be difficult to determine the weather conditions for highways between stations. Thus, it is challenging for decision-makers to determine the actual operation effort based solely on the information from RWIS stations.

Therefore, a decision support system is needed to utilize the weather data from a limited number of weather stations and help the operation planning process. This decision support system must: (a) be able to utilize the weather data collected from a limited number of weather stations, (b) be generic that can be reused on different projects, (c) generate reliable results to help choose appropriate fleet sizes and operation routes.

1.3 Research objectives

This research aims to develop simulation models to assist in operation planning in winter highway maintenance operations. The objectives are:

- Develop simulation models to support long-term and short-term lookahead operation planning.

- Develop generic algorithms for snow removal operation planning that can be deployed on different service sectors.

- Use simulation approaches to develop models that consider the uncertainty and randomness in operations.

- Use appropriate methods in the model to utilize the weather forecasts and observations collected at a limited number of weather stations.

1.4 Thesis organization

This thesis is divided into six chapters to discuss the research methodologies and developed simulation models.

Chapter 1 introduces the background and problem statement of winter highway maintenance operations. The research objectives for the thesis are also presented in this chapter.

Chapter 2 is a literature review for related studies. Current industry practice, different approaches for planning winter road maintenance operations, techniques to utilize weather data, and near real-time simulation methods are discussed in this chapter.

Chapter 3 introduces a generic simulation model developed in *Simphony.NET* for long-term project planning. It uses a performance-based approach to evaluate the overall fleet performance under various snow events, and the user can select a fleet size based on their confidence level.

Chapter 4 discusses the benefits of using interpolation approaches to estimate the weather conditions on the road network. A case study is provided to compare the results between the closest-station method and the kriging interpolation method.

Chapter 5 introduces a generic, data-driven simulation model for short-term lookahead operation planning. This model uses weather forecasts and road networks to create fleet size forecasts and operation plans. It can also generate updated results based on operation progress using weather observations and vehicle tracking data. Two case studies are presented to demonstrate this model.

Chapter 6 summarizes this thesis and provides recommendations for future research.

2 CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter reviews research methods to plan winter highway maintenance operations. Section 2.2 discusses the current industry practice in planning winter highway maintenance operations. Section 2.3 presents previous studies on related topics, including solutions to select appropriate vehicle fleet size, operation scheduling, and vehicle routing approaches. Section 2.4 discusses the impact of weather uncertainties. Research about winter road maintenance that considered the weather uncertainties are introduced. Section 2.5 presents different interpolation methods that are commonly used in meteorological studies to estimate intermediate values when available weather data is limited. Section 2.6 discusses approaches to estimate snow accumulation conditions on road surfaces. Section 2.7 discusses near real-time simulation approaches, and research that uses near real-time simulation for operation planning. Section 2.8 presents the gaps and limitations in previous research and gives a conclusion for this chapter.

2.2 Industry practice

In Alberta, Canada, the provincial government uses a model developed in Microsoft Excel to calculate the required fleet size for each depot and benchmark prospective proposals when hiring private contractors for winter highway maintenance operations (Otto, 2004). Contractors also use this model to estimate the required fleet sizes and create proposals based on the model result and their experience. This model calculates the required number of trucks to complete the maintenance work for the entire road network based on the level of service requirements (Otto, 2004). The four level of service classes for highways and maintenance standards were stipulated by the provincial government (Alberta Transportation, 2018). The limitation of this model is that it is a static model that does not consider the dynamics and randomness in operations. Variations in weather, vehicle speed, and operation routes are not considered. Furthermore, contractors find that the actual number of trucks used in operation often differs from the model's prediction. Thus, contractors usually adjust the fleet size based on their past experience when bidding and may end up over- or under-allocating trucks to the depots.

As for operation planning in the short-term, the operation schedule is planned manually based on weather forecasts from weather stations. In actual operations, truck drivers determine the operation route by assessing the actual snow accumulation level on roads. Thus, the operation route could be different each time depending on the road conditions and may not be efficient as the drivers cannot see the entire operation. This process relies heavily on workers' experience. Contractors want a decision support tool for easier and more efficient operation.

2.3 Previous research on winter road maintenance operation planning

Several studies have been conducted to ascertain reasonable fleet sizes for winter road maintenance operations. Chien, Gao, and Meegoda (2013) developed a mathematical model to determine the required truck fleet size that considered the impact of weather and traffic on truck speed. Fleet size is calculated using the total road surface area and the plowing area per plow. The result shows required fleet size is reduced when increasing the plowing speed, and a larger truck fleet is needed as the precipitation amount increases. However, in this model, the deadheading (vehicle travelling without doing any maintenance work) from the depot to the working road section is neglected, and the vehicle routing in the road network is also not considered.

Jafari et al. (2018) proposed a simulation model to select the optimal vehicle fleet size based on the maximum reaction time in operations, which is the duration between the snow start time and the time that the snow is plowed. This model uses pre-defined routes and weather information as input data. Each road section is assigned to a weather station, and if the weather station indicates snow precipitation, trucks will be dispatched from the depot to pre-defined routes. The maximum reaction time is evaluated for each route, and the best route with minimum reaction time can be selected. The result also shows that the maximum reaction time will remain unchanged after the truck fleet reaches a certain size.

Beaujon and Turnquist (1991) proposed a model to solve the fleet sizing problem in transportation operations. This model uses a non-linear objective function to optimize the operation, and it aims to achieve the maximum profit by finding the optimal fleet size and vehicle dispatching decisions. Uncertainties in operation demand and vehicle travel times are both considered in this model, and decisions on fleet size are considered together with the allocation of the vehicle fleet.

As for operation scheduling, Fu, Trudel, and Kim (2009) proposed a real-time optimization model to solve the winter road maintenance scheduling problem. In this research, pre-defined maintenance routes and weather information are used as inputs, and fleet size and service level are considered as constraints to create the operation schedule. This research also analyzed the impact of weather information quality; the road network is divided into multiple zones, and all roads within one zone use the same weather information. The results show that operations will have better performance when using detailed zone-level weather data as opposed to using averaged weather information.

Mahoney and Myers (2003) proposed a decision support tool for winter road maintenance operations. This tool integrates multiple sub-systems, including weather prediction system, chemical concentration algorithms, and a road mobility index algorithm. User-defined maintenance routes are used, and the model creates recommended operation plans for each route. This system also allows the user to compare operations plans and assess the potential impact of an operation plan.

Many studies have focused on the vehicle routing problem in winter road maintenance operations. Wang and Liu (2019) proposed a model to solve the resource location and allocation problem, along with the vehicle routing problem, in snow removal operations. This model uses a tabu search algorithm that aims to improve the recovery ability of the road network under snow events. The uncertainty of snow events is also considered in this model.

Xie, Li, and Jin (2013) proposed an algorithm to optimize vehicle routes for deicing salt spreading operations in winter highway maintenance. The algorithm aims to minimize the total driving distance in operation. Road network topology, vehicle capacity, and load balance are considered as constraints.

Zhang (2009) proposed an algorithm to optimize service routes in snow plowing and snow disposal operations. This algorithm can be used on road networks with multiple vehicle depots, and its objective is to minimize the operation cost by reducing the deadhead travel distance in operations.

2.4 Weather uncertainties in winter road maintenance operations

There are various ways to quantify weather uncertainties in simulation models. Resampling historical weather data using Monte Carlo simulation is one common approach. The advantage of using this method is that multiple weather variables from multiple weather stations can be sampled simultaneously while keeping their spatial correlations, which is difficult to do using other methods like Markov Chains (Young, 1994).

The spatial correlation between weather stations is important when investigating weather impacts on winter highway maintenance operations. The highway network usually crosses a large area, and sometimes it is snowing on only part of the road network. Therefore, the uncertainties in the area of impact can cause changes in maintenance demand (Hajibabai & Ouyang, 2016). Hajibabai and Ouyang (2016) proposed a stochastic model to plan winter road maintenance operations that aims to minimize the operation cost while maximizing the service level. In this model, random maintenance tasks are generated across the road network to represent stochastic snow events, and the cost for truck deadheading and repositioning is calculated.

Mohamed, Jafari, Siu, and AbouRizk (2017) proposed a data-driven simulation model to plan for snow removal operations. The model uses historical operation data to find the most used routes to plow each area, creates multiple operation scenarios, uses weather data to determine which area is snowing, and executes the corresponding operation scenario. Using weather forecast data, the model can output plowing hours and truck utilization to facilitate operation planning.

Wales and AbouRizk (1996) developed a simulation model to forecast construction projects and assist in project planning, which focused on estimating the impact of weather on project schedules. In this model, a first-order Markov chain was used to model the precipitation events. The precipitation amount was sampled from a distribution function based on historical records, and neural networks were trained to predict the productivity based on weather conditions. The weather impact on the project schedule can be determined using this model.

2.5 Interpolation methods for limited weather data

To estimate the detailed weather situation in a given area, interpolation methods have been used by researchers (Barnes, 1964). Kriging interpolation (Krige, 1951) has been widely used in meteorological studies to estimate precipitation amounts (Kastelec & Košmelj, 2002), temperature (Hudson & Wackernagel, 1994), and solar radiation (Alsamamra, Ruiz-Arias, Pozo-Vázquez, & Tovar-Pescador, 2009). It has several variants including simple kriging, ordinary kriging, universal kriging, and indicator kriging. Atkinson and Lloyd (1998) compared the accuracy between ordinary kriging interpolation and indicator kriging interpolation. The two algorithms are used to interpolate the same dataset, and the result shows that ordinary kriging interpolation can provide more accurate estimation results.

Another commonly used interpolation algorithm is inverse distance weighting interpolation. It is based on Tobler's first law that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). Chen and Liu (2012) used inverse distance weighting interpolation to estimate the distribution of rainfall in Taiwan. The result gives a correlation coefficient over 0.95 and shows that inverse distance weighting interpolation is suitable for rainfall data interpolation. Plouffe, Robertson, and Chandrapala (2015) compared the accuracy between four interpolation methods: inverse distance weighting, thin-plate splines, ordinary kriging, and Bayesian kriging. Their results show that the month of the weather data and the spatial pattern of rainfall can impact the performance of a certain interpolation method. Inverse distance weighting interpolation and spline interpolation produce better results than the other two methods when the annual rainfall amount is high.

2.6 Road snow accumulation estimating

The snow accumulation depth on the road depends on many factors. Several models have been developed to estimate the actual snow accumulation depth. Gladysheva (2008) developed a model that uses nine meteorological factors and fourteen road factors to calculate the snow accumulation amount on the road surface. Wind, temperature, and shape of the road are all considered in this model. Brasnett (1999) proposed a method to estimate the snow depth using precipitation forecasts and screen-level temperature data. It calculates the amount of snow being added to accumulation and uses a temperature-based algorithm to estimate the amount of snow melted.

Most accumulation models require a lot of data input. A simpler alternative approach is to directly convert the snow water equivalent (SWE) data observed at weather stations to snow depth using snow density value. A common approach to converting between snow and water is to assume the snow density is 100 kg/m^3, so the snow depth can be calculated from SWE amount using the 10-to-1 rule based on the 1000 kg/m^3 water density (Roebber, Bruening, Schultz, & Cortinas, 2003). However, this rule of thumb is not always accurate. Williams (1956) analyzed snow density observations at different weather stations across Canada, and found that the snow density varies by location and can change over time. Judson and Doesken (2000) found that the density of freshly fallen snow ranges from 10 to 257 kg/m^3, with the peak between 60 and 100 kg/m^3.

2.7 Near real-time simulation

For short-term lookahead operation planning, the initial simulation result based on the weather forecast may not be valid in actual operations due to the dynamic nature of weather (Vahdatikhaki & Hammad, 2014). In this case, near real-time simulation can be used to update simulation results dynamically.

Vahdatikhaki and Hammad (2015) proposed a near real-time simulation approach to evaluate the safety of earthmoving sites. It considers proximity-based and visibility-based risks in earthmoving operations and generates risk maps based on the collected data. Equipment operation paths are adjusted to ensure the planned paths are risk-free.

Other research by Vahdatikhaki and Hammad (2014) developed a simulation model for earthmoving projects using a near real-time simulation approach. The model continuously monitors equipment motion and environmental factors on the construction site. If the site data differ from the model, the simulation model is updated, and an updated schedule is created. This research also pointed out that updating the model too frequently can cause a frequent change of results, making it impractical. Thus, an appropriate update interval in near real-time simulations is important.

AlBahnassi and Hammad (2012) proposed a near real-time simulation model for crane motion planning. The model considers both the safety requirements and operation efficiency and aims to assist crane operators to plan crane paths in near real-time. The dynamics of other cranes are also considered in this research.

2.8 Gaps and limitations

The literature review presents various approaches that have been developed to plan for winter road maintenance operations. The uncertainties in weather, limitations in weather data, and operation route optimization are considered by some researchers, but few have considered multiple of these factors in a unified model. Approaches to utilize limited weather data and plan for operations that dynamically change have also been developed, but these approaches are rarely being used to assist operation planning in winter highway maintenance operations. Therefore, a unified model that considers the abovementioned aspects is needed. In this thesis, simulation models are designed with consideration of these impact factors and limitations. Interpolation methods and near real-time simulation approaches are used to achieve better simulation results.

3 CHAPTER 3: A GENERIC SIMULATION MODEL FOR SELECTING FLEET SIZE IN SNOW PLOWING OPERATIONS[1]

3.1 Introduction

Winter road maintenance is challenging for many northern countries (Shi, 2010). Notably, Canada spends around $1 billion dollars annually in winter road maintenance activities (Andrey et al., 2001). In practice, snow plowing plays a significant role in winter road maintenance to remove as much loose snow on the roads as possible, and to increase mobility and safety (Perrier, Langevin, & Campbell, 2006; Usman et al., 2010). In order to conduct snow plowing activities effectively, efforts have been made to improve planning efficiency. One major aspect of optimizing snow plowing activities is the selection of the truck fleet size and the plowing routes. In previous studies, snow plow routing optimization is considered as a Hierarchical Chinese Postman Problem (HCPP) (Cabral, Gendreau, Ghiani, & Laporte, 2004; Ghiani & Improta, 2000). The common solution for this problem is to divide the area into several sectors and set one depot at each sector with an assigned truck crew. When the snowstorm comes, trucks will depart from the depot to different road sections and return to the same depot after all roads are cleaned. Due to the complexity of snow plowing operations, however, the challenge is separating a large road network into small sectors and determining the crew size at each depot (Stricker, 1970). For example, the size of each sector will affect its crew size. Both the crew size and the combination of roads within this sector must be considered when selecting the plowing route. Additionally, uncertain weather conditions can stall this process because the snow coverage areas by storms are unknown. As such, the roads

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[1] A version of this chapter is published as Li, Y., Xu, S., Lei, Z., Wu, L., AbouRizk, S., & Kwon, T. J. (2019, December). A generic simulation model for selecting fleet size in snow plowing operations. In *Proceedings of the 2019 Winter Simulation Conference* (pp. 2966-2977). doi: 10.1109/WSC40007.2019.9004954 © 2019 IEEE

need to be plowed, and the plowing route varies for each snow event. Considering the random nature of weather events is necessary to resolve these problems. The process of developing simulation models often requires repetitive efforts; a generic model is needed to incorporate the planning process of snow plowing on various road networks. This chapter therefore proposes a generic model to simulate snow plowing processes under uncertain weather conditions. This model captures the nature of planning, and can be re-used for various project scenarios with minimal adjustments. Based on the proposed model, the performance of a given fleet size can be evaluated, and a reasonable fleet size can be selected based on a required confidence level.

3.2 Methodology

This research proposes a generic model to simulate the snow plowing process (as shown in Figure 3.1). The model has been developed in the *Simphony.NET* environment, a simulation engine developed at the University of Alberta (AbouRizk, Hague, Ekyalimpa, & Newstead, 2016). This model uses the following as inputs: the road network, historical weather data, and the level of service (LOS) class for each road section (usually assigned by the government), along with the maximum plowing time allowed for each LOS class. By changing the input data, the proposed model can be used at different snow removal projects with different road network layouts, weather conditions and LOS requirements. This model consists of three major parts: generating a random snow area, selecting the plowing route, and calculating the plowing time. First, this model will generate a random snow area using historical weather data; next, the plowing work will be assigned to trucks based on a selected truck fleet size; finally, the model will simulate when the plowing work on each road will finish. If the finish time exceeds the maximum allowed plowing time, the work on this road will be considered delayed, and the distance delayed will be calculated. The model generates a probability distribution of the total distance delayed as outputs, which can be used to evaluate the performance of a selected fleet size. Moreover, additional adjustments can be made based on the confidence level required.

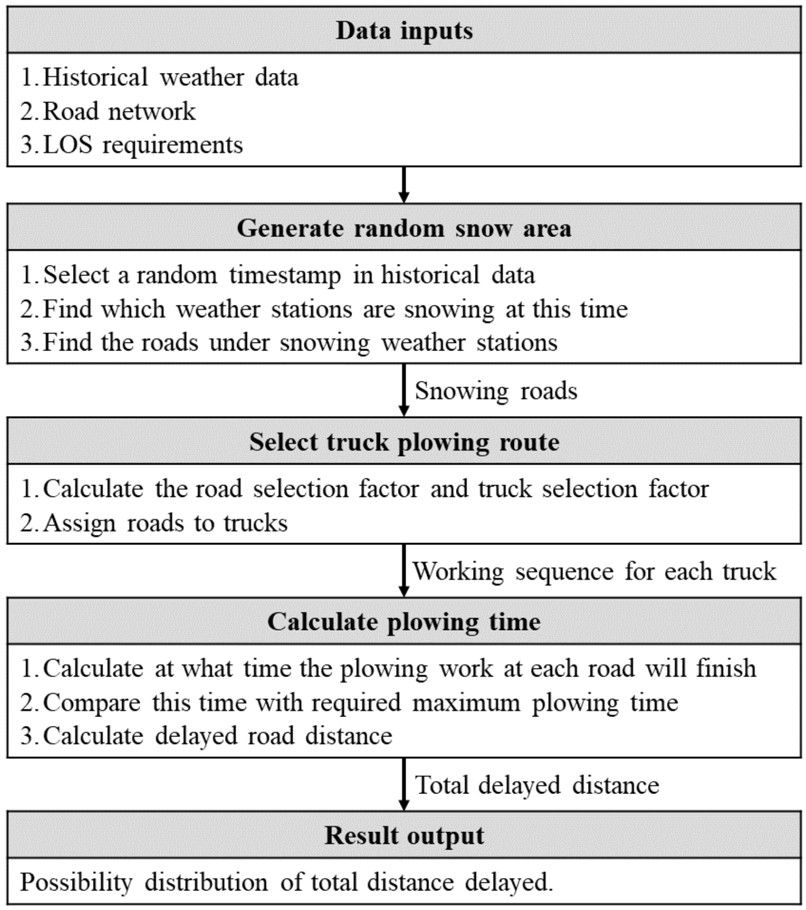

Figure 3.1: Simulation process. © 2019 IEEE

3.2.1 Assumptions

The proposed simulation model is developed based on four assumptions:

1) Only plowing operations are considered in this model. Sanding operations or any other activities that require using materials do not apply to this model since the process of truck reloading materials are not calculated (this can be included as future work).

