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Real-World Data Simulation Comparing GHG Emissions and Operational Performance of Two Sweeping Systems

Bechir Ben Daya [1,*], Jean-François Audy [1,2] and Amina Lamghari [1]

1 Department of Management, Université du Québec à Trois-Rivières, Trois-Rivières, QC G8Z 4M3, Canada; jean-francois.audy@uqtr.ca (J.-F.A.); amina.lamghari@uqtr.ca (A.L.)
2 Interuniversity Research Center on Enterprise Network, Logistics and Transportation (CIRRELT), Québec City, QC G1V 0A6, Canada
* Correspondence: bechir.ben.daya@uqtr.ca

Abstract: *Background*: In northern countries, spring requires the removal of large volumes of abrasive materials used in winter road maintenance. This sweeping process, crucial for safety and environmental protection, has traditionally relied on conventional mechanical brooms. Recent technological innovations, however, have introduced more efficient and environmentally friendly sweeping solutions; *Methods*: This study provides a comprehensive comparative analysis of the environmental and operational performance of these innovative sweeping systems versus conventional methods. Using simulation models based on real-world data and integrating fuel consumption models, the analysis replicates sweeping behaviors to assess both operational and environmental performance. A sensitivity analysis was conducted using these models, focusing on key parameters such as the collection rate, the number of trucks, the payload capacity, and the truck unloading duration; *Results*: The results show that the innovative sweeping system achieves an average 45% reduction in GHG emissions per kilometer compared to the conventional system, consistently demonstrating superior environmental efficiency across all resources configurations; *Conclusions*: These insights offer valuable guidance for service providers by identifying effective resource configurations that align with both environmental and operational objectives. The approach adopted in this study demonstrates the potential to develop decision-making support tools that balance operational and environmental pillars of sustainability, encouraging policy decision-makers to adopt greener procurement policies. Future research should explore the integration of advanced technologies such as IoT, AI-driven analytics, and digital twin systems, along with life cycle assessments, to further support sustainable logistics in road maintenance.

Keywords: street sweeping system; fuel consumption modeling; greenhouse gas emission modeling; simulation-based modeling; performance evaluation

Citation: Ben Daya, B.; Audy, J.-F.; Lamghari, A. Real-World Data Simulation Comparing GHG Emissions and Operational Performance of Two Sweeping Systems. *Logistics* **2024**, *8*, 120. https://doi.org/10.3390/logistics8040120

Academic Editor: Hao Yu

Received: 31 August 2024
Revised: 1 November 2024
Accepted: 11 November 2024
Published: 18 November 2024

1. Introduction

In northern countries such as Canada, winter road maintenance involves the application of several million tons of abrasive material. When spring arrives, a large portion of this material is removed by mechanical sweeping of the road network, a necessary step to enhance safety and minimize environmental and public health risks. Historically, conventional mechanical broom systems have been employed in the logistics of collecting and transporting these street sweepings. The modus operandi of these systems has remained unchanged until recently, when an innovative SME designed and manufactured a novel broom. This innovative broom brings a significant shift to road sweeping logistics by eliminating work interruptions inherent to conventional broom unloading. The novel broom operates by continuously loading sweepings into a dump truck while it sweeps, hence removing the bottleneck that often hampers sweeping operations.

This major technological shift of making the street sweeping collection container independent of the broom has the potential to enhance the broom's operational performance.

It is therefore imperative to evaluate this improvement opportunity in terms of productivity time, energy consumption, and associated greenhouse gas (GHG) emissions. However, no comparative evaluations have been made between this innovative broom mode and conventional brooms in terms of operational and environmental performance. Sweeping operations are carried out by a coordinated system of several vehicles working together to ensure safety and efficiency. This sweeping system is deemed innovative if the main broom is the novel one, in contrast to the conventional sweeping system that utilizes a traditional broom. The comparison of these two systems poses certain challenges due to the lack of real data on each system behavior and the necessity of developing appropriate emission models to assess the GHG emissions under varying contexts.

To surmount these obstacles, our research had two main objectives. Firstly, our goal was to develop effective data collection and processing methods to analyze the behavior of the sweeping systems, including their fuel consumption. Secondly, we aimed to design and develop simulation models, including GHG emissions models, to replicate sweeping behaviors and conduct a scenario-based sensitivity analysis to assess their emissions and operational performance.

These goals were achieved through a multi-stage integrated framework. Initially, cameras with embedded GPS were installed on brooms and trucks to collect real-world data. This approach was essential due to specific operational conditions, such as nighttime highway operations that raised safety concerns for researchers conducting extended on-site studies. Over two consecutive spring seasons, a substantial amount of data was collected, which introduced its own challenges. To address these, dual multi-classifier algorithms were employed to process the GPS data, allowing the extraction of relevant parameters.

Next, we developed simulation models to replicate the behavior of the sweeping systems studied to assess their performance. Alongside evaluating the operational performance indicator, the simulation models also incorporated GHG emissions calculation models to evaluate the environmental performance indicator. To enhance the comparative analysis, we applied a scenario-based sensitivity analysis approach, examining variations in key parameters—such as collection rate (CR), number of trucks and payload capacity, and truck unloading duration (TUD). This approach provides critical insights for decision-makers by highlighting the operational and environmental performance outcomes under different sweeping system configurations.

Our results show the superior performance of the innovative system, justified by its distinguishing attributes that ensure a faster, more efficient service with less waiting time than the conventional methods. Our study's findings have significant managerial and policy implications that can guide managers in reducing the GHG emissions of sweeping services. Policymakers can use these insights to develop lower-carbon-footprint public procurement procedures.

Following the Introduction, Section 2 reviews the relevant literature. Section 3 describes the materials and methods applied to evaluate and compare the performance of the sweeping systems. Section 4 presents the simulation results along with the sensitivity analysis and interpretations, while Section 5 provides concluding remarks.

2. Literature Review

This review begins by exploring the important role of spring street sweeping and the development of related technologies. It then examines the various tools facilitating data collection on logistics operations behavior. Following that, we discuss the potential for recreating these activities through simulation, culminating in the intricate task of modeling GHG emissions within logistics systems.

Street sweeping is a recognized strategy to mitigate various nuisances from remaining winter abrasive materials on the road network at springtime, as highlighted in [1]. Its significance is further emphasized by [2,3], who identify street sweeping as a paramount measure for controlling pollutants, especially in storm water runoff. Zhu et al. [4] emphasize the importance of these services, discovering a ten-fold surge in road dust emissions when a winter abrasive was employed. This aligns with the observation made in [5], who regard mechanical or manual street sweeping services as vital components of municipal solid waste management, a practice dating back centuries.

In response to the growing demand for efficient sweeping methods, advanced road sweeping vehicles have received increased interest, as noted in [6]. These technological advancements primarily target environmental objectives, such as dust control and eliminating contaminated fine particles. Amato et al. [5] categorize street sweepers by dividing them into three conventional types: mechanical, vacuum-assisted, and regenerative. Mechanical broom sweepers remain the preferred choice for many cities when managing considerable pollutants [6,7].

While research on sweeping technologies has primarily focused on strategies for gathering and handling fine particles, it often neglects logistics operations efficiency aspects. Traditional street sweeping collection and transportation logistics are firmly tied to conventional mechanical broom systems. This practice, however, has seen little progress. Arsenault Brothers' 2011 innovation—a mechanical front-loading conveyor broom developed in Quebec, Canada—sought to decouple the collection process from the unloading operation. This simple adjustment, shifting the collection container from the broom to a separate collector truck, has resulted in significant operational performance improvements. Continuous enhancements have positioned this model as a competitive contender in the sweeping market due to its expected higher operational efficiency compared to the conventional broom. To analyze the behavior of logistics systems, recent research relied on GPS data analytics, which can contain important information regarding vehicle movements, their waiting times, and their tasks

Laranjeiro et al. [8] demonstrated that detailed analysis of GPS data can effectively offer an in-depth perspective on the spatiotemporal patterns of freight vehicle movements. However, Shen and Stopher [9] note that while GPS trackers record individual locations and movements accurately, they lack information regarding the mode of travel or purpose of the trip. This sentiment is echoed by Pluvinet et al. [10], who acknowledge that GPS data often lack behavioral insights.

Broom behavior can be categorized into waiting, sweeping, or moving states based on average speed. Speed thresholds, as noted in [11], can be used to distinguish different vehicle states. The challenge lies in effectively utilizing GPS data to reconstruct the real behavior of complex logistical systems, all while managing the associated big data. To accomplish this, innovative analytical approaches capturing the true behavior of the sweeping system are needed.

