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Data-Driven Simulation Approach for Short-Term Planning of Winter Highway Maintenance Operations

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ABSTRACT

Winter highway maintenance operations are performed to ensure safe driving conditions during snow events. However, variability in truck speeds and changing weather conditions limit the ability of practitioners to optimize plans in a timely manner. The time required to manually adjust plans in response to actual conditions prevents modifications from being completed and applied during the operation phase. To overcome this challenge, a data-driven, near real-time simulation approach to assist short-term planning of winter highway maintenance operations is proposed. The approach integrates dynamic project data to quickly (1) predict required truck fleet size for upcoming operations, (2) devise operation schedules, and (3) recommend operation routes. Functionality and validity of the proposed approach was demonstrated using both an illustrative example and a real case study. The proposed approach was found capable of rapidly generating operation plans that were more efficient than current practice.

INTRODUCTION

Many studies have demonstrated that snow precipitation on roads significantly increases accident risk (Andrey et al. 2001; Eisenberg and Warner 2005; Mills et al. 2011). While winter road maintenance operations have been shown to reduce accident rates by maintaining safe driving conditions (Usman et al. 2010; Usman et al. 2012a; Usman et al. 2012b), a large amount of equipment is usually required to complete operations in a timely manner. Indeed, the annual cost of winter road maintenance in Canada is approximately $1 billion (Andrey et al. 2001), and is over $2 billion in the United States (Transportation Research Board and National Research Council 2004). Given these extensive budgets, optimization of operational efficiency can result in substantial cost savings for many municipalities.

Winter road maintenance planning can be categorized into four levels (Perrier et al. 2006): strategic, tactical, operational, and real-time. Several decision-support systems have been designed to address long-term strategic and tactical planning. These include studies examining the partitioning of maintenance areas, selection of vehicle depot locations, and fleet assignments to depots. In contrast, decision-support approaches focusing on short-term operational and real-time planning remain relatively unexplored. In fact, many practitioners in the winter highway maintenance industry continue to plan short-term operation schedules manually based on weather forecasts. This is a time-intensive process that cannot be performed in the time-frame necessary to exert real-time operational changes. Despite the best efforts of practitioners, plans created based on weather forecasts often result in the over- or under-allocation of resources to depots. Also, truck drivers often modify the prescribed operation route in response to actual road conditions. Since the route taken relies heavily on the subjective experience of individual drivers, inefficiency often results.

In winter road maintenance operations, variability in snow impact areas can cause changes in maintenance demand (Hajibabai and Ouyang 2016). Therefore, the consideration of regional weather events is particularly important. Due to the large geographical region of highway networks, a snow event may only affect part of a depot's service area. The use of predetermined routes and/or fleet sizes for all snow events can result in low operational efficiency. While decision-support systems for planning winter road maintenance operations have been developed, these systems are limited by their inability to simultaneously consider variations in weather, operation routes, and vehicle speed at an event-specific level. As such, they are unable to optimize the operation in response to specific snow events, which is essential for short-term planning of winter highway maintenance operations.

To enhance short-term planning of winter highway maintenance operations, a data-driven, near real-time simulation framework is proposed. The proposed approach uses road network information, weather data, and truck speeds as primary inputs to generate a short-term operation plan, which includes a forecast of the required fleet size range, recommended operation routes, and an operation schedule detailing the anticipated departure and return times of the maintenance trucks. By implementing a near real-time simulation approach, this model can be dynamically updated with actual weather and vehicle tracking data (i.e., GPS) to reflect the latest changes in operations. This is in contrast to conventional simulation analyses that only use historical statistical data and, therefore, cannot be dynamically updated (Vahdatikhaki and Hammad 2014).

The current model is referred to as "near real-time," as a short delay is required to accumulate the amount of data required to accurately reflect current operation progress, and time is needed to process simulation calculations. While results are not generated and updated instantaneously, new results can be obtained within several minutes. By allowing the operational plan to be adjusted in response to changes in weather, operation progress, or other sudden deviations, the near real-time simulation approach proposed here is expected to result in increased model accuracy and, consequently, in improved operational planning.

WINTER HIGHWAY MAINTENANCE OPERATIONS

While winter highway maintenance operations are typically accomplished by plowing or blowing the snow to the side of the road, maintenance operations may also include spreading sand or salt on the road. Note that all maintenance activities are hereafter referred to as "plowing."

Prioritization of winter road maintenance is determined by a road's level of service (LOS) class. Roads in the service area are categorized into different classes depending on their level of importance, and service requirements for each class are then specified. The LOS is usually defined by the operation contract. In this model, LOS classes are defined by two components:

1. *Trigger amount*, which is the amount of snow that can accumulate on a road before it must be maintained.
2. *Maximum reaction time,* which is the time within which maintenance operations must be initiated once the trigger amount is reached.

Operation planning is essential for optimizing the balance between the quality and cost of winter road maintenance operations. Improving operational efficiency through optimized operation planning allows costs to be reduced while ensuring that LOS requirements are met. The total travel distance of trucks can be decreased by reducing unnecessary plowing and the amount of deadhead travel (i.e., truck traveling without plowing). These modifications can, in turn, improve operational efficiency and lower the costs associated with operating maintenance trucks.

Winter highway maintenance operations can be optimized from various perspectives. First, maintenance routes can be optimized to reduce operation effort by decreasing the amount of time a truck is traveling without performing maintenance operations. This is often referred to in literature as a vehicle routing problem. Second, with a known set of maintenance routes, operation schedules can be optimized by selecting appropriate departure times for different operation routes. This is known as an operation scheduling problem, and it focuses on minimizing the operation effort while ensuring minimum LOS requirements are met (Fu et al. 2009). Finally, and known as a fleet sizing problem, the number of trucks assigned to a depot can be optimized to ensure sufficient trucks are available during the operation while reducing the number of idle trucks.

A discussion of the current state-of-the-art for fleet sizing, operation scheduling, and vehicle routing problems, as well as the consideration of weather uncertainty and operation variability in winter road maintenance operations, is detailed in the Literature Review section that follows.

LITERATURE REVIEW

Fleet sizing problem in winter road maintenance operations

Several studies have been conducted to determine required fleet sizes for winter road maintenance operations. Chien et al. (2013) developed a mathematical model that considered the impact of weather and traffic on vehicle speed to determine the required fleet size. In this model, fleet size was calculated using the total road surface area and the plowing area per plow. However, deadheading (i.e., vehicle traveling without performing maintenance work) from the depot to the working road was overlooked, and the model only considered worst-case weather scenarios. Therefore, the model cannot be used to forecast required fleet sizes for specific snow events.

Jafari et al. (2018) proposed a simulation model to determine the optimal fleet size based on the maximum reaction time. Each road was assigned to a weather station, and if the weather station detected snow precipitation, trucks were dispatched from the depot to predefined routes. The maximum reaction time was evaluated for each route, and the route with the minimum reaction time was selected. While weather data were incorporated into this model, they were only used to determine the precipitation (i.e., snowing) status. The impact of different snow intensity and uneven snow area distributions were neglected, which, as mentioned earlier, is not suitable for winter highway maintenance planning.

Operation scheduling for winter road maintenance operations

In 2003, Mahoney and Myers proposed a decision-support tool for winter road maintenance operations. This tool integrated multiple sub-systems, including a weather prediction system, chemical concentration algorithms, and a road mobility index algorithm. User-defined maintenance routes were input, and the model created recommended operation schedules for each route. Later, in 2009, Fu et al. proposed a real-time optimization model to solve the operation scheduling problem, which focused on maximizing the total service level across the road network while minimizing the operation cost. Operation schedules were generated in consideration of fleet size and level of service constraints.

Although these two models considered weather uncertainty in their calculations, both models require the input of predefined routes and lack a function to optimize routes based on the road network. Because of this, additional efforts are required to create routes specific to particular road networks for implementation during actual operations. Another limitation is that the quality of the model outputs is limited by the quality of the predefined routes.

Vehicle routing problems in winter road maintenance operations

Wang and Liu (2019) proposed a model to solve the resource location-allocation problem together with the vehicle routing problem. This model used a tabu search algorithm whose aim was to improve the “recovery ability” of the road network under snow events in consideration of weather uncertainty. An optimization algorithm for vehicle routing during deicing salt spreading operations in winter highway maintenance was proposed by Xie et al. (2013). The algorithm aimed to minimize total driving distance while considering road network topology, vehicle capacity, and load balance as constraints. The route optimization algorithms proposed in these two papers focused on optimizing the route that covers the entire road network, but overlooked continuous snow accumulation and uneven snow intensity occurring during snow events. Therefore, the practicality of these models for planning winter highway maintenance operations is limited.

Weather uncertainties in winter road maintenance operations

In 1996, Wales and AbouRizk developed a simulation model to forecast the impact of weather on construction schedules to assist with project planning. In this model, a first-order Markov chain was used to model precipitation events. The precipitation amount was sampled from a distribution function based on historical records, and neural networks were trained to predict productivity based on weather conditions. Although useful for forecasting the long-term impact of weather on operations, the approach is not suitable for short-time periods characteristic of specific snow events.

Hajibabai and Ouyang (2016) proposed a stochastic model that aimed to minimize operation costs while maximizing service levels in winter road maintenance operations. In this model, random maintenance tasks were generated across the road network to represent stochastic snow events, and the cost for truck deadheading and repositioning was calculated. Notably, while this model was capable of dynamically scheduling operations based on new tasks, the tasks were generated randomly and independently of weather data. As such, the problem of how to determine and schedule tasks based on actual weather information remained unsolved.

Near real-time simulation

Due to the dynamic nature of weather, plans derived using weather forecasts may not be representative of actual conditions. However, near real-time simulation can be used to dynamically update model results (Vahdatikhaki and Hammad 2014). In 2014, Vahdatikhaki and Hammad developed a near real-time simulation model for modeling earthmoving projects using location tracking technologies. The model continuously simulated equipment motion and environmental factors. When actual site data differed from model results, the simulation was updated. This research noted that updating models too often can make results difficult to apply in practice. Therefore, determining an appropriate update interval for near real-time simulation is important.

Research gaps

Various approaches have been developed to improve the planning of winter road maintenance operations. While fleet sizing, operation scheduling, vehicle routing, and uncertainties in weather have been explored, most previously-developed approaches cannot dynamically adjust optimization results during the operation phase, resulting in poor operational efficiency. Additionally, most models lack certain components required for implementation in industry, and do not address these problems in a unified model. Specific research gaps and limitations of the current state-of-the-art are listed as follows:

- Near real-time simulation approaches for dynamic planning, which focus on adjusting schedules based on operation progress and changing weather conditions, have not been thoroughly explored and implemented for winter highway maintenance operations.
- Many approaches overlook weather uncertainty. Uneven distribution of snow events and continuous accumulation of snow are not considered.
- Many operation scheduling approaches use predefined routes. This requires extra effort prior to implementation and may limit output performance.