2) Each road is assigned to its closest weather station. If a weather station indicates precipitation, all roads assigned to this weather station are considered as snowing and need to be plowed.

3) All roads are two-way roads. Therefore, trucks are required to return to the starting location after plowing each road.

4) Roads remains passable when covered with snow, and it does not affect the truck speed. Both deadhead travel and plowing speed stays the same under all weather conditions.

3.2.2 Generate random snow area

Figure 3.2 shows the flowchart of the "generate random snow area" process. Here, the model uses historical weather data and Monte Carlo simulation to generate a random snow area. All roads within this area will be assigned to trucks for plowing work in the following step. First, the model generates a random number and finds a random timestamp from the database using both this random number and the sequential IDs of the timestamps; next, the model checks the weather status of each weather station at this time. If there is at least one weather station indicating snow at this time, the model will output the roads under snowing weather stations for the next step, otherwise the model will generate a new random number and repeat this process.

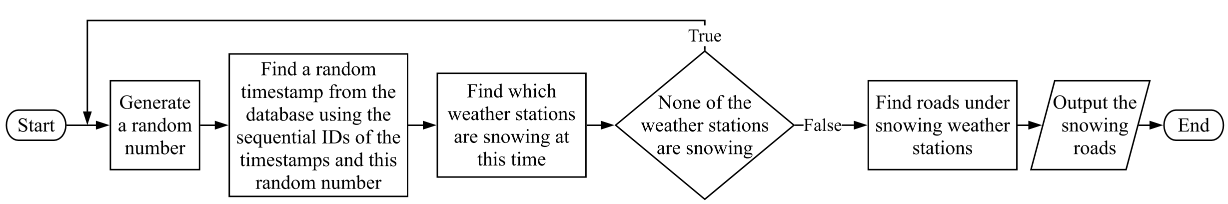

Figure 3.2: Generate random snow area process. © 2019 IEEE

3.2.3 Select plowing route

After a random snow area is generated, the simulation model assigns the plowing work triggered by weather events to the trucks. Figure 3.3 shows the flowchart of this process starting with a calculation of the road selection factor for each road. This factor is calculated by satisfying Equation 3.1

$$F_R = \frac{L_R \times N_L \times 2}{T_{MAX}} \tag{3.1}$$

where F_R = road selection factor; L_R = road length; N_L = number of lanes; and T_{MAX} = LOS class-stipulated maximum plowing time.

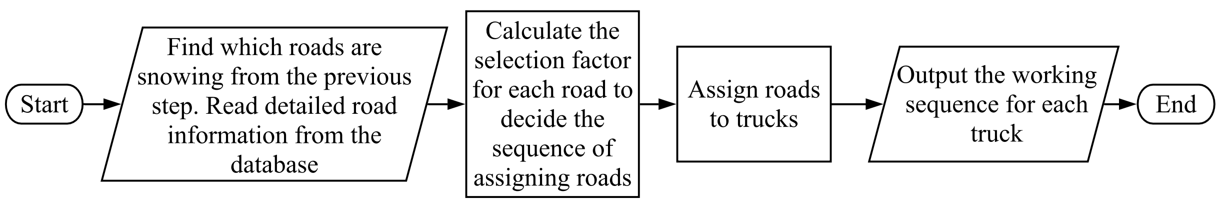

Figure 3.3: Select plowing route process. © 2019 IEEE

Roads are assigned to trucks starting from the road with highest road selection factor value. Notably, the value of this factor is also the average speed for one truck to plow this road. The higher the value is, the less float time the truck has for the work. Since the truck will conduct plowing work starting from the first road assigned to this truck, this road assignment order makes the best effort possible to avoid work delays. When this value exceeds the average plowing speed, there is a high possibility that one truck cannot finish plowing this road in time, considering additional deadhead travel may be needed before trucks arrive to this road. Therefore, multiple trucks are assigned to this road and share the plowing work. The number of trucks for each road is calculated by Equation 3.2

$$N_T = \left\lceil \frac{L_R \times N_L \times 2}{T_{MAX} \times V_P} \right\rceil \tag{3.2}$$

where N_T = number of trucks; L_R = road length; N_L = number of lanes; T_{MAX} = LOS class stipulated maximum plowing time; and V_P = average plowing speed.

When a road is assigned to multiple trucks, all trucks equally share the workload on the same road. When a road is plowed by one truck, the truck always returns to its starting location after plowing. Additional deadhead travel is added to each truck if one road is assigned to multiple trucks. This deadhead equals the total distance of the road subtracting the plowing distance for each truck, which ensures that the trucks can return to the starting location after plowing part of the road. This assignment process also considers a balance of the workload between trucks. The workload for the trucks is calculated using Equation 3.3

$$W = L_P + \frac{L_D}{2} \tag{3.3}$$

where W = truck workload; L_P = total plowing distance; and L_D = total deadheading distance.

To make sure all trucks share a similar workload, a truck selection factor is used in the model to decide which road will be assigned to which truck. This factor is calculated using Equation 3.4

$$F_T = W + \frac{D}{2} \tag{3.4}$$

where F_T = truck selection factor; W = trucks' current workload (calculated by Equation 3.3); and D = shortest deadhead distance between the road and the current truck location.

When calculating the shortest deadhead distance, the widely-used Dijkstra's algorithm determines the shortest path in the node-network (Dijkstra, 1959). The model recalculates the truck selection factor after every time that a road is assigned to one truck. Each road section is assigned to the truck with the smallest truck selection factor value. By using this factor, the priority is given to the truck that a) has the smallest workload and b) is closest to the road section. This approach can balance the workload between trucks and reduce the total deadheading distance. For instance, if the workload value (calculated using Equation 3.3) of truck A is 15 and the workload value for truck B is 10, and a road is 5 km away from truck A and 10 km away from truck B, then the truck selection factor calculated using Equation 3.4 would be 17.5 for truck A and 15 for truck B. Therefore, this road would be assigned to truck B based on the truck selection factor. This causes more deadhead travel in the work, but it balances the workload between the two trucks. If truck B were 20 km away from the road, however, the truck selection factor for truck B would become 20, and truck A would be selected due to a smaller selection factor value. Thus, trucks will avoid long-distance deadhead travel and can reduce the total workload of the operation. After the road sections are all assigned to trucks, the truck carries out the plowing work following the order of roads assigned. The time taken on each road section is calculated in the next step (section 3.2.4).

To be noted that this model aims to estimate the fleet performance instead of proposing optimized solutions. Thus, the algorithm proposed in this section does not generate optimized operation routes, but to generate a reasonable route that can results in a similar performance as contractors' current practice, so the overall fleet performance can be accurately evaluated.

3.2.4 Calculate plowing time

Figure 3.4 illustrates the process of calculating plowing time. After the plowing route for each truck is selected, the model calculates at what time the plowing work on each road will finish. Here, a probability distribution function of the plowing speed is used to calculate the plowing time. This distribution function is fitted using plowing speed data collected in real construction projects; it has a Laplace distribution with a mean of 42.71 and a scale of 10.60. Figure 3.5 shows the comparison between the original data and the fitted function. To eliminate extreme situations, a lower boundary at the 5th percentile and an upper boundary at the 95th percentile are added to this function. The plowing time on each road is calculated using a random deviate of this function. Next, the plowing time on each road will be compared with the LOS stipulated time to determine whether or not the operation meets the LOS requirement. If the plowing time exceeds the required time, the model calculates the distance that was plowed on time, and the rest of the road is output as delayed distance. For each snow event generated, multiple simulations of the plowing process under this snow event are executed in this model. Through multiple iterations, the model generates a distribution of the delayed distance under current selected truck fleet size. With this information, further adjustments can be made based on the confidence level required.

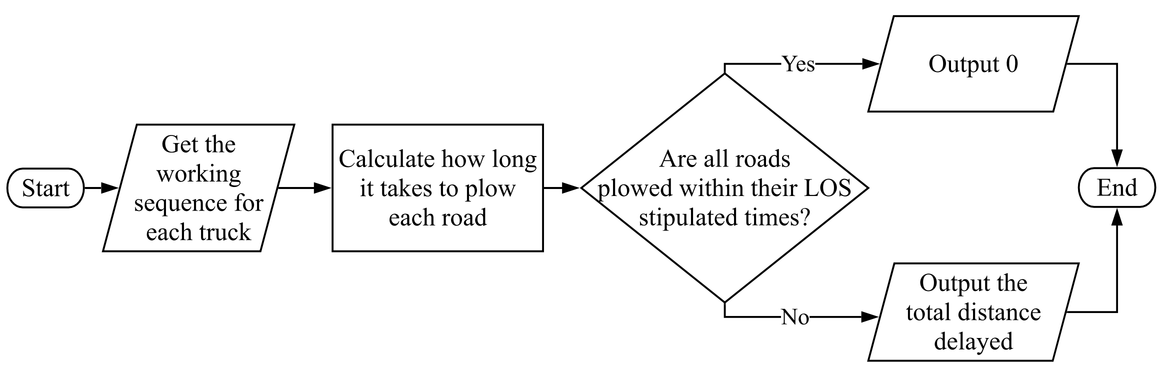

Figure 3.4: Process to calculate plowing time. © 2019 IEEE

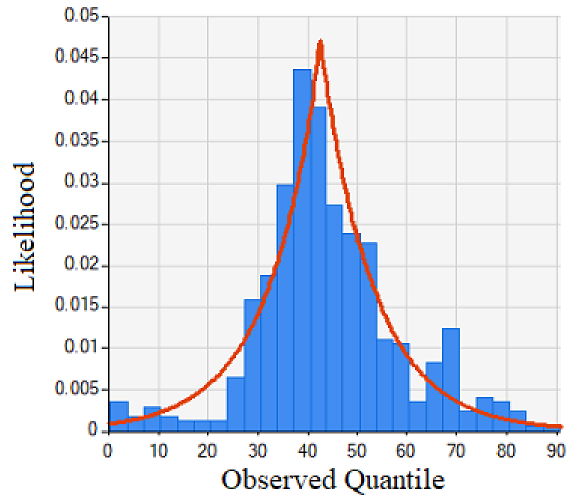

Figure 3.5: Comparison between original data and fitted distribution function. © 2019 IEEE

3.3 Implementation

3.3.1 Database structure

All input data of this model are prepared and stored in a Microsoft Access database following the structure shown in Table 3.1. By changing the input data, this model can be reused on different projects. Since most of the original data are stored in separate files and have different formats, data preprocessing is needed in order to: (1) convert original weather data into a uniform format, (2) convert the roadmap into a node-to-node format, and (3) remove redundant weather data to accelerate the simulation program. Notably, this model simulates the overall performance of the truck fleet within the entire period of available weather data, but the performance of a specific season can also be simulated by only using the weather data from that season. Normally, the weather data should have a duration that covers most of the snow season, and include various snow events with different precipitation levels in order to produce reliable results. This database uses a node-to-node format to store the road network information. The road intersections are considered as "nodes," and road sections are considered as connections between two nodes. Each road section should have a consistent LOS class and a continuous number of lanes. If the LOS class or number of lanes changes in the middle of a road section, it should be split into two sections and an additional node should be added at that position. For roads outside the service area, they can be added to the roadmap as “shortcut” roads to let trucks use it for deadhead travelling between nodes. “Shortcut” roads are added to the database without being assigned to a weather station; therefore, these roads will not be assigned to any truck for plowing, since they do not need to be plowed.

Table 3.1: Structure of the database. © 2019 IEEE

Table Name	Field Name	Description
GeneralInformation	NumberOfWeatherRecords	Total number of records in the “TimeRange” table
	NumberOfWeatherStations	Total number of weather stations under this shop
	NumberOfRoads	Total number of roads in the map
	NumberOfNodes	Total number of nodes in the map
	StartNode	The node where the shop is located at
	NumberOfTrucks	Total number of trucks in the fleet
Nodes	ID	ID of the node
	ConnectedNodes	ID of the nodes that this node is connected to
LOS	Class	LOS class
	MaxPlowingTime	Maximum plowing time allowed
Road	ID	ID of the road
	LOSClass	Road’s LOS class
	LengthKm	Road’s length in kilometers
	NumberOfLanes	Number of lanes in each direction
	WeatherStation	The weather station that the road belongs to
	StartNode	ID of the road’s one vertex
	EndNode	ID of the road’s another vertex
WeatherStation	StationID	Name of the weather stations
TimeRange	ID	ID of the timestamp
	WeatherTime	The timestamp of the weather record
WeatherStationData	StationID	Name of the weather station
	WeatherTime	The timestamp of the weather record

3.3.2 Simulation modeling

This model is developed in the *Simphony.NET* environment. Figure 3.6 illustrates its schematic. Notably, the proposed methodology is not limited to the *Simphony.NET* platform; other simulation software can also be used to achieve the same result. In *Simphony*, virtual entities are created at the beginning of the simulation process. These entities flow through a series of elements that represent different tasks. Calculations are executed when an entity arrives at an element (AbouRizk, Hague, & Ekyalimpa, 2016). *Simphony* provides multiple modeling elements with different functions by default; the user can use these elements to represent different tasks in the operation by setting unique attributes to each element. Extra codes can also be added to elements if additional calculation is required. In this model, entities that represent snow events are created at the beginning of the simulation process. The processes of generating random snow areas and selecting plowing routes are accomplished in two elements named "Generate Snow Area" and "Select Route" using Visual Basic codes. After the plowing route for each truck is selected, new entities that represent plowing trucks are created. Next, each entity will go through the "Plow" element where the plowing time for each road section will be calculated. The model will then collect the delayed distance, and the possibility distribution of this number will be generated through multiple iterations. *Simphony* also allows users to export the simulation result of each iteration to a Microsoft Excel file. The mean, median, and the confidence interval of the results can be calculated using the exported data.

This model aims to estimate the overall fleet performance and assist in operation planning in the long term. Thus, operation route and schedule are not generated as outputs here as different snow scenario creates different routes and schedules, and detailed operation planning for specific snow events is not in the scope of this model.

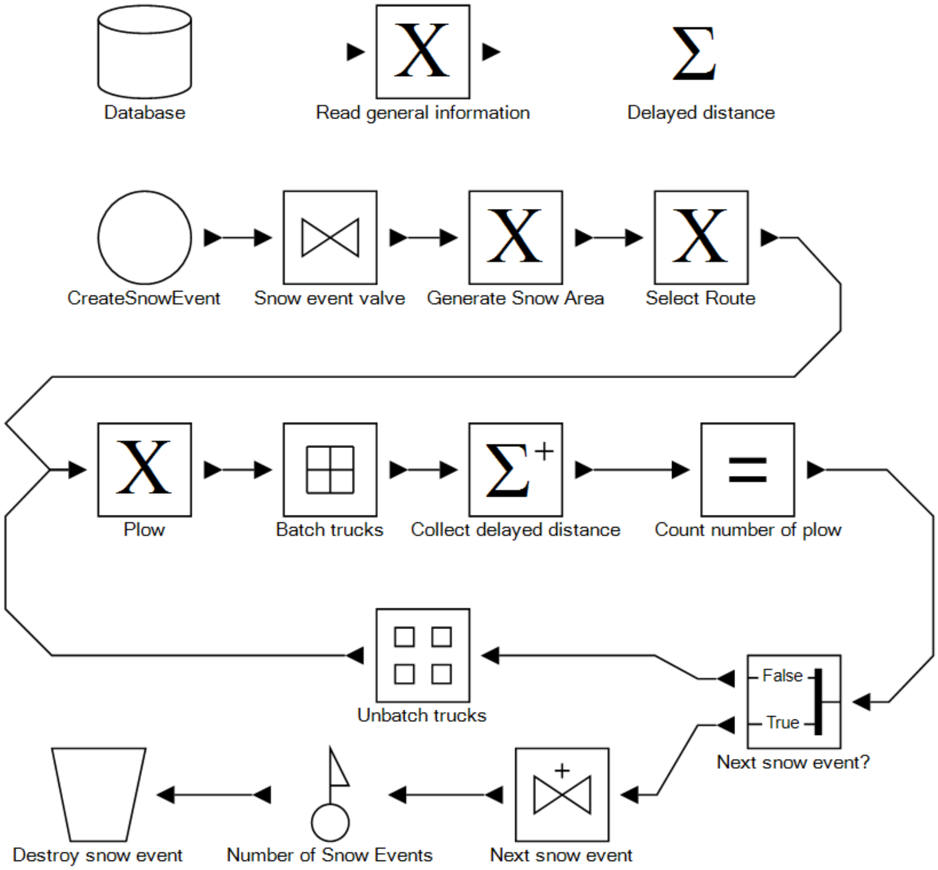

Figure 3.6: *Simphony.NET* simulation model. © 2019 IEEE

3.4 Illustrative case study

A case study is provided here to demonstrate the functionality and practicality of the proposed model. Figure 3.7 illustrates the road network, shop location, and weather station locations for this case study. This road network structure is created based on an actual road network, but this data has been normalized.

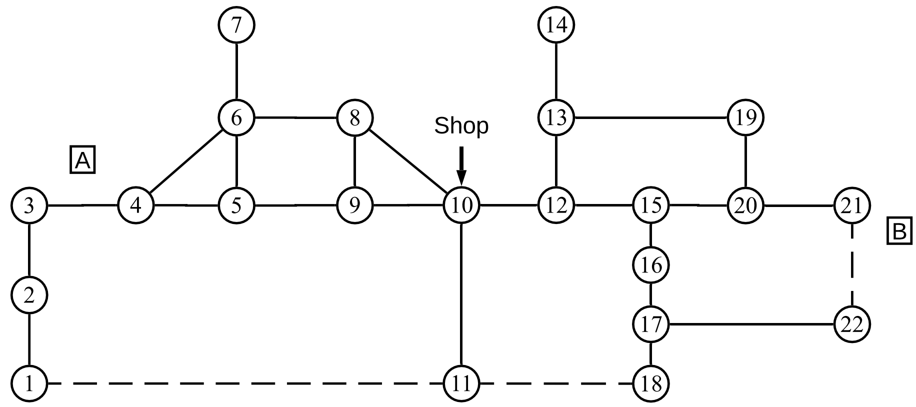

Figure 3.7: Road network for the example case study. © 2019 IEEE

This road network has 25 roads and 22 nodes; 3 additional shortcut roads are also added to the road network, which are shown as dashed lines in Figure 3.7. The shop is located at Node 10. Weather data from two weather stations, marked in Figure 3.7 as A and B, are used to determine the weather situation in this area, and the weather on each road is determined by its closest weather station. The data used here has a 5-minute observation interval within a 108-day period in winter. It has a total of 29501 observations after removing some missing data. To be noted that due to the limitation in available weather data, this dataset may not cover all types of snow events, and a dataset with a longer time duration could result in better simulation results.