Within the transportation and logistics system modeling realm, Milne and Watling [12] predicted that future models would be empirically driven rather than theoretically constructed. Simulation, as noted in [13], is useful in providing predictive, diagnostics, and prescriptive analytics for decision-makers. Vieira et al. [14], supporting this notion, proposed that simulation techniques could serve as proactive decision support systems in the supply chain. However, as pointed out in [15], these models and parameters are often based on outdated research or theoretical scenarios. This highlights the need for data replication from other sources and analysis grounded in modern Global Positioning Systems (GPS) and Geographic Information Systems (GIS). Furthermore, de Bok and Tavasszy [16] noted that while simulation models are sometimes used to assess freight transport policies strategically, many operational models lack the necessary behavioral detail to effectively simulate impacts of developments in logistic services, policy measures, or planning scenarios. Some supply chains require more complex variables for optimal logistics management, such as utilizing advanced technologies like the IoT and automated monitoring systems to enhance decision-making (see, e.g., [17,18] in the cold supply chain).

When analyzing the performance of a supply chain, the environmental aspect becomes crucial, as reducing GHG emissions is key in working toward carbon neutrality. The transportation sector—to which street sweeping belongs—is responsible for 20–25% of global energy consumption and emissions, making it a key contributor to climate change [19].

While much research has focused on using cleaner energy sources, the potential of technological innovations and process optimization, crucial for lowering emissions in the coming decades, has been overlooked. These innovations can complement the transition to alternative energy sources.

The environmental footprint of municipal solid waste management, such as street sweepings, has been a growing topic of interest in academic [20]. The authors conducted a comparative study of sweeping services in the medium-sized Italian cities of Pisa and Livorno, using a life cycle assessment methodology. They found substantial and unaccounted differences in GHG impacts between the two cities due to various assumptions, thereby amplifying the uncertainty of the results. Their research concluded that fuel consumption accounts for about 88% of climate change impact, underscoring its importance in the carbon footprint of sweeping services.

Concerning GHG emissions from logistics systems, the integration of fuel consumption and emission models is a common approach. Chen et al. [21] have proposed a framework that leverages data collected from GPS devices for map-matching, which, in turn, captures speed trajectories. The primary aim of this framework is to generate valuable insights into both the amount and distribution of energy consumption and emissions. Kan et al. [22], echoing these findings, noted that examining GPS big data collected from vehicles can further reveal crucial insights into the patterns of energy consumption and emissions. Additionally, Gan et al. [23] highlighted that most characteristics of trucking activities, a significant contributor to GHG emissions, can be effectively tracked using GPS data from the vehicles involved. The GHG emissions calculation model developed in [19] is built on experimental emission data adopted by the San Pedro Bay ports of Long Beach and Los Angeles [19]. This model correlates emissions by truck speed for evaluation purposes. However, the speed data used were derived from experimental measurements using trajectory detectors placed at significant distances. This detection method fails to capture micro-delays in truck movement, leading to an underestimation of average speeds between detection points. Consequently, this limitation compromises the accuracy of traffic simulation, which in turn affects the precision of the emission calculations.

Despite the limited literature on the street sweeping, the evaluation of both environmental and operational performance is rarely explored. Furthermore, research on assessing the carbon footprint of sweeping systems is virtually non-existent, with only one article [20] identified, which represents an initial partial attempt to address this topic. To fill this gap, there is a need for quantitative methods to establish procedures and standards for assessing the operational and environmental performance of various street sweeper technologies. These methods would also create a framework for ongoing assessment and improvement of sweeping practices. Currently, no evaluation has been conducted on the newly developed broom technology designed to contribute to a more sustainable and low-carbon future in road maintenance. This paper aims to bridge this gap.

Specifically, this study evaluates the operational and environmental performance of two different street sweeping technologies, demonstrating how technological advancements can play a key role in reducing emissions and enhancing operational efficiency. Through sensitivity analysis, the study provides valuable insights into how system configuration, based on specific contextual parameters, significantly impacts environmental and operational performance. By adjusting key parameters, the analysis helps identify effective configurations that minimize emissions, showing how system setup can be tailored to specific conditions for improved outcomes.

This paper offers the following scientific contributions, which have important managerial and policy implications:

- Designing an on-board data acquisition system and processing large datasets using machine learning (ML) for supervised dual multi-classification algorithms;
- Developing GHG emissions models based on fuel consumption (FC) models through regression analysis and probability distribution;

- Developing, implementing, and validating simulation models for complex sweeping logistics systems, integrating GHG emissions models;
- Conducting an extensive sensitivity analysis across 240 scenarios to strengthen simulation recommendations and guide decision-makers on effective system configurations, considering operational and environmental performance.

3. Materials and Methods

This study employs an integrated framework that merges a simulation model with a GHG emissions model. This unified structure replicates the real-world behavior of the investigated sweeping systems, enabling a comprehensive assessment of their operational efficiency and environmental impact. The framework is guided by a data collection and processing methodology. The framework consists of several key components:

- Description of sweeping systems: provides a detailed description of the sweeping systems being evaluated;
- Data acquisition and processing methodology: outlines the methods used to collect and process data relevant to the sweeping systems' operations;
- Development and validation of the simulation model: describes the development and validation process for the simulation model that will replicate the sweeping systems' behavior;
- Creation and integration of a GHG emissions model: details the development and integration of a GHG emissions model based on the sweeping systems' fuel consumption patterns;
- Result presentation, sensitivity analysis, and interpretive discussions: incorporates methods for presenting the results, conducting sensitivity analyses, and interpreting the findings to provide valuable insights.

This methodological blueprint serves as the foundation of our study, systematically guiding us through the evaluation of sweeping systems for both operational and environmental performance. Figure 1 illustrates the data processing framework, starting from raw data and progressing to the development of simulation models, which incorporate fuel consumption models.

3.1. Description of Sweeping Systems

In North America, conventional mechanical sweepers dominate the streetscape. These machines utilize spinning gutter brooms and water sprays to control dust and effectively handle a wide variety of debris, from trash and road scraps to vegetation. An innovative sweeping system (ISS) disrupts this traditional approach by eliminating some of the operational interruptions that plague conventional sweeping system. Unlike its counterparts, the ISS boasts a novel broom design (Figure 2b) that enables continuous loading onto a dump truck (Figure 2a). This eliminates the need for frequent stops to unload sweepings, a significant bottleneck in conventional sweeping. This technological leap translates to a substantial improvement in operational efficiency.

The ISS typically comprises one or two collector trucks, an innovative front broom for the first pass, a conventional broom for finishing, a water tanker, and an impact attenuator truck (Figure 2c). In contrast, the conventional sweeping system (CSS) typically includes one or two collector trucks, two conventional brooms, a water tanker, and an impact attenuator truck (Figure 2d).

Our research delves into a detailed comparison between these two systems. We leverage both real photographs and visuals derived from simulation models to provide a comprehensive understanding of each system's operation. This research extends beyond theoretical analysis, aiming to provide practical insights that can enhance the efficiency and environmental sustainability of real-world street sweeping practices.