METHODOLOGY

To address these challenges, a unified, data-driven, near real-time simulation approach is proposed. The approach is capable of providing decision-makers with dynamic operation plans in response to actual site conditions. To achieve this, several advances to the existing state-of-the-art are proposed:

- Near real-time simulation is used to dynamically adjust the operation plan based on actual snow precipitation levels and truck GPS data.
- Inverse distance weighting interpolation is used to estimate and account for uneven snow accumulation on roads.
- Operation routes are optimized and corresponding operation tasks are scheduled based on snow accumulation amounts.

The proposed simulation-based framework consists of four components:

1. *Snow accumulation component*, which uses weather data and road network information to estimate the amount of accumulated snow on the road network.
2. *Operation scheduling and simulation component*, which optimizes the route and creates the operation schedule based on snow accumulation amounts and LOS requirements.
3. *Result output component*¸ which visualizes the simulation results and creates outputs. Outputs consist of a fleet size forecast, an optimized operation schedule, and operation routes.
4. *Near real-time update component*, which uses actual weather observations and GPS tracking data to dynamically update the model during the operation phase.

The framework is summarized in Figure 1, and the functionality of each module is detailed in the following subsections:

Snow accumulation component

First, the model uses weather data and road network information to estimate the amount of snow that is accumulating on each lane of the maintenance area. The model assumes that trucks always plow the lanes they pass if snow has accumulated. One lane of a multi-lane road may be plowed before it reaches its trigger amount by a truck that is traveling to plow another road. Although the snow accumulation rate is the same for all lanes within the road, the amount of snow that will accumulate on each lane can, therefore, differ. Consequently, the model is designed to individually forecast snow accumulation on each lane of a road. Weather data can be either a forecast of future conditions for pre-operation planning or actual data obtained during the operation phase for near real-time updating.

Snow water equivalent

Weather stations usually measure snow precipitation using a snow water equivalent value, which can be converted to snow depth on roads using the snow density value. Previous studies have found that snow density can change over time and vary by location (Williams 1956). The typical density of new snow is between 50 to 70 kg/m^3 and increases to 200 to 300 kg/m^3 when snow has settled (Paterson 1994). Equation 1 shows the relationship between the snow water equivalent value, snow density, and snow depth (Liang and Wang 2020):

$$W = \frac{\rho_s d}{\rho_w} \tag{1}$$

where W is the snow water equivalent value; 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 the calculation. A common approach is to assume the snow density is 100 kg/m^3. Then, based on the 1000 kg/m^3 water density, the snow depth can be calculated using the 10-to-1 rule (Roebber et al. 2003). In this model, if the snow density is not given by the user, a default value of 100 kg/m^3 will be used.

Inverse distance weighting interpolation

Typically, weather data are only collected at weather stations. Stations are usually spaced far apart, which it makes it difficult to estimate road conditions between the stations. To account for this, the inverse distance weighting interpolation method is applied. Based on Tobler's first law, which states that "everything is related to everything else, but near things are more related than distant things" (Tobler 1970), this method functions to reduce the weight of a data point as its distance from the interpolated point is increased. It estimates the snow precipitation amount at a given location using the following equation (Kalkhan 2011),

$$\widehat{Z_0} = \frac{\sum_{i=1}^{n} \frac{Z_i}{d_i^p}}{\sum_{i=1}^{n} \frac{1}{d_i^p}} \tag{2}$$

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 number of neighboring data points used to estimate the unknown location; and p is the power parameter. In this model, a value of 2 is used as the power parameter based on recommendations from previous precipitation interpolation research (Chen et al. 2010; Xu et al. 2015).

Snow accumulation amount

The accumulated snow amount on each lane is individually calculated by summing the accumulated snow amounts for each time interval. First, the entire road network area is divided into equally-sized grids (here, 500 m^2), and a snow precipitation rate is determined for each grid by interpolating the precipitation rate at weather stations. Snow precipitation rates are then overlayed on the road network to determine the rate for each road. All lanes belonging to a road are assumed to have the same precipitation rate as the road. Finally, the precipitation amount is calculated by multiplying the precipitation rate by the time interval; the accumulated snow amount for each grid of a lane is calculated using Equation 1.

The road network used in this model is a weighted, non-directional graph, with weights used to represent the length of a road, lines to represent the main highway roads, and nodes to represent the intersections. All highways are assumed to be bidirectional, and trucks are able to make turns in all directions at nodes. Ramp lengths, which are short compared to the length of maintenance routes, are omitted from the road network. When overlaying the interpolated data onto the road network, each line, which represents a road, can cross multiple grids. The snow precipitation rate on different grids are calculated separately to ensure that the snow precipitation rate at different locations along long roads are calculated and evaluated correctly.

Operation scheduling and simulation component

Operation tasks are created and scheduled according to the algorithm summarized in Figure 2. In this model, a road consists of multiple lanes, and all lanes in a road are assumed to have the same LOS class. After a lane reaches its trigger amount, maintenance operations must be initiated within the maximum reaction time. Operation schedules are created based on the following assumptions:

- The maintenance operation performed by a single truck removes all snow on the lane that is driven, thereby restoring the lane to a satisfactory driving condition in one pass.
- Operations, including plowing, blowing, and spreading sand or salt, are combined as a single maintenance operation that is referred to as "plowing." Material limitation for spreading sand or salt is incorporated as a limit in route length.

- When a truck plows a road with multiple lanes, it will plow the lane that has accumulated the most snow.
- Trucks always plow the lane they pass if snow has accumulated.
- Trucks return to the depot following the reverse route from which they departed.

Creation of operation tasks

First, the model creates a base-accumulation. Unless otherwise specified, the model assumes that no snow has accumulated on all lanes in the road network. Using the snow accumulation amount determined previously, newly accumulated snow is added to the base-accumulation. Then, the time required for each lane to reach its trigger amount, and the time to reach the maximum reaction time is determined. Once a lane reaches its trigger amount (Time = T1), an operation task is created.

Selection of optimized route for an operation task

After an operation task is created, the model updates the base-accumulation to include the amount of snow that had accumulated until T1. Next, an optimized operation route, which consists of the operations for a sequence of roads, is selected. Lanes are not specified in the output because it is assumed that trucks always plow the lane with the most snow accumulated. Rather, accumulation levels of lanes are used to determine priority of the roads when selecting routes.

Optimization of the operation route is based on four criteria:

1. Route length must be within the maximum operation distance, which is limited by the storage capacity (for salt or sand) of the truck.
2. Priority is given to longer roads.
3. Priority is given to roads with lanes that have less amount of time remaining until their maximum reaction time is reached.

4. A penalty is given to roads with no snow accumulated or that will not have snow accumulated after other previously-created tasks.

Simple paths in the road network, which do not have repeated vertices in the path (Sedgewick and Wayne 2011), are used as candidate paths for the operation. The candidate path is selected from all simple paths in the road network that begin at the depot node. The operation route begins from the depot, travels along the path to its ending vertex, and returns to the depot following the path in reverse. After returning to the depot, trucks are reloaded with material as required.

The objective function for route optimization is represented by Equations 3 through 5. Equation 3 determines the optimal route with the largest sum of priority factors on all roads in this route. Equation 4 limits the route length within the maximum operation distance. Equation 5 calculates the priority factor of each road according to the four aforementioned criteria.

Maximize

$$\sum_{i \in I} \sum_{j=1}^{n} P_{i,j} \tag{3}$$

Subject to

$$\sum_{j=1}^{n} L_{i,j} \leq L_{max} \tag{4}$$

$$P_{i,j} = \begin{cases} \dfrac{L_{i,j}}{min\{T_{i,j,k}\}} & (max\{S_{i,j,k}\} > 0) \\ -L_{i,j} & (max\{S_{i,j,k}\} \leq 0) \end{cases} \tag{5}$$

where I is the candidate route set; n is the number of roads in route i; $P_{i,j}$ is the priority factor of road j in route i; $L_{i,j}$ is the length of road j in route i; $T_{i,j,k}$ is the time from now to the maximum reaction time for lane k on road j in route i; $S_{i,j,k}$ is the maximum snow accumulation on lane k on road j in route i; and L_{max} is the maximum operation distance.

Operation task duration

A discrete-event simulation approach is used to stochastically model task (i.e., route) durations. Each time the operation duration for a task is calculated, multiple sub-tasks are created, with each sub-task representing a one-time operation for a particular road in the route. Notably, the same road assigned to another task is represented by different sub-tasks, as the start time, duration, and the truck assigned to the task can differ. Precedence relationships between newly-created sub-tasks are scheduled according to their route sequence.

The time that a truck spends on each sub-task is calculated by dividing the length of the road by a randomly-sampled value from the truck speed distribution functions. Due to variations in speed limits and traffic volumes, truck speed distributions cannot be used interchangeably between different regions, and should be derived using local historical operation data or created by experts based on their experience. Two types of speed distributions are input into the model. A *working speed distribution*, which is the speed a truck travels while performing the maintenance task, and a *deadheading speed distribution*, which is the speed when the truck is not performing maintenance work. When a truck is traveling on a road where at least one lane in the traveling direction has accumulated snow, the model will sample a random value from the working speed distribution. If there is no snow accumulation, the model will sample from the deadheading speed distribution. The impact of traffic queues resulting from multiple trucks arriving to or departing from the depot at the same time is omitted from the speed distribution functions. Due to the staggered operation schedule, trucks rarely depart from or arrive to the depot at the same time. As such, the duration of any potential delays are minimal compared to the total duration of the operation.

Using the length of each road and the speed distribution functions, the total duration of the operation task, and the durations of each sub-task, are then determined. The realization of the task duration calculation process is presented as pseudo-code in Appendix A.

Scheduling operation tasks

After a route for the operation task is selected and its duration is determined, the task is scheduled to ensure LOS requirements are met. In other words, for each road in the route, the truck must arrive earlier than the maximum reaction time of the lane with the most snow accumulation. To reduce the number of passes (i.e., times a lane is plowed), the model schedules the departure of the truck as late as possible within the permitted reaction time, thereby allowing more snow to accumulate. In this way, a greater amount of snow is removed per pass, thereby improving operational efficiency.