Table 3.2 shows detailed road data. The maximum plowing time allowed for each LOS class is shown in Table 3.3. The simulation model was run for 5000 iterations. Table 3.4 and Table 3.5 show the model output result for fleet sizes ranging from 5 to 9 trucks. The average simulation time was about 20 minutes on a computer with 3.2 GHz CPU and 16 GB memory.

Table 3.2: Road information for the case study. © 2019 IEEE

ID	LOS Class	Length (km)	Lanes	Weather station	Vertex 1	Vertex 2
1	H	14.2	1	A	1	2
2	J	10.54	1	A	2	3
3	C	25.23	2	A	3	4
4	K	3.06	1	A	4	6
5	G	0.75	1	A	5	6
6	G	13.24	1	A	6	7
7	A	3.01	2	A	4	5
8	D	6.82	2	A	5	9
9	B	3.42	2	A	9	10
10	C	1.06	1	A	8	9
11	F	6.22	1	A	6	8
12	H	5.2	1	A	8	10
13	D	23.63	1	A	10	11
14	E	8.75	2	A	10	12
15	I	2.33	1	A	12	13
16	G	13.35	1	A	13	14
17	D	8.77	2	B	12	15
18	I	22.23	1	B	13	19
19	G	11.18	1	B	17	18
20	H	9.98	1	B	16	17
21	F	4.95	1	B	15	16
22	C	10.11	2	B	15	20
23	H	9.7	1	B	19	20
24	F	19.95	1	B	17	22
25	C	5.02	2	B	20	21
Shortcut 1	—	42.89	—	—	1	11
Shortcut 2	—	12.22	—	—	11	18
Shortcut 3	—	26.3	—	—	21	22

Table 3.3: Maximum plowing time allowed for each LOS class. © 2019 IEEE

LOS Class	A	B	C	D	E	F	G	H	I	J	K
Time (hours)	1.25	1.5	1.75	2	2.25	2.5	2.75	3	3.25	3.5	3.75

Table 3.4: Possibility of the distance delayed in one operation. © 2019 IEEE

Distance delayed (km)	5 trucks	6 trucks	7 trucks	8 trucks	9 trucks
0	38.60%	43.75%	51.12%	64.84%	66.41%
< 1	40.05%	45.43%	53.67%	67.26%	68.73%
< 3	42.50%	53.14%	64.15%	72.67%	72.75%
< 5	44.25%	57.14%	67.95%	75.50%	76.59%
< 10	49.32%	66.29%	76.00%	82.35%	83.80%
< 20	63.66%	79.94%	87.72%	89.78%	91.70%
< 30	75.72%	85.80%	91.34%	92.71%	95.35%
< 50	88.20%	90.18%	93.15%	95.58%	98.08%
< 100	93.90%	90.91%	97.74%	99.49%	99.90%
< 200	94.24%	95.19%	99.98%	100.00%	100.00%
≥ 200	5.76%	4.81%	0.02%	0.00%	0.00%

Table 3.5: Maximum distance delayed in one operation. © 2019 IEEE

Number of trucks	5	6	7	8	9
Maximum distance delayed (km)	365.0	307.7	211.2	157.0	113.9

The simulation shows the delay possibilities (for different fleet sizes) of one snow removal operation to clean up all snow-covered roads after one snow event. It provides valuable information for selecting a reasonable fleet size with different confidence level requirements. Since the simulation model provides a range estimation of the performance, criteria can be set at any level to find the minimal fleet size required. For example, if having a 60% confidence level is required that no road will be delayed in the operation, a minimal fleet size of 8 trucks will be needed based on the simulation result. Similarly, if a 70% confidence level is required for having fewer than 10 kilometers delayed in a single operation, the minimal fleet size needed will be 7 trucks. Criteria like "maximum distance delayed" in a worst-case scenario, or "maximum possibility allowed" to limit distances delayed can also be used to select a reasonable fleet size.

3.5 Validation techniques

This model is validated using real-world data obtained from a shop with 4 trucks during its operations in November and December 2018. For each truck at this shop, an average delayed road distance in one trip is calculated using data from 5 trips of the truck. The total delayed distance is determined by the sum of the 4 trucks. The simulation model was run for 5000 iterations, the real operation data is on the 49th percentile of the simulation result; it has a 1.19% difference with the median value and a 16.53% difference with the mean value. Considering the time waiting for traffic lights, time spent making turns, and other factors affecting the trucks' productivity are not calculated in this model, this result is considered to be acceptable. It shows that the model can mimic the current winter highway maintenance operations, and its result is similar to the fleet performance in actual operations.

3.6 Conclusion

This study is aimed at selecting a reasonable fleet size under uncertain weather conditions. By evaluating the performance of a given fleet size, a reasonable fleet size can be selected based on a required confidence level. The simulation approach includes: using the Monte Carlo method to sample random snow areas based on historical data, selecting the plowing route for trucks, and calculating the time-cost of plowing operations based on real-world speed data. The feasibility of proposed model was demonstrated through an illustrative case study. The performance of different truck fleet sizes is simulated, and the results show the potential risk of failure for different fleet sizes. This model provides a new decision support tool for developing policies and strategies for the assignment of different numbers of trucks to a depot. Proposed model can also incorporate advanced weather information from a forecast system, which provides detailed weather information for every road section. Future work may include adding a feature to the model to automatically select the minimal fleet size for a given confidence level, incorporating the effects of truck breakdowns, and generalizing the model for other fleet types, such as sand trucks, to include loading and unloading materials. The authors recommend that future studies be conducted focusing on these issues.

4 CHAPTER 4: A PREDICTIVE SIMULATION MODEL OF REGIONAL WEATHER EVENTS FOR WINTER ROAD MAINTENANCE OPERATIONS[2]

4.1 Introduction

Many construction operations are sensitive to weather conditions, as adverse weather events can bring negative impacts to the project. Moselhi et al. (1997) pointed out that labor productivity can be affected and work stoppage can occur under abnormal weather conditions. Weather also affects the cost of construction projects. Research conducted by Russo Jr. (1966) suggests that appropriate use of weather information could potentially save $0.5 to $1.0 billion for the construction industry annually. Due to the resulting project delays and cost overruns, weather is one of the main reasons for construction claims as well (Moselhi & El-Rayes, 2002). Accurately estimating the potential impact of weather on a project before commencing construction operations can save both time and money. Multiple studies have been conducted to estimate the weather impact on a construction project (Moselhi et al., 1997; Shahin, AbouRizk, Mohamed, & Fernando, 2014), and historical weather data is a common component in these approaches. Usually, historical weather information is limited to the data collected at weather stations. For a project with a large spatial magnitude, which has multiple activities taking place at different locations with various weather conditions, detailed weather information between weather stations is sometimes needed to accurately estimate the weather impact on each individual task. Breaking down the project this way presents challenges: it is difficult, for example, to estimate the weather situation between stations due to

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[2] A version of this chapter is published as Li, Y., Liu, C., Lei, Z., & AbouRizk, S. (2020, March). A predictive simulation model of regional weather events for winter road maintenance operations. In *Proceedings of Construction Research Congress 2020*. doi: 10.1061/9780784482865 and has been reprinted with permission from the American Society of Civil Engineers (ASCE).

their vast spacing. A scientific method is needed to estimate detailed weather situations using limited historical data. In this chapter, kriging interpolation is used to generate detailed weather information using historical data from weather stations; a simulation model is developed using this data to solve the fleet sizing problem in winter road maintenance operations (Perrier, Langevin, & Campbell, 2007). The result is compared with the outcome of another approach (using the weather information from the closest weather station) to demonstrate how kriging interpolation and detailed weather information helps the project planning process.

4.2 Methodology

This research proposes a simulation model to estimate the truck fleet size needed in winter road maintenance operations. Figure 4.1 shows the framework of the proposed model. Historical weather data from weather stations, road network information, and road Level of Service (LOS) requirements are used as inputs of the model. Kriging interpolation is used to estimate detailed precipitation amounts in the working area. Compared with inverse distance weighting interpolation and spline interpolation, kriging interpolation can measure the possible error when estimating unknown values, but also requires more data input (Wu & Hung, 2016). A resource scheduling approach is used to calculate the fleet size needed for the tasks. Finally, Monte Carlo simulation is used to generate a probability distribution of the fleet size as the output result.

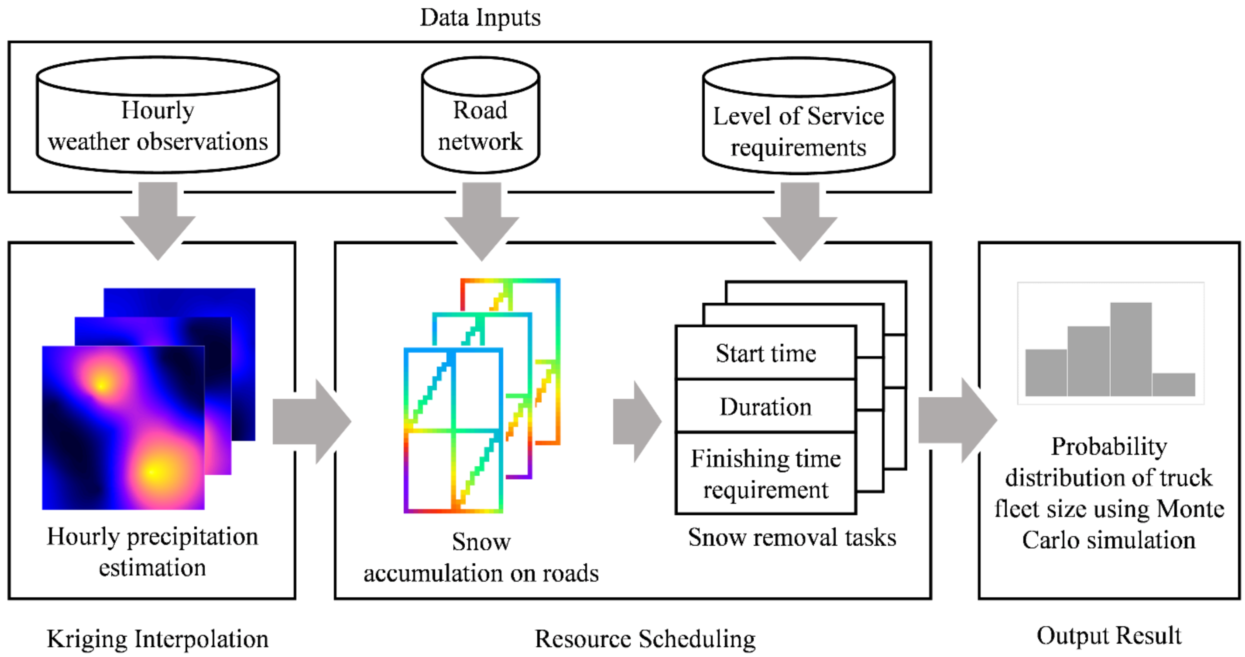

Figure 4.1: Model framework.

4.2.1 Kriging interpolation

Historical observation data from nearby weather stations around the working area are used here as inputs. To improve the accuracy in resource scheduling, data observation intervals should be as short as possible and should be consistent among all weather stations. In this research, hourly precipitation data from Alberta Climate Information Service (ACIS) are used. In each hour during a snow event, precipitation amounts in the working area are calculated using ordinary kriging interpolation (Cressie, 1988). Equation 4.1 shows the expression of ordinary kriging method (Goovaerts, 1997)

$$Z^*(u) = \sum_{\alpha=1}^{n(u)} \lambda_\alpha(u) Z(u_\alpha) + \left[1 - \sum_{\alpha=1}^{n(u)} \lambda_\alpha(u)\right] m(u) \tag{4.1}$$

where $Z^{*}(u)$ is the estimation value at location u, $\lambda_{\alpha}(u)$ is the weight assigned to datum $Z(u_{\alpha})$, and $m(u)$ is a constant mean of local value.

Kriging interpolation calculates predicted data as a weighted average of available sample data (Kwon, Fu, & Melles, 2017). The weight of each sample data is determined by the semivariogram, which gives the relation between the distance between two data points and their semivariance. The semivariogram can be modeled by calculating the semivariance between the known data points and find the relation between their distance and the semivariance value.

Kriging interpolation has several variants including simple kriging, ordinary kriging, and universal kriging. Among these variants, ordinary kriging is relatively easy to use and requires less input data (Kwon et al. 2017), thus it is selected for use in this research.

4.2.2 Resource scheduling

In winter road maintenance operations, the LOS class on each road is one of the most important constraints in operations as the resources needed in the operation are greatly affected by this factor. The class of each road is usually assigned by the government to specify time requirements as well as acceptable road conditions in maintenance operations. This research uses two components in the LOS classes: trigger-accumulation levels and time requirements. Trigger-accumulation levels define when the road needs to be cleaned in a snow event. When the maximum snow accumulation reaches the trigger-accumulation level, trucks will be sent to this road for maintenance work. Time requirements specify the maximum-allowed duration for the maintenance work. Operation on each road section must finish within this duration to minimize traffic disruptions; a contractor's proposal will be rejected if the planned work duration exceeds this limit (Siu, Liu, Wales, & AbouRizk, 2017). The proposed model allows users to set multiple LOS classes. Both the trigger-accumulation level and the time requirement can be set individually for each class.

Here, a resource scheduling approach is used to find the fleet size needed for a snow event. After calculating detailed hourly precipitation during the snow event, the model calculates the snow accumulation on each road starting from the beginning of the snow event. Precipitation amounts on each road are added up until the maximum accumulation amount reaches the triggering amount of snow. A maintenance task is then created and the resources are assigned to this task. Multiple trucks can be assigned to one task in order to meet the LOS requirements. Equation 4.2 is proposed by the authors to calculate the number of trucks assigned to each task

$$R_n = \left\lceil \frac{\frac{L \times N_L \times 2}{S} + T_M}{T} \right\rceil \tag{4.2}$$

where R_n is the number of trucks needed for the task, L is the length of the road section, N_L is the number of lanes in each direction, S is the truck working speed, T is the time requirement value for this road, and T_M is a maneuvering and operating time for trucks to travel to this road section and return back, which is pre-defined and should be related to the distance between the road and truck's original parking location.

After calculating the number of trucks needed for the task, the authors propose Equation 4.3 to calculate the duration of the task

$$D = \frac{L \times N_L \times 2}{S \times R_n} + T_M \tag{4.3}$$

where D is the duration of the task, L is the length of the road section, N_L is the number of lanes in each direction, S is the truck's working speed, R_n is the truck number for this task (calculated by Equation 4.2), and T_M is the maneuvering and operating time.

Following the method presented above, tasks are created at different times throughout the snow event. Next, the model calculates the number of trucks needed to finish all tasks on time. Fleet size is set to 0 at the beginning of this process. Trucks are assigned to tasks and are occupied until the task is finished, and more trucks are added when the fleet size is not enough for the tasks. The total resulting fleet size will be the number of trucks needed for the timely completion of all tasks for the full duration of the snow event. Random snow events are retrieved from historical weather data using Monte Carlo simulation. Each snow event gives a fleet size number for this event and a probability distribution of the fleet size is generated as the final output result.

4.3 Implementation

The simulation model is developed using the R programming language, a free software environment for statistical computing and graphics (R Core Team, 2020). The *gstat* package is used in this model for kriging interpolation calculations (Gräler, Pebesma, & Heuvelink, 2016; Pebesma, 2004). Notably, the proposed methodology is generic. As such, other programming platforms can also be used to achieve the same result.

4.4 Illustrative case study

An illustrative case study is provided here to demonstrate the proposed model. Figure 4.2 shows the locations of the weather stations and the roads in this case study. The road network consists of 14 roads. Weather data from 18 weather stations in Alberta, Canada during a 128-day period in winter are used here as inputs. Table 4.1 shows the trigger-accumulation level and time requirements of different LOS classes. Table 4.2 shows the road information in detail.

Table 4.1: LOS class requirements.

Class	Time requirement (hours)	Trigger-accumulation level (mm)
A	3	0.2
B	5	0.4
C	8	0.8
D	12	1.5

Table 4.2: Road information.

Road ID	Length (km)	Lanes	LOS	Maneuvering (hours)
a	15	1	C	0.9
b	18	1	A	0.7
c	20	1	B	0.9
d	25	1	C	0.9
e	20	1	B	0.7
f	20	2	C	0.5
g	15	1	A	0.7
h	18	1	D	0.5
i	24	1	D	0.9
j	24	2	D	0.7
k	30	1	C	0.5
l	24	1	C	0.5
m	15	1	D	0.9
n	18	2	B	0.7

The model was run for 100 iterations, as additional iterations do not result in a significant change to the result. Figure 4.3 shows the simulation result. This result provides decision support in project planning and can be used to select the fleet size needed in the area or estimate the possibility of delays if not enough pieces of equipment are prepared for the project. It can also be further incorporated with the truck and operation cost to find a balanced fleet size for both performance and cost based on the confidence level required.

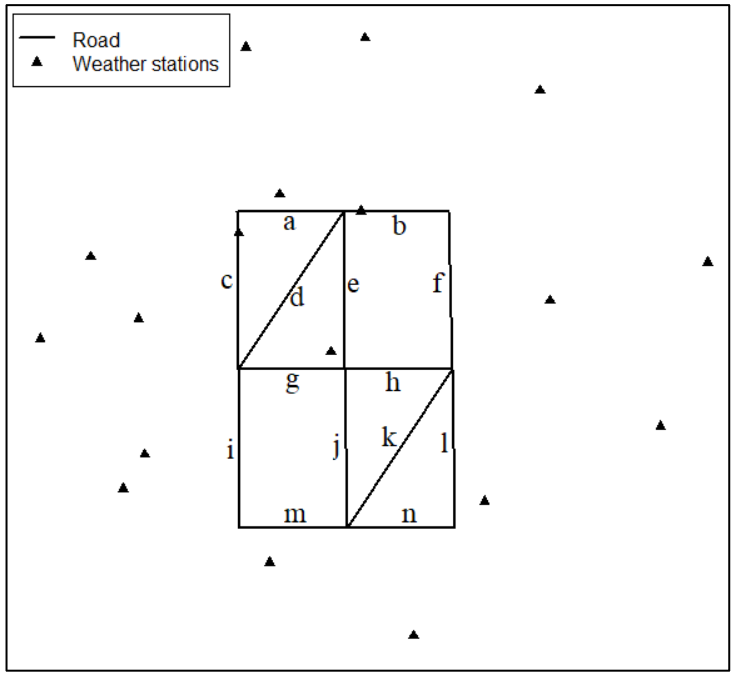

Figure 4.2: Locations of roads and weather stations.