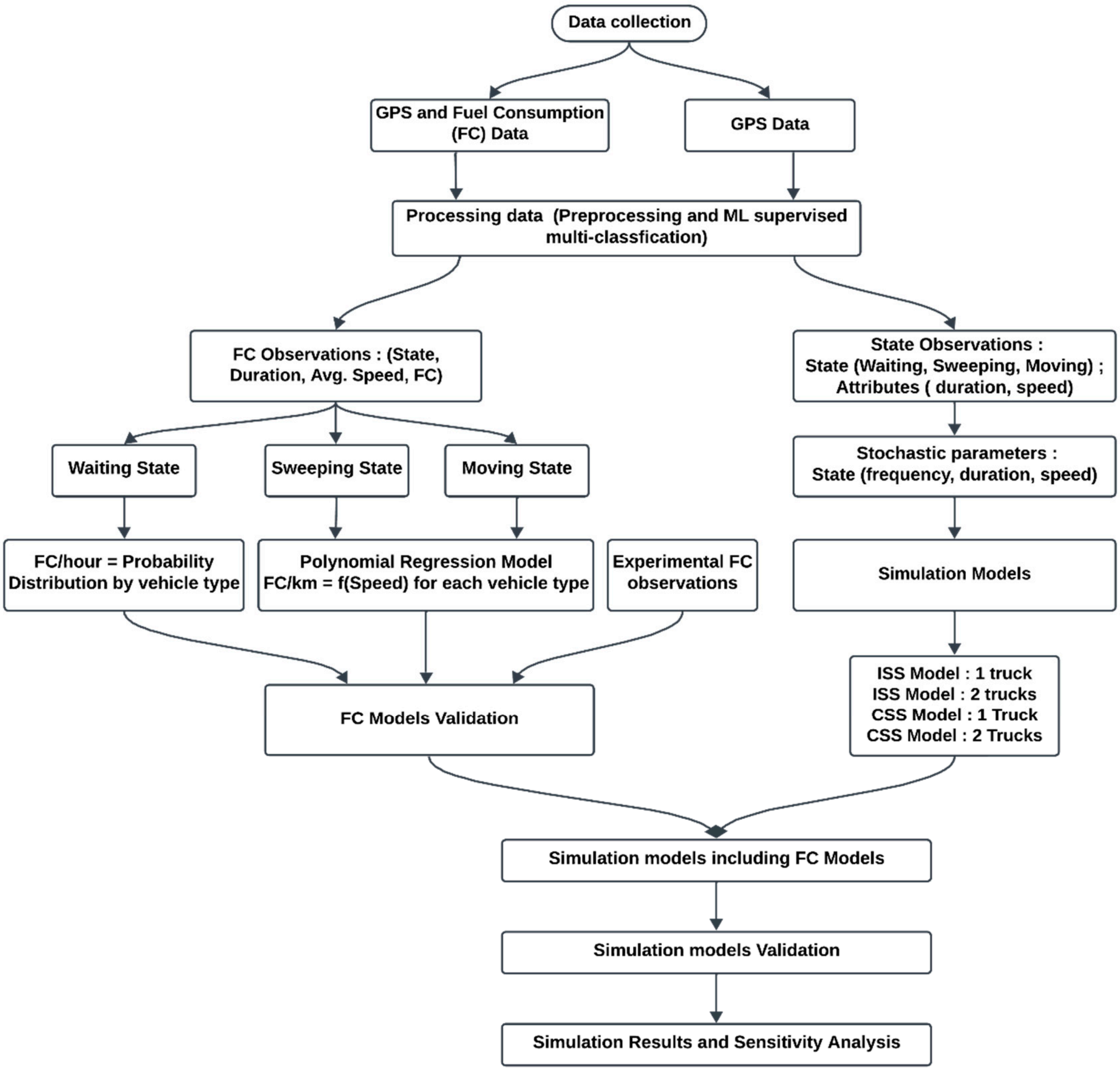


Figure 1. Flowchart of data processing from raw data to simulation models.

3.2. Simulation Models Building

To accurately replicate sweeping operations, we begin by meticulously outlining the process. This detailed breakdown helps us pinpoint key parameters and variables relevant to our study's objectives. Following this initial step, we construct conceptual models and populate them with parameters derived from real-world data. Finally, these models undergo a rigorous validation process before being deployed for evaluative and predictive purposes. The notation used for these steps is outlined in Table 1 and will be consistently applied throughout this paper.

3.2.1. Sweeping Process Description

The description of the sweeping process involves identifying the tasks and states related to the sweeping system during the performance of a sweeping activity. The goal is to identify simulation parameters and variables that could be used to assess the system's performance.

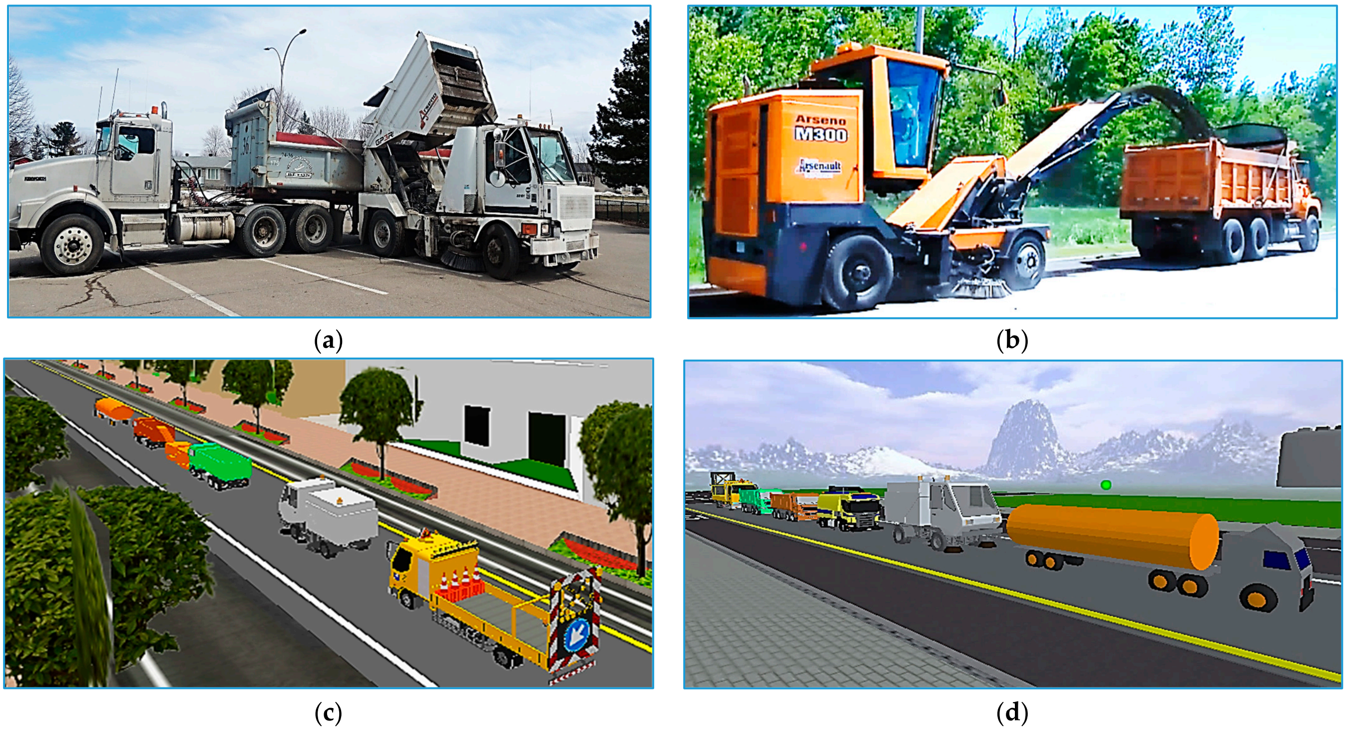


Figure 2. Description of sweeping systems. (**a**) Unloading interruption for the conventional broom sweeper. (**b**) The novel broom sweeper in operation. (**c**) Components of the ISS: tanker, front-loading truck, novel broom, secondary collector truck, conventional broom for finishing, and an impact attenuator truck. (**d**) Components of the CSS: tanker, primary conventional broom, secondary conventional broom for finishing, two collector trucks, and an impact attenuator truck.

Table 1. Abbreviations and notations.

Sweeping systems	
ISS	Innovative sweeping system
CSS	Conventional sweeping system
Parameters	
SRT	Simulation run-time
SS (Stochastic)	Sweeping speed
MS (Stochastic)	Moving speed
EF	Emission factor
TN	Truck number as the number of trucks involved in the sweeping activity
N_w (Stochastic)	Number of waiting states per shift or SRT
d_w (Stochastic)	Duration of a waiting state
N_s (Stochastic)	Number of sweeping states per shift or SRT
d_s (Stochastic)	Duration of a sweeping state
N_m (Stochastic)	Number of moving states per shift or SRT
d_m (Stochastic)	Duration of a moving state
N_u	Number of trucks moving for unloading per shift or SRT

Table 1. *Cont.*

F_w (Stochastic)	Waiting state frequency
F_s (Stochastic)	Sweeping state frequency
F_m (Stochastic)	Moving state frequency
d_u (Stochastic)	Duration of a truck moving for unloading
CR (Stochastic)	Collection rate of sweeping
Variables	
QSC_{ISS}	Quantity of sweepings collected by the ISS per shift or SRT
QSC_{CSS}	Quantity of sweepings collected by the CSS per shift or SRT
DistSweepISS	Distance traveled in the sweeping states for ISS per shift or SRT
DistMovISS	Distance traveled in moving states for ISS per shift or SRT
DistSweepCSS	Distance traveled in sweeping states for CSS per shift or SRT
DistMovCSS	Distance traveled in moving states for CSS per shift or SRT
DurWaitISS	ISS waiting duration per shift or SRT
DurWaitCSS	CSS waiting duration per shift or SRT
Fuel consumption model	
FCh_{NbWait}	FC per hour for the novel broom in the waiting state
$FCkm_{NbSweep}$	FC per Km for the novel broom in the sweeping state
$FCkm_{NbMov}$	FC per Km for the novel broom in the moving state
FCh_{CbWait}	FC per hour for the conventional broom in the waiting state
$FCkm_{CbSweep}$	FC per Km for the conventional broom in the sweeping state
$FCkm_{CbMov}$	FC per Km for the conventional broom in the moving state
FCh_{TrWait}	FC per hour for the truck in the waiting state (all types of trucks)
$FCkm_{TrSweep}$	FC per Km for the truck in the sweeping state (all types of trucks)
$FCkm_{TrMov}$	FC per Km for the truck in the moving state (all types of trucks)
$FCkm_{MovTrUnload}$	FC per Km for the truck in the unloading moving trip
GHG Emission Model	
$GHG_{Total-ISS}$	Total GHG emissions by the ISS per shift or SRT
$FC_{WaitISS}$	Total ISS GHG emissions resulting from waiting states per shift or SRT
$FC_{SweepISS}$	Total ISS GHG emissions resulting from sweeping states per shift or SRT
FC_{MovISS}	Total ISS GHG emissions resulting from moving states per shift or SRT
$FC_{MovTrUnload}$	Total ISS GHG emissions resulting from moving of trucks for unloading per shift or SRT
Performance indicators	
Environmental	
GHG_{ISS-T}	GHG emissions of the ISS per sweepings ton
GHG_{CSS-T}	GHG emissions of the CSS per sweepings ton
Operational	
DistSweepISS	ISS distance swept (Km) per shift or SRT
DistSweepCSS	CSS distance swept (Km) per shift or SRT

On highways, the planned sweeping service covers bridges, junctions, and highway exits/entrances. Hence, transitioning between different zones and waiting periods for various reasons (e.g., coordination among the vehicles of the fleet, maintenance, refueling, and personal needs) are considered integral to the sweeping activities. Accordingly, the sweeping service encompasses three states: sweeping, moving, and waiting. The key distinguishing factor among these states is the speed of the vehicles involved. This distinction is vital to understand the behavioral logic of the sweeping system.