Once a lane is plowed, its accumulation level returns to zero. For lanes that finish before T1, their base-accumulations are updated by the amount of snow that accumulates between the operation finish time (Time = T0) and T1, assuming that, at time T0, there is no snow on this lane. Conversely, for lanes that finish after T1, their base-accumulations are updated as the negation of the snow accumulated between T1 and the operation finish time (Time = T2). In this case, if new snow accumulations are added to the base-accumulations, snow accumulation on these lanes will become zero at T2, ensuring the correct calculation when these lanes reach their trigger amount again. Using the updated base-accumulation, the model again calculates when each lane will reach its trigger amount and repeats the process until trigger amounts are no longer reached during the specified forecast time period. Then, an operation schedule, which consists of all tasks created in this process, is derived.

Fleet size forecast

After an operation schedule is created, the fleet size required to complete the operation is determined by the number of concurrent tasks, as one truck is required to perform each simultaneously-scheduled task. To account for uncertainties in truck speed, random deviates from truck speed distributions are used to calculate the durations of each task. Therefore, task start times, end times, and operations routes will differ each time the model is run. Monte Carlo simulation is used to quantitatively represent the uncertainties in fleet size resulting from variations in truck speed. Multiple operation schedules are generated by repeating the simulation for multiple iterations. The number of tasks scheduled for the same time period may vary between simulation iterations, thereby requiring a different number of trucks (i.e., fleet size) for different iterations of the operation. An estimate of the required fleet size range is then obtained.

Result output component

The result output component is responsible for visualizing the simulation results. The first output of the model is the fleet size forecast. This is presented as a box and whisker plot that visualizes the range of fleet sizes required throughout the duration of the forecast time period. Notably, the model allows users to define the time interval of the forecast. The second output of the model is a recommended operation plan. This is visualized as a Gantt chart showing the departure time, end time, and route IDs for each operation task. This schedule is generated using the average truck speed for working and deadheading or an expected speed provided by the user. Operation routes are generated separately based on road network topology.

Near real-time updating component

Since the fleet size forecast and the operation plan are created based on weather forecasts in the pre-operation phase, accuracy of these results may be reduced when actual weather conditions differ or when delays caused by traffic congestion occur during the operation phase. To improve the accuracy and practicality of the fleet size forecast and operation plan, a function allowing users to update the model in a near real-time manner is incorporated.

First, observations from weather stations are used to calculate the actual amount of snow that has accumulated on each lane. Here, the actual amount of snow that has accumulated since the beginning of the operation is added to the base-accumulation. Then, the model uses GPS coordinates to determine roads that have been plowed as well as the direction the trucks are traveling. Each time a truck passes a road, the lane in the truck's traveling direction with the largest snow accumulation is assumed to be cleared, and its base-accumulation is updated accordingly. Finally, speed distribution functions are updated using all historical speed data, and updated results are created using the updated speed functions and latest weather forecasts.

Depending on the complexity of the road network, the length of the forecast period, and computer configurations, the model requires several minutes for simulation calculations to be performed. As mentioned previously, the process is referred to as "near real-time." Notably, the time lag required does not limit practical application of the model. Since the operation duration of a route usually takes a few hours, frequent, real-time result updates do not add value, as only minor changes will be observed. To achieve the most accurate results, the model should only be updated when there are no active trucks; if any trucks are active when the model is updated, unfinished roads may be reassigned to other trucks and may result in errors.

MODEL APPLICATION

A decision-support tool implementing the proposed framework was developed using *R* (R Core Team 2020) and was applied to two winter highway maintenance problems. The first is an illustrative example used to demonstrate the ability of the model to create optimal output results.

The second is a case study of actual operations used to evaluate the model by comparing outputs of the proposed method with real project data. To reduce errors arising from inaccurate weather forecast data, actual weather observations were used in the case study.

Illustrative example

This illustrative example uses a road network with six roads and four weather stations. All roads are 10 km in length, with one lane in each direction. Figure 3 illustrates the road network, depot location, and weather station locations. The roads are categorized into four LOS classes. The trigger amounts and reaction times for each class are listed in Table 1.

Six simple paths in this road network are used to create candidate operation routes. For each route, trucks depart from the depot, follow the simple path to its ending vertex, and return to the depot following the path in reverse. Figure 4 illustrates the operation routes in this road network. The illustrative example assumes there was a snow event on January 7, 2020. The snow precipitation rate was 1 cm/h at all weather stations on this day, and truck speed was 40 km/h for both working and deadheading. Based on these assumptions and the LOS requirements, the optimal operation schedule was calculated. An example is provided as follows:

- Road *a* is a class A road that has a 2-cm trigger amount and a 0.5-hour reaction time.
- Operation route 2 is the only route that includes road *a*. In this route, a truck needs 0.25 hours to arrive at road *a*, 0.25 hours to plow one lane of the road before plowing the lane in the opposite direction, and 0.25 hours to return to the depot after plowing.
- Since the stipulated reaction time is 0.5 hours, a truck must depart from the depot at the same time that road *a* reaches its trigger amount to ensure the LOS specification is met.
- Based on the snow precipitation rate, road *a* reaches its trigger amount every two hours.

- Therefore, it is optimal to schedule the first task for route 2 two hours after the snow event begins, with subsequent tasks for this route scheduled to begin every 1.75 hours.

Using a similar calculation approach, optimal scheduling intervals for routes 3, 5, and 6 were determined to be 4.25, 5.25, and 6.75 hours, respectively. Service requirements on roads *c* and *d* can be met by operations on routes 2, 3, 5, and 6, and tasks on routes 1 and 4 are not required. An operation schedule was then generated using the proposed framework, as illustrated in Figure 5.

Consistent with the optimal solution, operation tasks were scheduled for routes 2, 3, 5, and 6, with the scheduling intervals for each route equivalent to the optimal solution. The illustrative example demonstrates the ability of the proposed model to select appropriate operation routes, schedule tasks at optimal times, and achieve optimal solutions.

Case study

This case study is based on a real project in Alberta, Canada. The road network, depot location, and weather station locations are shown in Figure 6. A snow event from March 27–30, 2020, is used in this case study, with the observed snow precipitation rate at each weather station shown in Figure 7. The snow event began on the afternoon of March 27, 2020, and ended on the afternoon of March 29, 2020. At the beginning of the snow event, station A had the highest precipitation rate. As time progressed, the snow event moved towards the road network, and a higher precipitation rate was observed at station C. Station B observed no snow precipitation during this time. Truck speed distribution functions were derived from historical data using the *R* package *fitdistrplus* (Delignette-Muller and Dutang 2015). The process for obtaining the speed distribution functions is detailed in Appendix B. Working and deadheading speed distributions were determined to be Logistic (43.24, 7.62), and Laplace (45.00, 14.27), respectively.

The operation area in this case study is close to Edmonton, Alberta, and the average snow density in Edmonton has been reported to be 224 kg/m^3 (Williams 1956). The typical density of new snow is between 50 to 70 kg/m^3 and increases when snow is settling (Paterson 1994). Considering that snow removal operations typically begin shortly after snowfall, the snow density for this case study was assumed to be 150 kg/m^3. Following the process described in the methodology section, an operation plan was generated. The efficiency of the operation plan was evaluated using a maintenance efficiency factor and by comparing it with actual operations.

Maintenance efficiency factor

Here, the operational efficiency was determined by averaging the amount of snow that a truck plowed per pass. A greater amount of snow plowed per pass reduces the total operation effort required to maintain the maintenance area, thereby increasing operational efficiency. A maintenance efficiency factor, shown as Equation 6, was used to quantify the amount of snow that a truck plowed per pass as a ratio of the road's trigger amount.

$$ME = \frac{S}{\left(\frac{P}{N_L} + 1 \text{ clean-up plow}\right) \times S_T} \tag{6}$$

where ME is the maintenance efficiency; S is the total snow accumulation during the operation; P is the plow count; N_L is the total number of lanes in both directions; and S_T is the trigger amount.

An efficiency factor equal to 1 indicates that the amount of snow plowed per pass equals the road's trigger amount. As the value increases, more snow is plowed per pass and the operational efficiency increases. Figure 8 summarizes the maintenance efficiency for each road. Over 70% of the roads had an efficiency factor greater than 0.5, indicating that the average amount of snow plowed on these roads was at least half of the road's trigger amount. The efficiency factor was greater than 0.6 for more than 50% of the roads, and exceeded 0.8 on 35% of the roads. Less than 20% of roads had an efficiency factor lower than 0.4.

Comparison of plow counts

The plow count for each road was also compared with actual operations. Differences in plow counts are summarized in Figure 9. It was observed that:

1. On most roads, the plow count for the actual operation was greater than the model result.
2. On 70% of roads, the difference in plow count was less than 5.
3. Two roads in the southeast area had the greatest difference in plow counts.

Two potential reasons for the differences in road plow counts were identified. First, the two roads with the greatest differences were both class A roads, and both had two lanes in each direction. Therefore, to make sure these roads were well-maintained, they were plowed more often in actual operations—even if the trigger amount was not reached—thereby causing actual plow counts to be greater than the model-derived operation plan. Second, actual maintenance operations began earlier than the start time suggested by the model-derived operation plan. This meant that some roads were plowed before their trigger amounts were reached, and less snow was removed per pass. Therefore, for the same total snow precipitation amount, roads were plowed more times, increasing the plow count on certain roads.

Comparison of fleet size

Figure 10 shows a comparison between the actual fleet size used in the operation and the fleet size recommended by the model. Actual operations began earlier than the model and used a smaller truck fleet. However, the total active time of the actual operation was longer. Actual operations may have been started early because of a limitation in the number of available trucks. Instead of pursuing higher operational efficiency, which requires more trucks, the duration of the actual operation was extended to reduce the required number of trucks. By plowing roads before their trigger amounts are reached, certain tasks can be scheduled later, and consequently, the peak truck demand is reduced. However, this approach will increase plow counts on certain roads, thereby reducing operational efficiency. This model aims to generate an operation plan with optimized operational efficiency. As such, truck availability is considered an unlimited resource, which may result in a larger truck fleet.

Updating capabilities of model

The ability of the model to update its results based on new input information was evaluated. Since the actual operation was different from the operation plan, actual progress data collected on March 28, 2020, at 19:00 were input into the model. The fleet size forecast obtained following model updating is shown in Figure 11. The model was capable of producing realistic updating results: the maximum truck fleet size was reduced when the operation began earlier, and the first peak in truck demand was delayed.

Conclusions

The operation plan generated by the model avoided unnecessary travel and resulted in high maintenance efficiency. Plow counts of the model-generated plan were comparable to actual operations, and reductions in plow counts were observed for most roads. Reductions in plow counts equate to a reduction in the total traveling distance of the trucks, lowering fuel costs. The model-generated operation plan also shortens the total active time of the operation, potentially reducing labor costs. However, the more efficient plan proposed here requires a larger fleet size, which increases truck-associated costs, such as purchase and maintenance costs. Identifying the ideal balance between long-term cost and performance for winter highway maintenance operations should be investigated in future research studies.