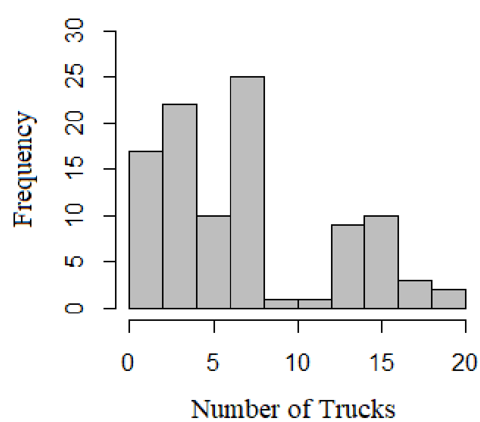

Figure 4.3: Probability distribution of truck fleet size.

The same problem is calculated using another approach to demonstrate the benefits of using kriging interpolation in project planning. Here, weather data from the closest weather station is used to calculate the precipitation amount on each road section. Figure 4.4 and Figure 4.5 compare the predicted precipitation amounts in a one-hour period between the two methods. As shown in the figures, only 2 roads are estimated as having precipitation over 0.1 mm if using data from the closest weather station compared with 8 roads when using the proposed method. This can result in not enough trucks being prepared for the project as the actual number of roads needing maintenance can be larger than the predicted number. Notably, the result from kriging interpolation is an estimation, and may contain errors; however, the authors predict higher accuracy than the closest-station method as the proposed method shows the gradient change in precipitation amounts.

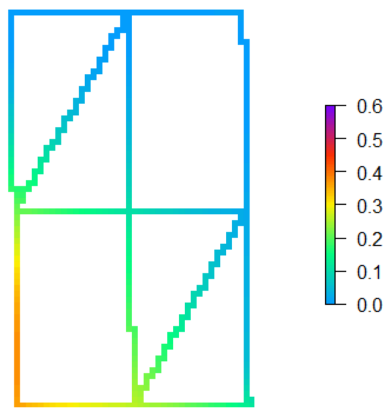

Figure 4.4: Estimated precipitation amount (mm) using kriging interpolation.

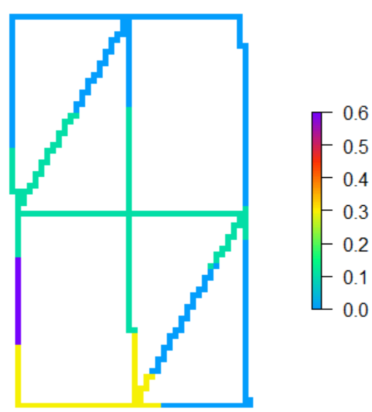

Figure 4.5: Estimated precipitation amount (mm) using data from the closest weather station.

Figure 4.6 shows the simulation result of 100 iterations using the closest-station method. Compared with the result calculated using kriging interpolation, the closest-station result has a smaller maximum-truck number, and the frequency at 0 to 5 trucks is relatively higher. This will result in fewer trucks being prepared for the operation, potentially causing operation delays and cost overruns in a worst-case weather scenario.

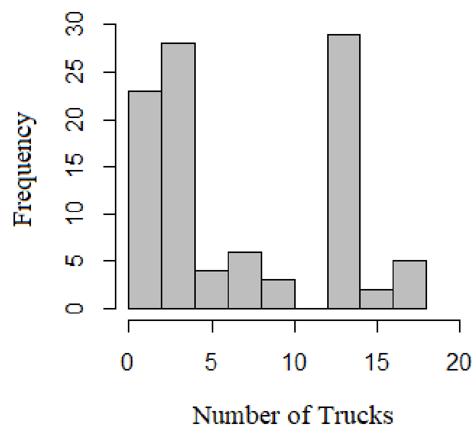

Figure 4.6: Simulation result using the closest-station method.

4.5 Cross validation

The accuracy of the kriging interpolation method was tested using cross validation. Using weather observations at 100 random times from historical data, the residuals was calculated using leave-one-out cross validation. Figure 4.7 shows the histogram of cross validation residuals, Figure 4.8 shows the histogram of observed precipitation values, Figure 4.9 shows the histogram of residuals' z-score.

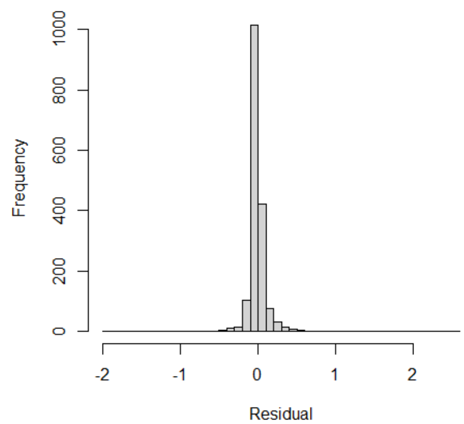

Figure 4.7: Histogram of cross validation residuals.

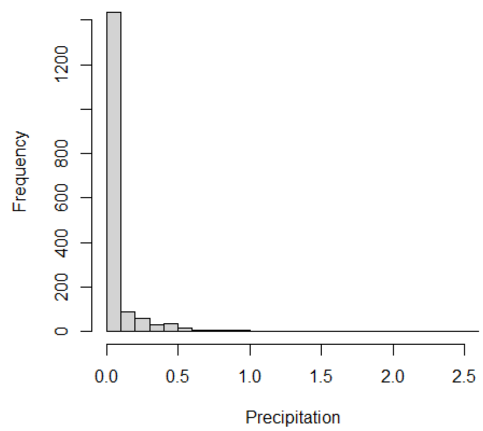

Figure 4.8: Histogram of observed precipitation values.

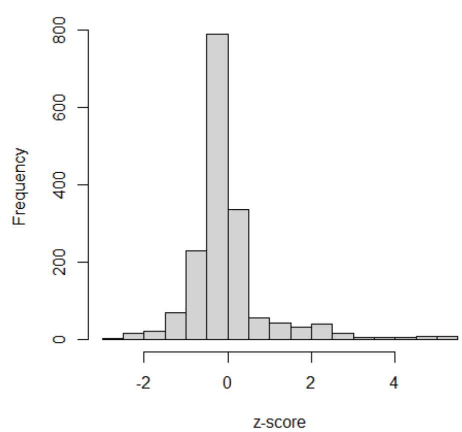

Figure 4.9: Histogram of residuals’ z-score.

The distribution of the residuals has an RMSE of 0.145, the standard deviation of the observed precipitation data is 0.186, and over 93% estimations the z-score is between ±2.

4.6 Conclusion

This study uses ordinary kriging interpolation to estimate the weather situation in a winter road maintenance project area. The resulting detailed weather information is then used to estimate the impact of regional weather events on the project. A simulation model is developed to estimate the fleet size needed in an operation area. Detailed hourly weather information is used to generate tasks in the operation, and a resource scheduling approach is used to find the fleet size needed. A probability distribution of the fleet size is generated using Monte Carlo method to provide decision support in project planning. Future work may include applying this methodology to other large-scale construction operations and developing a generic simulation model that will model weather events as disruptions, add disruptions to an existing operation schedule, and simulate its impact on the project duration and cost.

4.7 Acknowledgments

Weather data and geological information of the weather stations used in this chapter were obtained from Alberta Agriculture and Forestry, Alberta Climate Information Service (ACIS), found at https://agriculture.alberta.ca/acis.

5 CHAPTER 5: A GENERIC DATA-DRIVEN SIMULATION MODEL FOR LOOKAHEAD PLANNING IN WINTER HIGHWAY MAINTENANCE OPERATIONS

5.1 Introduction

For winter highway maintenance operations that cover a large area, project planning must consider the snow precipitation variations across the road network and the travel time vehicles spend on the road. In this chapter, a generic, data-driven simulation model is proposed to support short-term decision making on winter highway maintenance operations. The proposed model uses road network information and weather forecasts obtained from weather stations as primary data inputs, and it generates the required fleet size forecast and maintenance operation schedule as outputs. Using Monte Carlo simulation and considering the variations in vehicle speed due to traffic and road conditions, the fleet size forecast can provide an estimate for the number of vehicles needed during operation. The maintenance operation schedule suggests vehicle operation routes, as well as vehicle departure times and expected return times, to meet stipulated time constraints. When the actual operation progress does not match the operation plan, or the actual snow precipitation amount is different from the weather forecast, this model can also be updated dynamically during operations using weather observation data and vehicle GPS tracking data. The updated results can be created based on actual operation progress and weather conditions.

5.2 Methodology

The proposed simulation model consists of three main components: road snow accumulation forecast, operation scheduling, and operation simulation. Figure 5.1 shows the framework of the simulation model.

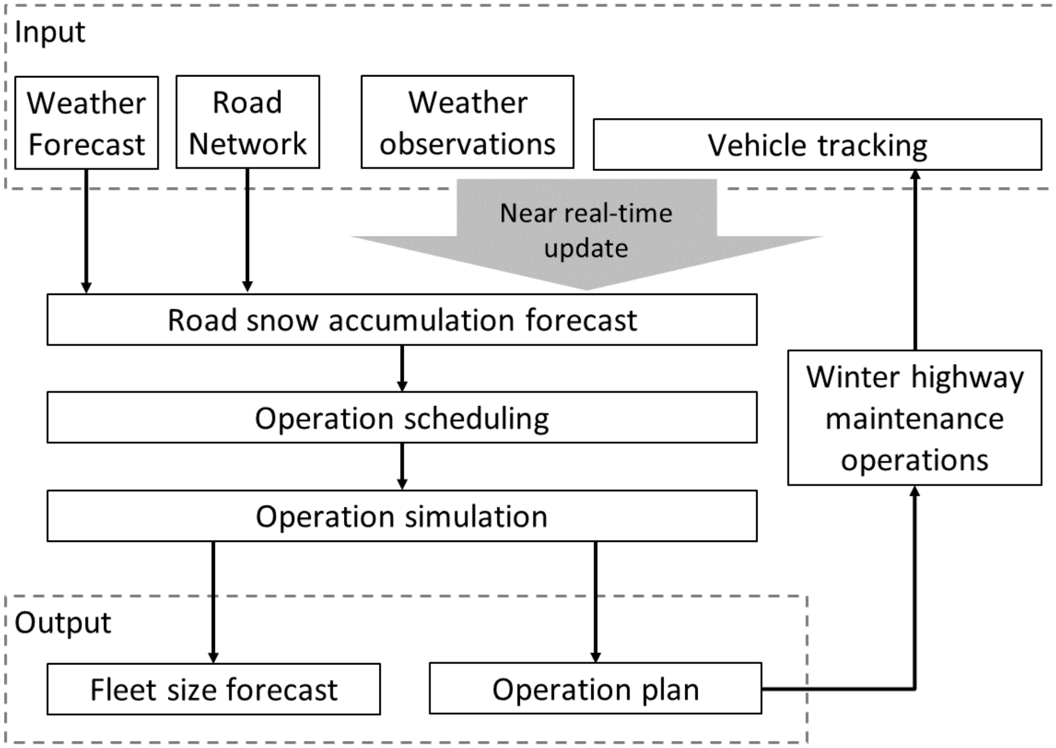

Figure 5.1: Framework of the simulation model.

The model first uses weather forecast and road network information to forecast the snow accumulation progress on each road. Then based on the accumulation forecast and road LOS requirements, the model calculates at what time snow removal operations are needed for each road section and finds the best operation route to achieve the maximum operation result at this time. Truck speed distribution functions are used to stochastically model the duration of each snow removal operation task, and tasks are scheduled to meet the time requirements. Using the generated schedule, the required fleet size at each time is calculated, and an estimate of the required fleet size is created through multiple iterations using Monte Carlo simulation.

An operation plan is generated using the average truck speed, which provides the operation routes and expected vehicle departure and return times. To enhance the accuracy of the operation plan due to the potential discrepancy between weather forecast data and the actual precipitation amount, as well as between the generated plan and actual operation, the model can use vehicle tracking data and weather observations to dynamically update the plan based on the actual precipitation amount and operation progress.

5.2.1 Assumptions

The proposed model was developed based on the following assumptions:

1) The input weather forecasts can accurately forecast the weather conditions in the future; actual precipitation amount and snow event duration will be the same as the forecast.

2) Trucks can remove all snow on the lane that they pass and restore roads to optimal driving conditions in one pass.

3) Plowing and sanding operations are combined as a single maintenance operation. Material limitation in sanding operations is considered as a limit in operation route length.

4) When there are multiple lanes on the road, the truck will plow the one with maximum snow accumulation amount.

5) Trucks will plow the lane they pass if there is snow accumulation, regardless of the amount.

6) Trucks return to the depot following the same route that they left.

5.2.2 Road snow accumulation forecast

In the road snow accumulation forecast process, the model uses weather forecast data and road network information to forecast the snow accumulation progress on the roads. Figure 5.2 shows the calculation process.

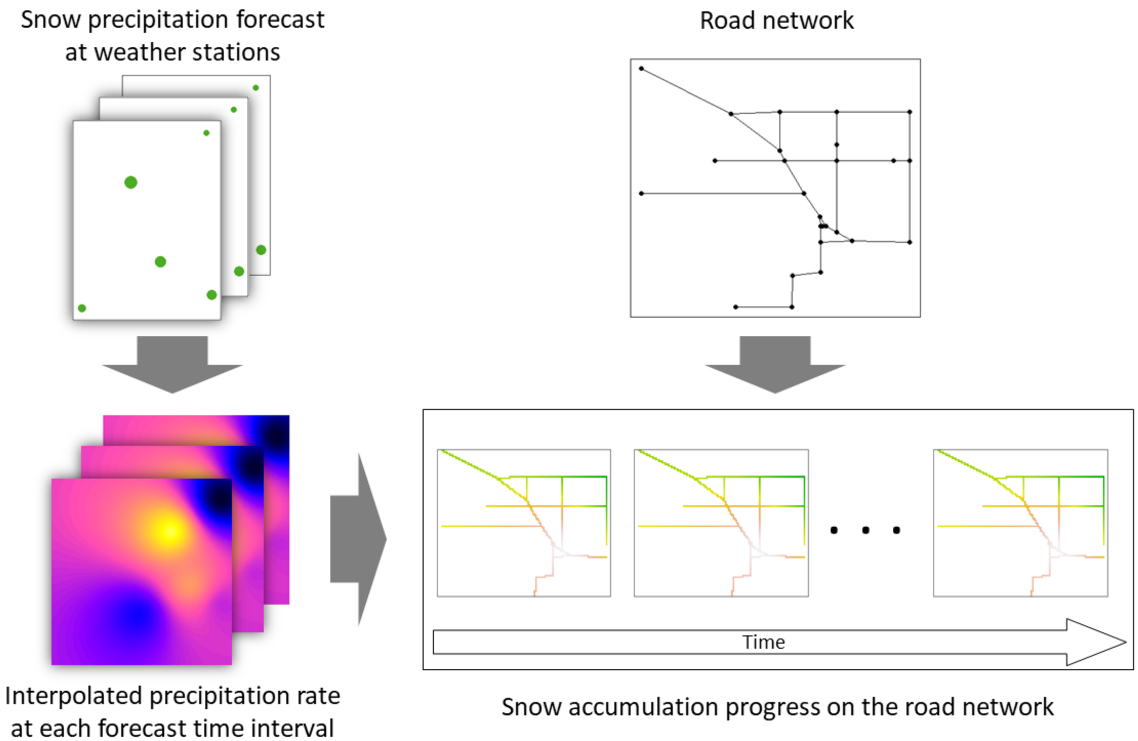

Figure 5.2: Road snow accumulation forecast process.

First, the snow precipitation forecasts from weather stations are interpolated using inverse distance weighting interpolation. Compared with ordinary kriging interpolation, the benefit of using inverse distance weighting interpolation is that it does not use a semivariogram in the interpolation calculations. Using ordinary kriging interpolation requires constructing a semivariogram using the available data set. Therefore, when only a small number of data points are available, it is difficult to build a reliable semivariogram. For the highways, the number of weather stations around the road network area varies by location, and in some cases, only two or three stations are available. Thus, inverse distance weighting interpolation is used in this model to accommodate various data scenarios. Equation 5.1 shows the expression of inverse distance weighting interpolation method (Kalkhan, 2011):

$$\widehat{Z_0} = \frac{\sum_{i=1}^{n} \frac{Z_i}{d_i^p}}{\sum_{i=1}^{n} \frac{1}{d_i^p}} \tag{5.1}$$

where $\widehat{Z_0}$ is the estimated value at a given location; Z_i is the observed value at point i; d_i is the distance between observation i and the given location; n is the total number of neighbors used to estimate the unknown location; and p is the power parameter.

For each forecast time interval, an interpolated snow precipitation rate forecast for the working area is generated. The entire road network area is divided into 500-m^2 grids, and each grid has an individual precipitation rate for each time interval. By overlaying the interpolated data on the road network, the snow precipitation rate on each road section can be determined. Each road section will overlay multiple grids, and the snow accumulation amount on each grid is separately calculated using the corresponding grid in the interpolated weather forecast. Accumulation on different lanes of the same road section is also calculated separately since their operation progress can differ. This approach ensures that the snow accumulation at different locations are calculated accurately, so the accumulation situation on long roads can be evaluated correctly. Figure 5.3 shows an example of the snow accumulation amount on a road lane.

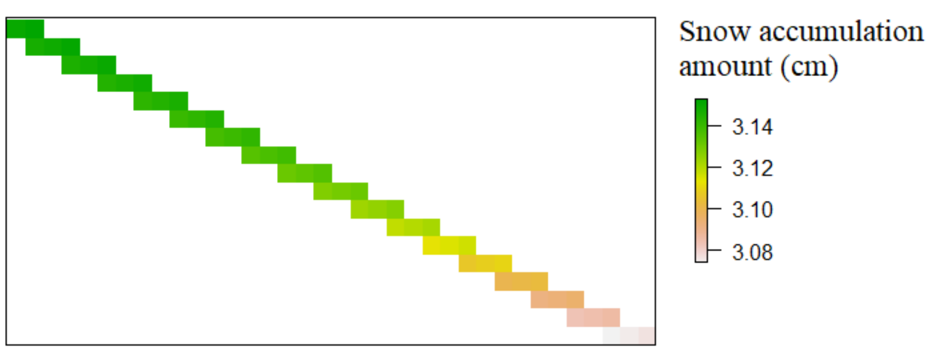

Figure 5.3: An example of the snow accumulation amount on a road lane.