The simulation begins when the brooms and trucks arrive at the highway area designated for sweeping. The steps for the sweeping process, taking into account the use of one or two collector trucks for both the ISS and the CSS, are detailed bellow.

For the ISS

(a) The system initiates the sweeping activity, with all participating vehicles assumed to move at the same speed and in the following sequence:
   - The leading tanker sprays water to control dust.
   - The collector truck follows, trailed by the novel broom performing the primary sweeping activity.
   - The second collector truck follows, if any are available.
   - The conventional broom performs the finishing sweeping activity following the novel broom or the second collector truck, when present.
   - The impact attenuator truck brings up the rear to ensure the safety of the fleet and highway users.

(b) The entire sweeping system enters a waiting state when the truck transports the sweepings for unloading, in the case of a single collector truck. However, when two trucks are available, the sweeping activity continues using the second collector truck.

(c) The truck then travels to the designated dump area to empty its load and returns to serve as the collector truck directly if any truck is present or comes behind the novel broom, ready to replace an upcoming full collector truck

(d) The broom resumes sweeping as soon as the truck arrives, in the case of a single collector truck. However, when two trucks are present, the arriving truck assumes the position behind the brooms as the secondary collector truck.

(e) Steps (a) to (d) are repeated until the scheduled work concludes, accounting for various waiting periods and transitions between different sweeping areas, all conducted at the same speed.

For the CSS

(a) The system begins the sweeping activities, with all involved vehicles moving at the same speed and in the following sequence:
   - The leading tanker sprays water to control dust.
   - The two conventional brooms follow; the first performs initial sweeping, and the second provides finishing.
   - One or two collector trucks follow.
   - The impact attenuator truck brings up the rear to ensure the safety of the fleet and highway users.

(b) When a conventional broom reaches full capacity, it unloads its contents onto the available truck at the nearest highway exit.

(c) When a truck is full, it drives to the designated dumping area to empty its load and then returns to the next highway exit near the broom's location. If only one truck is available and one of the brooms is full when the truck is unavailable, the sweeping system halts at the first highway exit until the collector truck arrives.

(d) Steps (a) to (c) are repeated until the scheduled work concludes, factoring in various waiting periods and transitions between sweeping areas, all carried out at the same speed.

Building on the mapped processes described above, the parameters and variables for the simulation model are identified as follows:

Deterministic Parameters

These parameters pertain to the truck capacity, assumed 16t or 24t, based on the trucks actually used by the service provider. The capacity of the conventional broom is assumed to be 4 tons. The speed of the truck going for unloading is assumed to be 50 km/h, an average value provided by experienced personnel of a sweeping service provider.

Stochastic Parameters

The stochastic parameters encompass the following:

- States Frequency: The frequency of each state—sweeping (Fs), waiting (Fw), and moving (Fm). The frequency Fi for each state i (where i corresponds to "m" for moving, "w" for waiting, and "s" for sweeping) is calculated by dividing the number of occurrences of that state Ni by the total sum of occurrences for all states $\sum Ni$ (i: s, w, m).
- Sweeping Speed: This is the speed of the broom in the sweeping state and is assumed to be constant during a particular state for the different vehicles within the same system (whether ISS or CSS).
- Moving Speed: This is the speed of the broom in the moving state between sweeping areas and is assumed constant during a particular state for the different vehicles of both the ISS and CSS.
- State Time Duration: This refers to the duration of the sweeping, moving, and waiting states.
- Sweepings CR: Sweepings are collected at this rate per unit of distance (tons/km).
- TUD: This is the time required for unloading a truck, including the round-trip travel time to the depots (temporary storage of sweepings) and the actual unloading time.

Variables and Performance Indicators

To generate results and assess the performance of the sweeping systems, we consider a range of variables and indicators. These include the following:

- Time allocated to sweeping, waiting, and transition during a given work shift or simulation duration.
- Distance covered and amount of material collected over a work shift or simulation duration.
- Fuel consumption, which varies based on the system's state and type of vehicle involved.
- GHG emissions, broken down by state of operations and vehicle type.
- Emissions per tonne of material collected, serving as an environmental performance metric.
- Distance swept per unit of time or per work shift, used as an operational performance indicator.

3.2.2. Methodology for Gathering and Refining Simulation Parameters

Data Collection

To gain a deep understanding of how sweeping systems operate under various conditions, we outfitted sweepers with front and rear cameras integrated with GPS. Real-world data collection was crucial due to the unique challenges of sweeping operations, such as nighttime work, safety considerations, and dust emissions. These cameras captured comprehensive datasets encompassing sweeping locations, equipment used, weather conditions, and truck fill levels. They also aided in identifying the causes of waiting states during operations.

Over the spring of 2019, we collected over 415 h of video footage across 67 shifts, resulting in 3.5 Tb of data. Using Dashcam Viewer software Version 3.3.2, we extracted geolocation data into KML (Keyhole Markup Language) and CSV files. Each second of video corresponded to a line of GPS data. In total, the footage yielded nearly 1.5 million lines of structured GPS data, which were then organized in a database segmented by shifts and sweeping system types.

Data Processing

We manually processed approximately 17% of the GPS data using classification and clustering methods in MS Excel to identify the different states of sweeping activity based on speed metrics. The speed thresholds were informed by empirical findings, as indicated in [24]. This process involved classifying records into sweeping, waiting, and moving states, with video footage used to validate the classifications.

This manual classification served two key purposes. First, it verified the accuracy of the identified states, allowing for any corrections to be made. Second, short-duration states were consolidated with adjacent states based on corroborating video evidence. Additional information, such as the quantity of sweeping collected (full truckload of 16t or 24) and unloading time, was also inferred from the video records.

Given the vast amount of data, this manual approach is not suitable for real-world applications. Therefore, we employed supervised dual multi-classification machine learning techniques for the remaining 83% of the data, following the methodology outlined in [24]. This approach achieved an accuracy rate of over 87% and was used to infer the behavior of the sweeping systems.

Based on these structured and validated data, we identified various observation vectors for both ISS and CSS systems, including the follows:

- Sweeping and moving speeds;
- Sweeping, moving, and waiting duration;
- State frequencies (proportion of observations for sweeping (Fs), waiting (Fw), and moving (Fm));
- Additional parameters, such as CR and TUD, were inferred from video observations, and probability distributions were then fitted to these observations to generate random variables for the simulation models.

Finally, we fitted probability distributions to these empirical observations. These distributions will be used to generate random variables that will inform our simulation models.

3.2.3. Simulation Models Design

SIMIO software facilitates the implementation of the conceptual model through its predefined library of objects, processes, and entities. The conceptual model is organized into six logical subsystems, denoted as P1 to P6. Each subsystem has a specialized function and interacts cohesively with the others through algorithms embedded within SIMIO's processes. Presented below is a breakdown of the specific roles each subsystem performs:

- P1: Initiating states;
- P2: Monitoring states;
- P3: Reinitiating triggered states;
- P4: Managing truck's fill levels;
- P5: Supervising truck unloading;
- P6: Regulating truck shifts.

Each of these components is governed by a set of processes triggered at the beginning and end of each state. These processes manage statistics, calculate variables, and allocate parameters to various resources and states. They also monitor the fill levels in the trucks and oversee the unloading process.

A more detailed explanation of the roles of the different components is provided in Figure 3.