MODEL VALIDATION

The model was validated using various techniques proposed by Sargent (2003). First, extreme condition tests were performed. The model was tested on scenarios with zero snow precipitation, zero roads in the road network, and a route length limited to zero. In all three scenarios, the model produced an empty operation plan, as expected. These validation results demonstrate that the model's behavior is plausible under extreme scenarios.

Second, traces were used to verify truck behavior. Truck locations were traced to ensure they followed the designated route, and operation durations were verified by comparing model-derived durations with hand calculation results. All trucks followed the designated route, and all durations matched hand calculations, demonstrating that trucks in the model behave as directed.

Third, the model was validated by comparing its results to a valid model using an illustrative case study. In this case, the model-generated result of a simple case was compared to the known optimal solution. Model-generated outputs matched the optimal solution (Figure 5), thereby validating the proposed model.

Finally, the model was also validated using predictive validation and an event validity test. The model was run using data from a real project, and model-derived plow counts for each road were compared with actual operations. Actual plow counts were similar to model results for 70% of roads (Figure 9), demonstrating that the model is capable of generating operation plans that are realistic. Furthermore, the plow count for most roads was lower than actual operations, indicating that the model is capable of generating plans that are more efficient than those derived using current industrial approaches.

LIMITATIONS AND FUTURE WORK

Practicality and functionality of the proposed model should be evaluated in consideration of certain limitations. First, the model schedules maintenance tasks as close to their maximum reaction times as possible to improve operational efficiency. While this approach reduces the plow count on roads and shortens the total operation duration, it may require a larger truck fleet. A resource leveling function could be added in the future to apply a resource constraint on the model when available trucks are limited. The cost efficiency of this approach should also be explored to determine the impact of improved operational efficiency on long-term project outcomes and cost.

Second, operation route optimization is simplified in this model, and the resulting plan may not represent the most efficient operation route. Further studies can be conducted to incorporate a more sophisticated route optimization algorithm to identify the optimum route.

Third, snow accumulation calculations are simplified to convert precipitation data into accumulation amounts using a snow density value. More sophisticated approaches, which consider additional factors such as road surface temperature, wind speed, and traffic volume, can be further explored.

Fourth, the proposed framework only applies to short-term operation planning. While detailed precipitation data with short intervals are required to capture sudden changes in weather, these data are only available for short-term forecasts due to limitations in meteorological technologies.

CONCLUSION

In this paper, a data-driven, near real-time simulation approach that can be used to assist short-term operation planning of winter highway maintenance operations was developed. Weather data, road network information, and vehicle tracking data were used to generate fleet size forecasts and operation plans that aim to maximize operational efficiency. The model was validated by comparing results with an optimal solution in an illustrative example and with real operation data in a case study. The model was also shown to be capable of using weather observation and vehicle tracking data to update results during operations, ensuring that results remain valid and practical when actual operations deviate from the operation plan.

This model allows resource requirements, working schedules, and operation routes to be rapidly and automatically generated in near real-time—all while providing a solution that is likely more efficient than current practice. Notably, the framework developed in this study is generic and can be adapted for solving problems of a similar nature.

APPENDIX A. Pseudo-Code for Calculating Operation Task Durations

The following pseudo-code describes the realization of the discrete-event simulation process for calculating the operation task durations in this study. Note that the pseudo-code presented here is for an individual iteration. Additional loops and data summarization is required for a full simulation.

```
Input: operation route sequence, Route = {Road a, Road b, Road c, …}; length of each road; working speed distribution; deadheading speed distribution
Output: operation duration for each road (i.e., sub-task); total operation duration of the route (i.e., task)
Total duration ← 0
FOR each Road in Route
        IF Road has snow accumulated THEN
                Speed ← a random value sampled from working speed distribution
        ELSE
                Speed ← a random value sampled from deadheading speed distribution
        Sub-task duration ← Road length / Speed
        Total duration ← Total duration + Sub-task duration
Total operation duration of the route ← Total duration
```

APPENDIX B. Process of Obtaining Speed Distribution Functions

The *R* package *fitdistrplus* (Delignette-Muller and Dutang 2015) was used to automatically create and update speed distribution functions with available historical operation data. The steps of this process are as follows:

1. Randomly sample speed data points from available historical data (in the case study, 5000 working speeds and 5000 deadheading speeds were sampled).
2. Use the *fitdistrplus* package to fit normal, Laplace, logistic, Weibull, gamma, and beta distribution functions for working and deadheading speeds using the maximum likelihood estimation method.
3. Use the KS test to compare the distribution functions, choose the most likely working and deadheading speed distributions based on the KS test results.

In the case study, working and deadheading speed distributions were determined to be Logistic (43.24, 7.62) and Laplace (45.00, 14.27), as shown in Figures B.1 and B.2, respectively. Since the speed distribution data were provided by a third party, x-axis labels have been removed to maintain confidentiality.

DATA AVAILABILITY STATEMENT

Code for the decision-support system was developed in collaboration with a third party. Requests for this material should be made to both the corresponding author and the collaborator listed in the Acknowledgements. Weather, GPS tracking, and road network data used in the study were provided by a third party. Direct request for these materials may be made to the provider indicated in the Acknowledgments.

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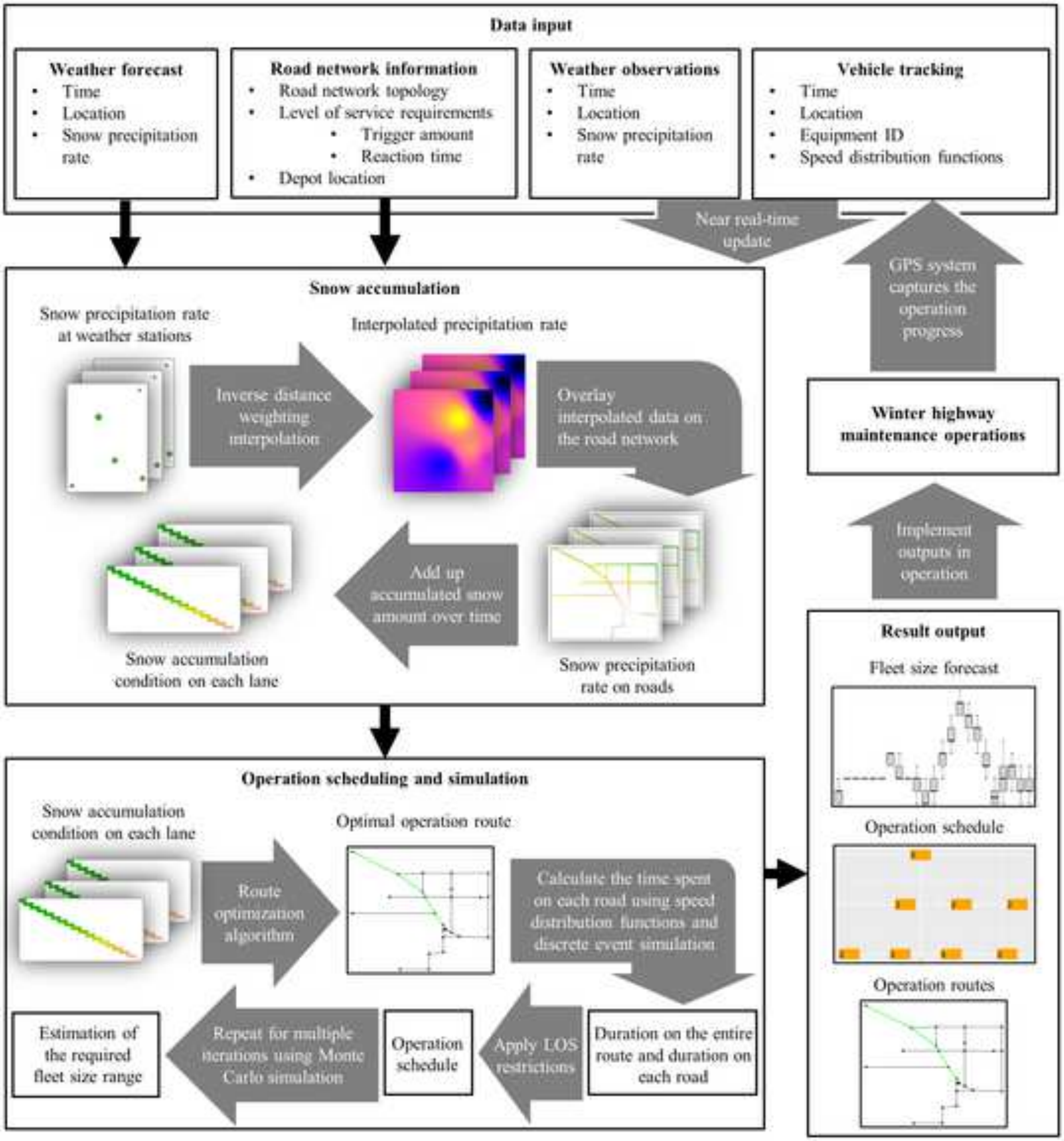
TABLES

Table 1. LOS class requirements for the illustrative example

Class	Trigger Amount (cm)	Maximum Reaction Time (h)
A	2	0.5
B	4	1
C	5	1
D	6	1.5

Figure 1



Data input
Weather forecast
Time
Location
Snow precipitation rate
Road network information
Road network topology
Level of service requirements
Trigger amount
Reaction time
Depot location
Weather observations
Time
Location
Snow precipitation rate
Vehicle tracking
Time
Location
Equipment ID
Speed distribution functions
Near real-time update
GPS system captures the operation progress
Snow accumulation
Snow precipitation rate at weather stations
Inverse distance weighting interpolation
Interpolated precipitation rate
Overlay interpolated data on the road network
Snow precipitation rate on roads
Add up accumulated snow amount over time
Snow accumulation condition on each lane
Winter highway maintenance operations
Implement outputs in operation
Operation scheduling and simulation
Snow accumulation condition on each lane
Route optimization algorithm
Optimal operation route
Calculate the time spent on each road using speed distribution functions and discrete event simulation
Duration on the entire route and duration on each road
Apply LOS restrictions
Operation schedule
Repeat for multiple iterations using Monte Carlo simulation
Estimation of the required fleet size range
Result output
Fleet size forecast
Operation schedule
Operation routes