Weather stations usually measure snow precipitation as snow water equivalent value. To estimate the actual snow accumulation amount on roads, the snow water equivalent value needs to be converted to snow depth using snow density. Equation 5.2 shows the relationship between snow water equivalent, snow density, and snow depth (Liang & Wang, 2020):

$$W = \frac{\rho_s d}{\rho_w} \tag{5.2}$$

where W is the snow water equivalent, ρ_s is the density of snow, ρ_w is the density of liquid water, and d is the snow depth.

This model allows the user to define the snow density value used in calculations. If the snow density at the operation area is not known, a default value of 100 kg/m^3 will be used based on the rule of thumb approach.

For each road lane, the accumulated snow amount at each forecast time interval can be calculated using Equation 5.2, and the snow accumulation progress can be determined by summing the accumulated amount over time. The snow depth on each road lane at any time during the forecast period can be calculated using this approach.

5.2.3 Operation scheduling

Operation tasks are created and scheduled based on the LOS class for each road section. In this model, trigger accumulation amount and operation reaction time are used to define the service requirements. All lanes in one road section will have the same LOS class, and each class can have different trigger accumulation amount and reaction time.

The trigger accumulation amount defines when the operation is required. When the maximum accumulated snow amount on a road lane reaches its trigger accumulation amount, snow removal operation is needed. Operation reaction time defines the latest time to start the operation. After the maximum accumulation on a road lane reaches its trigger accumulation amount, the snow removal operation on this lane must start within the reaction time. Based on these rules, operation tasks are created and scheduled following the process shown in Figure 5.4.

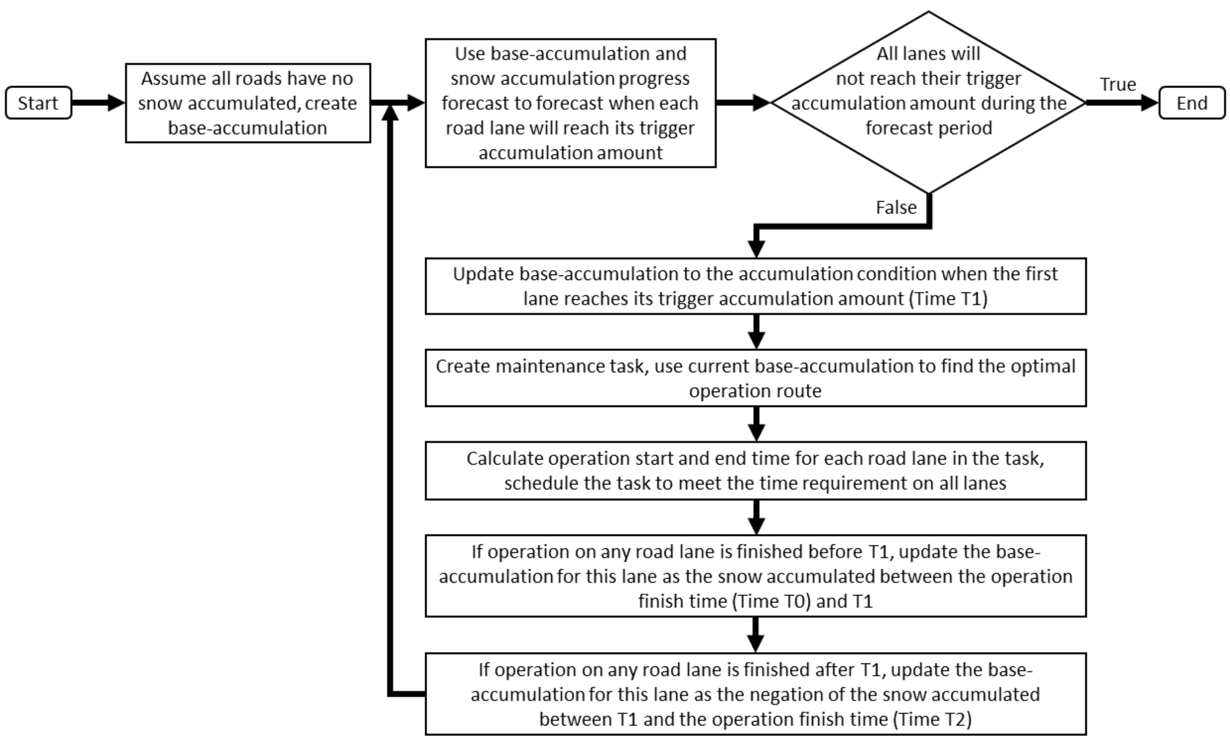

Figure 5.4: Create operation tasks and operation scheduling process.

The model first creates a base-accumulation assuming that the entire road network has no snow accumulated at the beginning of the operation. Using the snow accumulation progress forecast, newly accumulated snow is added to the base-accumulation, and the time that each road lane reaches its trigger accumulation amount can be predicted. An operation task is created if there is at least one road lane that will reach its trigger during the forecast period.

When creating operation tasks, the model first updates the base-accumulation to the accumulation condition when the first lane reaches its trigger accumulation amount (Time T1). Next, an optimal operation route for the task is selected. Simple paths in the road network, which do not have repeated vertices in the path (Sedgewick & Wayne, 2011), are used as candidate paths for the operation. The candidate path is selected from all simple paths in the road network that start from the depot vertex. The operation route will start from the depot, travel along the path to its ending vertex, and return to the depot following the reversed path. The total travel distances should be within the maximum working distance of the vehicles. Thus, only paths shorter than half of the maximum working distance are selected as candidate paths.

The optimal operation route is selected based on the snow accumulation conditions in the base-accumulation. The objective function is given below:

Maximize $$\sum_{i \in I} \sum_{j=1}^{n} P_{i,j} \tag{5.3}$$

Subject to $$\sum_{j=1}^{n} L_{i,j} \leq L_{max} \tag{5.4}$$

$$P_{i,j} = \begin{cases} \dfrac{L_{i,j}}{min\{T_{i,j,k}\}} & (max\{S_{i,j,k}\} > 0) \\ -L_{i,j} & (max\{S_{i,j,k}\} \leq 0) \end{cases} \tag{5.5}$$

where I = candidate routes set, n = number of road sections in route i, $P_{i,j}$ = priority factor of road j in route i, $L_{i,j}$ = length of road j in route i, L_{max} = maximum operation distance, $T_{i,j,k}$ = the time from now to trigger time for lane k on road j in route i, $S_{i,j,k}$ = maximum snow accumulation amount on lane k on road j in route i.

Function 5.3 finds the best route with the largest sum of priority factors on all road sections in this route. Function 5.4 limits the route length within the maximum operation distance. Function 5.5 calculates each road section's priority factor using the time duration before it reaches the snow trigger accumulation level, higher priorities are given to long road sections and roads that accumulations are close to their trigger accumulation level.

After an operation task is created, the task is scheduled at a time that meets the service time requirements of all road lanes that it passes. The time that the vehicle spends on each road lane is calculated using the length of the road and a random deviate from the vehicle speed distribution. Historical operation data is used in this model to fit the speed distribution functions, but it can also be created based on expert knowledge or experience. Two distribution functions are used in this model to represent the vehicle speed at different scenarios. The first one is working speed, which is the speed when the vehicle is conducting plowing or sanding work. The other one is deadheading speed, which is the speed vehicle travels without doing any maintenance work. The model assumes that when a vehicle travels on a road lane that the snow accumulation amount is not zero, the vehicle speed will follow the working speed distribution, otherwise, the speed will follow the deadheading speed distribution.

Since vehicles are required to arrive at the road lane within the reaction time once the trigger accumulation level is reached, the latest time to depart from the depot can be calculated using the trigger time for each road lane and the duration vehicle spends on each road. Operation tasks are scheduled at the latest time possible, allowing more snow to accumulate on the road and increase the amount of snow removed in operation, improving the operation efficiency.

The model then calculates the accumulation conditions after the newly created task and updates the base-accumulation. If the operation on any road lane is finished before T1, the base-accumulation for this lane is updated as the snow accumulated between the operation finish time (Time T0) and T1, assuming that at time T0 there is no snow on this lane. If the operation on any road lane is finished after T1, the base-accumulation for this lane is updated as the negation of the snow accumulated between T1 and operation finish time (Time T2). In this case, snow accumulation on this lane will become zero at T2 if new snow precipitations are added to the base-accumulation, and when this lane reaches its trigger level again can be calculated correctly.

Using the updated base-accumulation, the model again calculates when each road lane will reach its trigger accumulation amount, schedule tasks accordingly, and repeats this process until all lanes will not reach their trigger accumulation amount during the forecast period.

5.2.4 Operation simulation and result output

The first output of the model is the fleet size forecast, which is a box and whisker plot showing the range of required fleet sizes at different times during the forecast period. This result is generated through multiple simulation iterations. In each iteration, an operation schedule is created following the process described in section 5.2.3, and the required vehicle fleet size for a certain time period is the maximum number of tasks being scheduled simultaneously during this time. Since the durations for each task are calculated using random deviates from the vehicle speed distribution functions, task start time, end time, and operation route can be different between iterations. Using

Monte Carlo simulation, different operation schedules are generated from multiple iterations, and an estimate of the required fleet size in each time interval can be obtained. The model allows users to define the time step interval in the fleet size forecast. Figure 5.5 shows an example of the fleet size forecast with a time step interval of 1 hour. Each box encloses the 25th to 75th percentile of the fleet size distribution, with the median shown as a black bar; the minimum and maximum values are shown as whiskers.

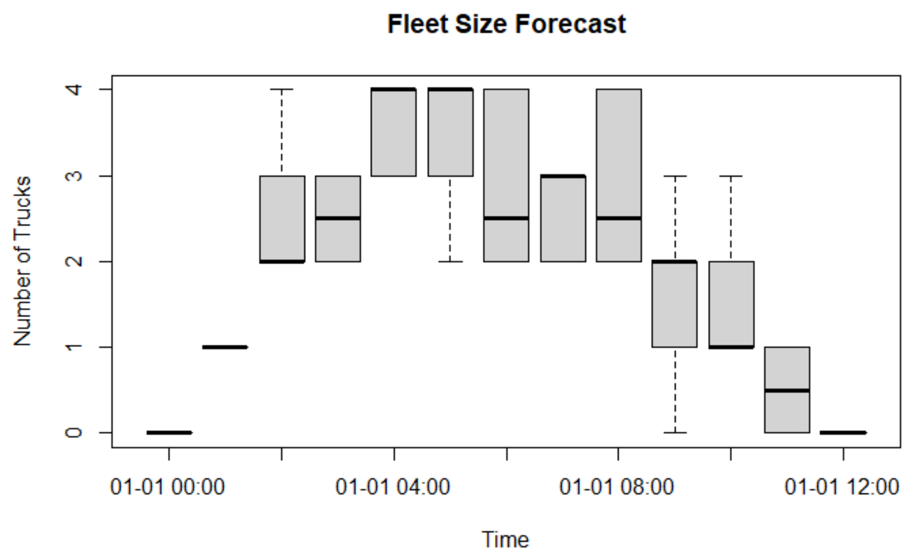

Figure 5.5: An example of the fleet size forecast with a 1-hour time step interval.

A suggested operation plan is the second output of the model. It is a Gantt chart showing the start and end time for the tasks, as well as the operation route ID for each task. This operation plan schedule is generated using the average vehicle speed for working and deadheading, or an expected speed provided by the user. Figure 5.6 shows an example of the operation plan.

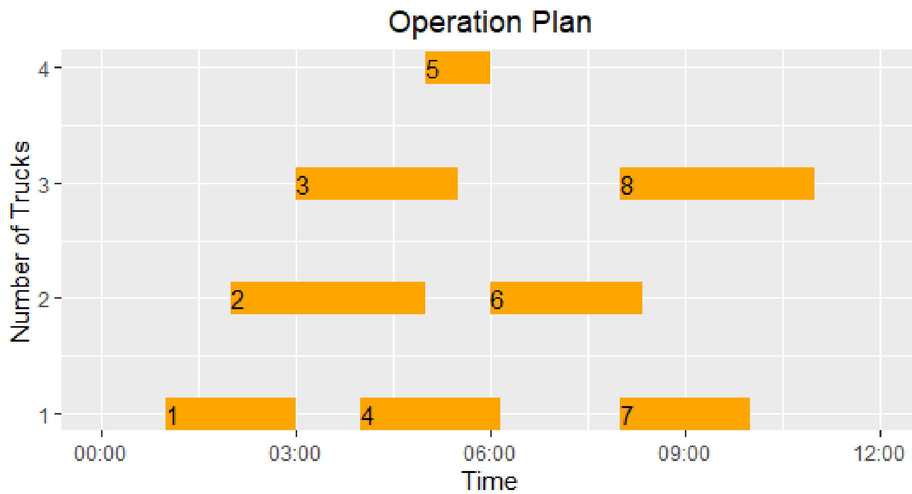

Figure 5.6: An example of the operation plan.

5.2.5 Near real-time result update

As the fleet size forecast and the operation plan are created based on weather forecasts, the usability of these results may be reduced when the forecasts differ from actual weather conditions. Hence, to ensure the fleet size forecast and operation plan is accurate and practical, a function was incorporated to the model allowing users to update the model in near real-time.

The updating process starts with estimating the actual snow accumulation amount on the road network. Observations from the weather stations are used to calculate the actual accumulation amount on each lane since the beginning of the operation (or last time updating the simulation model), and a base-accumulation is created. Then, vehicle GPS data are used to track operation progress. The model uses the GPS coordinates to determine which roads trucks have been to and the trucks' traveling directions on each road. Every time a truck passes a road section, the lane with the largest amount of snow accumulation amount in the truck moving direction is assumed to be cleaned, and its base-accumulation is updated to the snow precipitation amount between the last time a truck passed and the current time. Next, newly collected GPS data are added to the historical vehicle tracking database, and new speed distribution functions are fitted using all historical speed data. Finally, an updated fleet size forecast and operation plan are created using the latest weather forecasts and the updated speed distribution functions.

"Near real-time" update implies time is needed for collecting operation data and model calculations. For example, the operation duration on a road section ranges from several minutes to more than half an hour, and the operation for the entire route can take several hours. Therefore, frequent result updates within a short time is impractical and does not add value because of little changes in the model. Also, depending on the complexity of the road network, the length of the forecast period, and the computer configurations, the model needs several minutes for simulation calculations and cannot provide a result in real-time, so the update process is considered "near real-time."

The limitation of this process is that the updated fleet size forecast and operation plan are still based on the candidate operation routes that start and end at the depot location. Therefore, if any truck is not at the depot when updating the model, the process of truck returning to the depot is not considered. Thus, it is recommended to only update the model when all trucks are returned to the depot.

5.3 Model implementation

5.3.1 Database structure

The model was developed using the *R* language (R Core Team, 2020). A SQLite 3 database is used to store the input data. The database consists of six tables: Road, LOS, Forecast, Observation, WeatherStations, and Tracking.

The Road table stores the road network information. Table 5.1 shows the structure of the Road table.

Table 5.1: Data structure of the Road table.

Field	Data Type	Description
ID	Integer	ID of the road section
Length	Double	Road section length (in kilometers)
Lanes	Integer	Number of lanes in each direction
LOS	Text	Level of service class
Lat1	Double	Latitude of the road start location
Lon1	Double	Longitude of the road start location
Lat2	Double	Latitude of the road end location
Lon2	Double	Longitude of the road end location
Error	Double	Allowable GPS deviate range

It should be noted that all road sections are simplified to straight lines in this model, and an "Error" value is used to determine the allowable deviate range from a GPS coordinate point to the straight line. When using GPS data to find the vehicle is located at which road, the closest road from the GPS coordinate point is used, and the distance between the coordinate point and the road must be within this "Error" range. In the case of a curved road, the "Error" value must also consider the tracking point drifting caused by the shape of the road.

The second table is the database is the LOS table, which stores the service requirements for each LOS class. Table 5.2 shows the structure of the LOS table.

Table 5.2: Data structure of the LOS table.

Field	Data Type	Description
Class	Text	Level of service class
Trigger	Double	Trigger snow accumulation amount
React	Double	Operation reaction time

The third table in the database is the Forecast table, which stores the weather forecast data from all weather stations. Table 5.3 shows the structure of the Forecast table.

Table 5.3: Data structure of the Forecast table.

Field	Data Type	Description
ID	Text	Weather station ID
Lat	Double	Latitude of the weather station location
Lon	Double	Longitude of the weather station location
ValidTime	DateTime	The time that the weather forecast record forecasts
IssueTime	DateTime	The time that the weather forecast record is issued
SnowRate	Double	Snow precipitation rate

The fourth table is the Observation table, which stores the weather observation data form all weather stations. Table 5.4 shows the data structure of the Observation table.

Table 5.4: Data structure of the Observation table.

Field	Data Type	Description
StationID	Text	Weather station ID
Lat	Double	Latitude of the weather station location
Lon	Double	Longitude of the weather station location
Time	DateTime	Time of the observation record
PrecipRate	Double	Snow precipitation rate

The fifth table is the WeatherStations table, which stores the weather station information, such as the station ID and location coordinates. Table 5.5 shows the data structure of the WeatherStations table.

Table 5.5: Data structure of the WeatherStations table.

Field	Data Type	Description
ID	Text	Weather station ID
Lat	Double	Latitude of the weather station location
Lon	Double	Longitude of the weather station location

The last table in the database is the Tracking table, which stores the historical equipment tracking data. Table 5.6 shows the data structure of the Tracking table.

Table 5.6: Data structure of the Tracking table.

Field	Data Type	Description
Equipment	Integer	Equipment ID
DateTime	Date	Time of the tracking record
Latitude	Double	Latitude of the equipment location
Longitude	Double	Longitude of the equipment location
Function	Text	Active equipment function
Speed	Double	Speed of the vehicle

The “Function” field in this table is used to distinguish the vehicle working speed from the deadheading speed, so the tracking equipment installed on vehicles must be able to provide the current working status of the vehicle.

5.3.2 *R* packages

Multiple *R* packages are used to implement the model algorithm. The *sp* package and the *gstat* package are used for inverse distance weighting interpolation calculations (Bivand, Pebesma, & Gomez-Rubio, 2013; Gräler et al., 2016; Pebesma & Bivand, 2005; Pebesma, 2004). The *gstat* package generates the interpolated output result as a SpatialPixelsDataFrame object, which is defined in the *sp* package. The road network is stored as SpatialLines objects also using the *sp* package.

The *raster* package is used to find the overlaying grids between road sections and interpolated weather data (Hijmans, 2020). The “mask” function is used to find the overlaying grids, and the “crop” function is used to remove redundant cells.