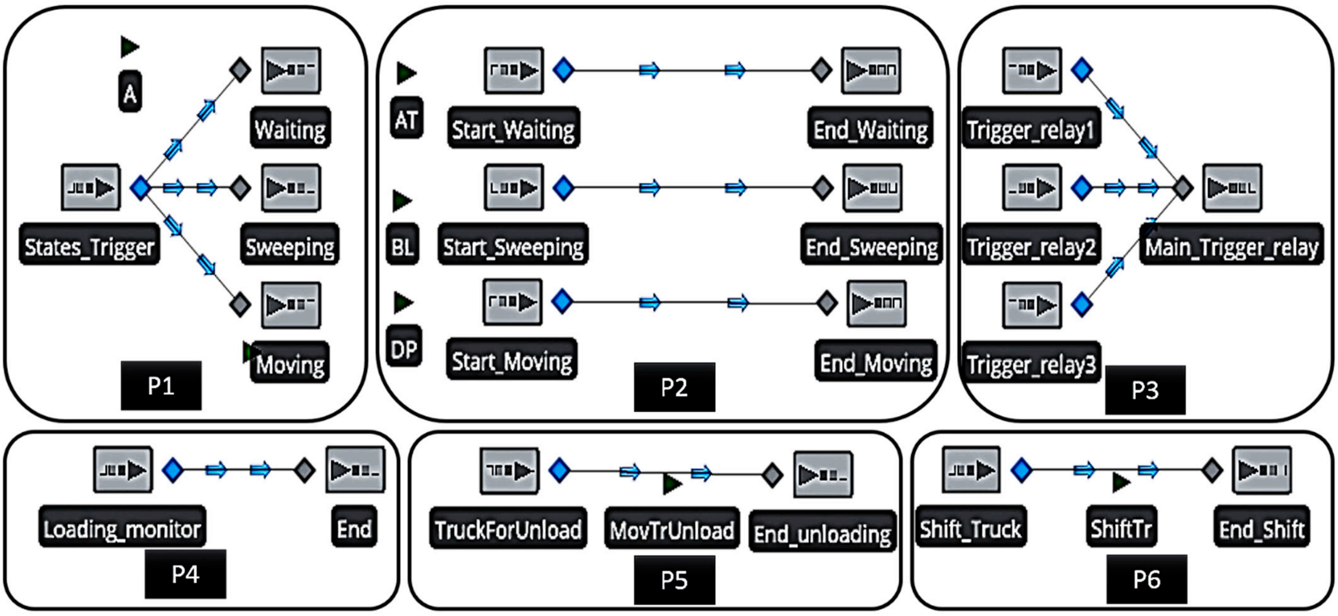
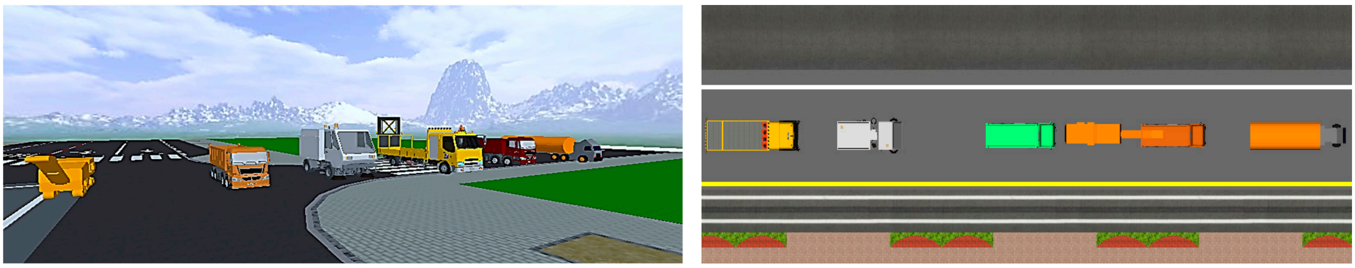


Figure 3. Architectural framework of the simulation model components.

P1: Initiating States

The State Initiation System, or Triggering States, includes a single source, a linked entity, and three distinct sinks. These sinks connect to the source through specialized connectors, each allowing entities to pass at predetermined frequencies. Each sink plays a specific role: initiating an operational state. The first sink triggers the "waiting" state, the second initiates the "sweeping" state, and the third activates the "moving" state. A pre-launch 3D visual representation of this configuration is depicted in Figure 4a.



(**a**) (**b**)

Figure 4. Two- and three-dimensional visualizations of the innovative sweeping system. (**a**): ISS before starting activity (3D image); (**b**) ISS after starting activity (2D image).

P2: Monitoring States

The duration and speed allocation system, designated as P2, comprises three distinct sources, each aligned with a unique entity and corresponding sink. Activation for this system stems from the state initiation mechanism in P1. Once activated, the particular source initiates a process that governs the state in question, allocating both speed settings for the involved vehicles—such as brooms and trucks—and specifying the duration of the current state. A 2D visualization of this system configuration post-activation is provided in Figure 4b. Upon the conclusion of the allocated state duration, the entity proceeds to the terminating sink, which subsequently cues the subsequent system, P3, to instigate a new state.

P3: Reinitiating Triggered States

The reinitiating triggered state, also known as P3, consists of a trio of sources, a singular entity, and a dedicated sink. Each source is triggered by its corresponding sink from the monitoring states (P2), signifying the end of the specific state in operation. These sources collectively funnel into a single sink, which serves as the launching pad for instigating a new state. Essentially, this system operates as a relay hub that facilitates the re-initiation of original states.

While the three subsystems (P1–P3) generally operate in a cyclical fashion, subsystem 4 serves as an exception by overseeing truck load levels and temporarily pausing sweeping activities for any truck that reaches full capacity.

P4–P5: Managing Truck's Fill Levels and Unloading

The fill level management component (P4) springs into action once the sweeping state is initiated, keeping track of the collector truck's fill level. Comprising a single source and sink, this subsystem checks the loading status at five-second intervals through a specialized process. When a truck reaches full capacity, especially in scenarios involving just one collection vehicle, this system interrupts the sweeping phase, momentarily suspends all vehicular activities, and orchestrates the truck's round trip to the designated unloading area, managed by the supervising truck unloading components (P5). Upon the truck's return, sweeping operations resume, with the system continuously cycling through these steps until the simulation concludes.

P6: Regulating Collector Truck Changeover

In scenarios involving a second collector truck, the sweeping operations are seamlessly maintained by utilizing the second truck during the unloading of the first. In this system's visual representation, the second truck transitions to a lead role in proximity to the new broom ISS, facilitated by the regulating collector truck changeover component (P6). Once the first truck completes the unloading process and returns, it assumes a trailing position behind the broom, serving as a secondary collection unit.

A comprehensive depiction of the simulation model is provided in Figure 5.

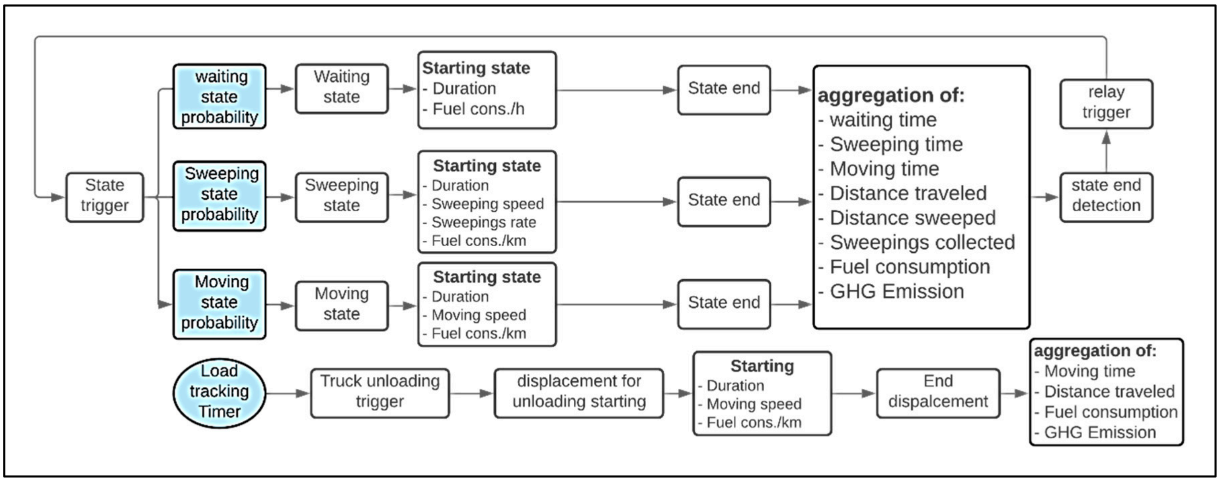


Figure 5. Comprehensive overview of the conceptual simulation model.

The simulation model, as outlined and elaborated upon, has been executed using the 64-bit version of SIMIO software, Version 14. The setup was implemented on a laptop PC equipped with an i5-4300u CPU running at a speed range of 1.9–2.5 GHz and bolstered by 16 GB of RAM. In total, four unique simulation models were created, representing two separate sweeping systems and two operational scenarios. These scenarios considered configurations involving either a single collector truck or a dual-truck setup.

3.2.4. Validation of Simulation Models

The simulation models are run for a duration of 500 h. Validation is carried out by juxtaposing the average outcome of various parameters against the benchmarks set by static models, which were developed using MS Excel. The discrepancies observed are minimal: for the ISS model, the average deviation is around 2.2% with a standard deviation of 2%, and for the CSS model, the average deviation is approximately 1.2% with a standard deviation of 1.1%.

3.3. Greenhouse Gas Emission Models

This section outlines the sequential steps taken in the formulation of the greenhouse gas emission models (GHGEMs), as illustrated in Figure 6. The methodology encompasses the data acquisition, their subsequent processing, and the ultimate construction of the GHGEMs.