Figure 2

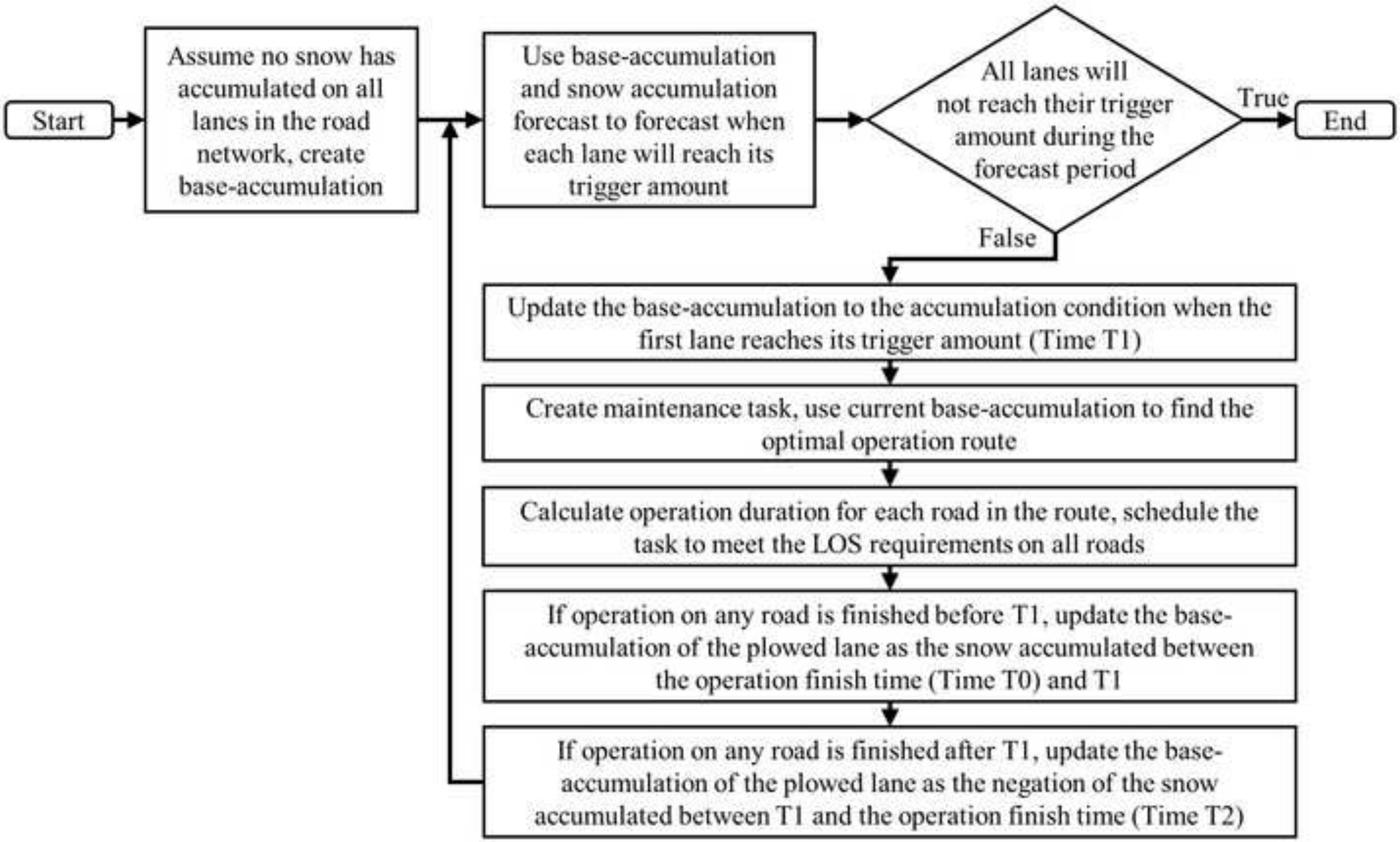

Start
Assume no snow has accumulated on all lanes in the road network, create base-accumulation
Use base-accumulation and snow accumulation forecast to forecast when each lane will reach its trigger amount
All lanes will not reach their trigger amount during the forecast period
True
End
False
Update the base-accumulation to the accumulation condition when the first lane reaches its trigger amount (Time T1)
Create maintenance task, use current base-accumulation to find the optimal operation route
Calculate operation duration for each road in the route, schedule the task to meet the LOS requirements on all roads
If operation on any road is finished before T1, update the base-accumulation of the plowed lane as the snow accumulated between the operation finish time (Time T0) and T1
If operation on any road is finished after T1, update the base-accumulation of the plowed lane as the negation of the snow accumulated between T1 and the operation finish time (Time T2)

Figure 3

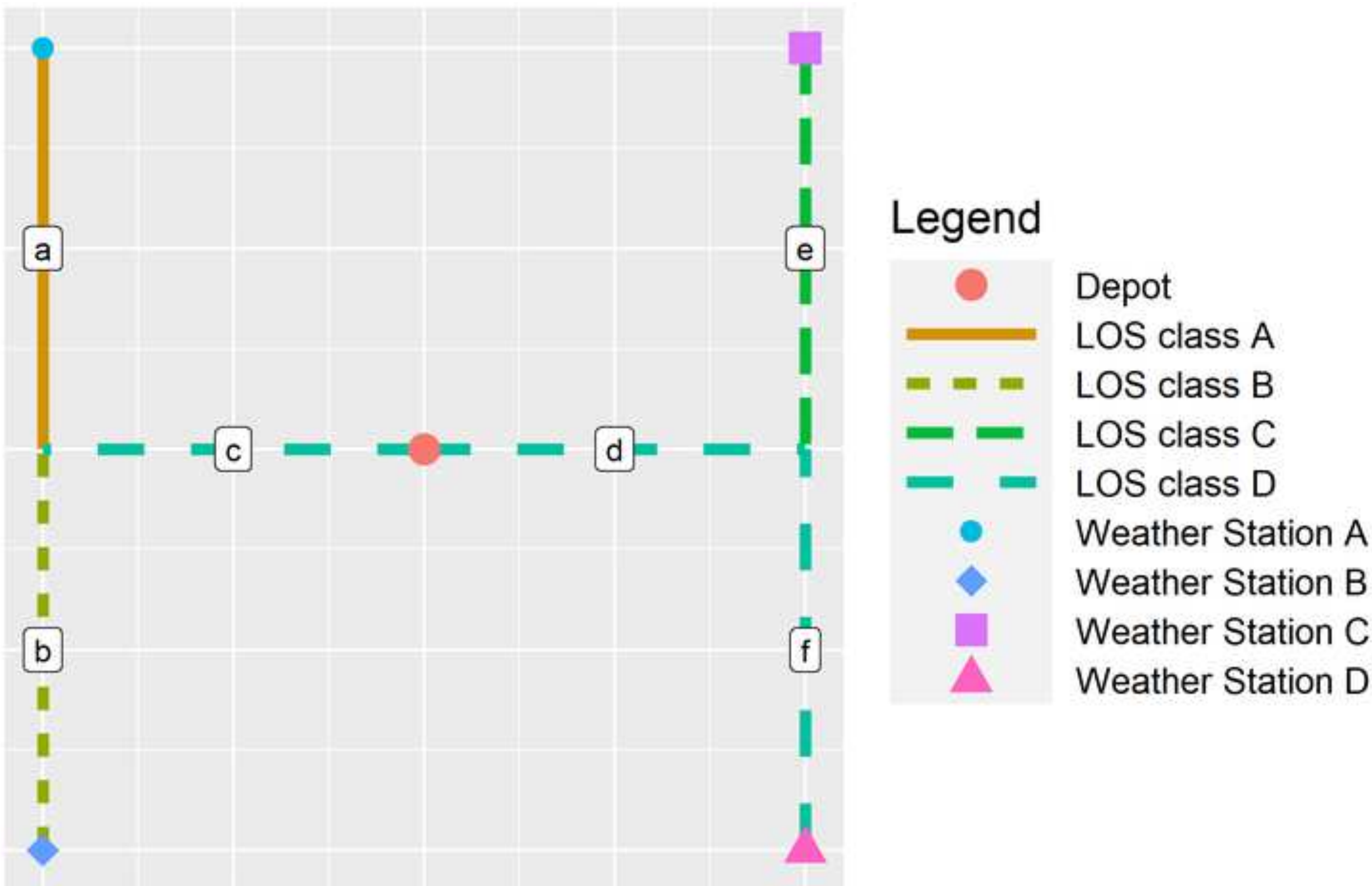
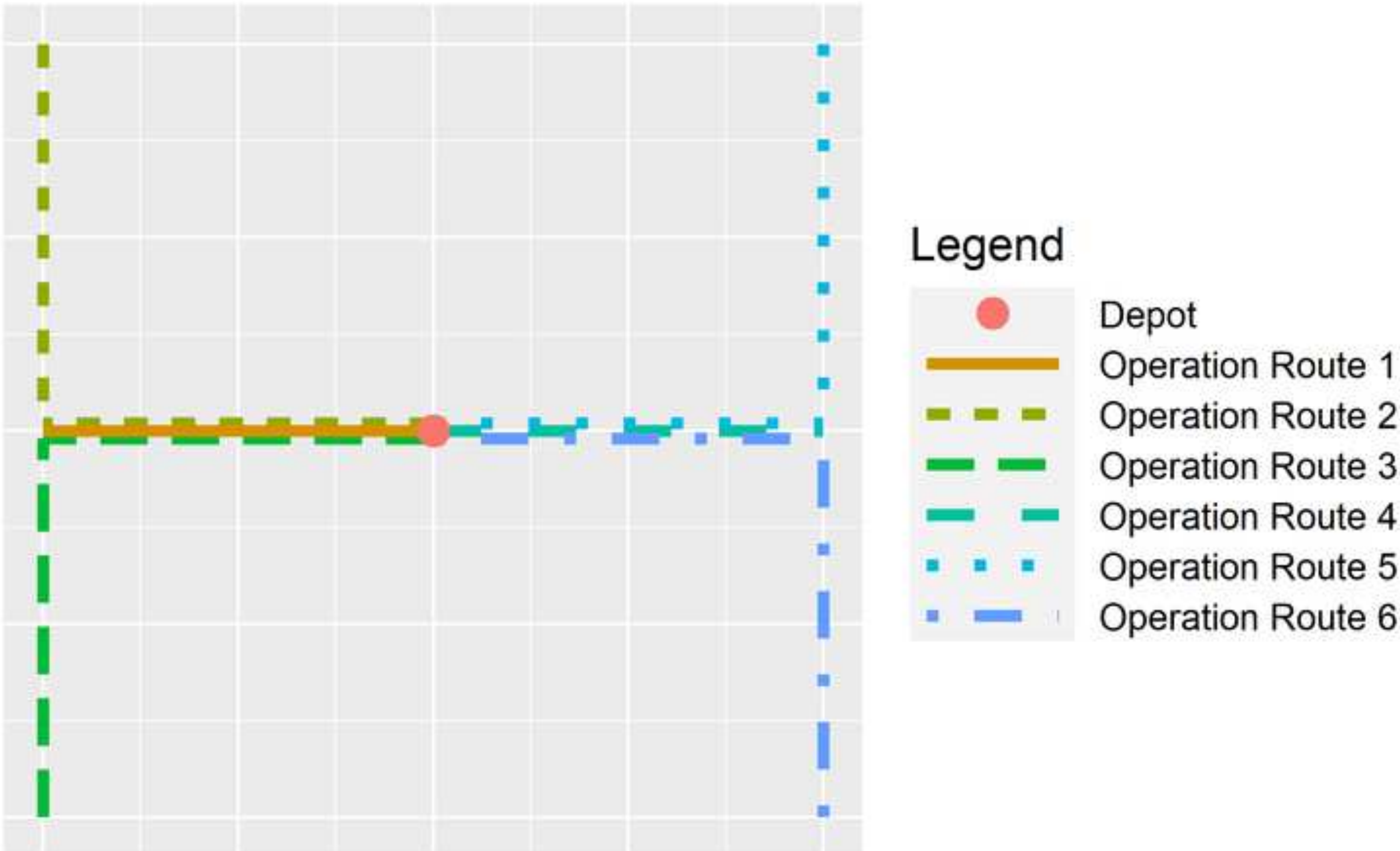
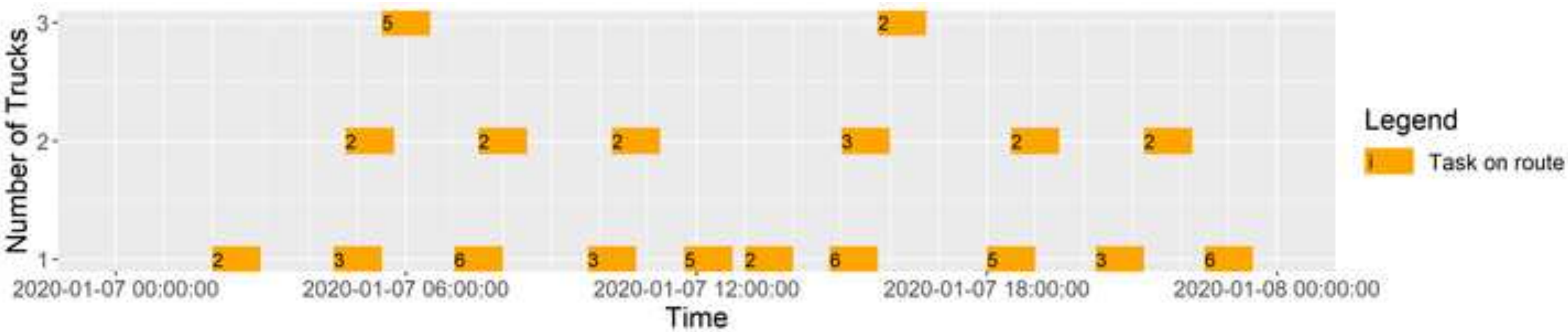