The *geosphere* package is used to convert coordinates between the geographic coordinate system and the Cartesian coordinate system (Hijmans, 2019). The geographic coordinate system is used for original road network data and vehicle tracking data, and all coordinates are converted to a Cartesian coordinate system using the *geosphere* package for interpolation calculations.

The *igraph* package is used to store the road network information and find simple paths in the road network (Csardi & Nepusz, 2006).

The *fitdistrplus* package and the *rmulti* package are used to fit vehicle speed distribution functions (Delignette-Muller & Dutang, 2015; Swihart & Lindsey, 2020). Historical speed data are fitted to beta, normal, Laplace, logistic, Weibull, and gamma distributions using maximum likelihood estimation, and the best distribution function is selected using the KS test.

The *foreach* package and the *doParallel* package are used to run multiple simulation iterations in parallel (Microsoft Corporation & Weston, 2019; Microsoft & Weston, 2020). This approach can accelerate the computation speed more than ten times, depending on the computer configuration.

5.4 Case study and model validation

Two case studies are provided in this section to demonstrate this model. The first one is an illustrative case study to analyze the rationality of the output result. The second case study is based on actual operations, and its result is compared with actual operation data to validate this model. Validation techniques, result accuracy, and source of error are also discussed in this section.

It should be noted that this model was developed based on the assumption that the weather data input is accurate. To eliminate errors from the weather forecast data, actual weather observations were used in the second case study to validate the model algorithm. If weather forecasts are used as inputs, the resulting errors could be higher depending on the quality of the forecasts.

5.4.1 First case study

This case study uses a road network with six road sections and four weather stations. All roads have one lane in each direction, and the length is 10 km. Figure 5.7 shows the road network, depot location, and weather station locations.

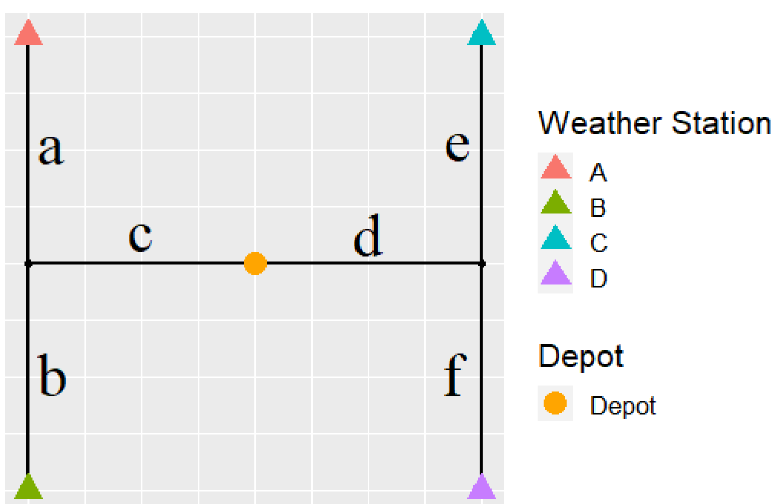

Figure 5.7: Road network, depot location, and weather station locations for the first case study.

Six simple paths in this road network are used to create candidate operation routes. For each route, trucks start from the depot, follow the simple path to its ending vertex, and return to the depot following the reversed path. Figure 5.8 shows the operation routes in this road network.

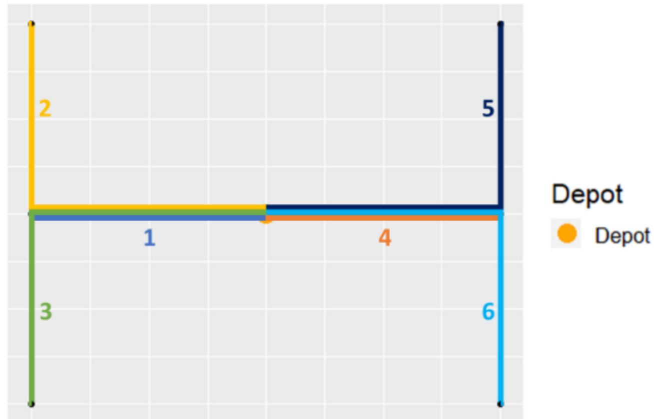

Figure 5.8: Operation routes in the road network.

The roads are classified into four LOS classes, and the class for each road section is shown in Figure 5.9. Table 5.7 shows the trigger accumulation level and reaction time for each class.

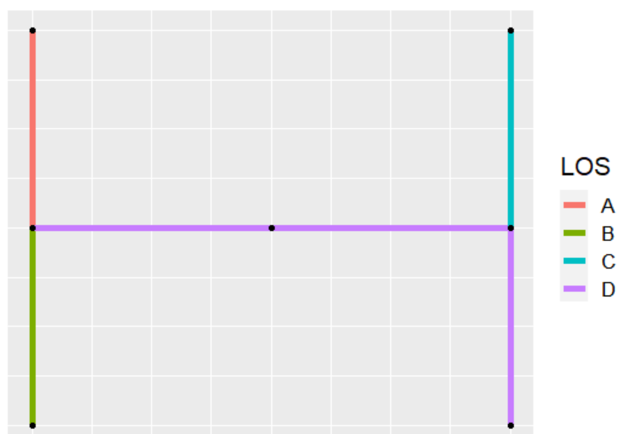

Figure 5.9: LOS class for each road section.

Table 5.7: LOS class requirements for the first case study.

Class	Trigger Accumulation (cm)	Reaction Time (hour)
A	2	0.5
B	4	1
C	5	1
D	6	1.5

The case study assumes there was a snow event on January 7, 2020, and the snow precipitation rate was 1 cm/h at all weather stations during this day. It also assumes that the truck speed was 40 km/h for both working and deadheading and that the optimal operation schedule can be calculated based on the road network and LOS requirements. For example, road *a* is a class A road that has 2 cm trigger accumulation level and 0.5 hour reaction time. Operation route 2 was the only route that includes road *a*. In this route, a truck needs 0.25 hours to arrive at road *a*, and it needs another 0.25 hours to plow one side of the road before it starts to work in the opposite direction. Since the reaction time is 0.5 hours, a truck should depart from the depot the same time that road *a* reaches its trigger accumulation level in order to meet the time requirement. Furthermore, road *a* reaches its trigger accumulation level every two hours when the snow precipitation rate was 1 cm/h, and a truck needs 0.25 hours to return to the depot after plowing both directions on road a. Thus, the first task on route 2 should be scheduled two hours after the snow event starts, and it is optimal to schedule tasks on this route with 1.75 hours between tasks. Similarly, it is optimal to schedule tasks on routes 3, 5, and 6 with an interval of 4.25, 5.25, and 6.75 hours, respectively.

Additionally, service requirements on roads *c* and *d* can be met by operations on routes 2, 3, 5, and 6 as they are included in these routes, and tasks on routes 1 and 4 are not needed. Therefore, the optimal operation plan does not have any tasks on routes 1 and 4.

Using this road network and precipitation data, the model-generated hourly fleet size forecast is shown in Figure 5.10. Figure 5.11 shows the generated operation plan, and Table 5.8 shows the details for each task in the operation plan.

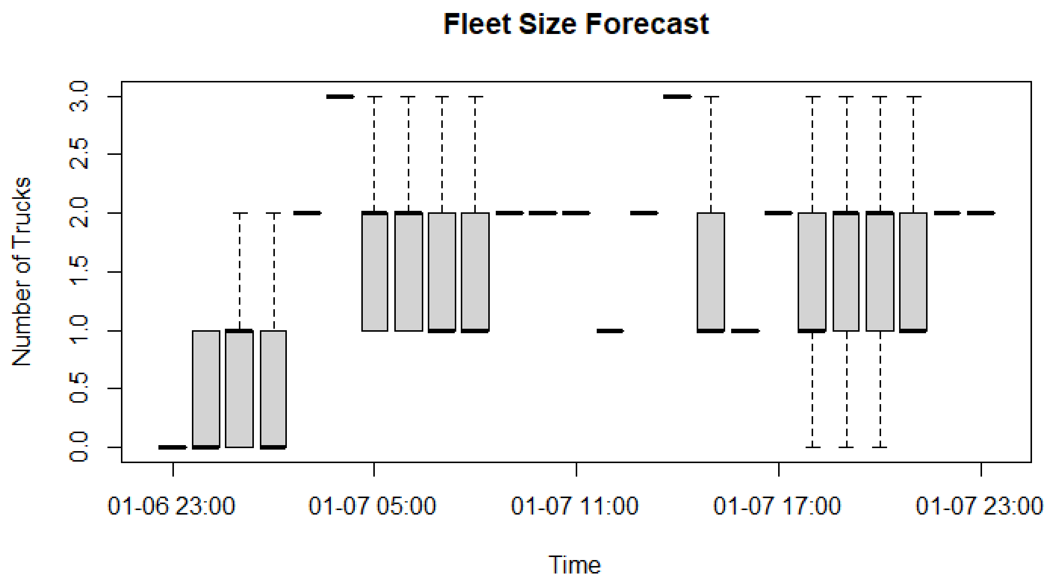

Figure 5.10: Fleet size forecast.

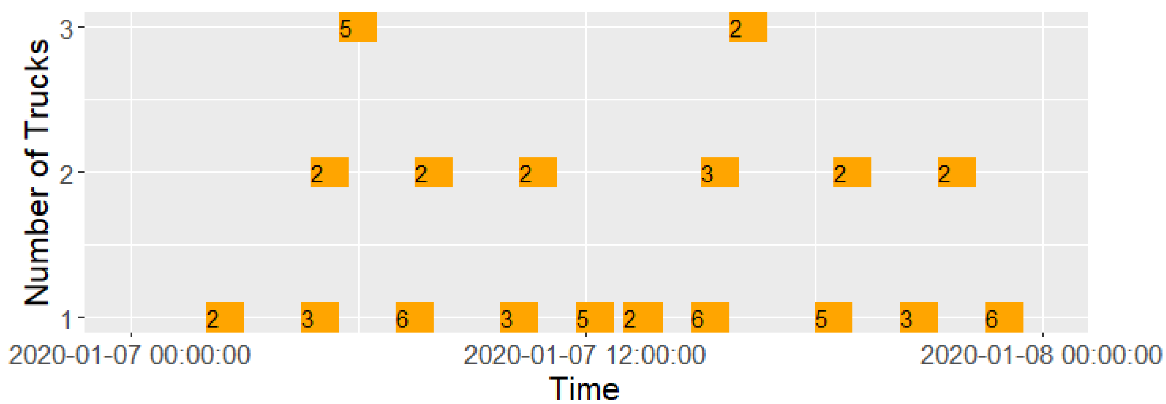

Figure 5.11: Operation plan.

Table 5.8: Operation plan details.

Route	Start time	End time
2	2020-01-07 02:00:00	2020-01-07 03:00:00
3	2020-01-07 04:30:00	2020-01-07 05:30:00
2	2020-01-07 04:45:00	2020-01-07 05:45:00
5	2020-01-07 05:30:00	2020-01-07 06:30:00
6	2020-01-07 07:00:00	2020-01-07 08:00:00
2	2020-01-07 07:30:00	2020-01-07 08:30:00
3	2020-01-07 09:45:00	2020-01-07 10:45:00
2	2020-01-07 10:15:00	2020-01-07 11:15:00
5	2020-01-07 11:45:00	2020-01-07 12:45:00
2	2020-01-07 13:00:00	2020-01-07 14:00:00
6	2020-01-07 14:45:00	2020-01-07 15:45:00
3	2020-01-07 15:00:00	2020-01-07 16:00:00
2	2020-01-07 15:45:00	2020-01-07 16:45:00
5	2020-01-07 18:00:00	2020-01-07 19:00:00
2	2020-01-07 18:30:00	2020-01-07 19:30:00
3	2020-01-07 20:15:00	2020-01-07 21:15:00
2	2020-01-07 21:15:00	2020-01-07 22:15:00
6	2020-01-07 22:30:00	2020-01-07 23:30:00

As shown in the operation plan, operation tasks are scheduled on routes 2, 3, 5, 6, and the interval between tasks on each route is the same as the optimal solution. The fleet size forecast takes into account the variations in vehicle speed, and it can be used to further support the operation planning process for winter highway maintenance operations.

In conclusion, this case study shows that the model can select appropriate operation routes and schedule tasks at proper times based on weather information. The model-generated operation plan can meet the optimal solution when only considering operation routes based on simple paths.

5.4.2 Second case study

The second case study is based on a project in Alberta, Canada. In this case study, there are three weather stations around the operation area. The road network, depot location, and weather station locations are shown in Figure 5.12.

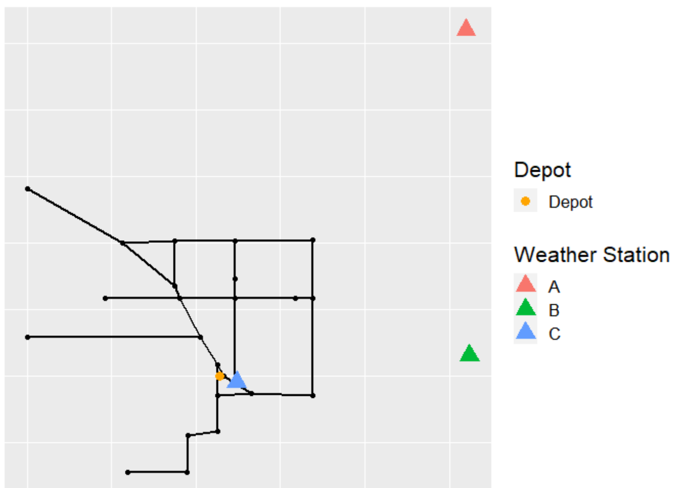

Figure 5.12: Road network, depot location, and weather station locations.

The observed snow precipitation amount at each weather station from March 27–30, 2020, is shown in Figure 5.13.

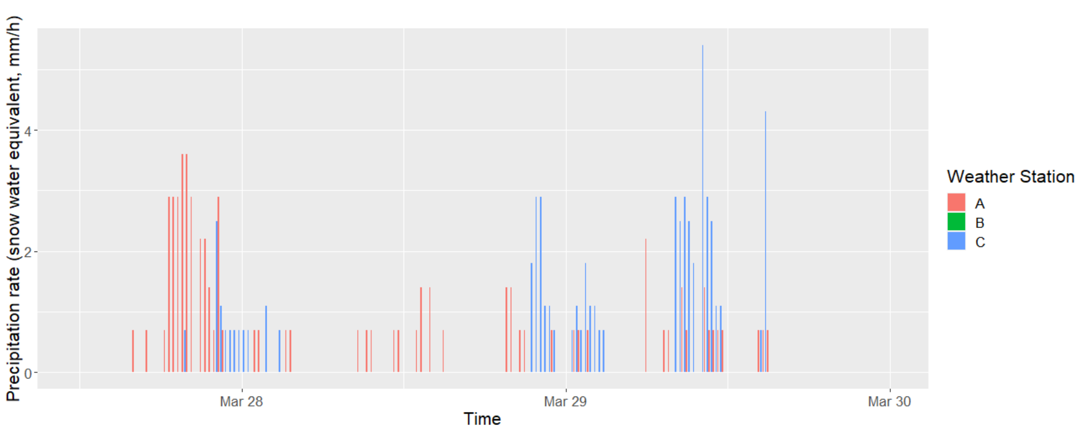

Figure 5.13: Observed snow precipitation rate from March 27–30, 2020.

As shown in Figure 5.13, the snow event started in the afternoon of March 27, 2020, and ended in the afternoon of March 29, 2020. At the beginning of the snow event, station A had a higher precipitation rate. As time progresses, snow area moved toward the road network and a high precipitation rate was observed at station C. Station B observed no snow precipitation during this time.

Using these weather data and assuming the snow density was 150 kg/m^3, the model-generated fleet size forecast is shown in Figure 5.14, and the operation plan is shown in Figure 5.15.

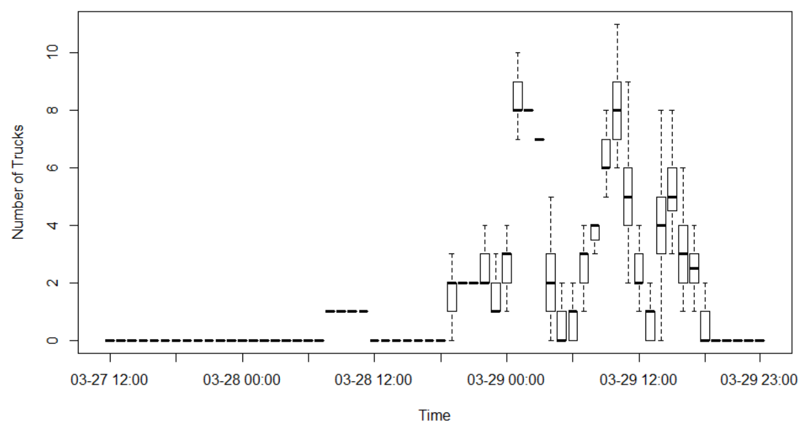

Figure 5.14: Fleet size forecast.

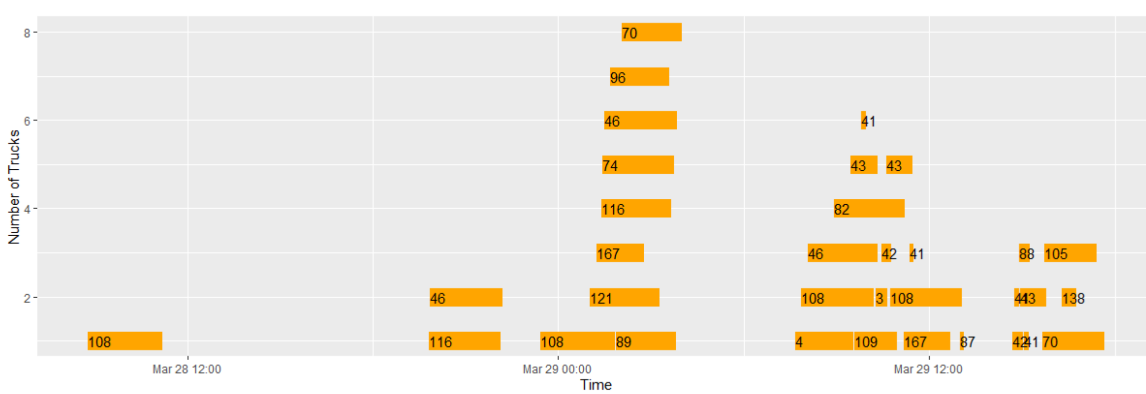

Figure 5.15: Operation plan.

To analyze the efficiency and feasibility of the operation plan, a count of how many times each road should be plowed in the operation plan is generated. The plow count of each road section is the sum of plow counts on all lanes in both directions. Figure 5.16 shows the planned plow count for each road section. Figure 5.17 shows the LOS class for each road section.