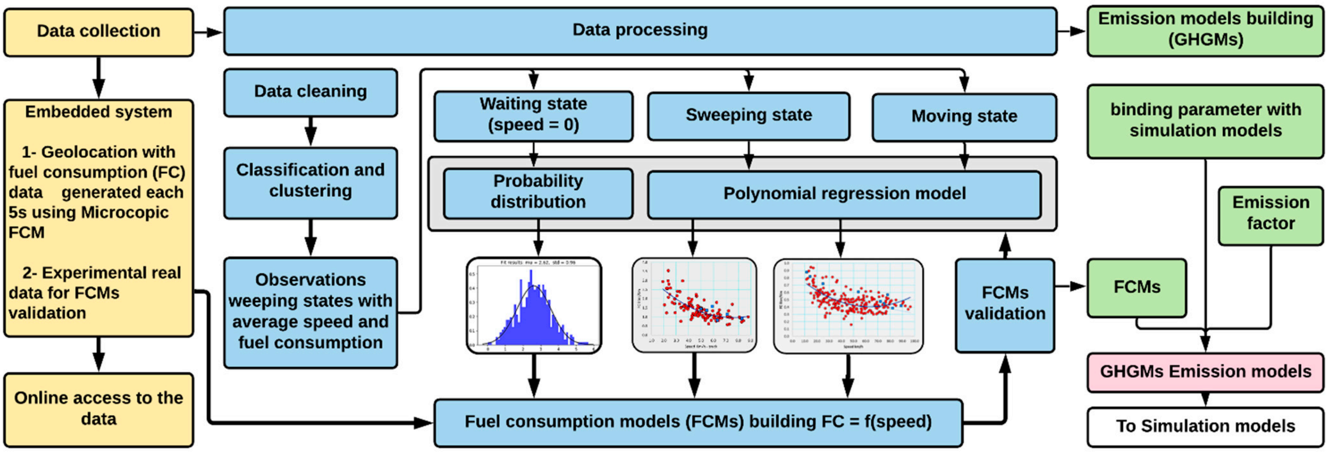


Figure 6. Framework for the GHG emissions models.

3.3.1. Data Collection Methodology

To gather the necessary data, a specialized monitoring system was installed on two vehicles: a Mercedes MBE 4000 truck with a 12.8 L engine and an innovative broom model equipped with an 8.3 L Cummins engine. This system collected data points at high resolution every five seconds, transmitting them to an online platform for easy access and analysis. The data captured a range of metrics including vehicle identification, time, geolocation (latitude and longitude), speed, distance traveled, and fuel consumption rates. During spring 2020, this system collected approximately 90,000 data observations from both vehicles. Fuel consumption was estimated using a detailed model that considers the engine's instantaneous power output.

3.3.2. Data Processing for State Classification

This stage focused on cleaning, classifying, and clustering the data to develop comprehensive models for the sweeping states. These models include associated variables such as duration, speed, distance traveled, and fuel consumption. Additionally, the fuel consumption model (FCM) was formulated and validated during this processing.

Data Cleaning

The raw data required meticulous preparation before classification. Our initial evaluation revealed several inaccuracies in the geolocation data due to challenges such as the odometer resets, missing data points, and duplicates. These inconsistencies were corrected through targeted manual data processing techniques.

Classification and Clustering

Following data cleaning, the data were classified and clustered. These processes were conducted using the methodology outlined in Section 3.2.2, which details how simulation parameters are determined.

3.3.3. Construction and Verification of Fuel Consumption Models

Based on the data analysis and classification, fuel consumption models were created for the "sweeping" and "moving" states using polynomial regression. For the "waiting" state, a probability distribution function was derived based on the observed engine idling times.

Since no direct fuel consumption data were available for the conventional broom vehicle, its models were approximated using data from the innovative broom model. These approximations were adjusted based on the difference in engine power between the two broom types. The accuracy of these estimated models was then verified using real-world fuel consumption data.

The fuel consumption models (FCMs) developed for the various sweeping vehicles are summarized in Table 2.

Table 2. Summary of FCMs across different sweeping vehicles and states.

Vehicles	States	Fuel Consumption Models (Liters Diesel/km for Moving and Sweeping States and Liters Diesel/h for Waiting States)	Equation Number	Figure 7
Novel broom	Waiting	FCh_{NbWait} : $normal\ (mean = 4.64,\ std = 2.17)$	(1)	
	Sweeping	$FCkm_{NbSweep} = 0.2163SS^2 - 3.2737SS + 15.432$	(2)	(c)
	Moving	$FCkm_{NbMov} = 0.0002MS^2 - 0.00246MS + 1.0622$	(3)	(a)
Conventional broom	Waiting	FCh_{CbWait} : $normal\ (mean = 3.71,\ std = 1.74)$	(4)	
	Sweeping	$FCkm_{CbSweep} = 0.17304SS^2 - 2.61896SS + 12.344$	(5)	
	Moving	$FCkm_{CbMov} = 0.00016MS^2 - 0.001968MS + 0.8496$	(6)	
Truck	Waiting	FCh_{TrWait} : $normal\ (mean = 2.62,\ std = 0.96)$	(7)	
	Sweeping	$FCkm_{TrSweep} = 0.0514SS^2 - 0.7676SS + 3.8222$	(8)	(d)
	Moving	$FCkm_{TrMov} = 0.0001MS^2 - 0.0143MS + 0.8579$	(9)	(b)
	Unloading	$FCkm_{MovTrUnload} = 0.0001MS^2 - 0.0143MS + 0.8579$	(10)	

FCh: fuel consumption per hour; *FCkm*: fuel consumption per km; SS: sweeping speed, MS: moving speed. *Nb*, *Cb*, and *T:* novel broom, conventional broom, and truck; *Wait*, *Sweep*, and *Mov*: waiting, sweeping, and moving states.

To validate the robustness of our fuel consumption models, we cross-validated them with actual experimental data, as illustrated in Figure 7a–d, highlighted in blue. It should be noted that for the innovative broom, our experimental data were somewhat limited in terms of the number of observations. Additionally, we referenced fuel consumption ratios provided by Transport Canada for heavy trucks weighing over 15 tons. According to this source, these trucks consume 48.1 L of fuel per 100 km at an average speed of 34.8 km/h. This empirical value closely aligns with the results generated by our fuel consumption models for the given speed and distance parameters.

Notably, these verified fuel consumption models were crucial in developing the GHGEMs, which were subsequently incorporated into our overarching simulation models, offering a more comprehensive understanding of the environmental impact.

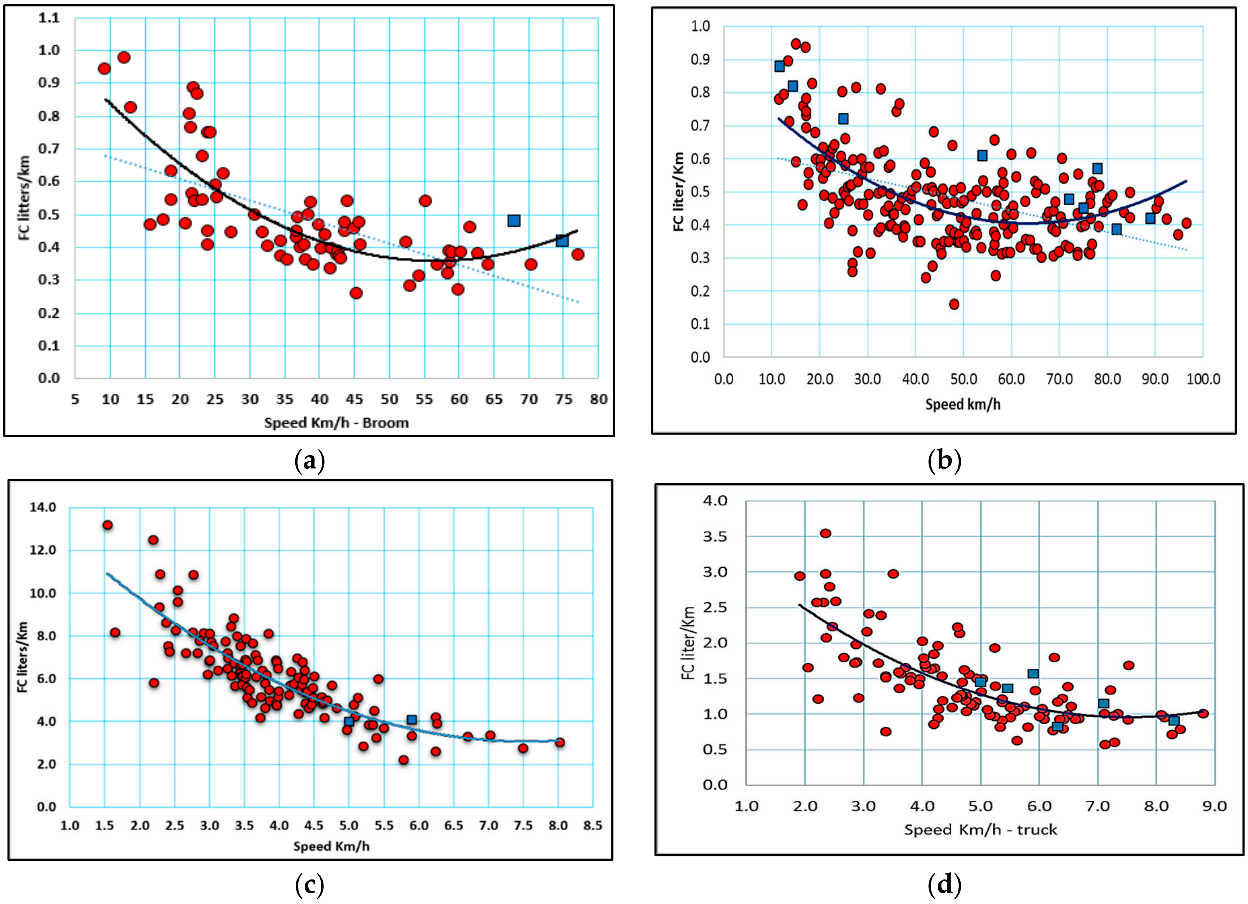


Figure 7. Validation of FCMs for sweeping and moving states (truck and novel broom). (**a**) Novel broom FCM for moving state. (**b**) Truck FCM for moving state. (**c**) Novel broom FCM for sweeping state. (**d**) Truck FCM for sweeping state.