a
b
c
d
e
f
Legend
Depot
LOS class A
LOS class B
LOS class C
LOS class D
Weather Station A
Weather Station B
Weather Station C
Weather Station D

Figure 4



Legend
Depot
Operation Route 1
Operation Route 2
Operation Route 3
Operation Route 4
Operation Route 5
Operation Route 6

Figure 5



Number of Trucks
3
2
1
5
2
2
2
2
3
2
2
2
3
6
3
5
2
6
5
3
6
2020-01-07 00:00:00
2020-01-07 06:00:00
2020-01-07 12:00:00
2020-01-07 18:00:00
2020-01-08 00:00:00
Time
Legend
i
Task on route i

Figure 6

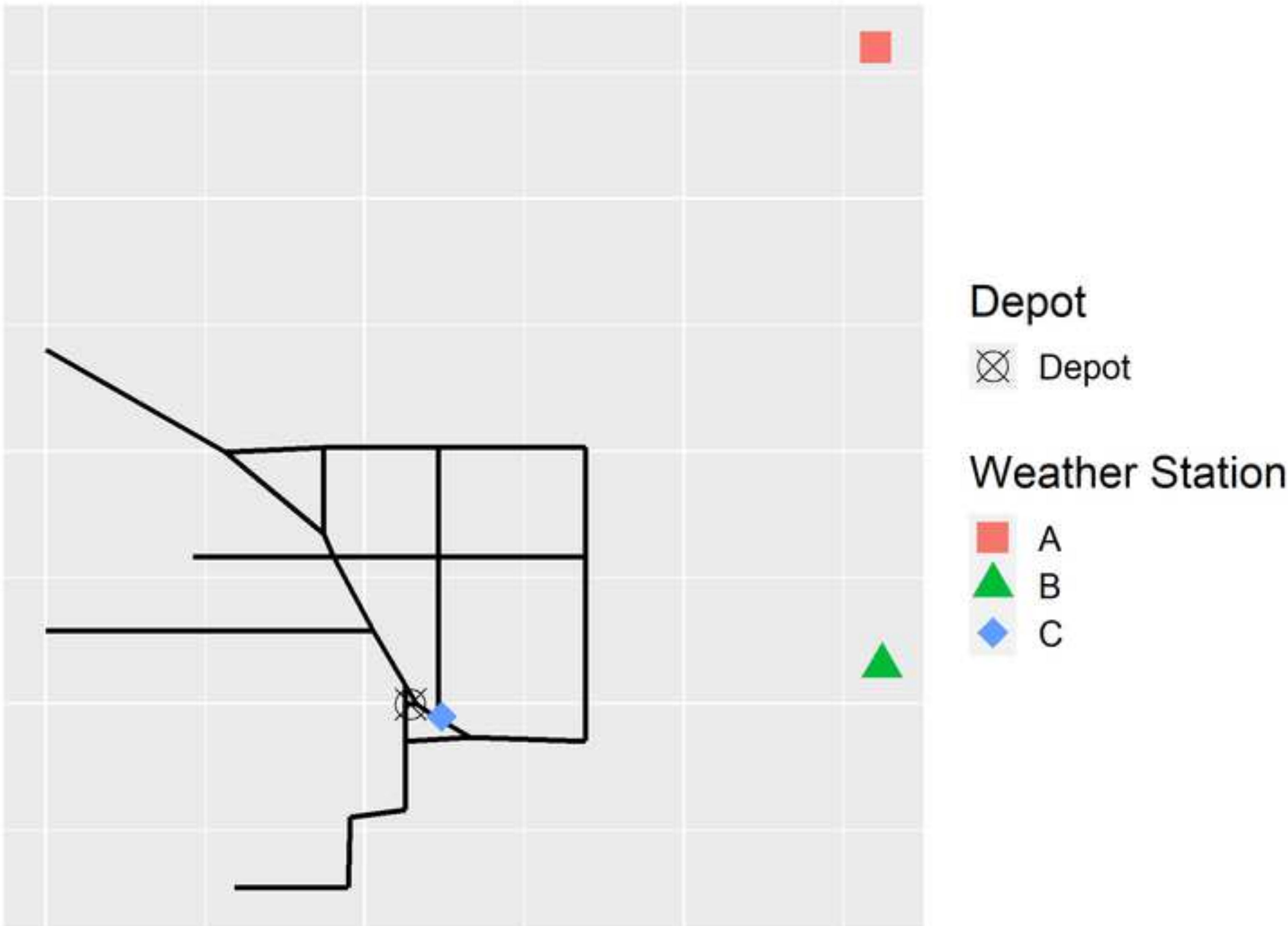
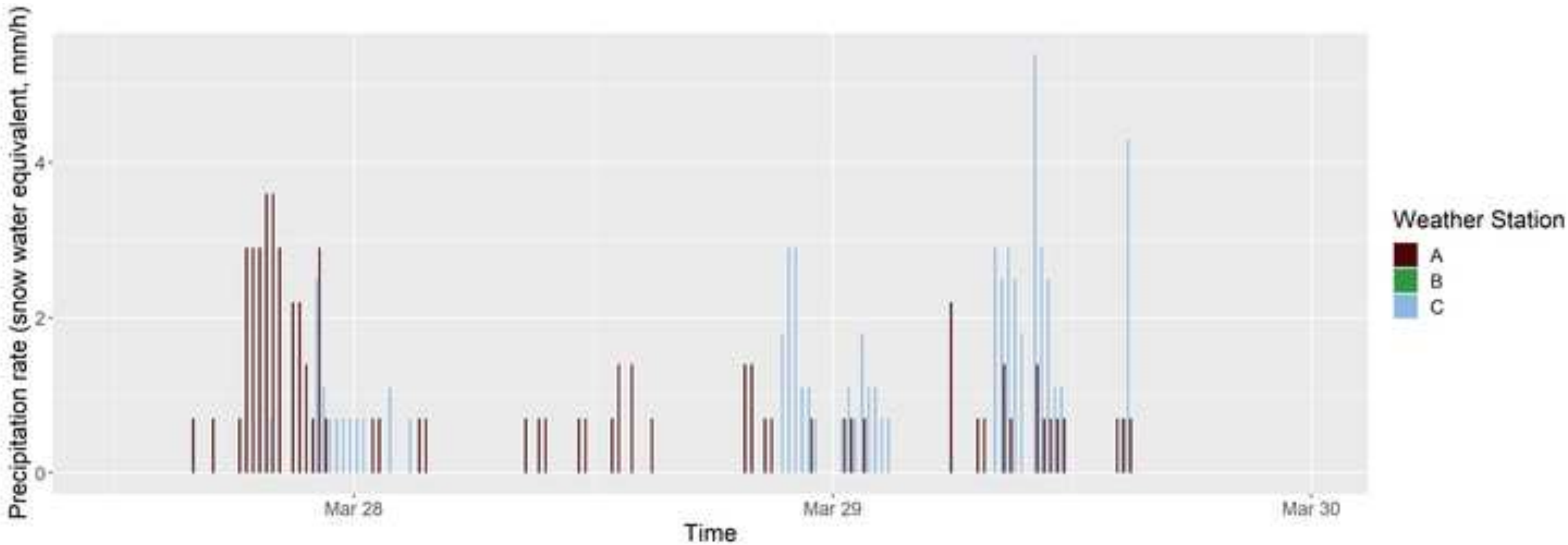


Figure 7



Precipitation rate (snow water equivalent, mm/h)
0
2
4
Mar 28
Mar 29
Mar 30
Time
Weather Station
A
B
C