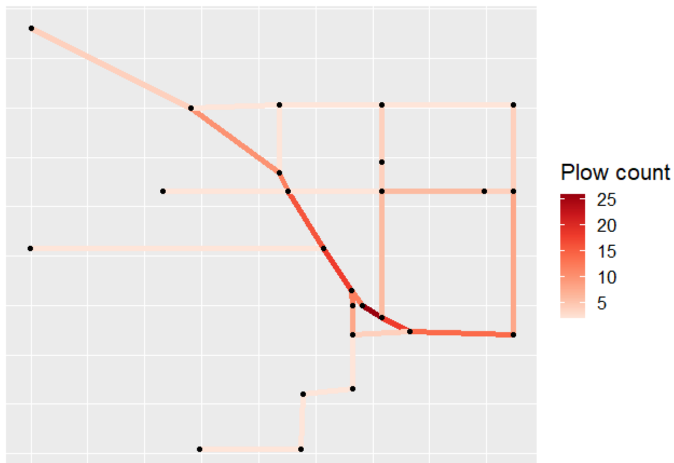

Figure 5.16: Plow count for each road in the operation plan.

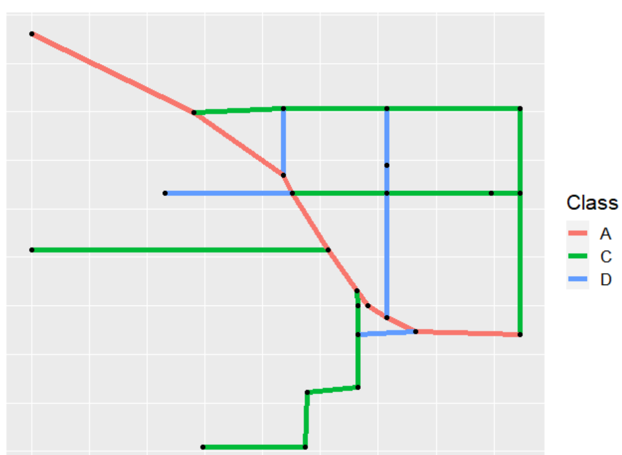

Figure 5.17: LOS class for each road section.

The results show that most maintenance tasks focused on class A roads due to their smaller trigger accumulation amount. Road sections close to the shop also had a higher plow count as trucks pass these roads when going to other areas. The operation efficiency is also related to the accumulation amount on each road, the road should be plowed when it has a high accumulation level, and plowing a road when not much snow has accumulated is considered low-efficiency. To analyze the overall operation efficiency, a maintenance efficiency factor is used to measure the operation efficiency on each road section, which is calculated using Equation 5.6.

$$ME = \frac{S_{max}}{\left(\frac{P}{N_L} + 1 \text{ clean-up plow}\right) \times S_T} \quad (5.6)$$

Where ME = maintenance efficiency; S_{max} = maximum snow accumulation amount; P = plow count; N_L = total number of lanes in both direction; S_T = trigger snow accumulation amount.

This maintenance efficiency factor measures the average amount of snow that a truck plows each time. An efficiency factor equal to 1 means the amount of snow plowed is the same as the road's trigger accumulation amount. A higher value means more snow is plowed from the road, and the operation is more effective. Figure 5.18 shows the maintenance efficiency value on each road. Figure 5.19 shows the cumulative distribution of the factor value.

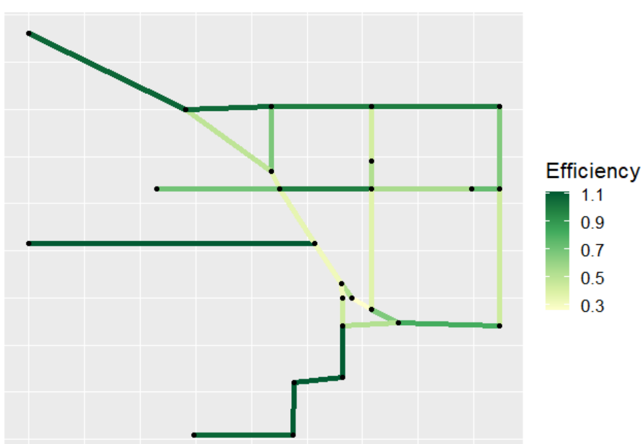

Figure 5.18: Maintenance efficiency factor for each road section.

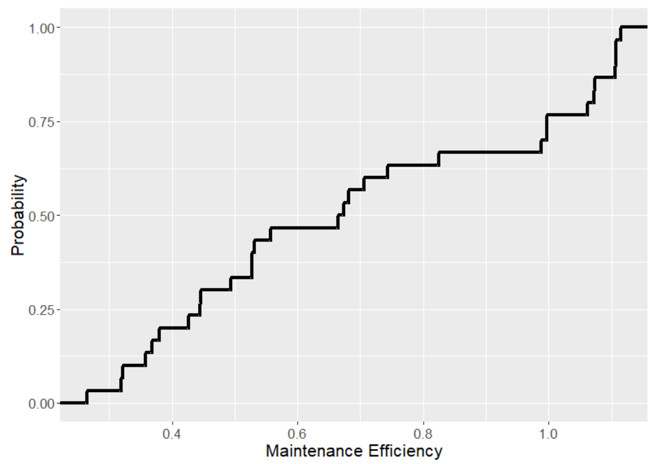

Figure 5.19: Cumulative distribution of the maintenance efficiency factor.

The results show that most roads have a high maintenance efficiency value. 70% of roads had an efficiency factor higher than 0.5, which means the average amount of snow plowed on these roads was at least half of the road's trigger accumulation amount. The efficiency factor was higher than 0.6 for more than 50% of roads, and on 35% of roads was higher than 0.8. Less than 20% of roads had an efficiency factor lower than 0.4.

Figure 5.20 shows the road plow count in actual operations, and Figure 5.21 shows the plow count difference between the operation plan and the real operation data. Figure 5.22 shows the cumulative distribution of the difference between actual data and the model result, and Figure 5.23 shows the difference range for each LOS class.

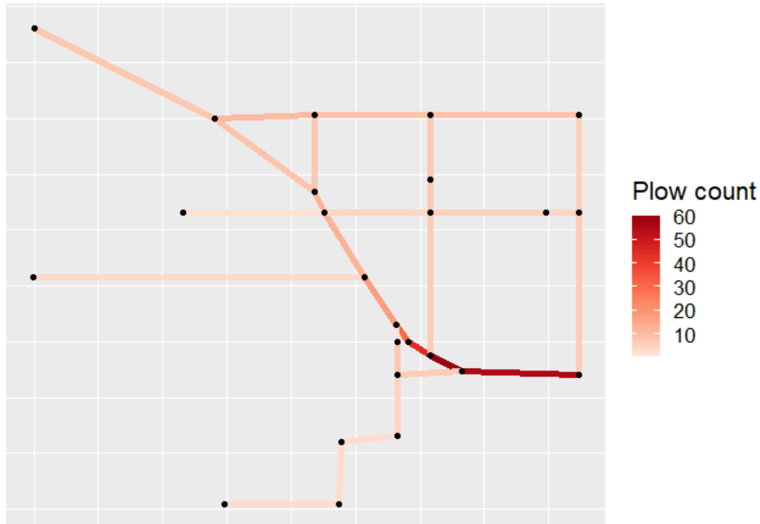

Figure 5.20: Plow count for each road in actual operation.

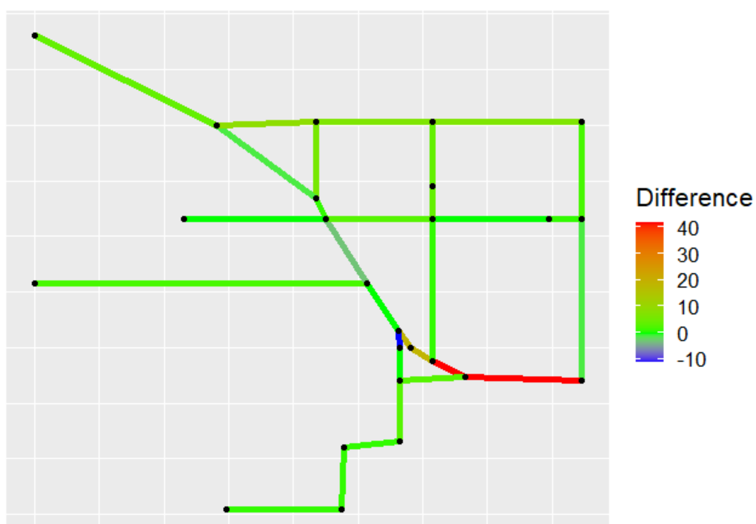

Figure 5.21: Plow count differences between actual operation and model result.

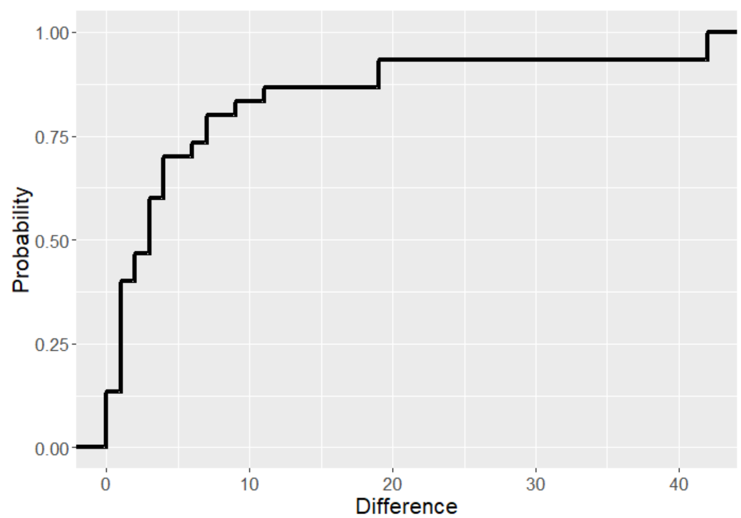

Figure 5.22: Cumulative distribution of plow count difference between actual operation and model result.

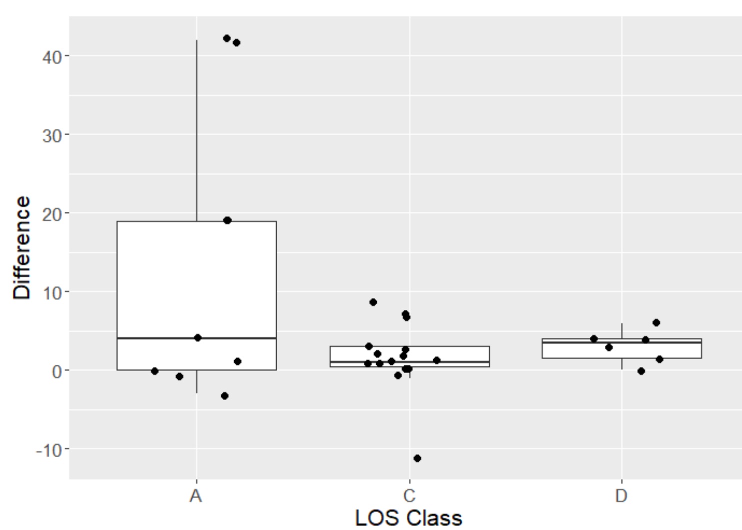

Figure 5.23: Plow count difference between actual operation and model result for each LOS class.

When the operation plan is compared with the actual operation data during this period, the results show that:

- On most roads, the plow count in actual operation was higher than the model predicted.

- On 70% of roads the plow count difference was less than 5.

- Two roads in the southeast area had the highest difference.

There are two possible reasons for the differences in road plow count:

- The two roads with the highest difference are both class A roads, and both have two lanes in each direction. Therefore, to make sure these roads maintained good driving conditions, they were plowed more often in actual operations even if the trigger levels were not reached. This caused the actual plow count to be significantly higher than the operation plan.

- In actual operations, maintenance started earlier than the operation plan suggested. This meant that some roads were plowed before their trigger levels were reached, and less snow was removed from the road each time. Therefore, for the same total snow precipitation amount, roads need to be plowed more times, increasing the plow count on some roads.

Figure 5.24 shows a comparison between the actual fleet size used in operation and the model's forecast. As shown in the figure, the truck fleet started to be active in operation earlier than the model's prediction, and the total active time was longer. But the maximum fleet size used was three trucks, which was smaller than the model's forecast.

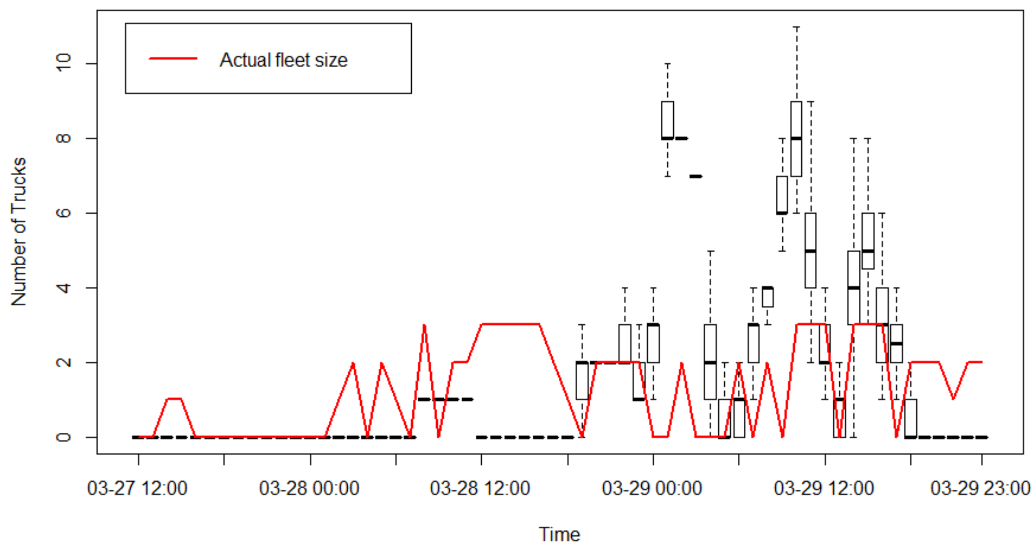

Figure 5.24: Comparison between the fleet size forecast and actual active fleet size in operation.

The actual operations may have started early because of a limitation in available fleet size. Therefore, a different operation strategy was used to complete the operation with limited trucks by extending the operation duration, instead of pursuing higher operation efficiency that requires more trucks. This model aims to find an operation plan with high operation efficiency, and truck availability is considered as an unlimited resource, which may result in a large truck fleet. By starting the operation early and cleaning roads before their trigger levels were reached, some roads will reach their trigger level at a later time, allowing certain tasks to be scheduled later and reducing the required fleet size. But this approach also increases the plow count on some roads and reduces the operation efficiency.

Since the actual operation started early and was different from the operation plan, an updated result was generated when the operation was partially complete. Figure 5.25 and Figure 5.26 show the updated operation plan and fleet size forecast when the model was updated on March 28, 2020, at 19:00.

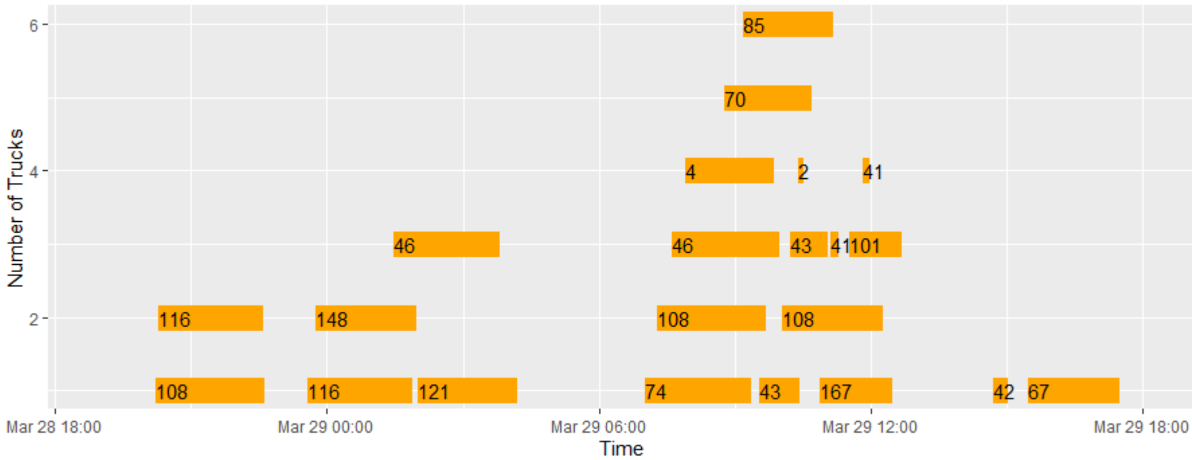

Figure 5.25: Updated operation plan.

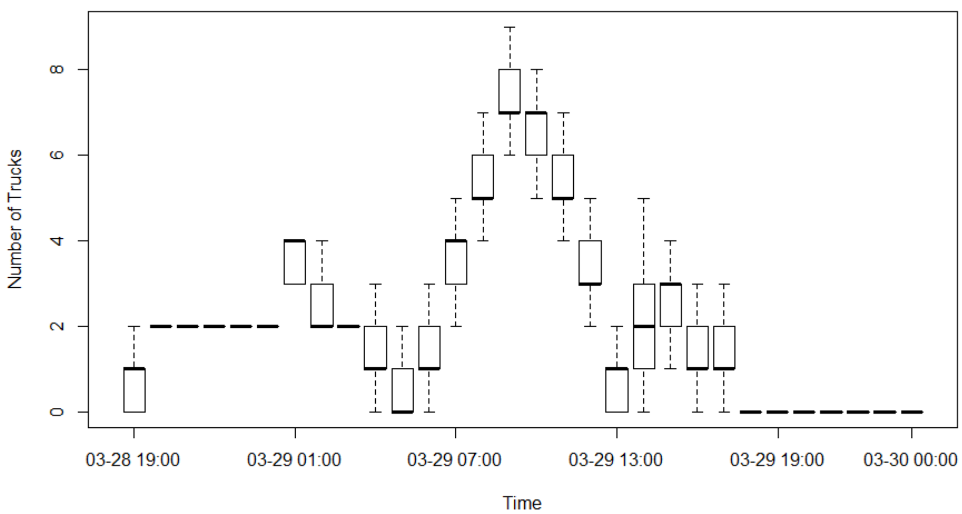

Figure 5.26: Updated fleet size forecast.

The updated results show that when the actual operation started early and was different from the operation plan, updating the model can create new results based on the operation progress. Some tasks are scheduled later, and the required maximum truck fleet size is reduced.