3.3.4. Development and Application of Greenhouse Gas Emission Models

Building on the established FCMs, the GHGEMs incorporates an emission factor (EF). This EF considers the cumulative impact of various greenhouse gases, as detailed in [25]. It is derived by assessing the composition of greenhouse gas emissions per unit of diesel consumption, including nitrous oxide (N_2O), methane (CH_4), and carbon dioxide (CO_2). Each element is then converted into standardized CO_2-eq (CO_2 equivalent) emissions using specific indices established by the Intergovernmental Panel on Climate Change (IPCC), the leading international body for assessing climate change science. Specifically, indices of 21 for CH_4 and 310 for N_2O are used, following the 100-year Global Warming Potentials from the IPCC Second Assessment Report, in accordance with general scientific practice.

According to [25], the CO_2 EF for 1 kg of diesel, regardless of vehicle types, is approximately 3.169 kg CO_2. Consequently, for 1 L of diesel (equivalent to 840 g), the EF for CO_2 is approximately 2.662 kg/L. In the context of CH_4 emission, the same reference indicates a value of 70 mg/km. Taking into account the fuel consumption model, which specifies that the truck uses 0.39 L per kilometer, the CH_4 emissions per liter consumed can be calculated as approximately 3.77 g of CO_2-eq per liter of diesel, using the formula $0.07 \times 21/0.39$. Lastly, the consumption of one kg of diesel gives rise to 0.051 g of N_2O emission, which translates to a CO_2 equivalent emission of approximately $0.051 \times 0.84 \times 310 = 13.28$ g CO_2-eq per liter of diesel. Consequently, the overall EF per liter of diesel is estimated at about $2662 + 3.77 + 13.28 = 2679$ g, or 2.68 kg CO_2-eq per liter of diesel.

For the ISS

The cumulative emissions over a work shift or simulation run-time are computed by summing the emissions generated by the vehicles across different sweeping states, including the emissions incurred during the unloading journey of the truck.

The total GHG emissions for the innovative sweeping system during one shift are calculated based on the fuel consumption in liters resulting from waiting, sweeping, moving between sweeping areas, and transporting the collected sweeping to the depots. This value is then multiplied by the *EF* in kg CO_2-eq per liter as illustrated in Formula (11).

$$GHG_{Total-ISS} = EF(FC_{WaitISS} + FC_{SweepISS} + FC_{MovISS} + FC_{MovTrUnload}) \tag{11}$$

where:

- Fuel consumption in liters ($\boldsymbol{FC_{WaitISS}}$) due to waiting periods is calculated by summing the fuel usage from all waiting states during a work shift as illustrated in Formula (12). For each state i, the duration is multiplied by the hourly fuel consumption of the vehicles involved in the sweeping activity (two brooms and a total of TN trucks).

$$\boldsymbol{FC_{WaitISS} = \sum_{i=1}^{N_w} d_w(i)\left(\frac{1}{3600}(FCh(i)_{NbWait} + FCh(i)_{CbWait} + TN.FCh(i)_{TrWait})\right)} \tag{12}$$

- Fuel consumption in liters ($\boldsymbol{FC_{WaitISS}}$) due to sweeping activity is calculated by summing the fuel usage from all sweeping states during a work shift, as illustrated in Formula (13). For each state j, the duration is multiplied by the sweeping speed to obtain the sweeping distance, which is then multiplied by the fuel consumption per kilometer swept for each vehicle involved.

$$\boldsymbol{FC_{SweepISS} = \sum_{j=1}^{N_s} d_s(j)\left(\frac{SS}{3600}\left(FCkm(j)_{NbSweep} + FCkm(j)_{CbSweep} + TN.FCkm(j)_{TrSweep}\right)\right)} \tag{13}$$

- Fuel consumption in liters ($\boldsymbol{FC_{SweepISS}}$) due to moving between sweeping zones is calculated by summing the fuel usage from all moving states during a work shift, as illustrated in Formula (14). For each state k, the duration is multiplied by the moving speed to obtain the distance traveled, which is then multiplied by the fuel consumption per kilometer for each vehicle involved in the activity.

$$\boldsymbol{FC_{MovISS} = \sum_{k=1}^{N_m} d_m(k)\left(\frac{MS}{3600}(FCkm(k)_{NbMov} + FCkm(k)_{CbMov} + TN.FCkm(k)_{TrMov})\right)} \tag{14}$$

- The fuel consumption in liters ($\boldsymbol{FC_{MovISS}}$) due to truck movement for unloading is calculated by summing the fuel usage from all moving states related to unloading during a work shift as illustrated in the Formula (15). For each movement for unloading t, the duration is multiplied by the assumed moving speed of 50 km/h to determine the distance traveled, which is then multiplied by the truck's fuel consumption per kilometer.

$$\boldsymbol{GHG_{MovTrUnload} = \sum_{t=1}^{N_u} d_u(t)\left(\frac{50}{3600}(FCkm_{MovTrUnload})\right)} \tag{15}$$

For the CSS

The explanatory comments related to the emission calculation formulas for the CSS system are the same as those applicable to the ISS system, with a minor difference in the composition of each system.

The total GHG emissions for the conventional sweeping system ($GHG_{Total-CSS}$) are calculated based on the fuel consumption in liters resulting from waiting, sweeping, moving between sweeping areas, and transporting the collected sweepings to the depots, as illustrated in Formula (16). This value is then multiplied by the EF in kg CO_2-eq per liter.

$$GHG_{Total-CSS} = EF(FC_{WaitCSS} + FC_{SweepCSS} + FC_{MovCSS} + FC_{MovTrUnload}) \quad (16)$$

where:

$$FC_{WaitISS} = \sum_{i=1}^{N_w} d_w(i)\left(\frac{1}{3600}(2.FCh(i)_{CbWait} + TN.FCh(i)_{TrWait})\right) \quad (17)$$

$$FC_{SweepISS} = \sum_{j=1}^{N_s} d_s(j)\left(\frac{SS}{3600}\left(2.FCkm(j)_{CbSweep} + TN.FCkm(j)_{TrSweep}\right)\right) \quad (18)$$

$$FC_{MovISS} = \sum_{k=1}^{N_m} d_m(k)\left(\frac{MS}{3600}(2.FCkm(k)_{CbMov} + TN.FCkm(k)_{TrMov})\right) \quad (19)$$

$$GHG_{MovTrUnload} = \sum_{t=1}^{N_u} d_u(t)\left(\frac{50}{3600}(FCkm_{MovTrUnload})\right) \quad (20)$$

The GHG emissions per ton of sweepings collected by the ISS and CSS (Formulas (21) and (22)) are calculated by dividing the total emissions generated during a work shift by the quantity of sweepings collected during that shift, represented as QSC_{ISS} and QSC_{CSS} for the ISS and CSS systems, respectively.

$$\text{ISS: } GHG_{ISS-T} = GHG_{Total-ISS}/QSC_{ISS} \quad (21)$$

$$\text{CSS: } GHG_{CSS-T} = GHG_{Total-CSS}/QSC_{CSS} \quad (22)$$

3.4. Sensitivity Analysis

A comprehensive sensitivity analysis was performed using the same models across a wide range of scenarios to assess sweeping system performance under diverse operational contexts. This analysis considers various configurations, such as the number of trucks and their payload, TUD, and fluctuations in CRs. These fluctuations arise from year-to-year variations in winter weather conditions, which affect the quantity of abrasive material spread for winter road maintenance and subsequently affect the volume of material collected during spring sweeping operations. By incorporating these variables, the analysis provides an in-depth evaluation of both systems across different conditions, offering insights into their adaptability and efficiency.

Equivalent CRs were assumed for both systems to ensure a fair comparison. Additionally, a constant speed was maintained across all CRs as a modeling assumption to simplify the analysis. Key hyperparameters, including 10 replications, a 30 h warm-up period, and a 95% confidence interval, were applied to ensure a minimum of convergence errors.