Figure 8

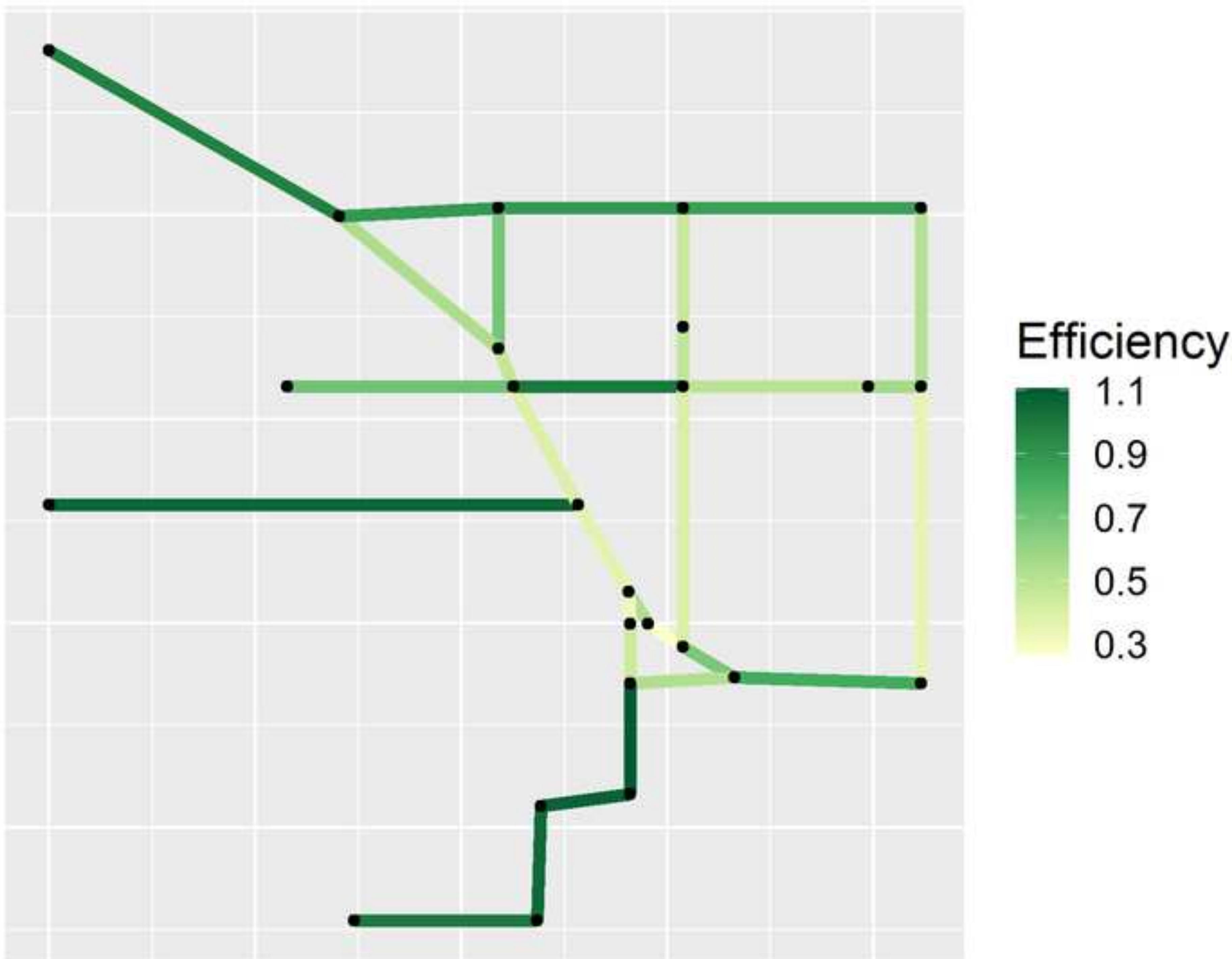


Figure 9

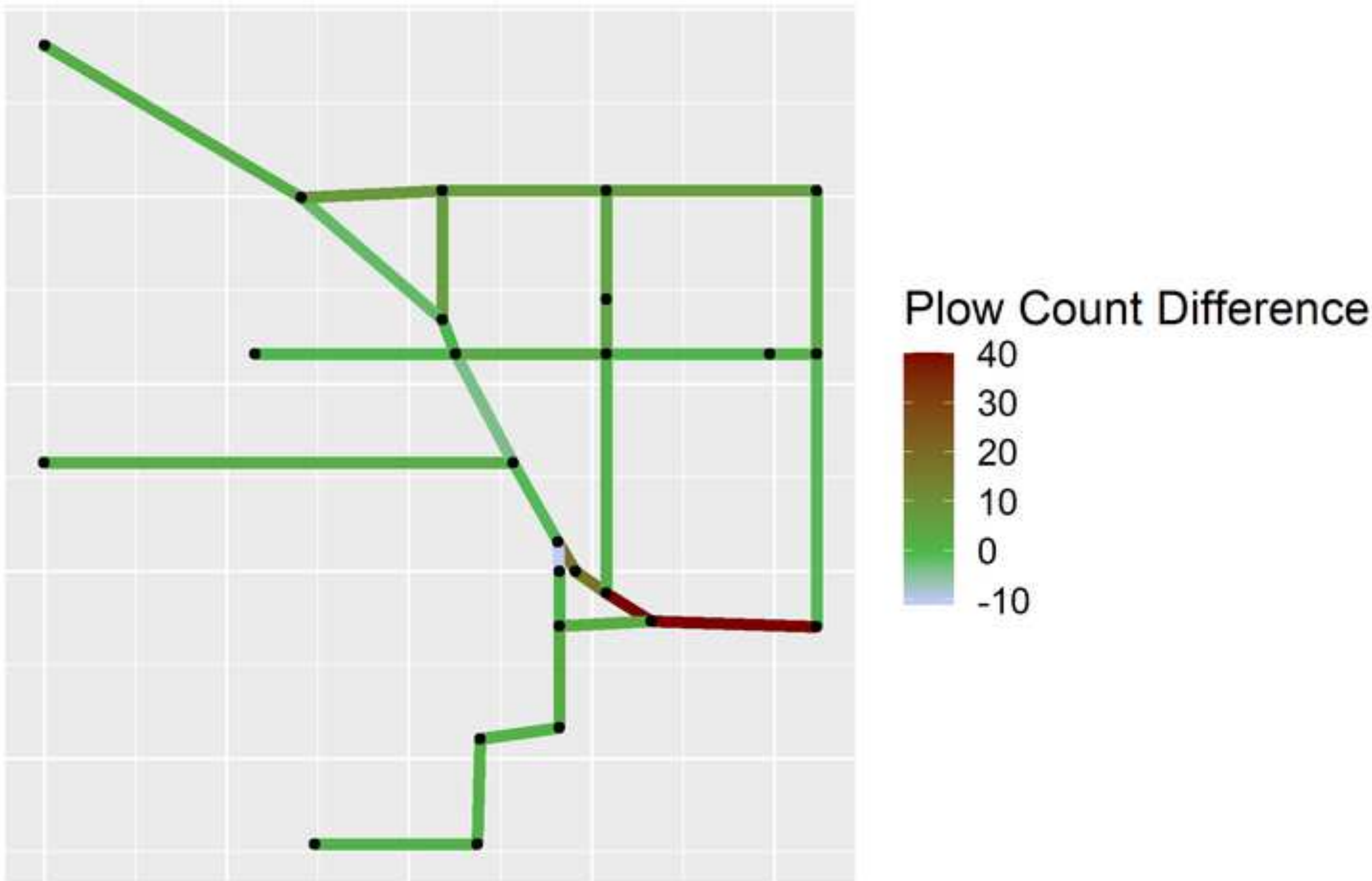


Figure 10

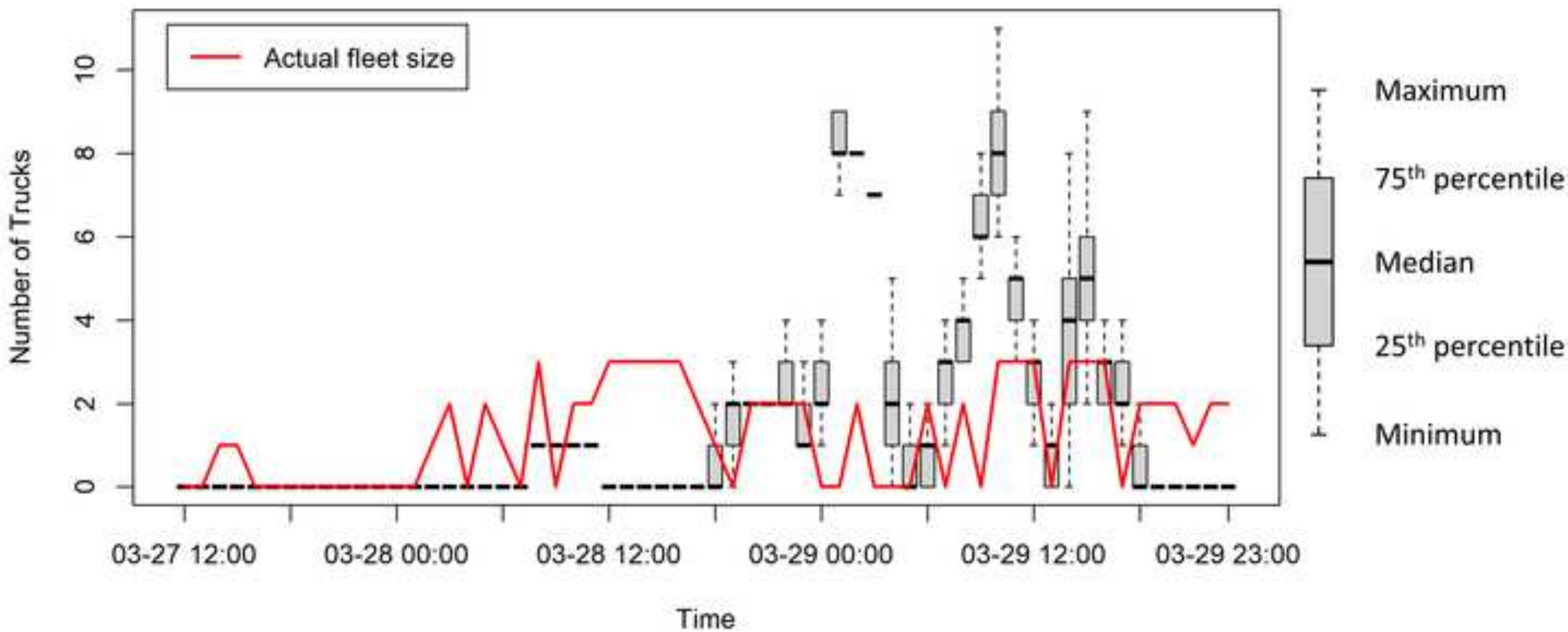
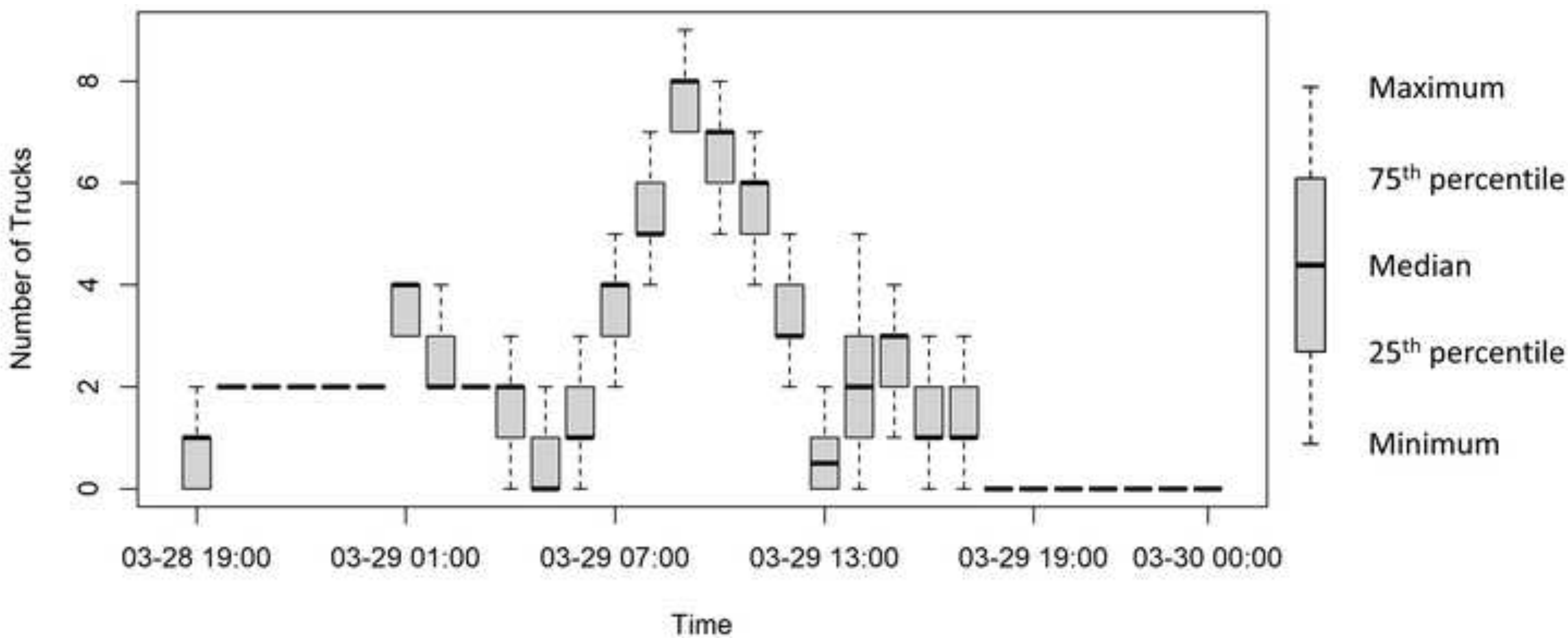