In conclusion, the model generated operation plan can avoid unnecessary travels and has high maintenance efficiency on most roads. When comparing to actual operations, the plow count of the simulation result is similar to that of actual operations on most roads. Differences could be caused by (a) a more frequent snow removal operation on important roads, (b) early start of the actual operation to reduce the required vehicle fleet size, and (c) errors from the weather observation data and snow accumulation calculations.

5.5 Limitations and conclusion

In this chapter, a generic, data-driven simulation model was developed, which can be used to assist the short-term, lookahead operation planning for winter highway maintenance operations. Weather forecasts and road network information are used to generate fleet size forecast and operation plan that provide efficient operation solutions. The model is validated by comparing its result with an optimal solution and actual operation data. It shows that the model result is similar to actual operations on most road sections, and errors caused by different approaches in actual operation remain in a reasonable range. This model can also use weather observation data and vehicle tracking data to update the results during operations, ensuring that the results remain valid and practical in cases where actual operation differ from the operation plan. The framework developed in this study is generic and can be adopted for solving problems with similar nature.

A few limitations exist in this model. First, the model algorithm schedules maintenance tasks as close to their deadlines as possible to achieve the highest operational efficiency, but this approach might require a large truck fleet. When the available trucks are limited, resource leveling needs to be done manually. Second, operation route optimization is simplified in this model, and it may not be the most efficient operation route. Further studies can be conducted to identify the optimum route considering the operation requirements and constraints. Third, snow accumulation calculations are simplified to directly convert the precipitation data to accumulation amount using snow density value. The impact of road surface temperature, wind speed, traffic volume, and other factors were not considered in this model. More sophisticated approaches for calculating the snow accumulation can be experimented in future to improve accuracy. Fourth, the model is sensitive to the quality of weather data; inherent uncertainties in weather data can reduce the result accuracy.

6 CHAPTER 6: CONCLUSION AND RECOMMENDATIONS FOR FUTURE RESEARCH

6.1 Conclusion

The objective of this thesis was to develop simulation models to assist the project planning process for winter highway maintenance operations. Due to the large spatial scale of highways, regional weather events and vehicle routing must be considered for operation planning. Limitations in weather data also bring challenges as the data are limited to a few weather station locations.

Two simulation models were developed in this thesis. Chapter 3 introduces a model that uses a performance-based approach to evaluate the overall fleet performance under various snow events. This model uses truck speed distributions to simulate the operation process, and the performance of certain a fleet size is evaluated by its possible operation delays in operations. An appropriate fleet size for the long-term can be selected based on the user's confidence level.

The second simulation model is presented in Chapter 5. It uses weather forecasts and road network information to forecast the required fleet size and create efficient operation plans for short-term, lookahead planning. This model can also be updated during operations using weather observations and vehicle tracking data, and updated results are created based on current operation progress.

The impact of regional weather events was considered in both model, and different approaches to estimate the impact area using limited weather data is discussed in Chapter 4. Results using the closest-station method and kriging interpolation method are compared, and they show that interpolation methods can provide a more reasonable estimation for the weather condition on roads between weather stations.

To conclude, generic simulation models to support the winter highway maintenance operation planning in both long-term and short-term were developed in this thesis, and the research objectives are achieved. Both models still have limitations and can be further improved through future research.

6.2 Recommendations for future research

In winter highway maintenance operations, the operation performance depends heavily on the operation route choices. An advanced optimization algorithm can help to reduce the required vehicle fleet size while maintaining high operation efficiency. In this thesis, road network and operation routes are both simplified, and future research is recommended to focus on route optimization to improve the operation efficiency further.

For short-term, lookahead operation planning, resource leveling approaches can be further included in the proposed model. This will allow the user to get a practical simulation result at the beginning when resources are limited and a warning if the available equipment is not enough for the operations.

Moreover, research on partitioning service areas and selecting vehicle depot locations are recommended. This will assist project planning in the long term, and could be integrated into the model to help selecting the optimal fleet size for each depot.

REFERENCES

AbouRizk, S., Hague, S., Ekyalimpa, R., & Newstead, S. (2016). Simphony: A next generation simulation modelling environment for the construction domain. *Journal of Simulation, 10*(3), 207-215. doi:10.1057/jos.2014.33

AbouRizk, S., Hague, S., & Ekyalimpa, R. (2016). *Construction simulation: An introduction using Simphony*. Edmonton, Canada: University of Alberta.

AlBahnassi, H., & Hammad, A. (2012). Near real-time motion planning and simulation of cranes in construction: Framework and system architecture. *Journal of Computing in Civil Engineering, 26*(1), 54-63. doi:10.1061/(ASCE)CP.1943-5487.0000123

Alberta Transportation. (2018). Provincial highway service classification map. Retrieved from https://open.alberta.ca/dataset/provincial-highway-service-classification-map/resource/b6e5b3e9-319d-44eb-bf54-15462c35d92b

Alsamamra, H., Ruiz-Arias, J. A., Pozo-Vázquez, D., & Tovar-Pescador, J. (2009). A comparative study of ordinary and residual kriging techniques for mapping global solar radiation over southern Spain. *Agricultural and Forest Meteorology, 149*(8), 1343-1357. doi:10.1016/j.agrformet.2009.03.005

Andrey, J., Mills, B., & Vandermolen, J. (2001). *Weather information and road safety*. Toronto, Ontario, Canada: Institute for Catastrophic Loss Reduction.

Atkinson, P. M., & Lloyd, C. D. (1998). Mapping precipitation in Switzerland with ordinary and indicator kriging. *Journal of Geographic Information and Decision Analysis, 2*(2), 65-76.

Barnes, S. L. (1964). A technique for maximizing details in numerical weather map analysis. *Journal of Applied Meteorology, 3*(4), 396-409. doi:10.1175/1520-0450(1964)0032.0.CO;2

Beaujon, G. J., & Turnquist, M. A. (1991). A model for fleet sizing and vehicle allocation. *Transportation Science, 25*(1), 19-45. doi:10.1287/trsc.25.1.19

Bivand, R. S., Pebesma, E., & Gomez-Rubio, V. (2013). *Applied spatial data analysis with R* (2nd ed.). New York: Springer. doi:10.1007/978-1-4614-7618-4

Brasnett, B. (1999). A global analysis of snow depth for numerical weather prediction. *Journal of Applied Meteorology, 38*(6), 726-740. doi:10.1175/1520-0450(1999)0382.0.CO;2

Cabral, E. A., Gendreau, M., Ghiani, G., & Laporte, G. (2004). Solving the hierarchical Chinese postman problem as a rural postman problem. *European Journal of Operational Research, 155*(1), 44-50. doi:10.1016/S0377-2217(02)00813-5

Chen, F. W., & Liu, C. W. (2012). Estimation of the spatial rainfall distribution using inverse distance weighting (IDW) in the middle of Taiwan. *Paddy and Water Environment, 10*(3), 209-222. doi:10.1007/s10333-012-0319-1

Chien, S. I., Gao, S., & Meegoda, J. N. (2013). Fleet size estimation for snowplowing operation considering road geometry, weather, and traffic speed. *Journal of Transportation Engineering, 139*(9), 903-912. doi:10.1061/(ASCE)TE.1943-5436.0000567

Cressie, N. (1988). Spatial prediction and ordinary kriging. *Mathematical Geology, 20*(4), 405-421. doi:10.1007/BF00892986

Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal, Complex Systems*, 1695. Retrieved from http://igraph.org

Delignette-Muller, M. L., & Dutang, C. (2015). Fitdistrplus: An R package for fitting distributions. *Journal of Statistical Software, 64*(4), 1-34. Retrieved from http://www.jstatsoft.org/v64/i04/

Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische Mathematik, 1*(1), 269-271.

Eisenberg, D., & Warner, K. E. (2005). Effects of snowfalls on motor vehicle collisions, injuries, and fatalities. *American Journal of Public Health, 95*(1), 120-124. doi:10.2105/AJPH.2004.048926

Fu, L., Trudel, M., & Kim, V. (2009). Optimizing winter road maintenance operations under real-time information. *European Journal of Operational Research, 196*(1), 332-341. doi:10.1016/j.ejor.2008.03.001

Ghiani, G., & Improta, G. (2000). An algorithm for the hierarchical Chinese postman problem. *Operations Research Letters, 26*(1), 27-32. doi:10.1016/S0167-6377(99)00046-2

Gladysheva, O. (2008, May). Estimation amount of snow deposit on the road. In *Proceedings of SIRWEC 14th International Road Weather Conference, Prague, Czech Republic* (pp. 19-23).

Goovaerts, P. (1997). *Geostatistics for natural resources evaluation*. Oxford, New York: Oxford University Press.

Gräler, B., Pebesma, E., & Heuvelink, G. (2016). Spatio-temporal interpolation using gstat. *RFID Journal, 8*(1), 204-218. Retrieved from https://edepot.wur.nl/427175

Hajibabai, L., & Ouyang, Y. (2016). Dynamic snow plow fleet management under uncertain demand and service disruption. *IEEE Transactions on Intelligent Transportation Systems, 17*(9), 2574-2582. doi:10.1109/TITS.2016.2520918

Hijmans, R. J. (2019). Geosphere: Spherical trigonometry. R package version 1.5-10. Available at: https://CRAN.R-project.org/package=geosphere

Hijmans, R. J. (2020). Raster: Geographic data analysis and modeling. R package version 3.1-5. Available at: https://CRAN.R-project.org/package=raster

Hudson, G., & Wackernagel, H. (1994). Mapping temperature using kriging with external drift: Theory and an example from Scotland. *International Journal of Climatology, 14*(1), 77-91. doi:10.1002/joc.3370140107

Jafari, P., Mohamed, E., Ali, M., Siu, M. F. F., Abourizk, S., Jewkes, L., & Wales, R. (2018, March). Reaction Time Optimization Based on Sensor Data-Driven Simulation for Snow Removal Projects. In *Proceedings of Construction Research Congress 2018, New Orleans, Louisiana, USA* (pp. 482-491). doi:10.1061/9780784481288.047

Judson, A., & Doesken, N. (2000). Density of freshly fallen snow in the central Rocky Mountains. *Bulletin of the American Meteorological Society, 81*(7), 1577-1588. doi:10.1175/1520-0477(2000)0812.3.CO;2

Kalkhan, M. A. (2011). *Spatial statistics: Geospatial information modeling and thematic mapping.* New York: CRC Press.

Kastelec, D., & Košmelj, K. (2002). Spatial interpolation of mean yearly precipitation using universal kriging. *Developments in Statistics, 17*, 149-162.

Krige, D. G. (1951). A statistical approach to some basic mine valuation problems on the Witwatersrand. *Journal of the Southern African Institute of Mining and Metallurgy, 52*(6), 119-139. Retrieved from https://journals.co.za/content/saimm/52/6/AJA0038223X_4792

Kwon, T. J., Fu, L., & Melles, S. J. (2017). Location optimization of road weather information system (RWIS) network considering the needs of winter road maintenance and the traveling public. *Computer-Aided Civil and Infrastructure Engineering, 32*(1), 57-71. doi:10.1111/mice.12222

Liang, S., & Wang, J. (2020). *Advanced remote sensing: Terrestrial information extraction and applications* (2nd ed.) Academic Press. doi:rg/10.1016/C2017-0-03489-4

Mahoney, W. P., & Myers, W. L. (2003). Predicting weather and road conditions: Integrated decision-support tool for winter road-maintenance operations. *Transportation Research Record, 1824*(1), 98-105. doi:10.3141/1824-11

Microsoft Corporation, & Weston, S. (2019). doParallel: Foreach parallel adaptor for the 'parallel' package. R package version 1.0.15. Available at: https://CRAN.R-project.org/package=doParallel

Microsoft, & Weston, S. (2020). foreach: Provides foreach looping construct. R package version 1.5.0. Available at: https://CRAN.R-project.org/package=foreach

Mills, B. N., Andrey, J., & Hambly, D. (2011). Analysis of precipitation-related motor vehicle collision and injury risk using insurance and police record information for Winnipeg, Canada. *Journal of Safety Research, 42*(5), 383-390. doi:10.1016/j.jsr.2011.08.004

Mohamed, E., Jafari, P., Siu, M. F. F., & AbouRizk, S. (2017, December). Data-driven simulation-based model for planning roadway operation and maintenance projects. In *Proceedings of 2017 Winter Simulation Conference* (pp. 3323-3334). doi:10.1109/WSC.2017.8248049

Moselhi, O., & El-Rayes, K. (2002). Analyzing weather-related construction claims. *Cost Engineering, 44*(8), 12-19. Retrieved from https://search.proquest.com/docview/220450510

Moselhi, O., Gong, D., & El-Rayes, K. (1997). Estimating weather impact on the duration of construction activities. *Canadian Journal of Civil Engineering, 24*(3), 359-366. doi:10.1139/cjce-24-3-359

Otto, S. (2004). Alberta's benchmark model for maintenance winter service delivery. In *Sixth International Symposium on Snow Removal and Ice Control Technology, Transportation Research E-Circular* (Vol. 63, pp. 487-502).

Pebesma, E. (2004). Multivariable geostatistics in S: The gstat package. *Computers & Geosciences, 30*(7), 683-691. doi:10.1016/j.cageo.2004.03.012

Pebesma, E., & Bivand, R. S. (2005). Classes and methods for spatial data: The sp package. *R News, 5*(2), 9-13. Retrieved from https://cran.r-project.org/doc/Rnews/

Perrier, N., Langevin, A., & Campbell, J. F. (2006). A survey of models and algorithms for winter road maintenance. part I: System design for spreading and plowing. *Computers & Operations Research, 33*(1), 209-238. doi:10.1016/j.cor.2004.07.006

Perrier, N., Langevin, A., & Campbell, J. F. (2007). A survey of models and algorithms for winter road maintenance. part IV: Vehicle routing and fleet sizing for plowing and snow disposal. *Computers & Operations Research, 34*(1), 258-294. doi:10.1016/j.cor.2005.05.008

Plouffe, C. C. F., Robertson, C., & Chandrapala, L. (2015). Comparing interpolation techniques for monthly rainfall mapping using multiple evaluation criteria and auxiliary data sources: A case study of Sri Lanka. *Environmental Modelling & Software, 67*, 57-71. doi:10.1016/j.envsoft.2015.01.011

R Core Team. (2020). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Roebber, P. J., Bruening, S. L., Schultz, D. M., & Cortinas, J. V. (2003). Improving snowfall forecasting by diagnosing snow density. *Weather and Forecasting, 18*(2), 264-287. doi:10.1175/1520-0434(2003)0182.0.CO;2

Russo Jr., J. A. (1966). The economic impact of weather on the construction industry of the United States. *Bulletin of the American Meteorological Society, 47*(12), 967-972. doi:10.1175/1520-0477-47.12.967

Sedgewick, R., & Wayne, K. (2011). *Algorithms* (4th ed.) Addison-Wesley professional.

Shahin, A., AbouRizk, S., Mohamed, Y., & Fernando, S. (2014). Simulation modeling of weather-sensitive tunnelling construction activities subject to cold weather. *Canadian Journal of Civil Engineering, 41*(1), 48-55. doi:10.1139/cjce-2013-0087

Shi, X. (2010). Winter road maintenance: Best practices, emerging challenges, and research needs. *Journal of Public Works & Infrastructure, 2*(4), 318-326.

Siu, M. F. F., Liu, C., Wales, R., & AbouRizk, S. (2017). Operation Effort Optimization for Planning Performance-Based Snow-Removal Projects. *Journal of Computing in Civil Engineering, 31*(6), 04017060.

Stricker, R. (1970). *Public sector vehicle routing: The Chinese postman problem* (Master's dissertation). Retrieved from https://dspace.mit.edu/bitstream/handle/1721.1/27901/06261040-MIT.pdf?sequence=2

Swihart, B., & Lindsey, J. (2020). rmutil: Utilities for nonlinear regression and repeated measurements models. R package version 1.1.4. Available at: https://CRAN.R-project.org/package=rmutil

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography, 46*, 234-240. doi:10.2307/143141

Transportation Research Board, & National Research Council. (2004). *Where the weather meets the road: A research agenda for improving road weather services*. Washington, DC: The National Academies Press. doi:10.17226/10893

Usman, T., Fu, L., & Miranda-Moreno, L. F. (2010). Quantifying safety benefit of winter road maintenance: Accident frequency modeling. *Accident Analysis & Prevention, 42*(6), 1878-1887. doi:10.1016/j.aap.2010.05.008

Usman, T., Fu, L., & Miranda-Moreno, L. F. (2012). A disaggregate model for quantifying the safety effects of winter road maintenance activities at an operational level. *Accident Analysis & Prevention, 48*, 368-378. doi:10.1016/j.aap.2012.02.005

Usman, T., Fu, L., Miranda-Moreno, L. F., & Perchanok, M. (2012, April). Application of Collision Prediction Models for Quantifying the Safety Benefits of Winter Road Maintenance. In *Proceedings of International Conference on Winter Maintenance and Surface Transportation Weather*. Coralville, Iowa. (pp. 29-42).

Vahdatikhaki, F., & Hammad, A. (2014). Framework for near real-time simulation of earthmoving projects using location tracking technologies. *Automation in Construction, 42*, 50-67. doi:10.1016/j.autcon.2014.02.018

Vahdatikhaki, F., & Hammad, A. (2015). Risk-based look-ahead workspace generation for earthwork equipment using near real-time simulation. *Automation in Construction, 58*, 207-220. doi:10.1016/j.autcon.2015.07.019

Wales, R. J., & AbouRizk, S. M. (1996). An integrated simulation model for construction. *Simulation Practice and Theory, 3*(6), 401-420.

Wang, J., & Liu, H. (2019). Snow removal resource location and allocation optimization for urban road network recovery: A resilience perspective. *Journal of Ambient Intelligence and Humanized Computing, 10*(1), 395-408. doi:10.1007/s12652-018-0717-3

Williams, G. P. (1956). *Study of snow density across Canada.* National Research Council of Canada. Division of Building Research. doi:10.4224/20337891

Wu, Y. H., & Hung, M. C. (2016). Comparison of spatial interpolation techniques using visualization and quantitative assessment. *Applications of Spatial Statistics*, 17-34.

Xie, B., Li, Y., & Jin, L. (2013). Vehicle routing optimization for deicing salt spreading in winter highway maintenance. *Procedia - Social and Behavioral Sciences, 96*, 945-953. doi:10.1016/j.sbspro.2013.08.108

Young, K. C. (1994). A multivariate chain model for simulating climatic parameters from daily data. *Journal of Applied Meteorology, 33*(6), 661-671. doi:10.1175/1520-0450(1994)0332.0.CO;2

Zhang, D. (2009). Optimization of vehicle routing for plowing and snow disposal. In *ICCTP 2009: Critical Issues in Transportation Systems Planning, Development, and Management* (pp. 1-7). doi:10.1061/41064(358)383