Actual fleet size
Number of Trucks
0
2
4
6
8
10
03-27 12:00
03-28 00:00
03-28 12:00
03-29 00:00
03-29 12:00
03-29 23:00
Time
Maximum
75th percentile
Median
25th percentile
Minimum

Figure 11



Number of Trucks
0
2
4
6
8
03-28 19:00
03-29 01:00
03-29 07:00
03-29 13:00
03-29 19:00
03-30 00:00
Time
Maximum
75th percentile
Median
25th percentile
Minimum

Figure B1

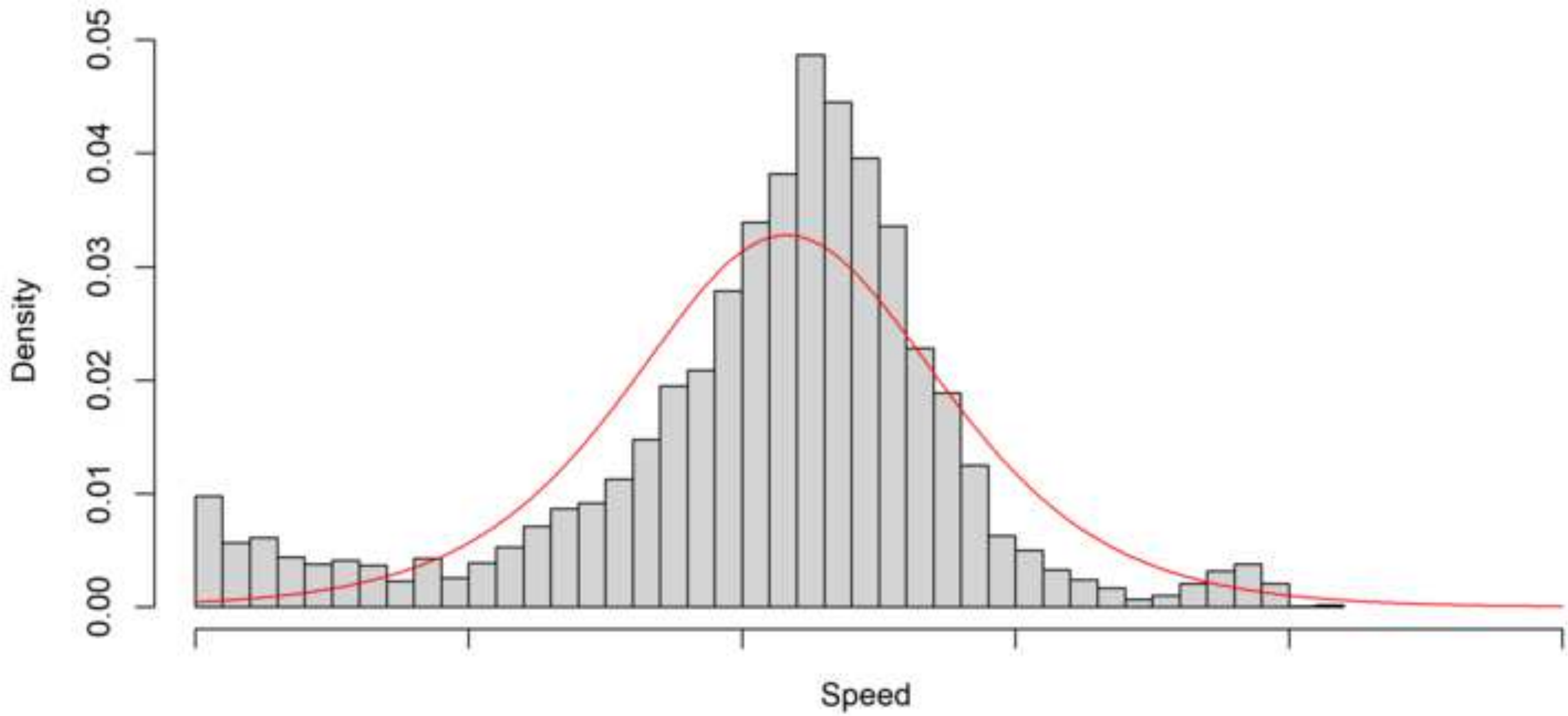


Figure B2

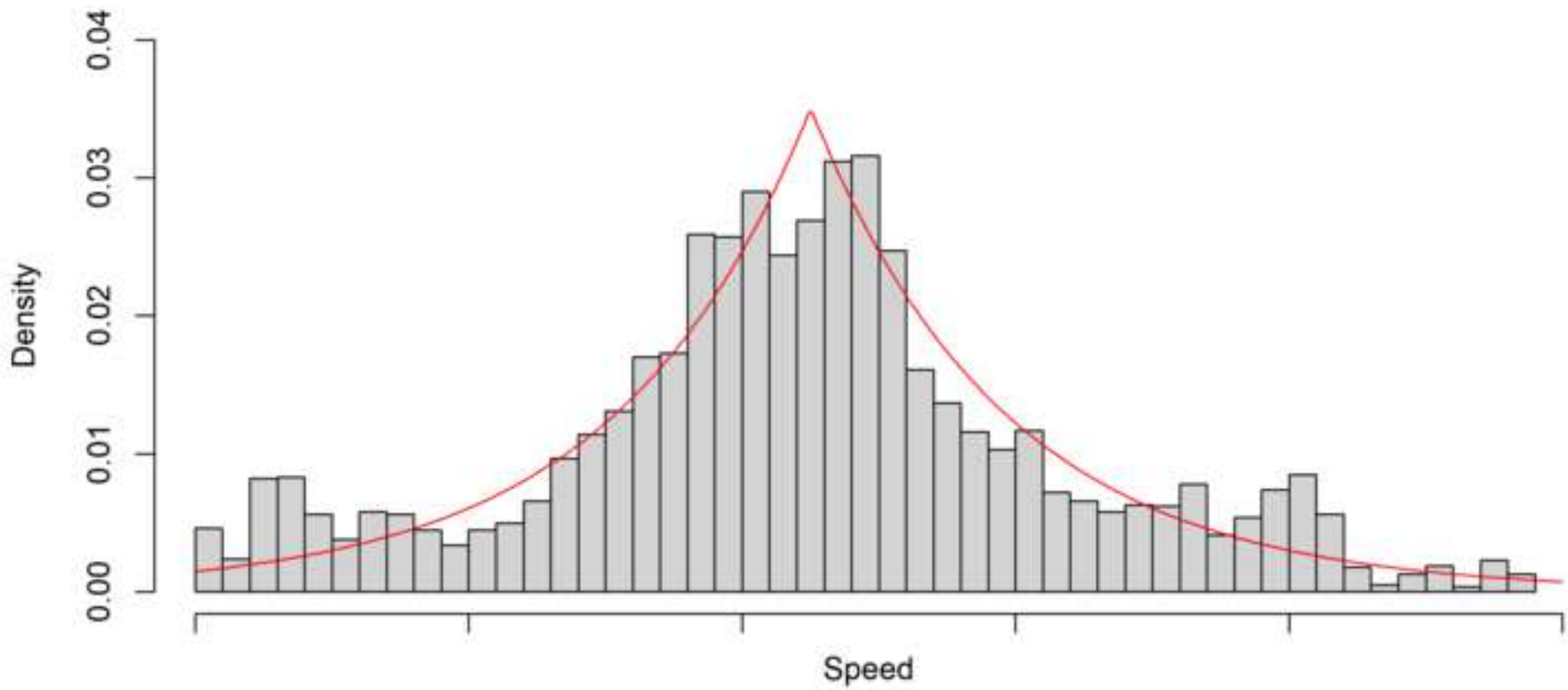


FIGURE CAPTION LIST