4. Results and Interpretations

The findings presented in this paper are derived from simulation studies focusing on sweeping systems that operate with either one or two collector trucks in the highway context. To enhance and broaden our comparative evaluation of these systems, we utilized a sensitivity analysis. This approach allows us to assess the impact of key parameters on overall system performance.

4.1. Simulation Results

Simulation results for both the ISS and CSS systems, operating with either one or two collector trucks, were gathered over a 500 h run-time in the highway context. Table 3 compiles these findings in alignment with the performance metrics under evaluation.

Table 3. Simulation outcomes and significant simulation parameters for each model.

Models	Operational and Environmental Performance				Main Simulation Parameters (Average)		
	GHG (kg CO_2-eq/ton)	Sweepings Collected (tons)	Distance Swept (km)	Sweeping Duration per Work Shift (%)	Avg CR (tons/km)	Avg Sweeping Speed (km/h)	Avg Moving Speed (km/h)
ISS One truck	29.5	1870	715	49.3	2.7	2.9	27.8
ISS Two trucks	32.8	2215	835	57.6	2.7	2.9	27.8
CSS One truck	46.8	1244	545	43.6	2.3	2.5	19.8
CSS Two trucks	54.1	1271	545	43.6	2.3	2.5	19.8

The innovative sweeping system demonstrates environmental and operational advantages over the conventional system in all scenarios:

- GHG emissions: Under a one-truck collector scenario, the innovative system emits 29.5 kg CO_2-eq per ton collected, compared to 46.8 kg CO_2-eq for the conventional system. Even with two collector trucks, emissions are lower for the innovative system (32.8 kg CO_2-eq per ton) compared to the conventional system (54.1 kg CO_2-eq per ton).
- Operational performance: Over a simulation run-time of 500 h, the innovative system sweeps greater distances: 715 km (one truck) and 835 km (two trucks) compared to the conventional system's 545 km.
- The innovative system's superiority stems from factors like sweeping speed, CR, and overall work efficiency.
- Interestingly, the two-truck scenario does not benefit the conventional system. While its GHG emissions increase significantly, operational performance remains unchanged. In contrast, the innovative system's improved performance with two trucks is primarily due to eliminating novel broom's waiting time during the unloading of the sole collector truck.
- CRs also vary between the systems. The conventional system may require multiple passes to effectively sweep an area, leading to a lower CR compared to the innovative system's single-pass design—a phenomenon observed particularly in urban settings.

4.2. Sensitivity Analysis

The sensitivity analysis is a fundamental part of the main study, as spring sweeping activities are conducted across a range of varying conditions. Each context uniquely impacts the performance of the sweeping systems, influenced by resource allocation and other situational factors. This analysis is structured to systematically explore the design, results, and interpretation phases, providing a comprehensive assessment of how varying operational contexts affect system performance.

4.2.1. Scenarios Design

The values, scenario counts, and averages of key parameters are derived based on resource availability and empirical observations, with TUD reflecting the distribution of observed values. CRs are estimated around the empirical values recorded in our dataset from different zones, as summarized in Table 4. Simulations are conducted for a single 8 h working shift to standardize comparisons. To ensure unbiased comparison, an equivalent CR is assumed for both systems. It is also assumed that there is no correlation between speed and CR since extended data collection over many spring seasons would be required to establish this relationship.

Table 4. Scenarios' design.

Parameters	Values	Unit	Number Scenarios
CR: Collection rate	1.5, 2, 2.5, 3, 3.5, 4	ton/km	6
TUD: Truck unloading duration	30, 45, 60, 75, 90	min	5
Truck payload capacity	16, 24	tons	2
Sweeping systems	ISS, CSS	-	2
Number of collector trucks	1, 2	-	2
Total number of scenarios			240

4.2.2. Performance Indicators Selection

The chosen performance indicators for evaluating the sweeping systems are as follows:

- GHG emissions per ton collected serve as an environmental performance indicator, highlighting the carbon footprint as a crucial aspect of the collected waste material. This metric is used to compare the environmental performance of various sweeping technologies, given its close connection to the transportation sector. This indicator is used in [26] to compare emissions from different transport modes, such as ocean-going vessels, rail, and road transportation by truck.
- Distance swept during a work shift serves as a key indicator of operational performance, closely tied to operational planning and sweeping service contracts. For performance indicators, kilometers swept per shift is chosen as a key metric because it clearly measures operational efficiency and resource allocation in the street sweeping operations. This metric, commonly used for the same activity in cities like Vancouver, San Francisco, and New York, help assess how effectively the fleet is utilized and ensures optimal deployment of sweepers [27].

4.2.3. Results of the Sensitivity Analysis

This sensitivity analysis systematically evaluates the environmental and operational performance of the ISS and the CSS in three structured phases. First, the analysis identifies the key factors driving variability in system performance, highlighting critical parameters that influence this performance. In the second phase, the impact of these parameters is examined to understand and analyze their effect on the performance of the systems under study. Finally, a functional unit is defined. This unit enables the management of trade-offs between performance indicators and allows for a comparison between ISS and CSS, facilitating meaningful benchmarking with other sweeping systems.

- **Factor Importance**

In sensitivity analysis, tornado plots help decision-makers visualize variable impacts, such as GHG emissions per ton collected and distance swept per km of roads during an 8 h shift. The x-axis displays effect sizes and confidence intervals, while the y-axis lists influential factors like TUD, CR, and truck configuration. This layout highlights the most significant and reliable factors.

- **GHG Emissions**

As shown in the tornado plot in Figure 8, the CR has the greatest impact on GHG emissions, with an average effect of 41.79 kg CO_2-eq/ton and a 95% confidence interval of $\pm$12.44 kg CO_2-eq/ton. This variability is due to external factors, such as previous winter conditions, which influence the amount of material collected. Although exogenous and uncontrollable, a higher CR reduces GHG emissions per ton by distributing emissions across a larger collected volume.

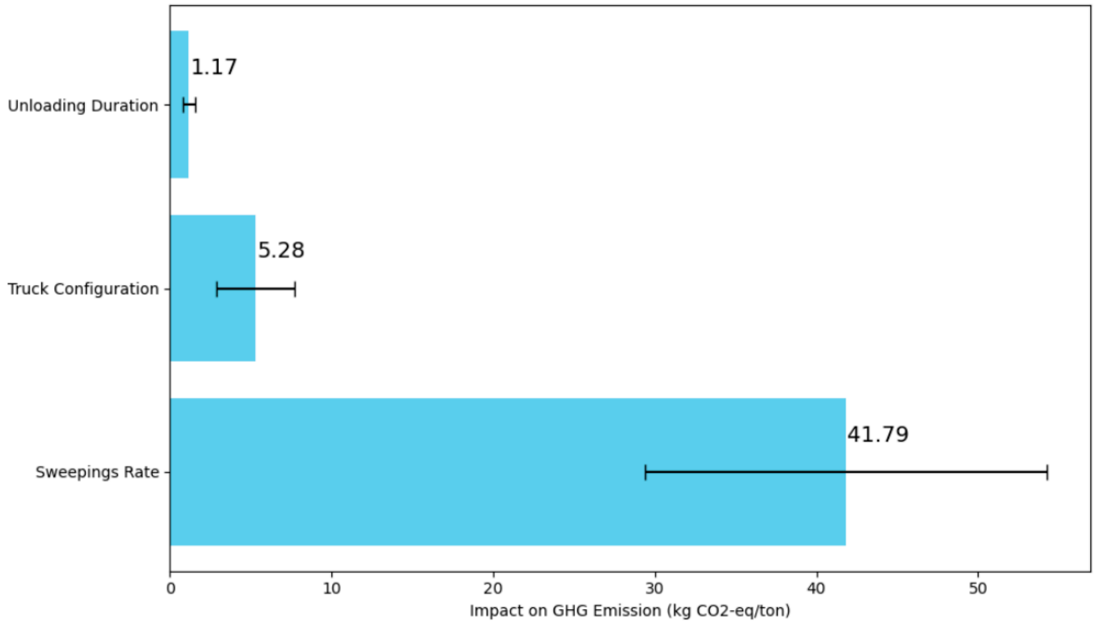


Figure 8. Factor importance influencing GHG emissions with 95% confidence intervals.

The truck configuration (i.e., the number of trucks and the payload capacity of each truck) also significantly affects emissions, with an average effect of 5.28 kg CO_2-eq/ton and a confidence interval of ±2.43 kg CO_2-eq/ton. This relatively narrow interval suggests that changes in the truck configuration have a consistent effect on emissions, making it a crucial adjustable factor. Optimizing configurations, like adjusting the number of trucks or modifying their payload capacity, can directly reduce emissions, making it a critical area for emissions management.

The TUD has the smallest impact on emissions, with an average effect of 1.17 kg CO_2-eq/ton and a confidence interval of ±0.40 kg CO_2-eq/ton, indicating low variability and limited influence on GHG emissions. Although adjustments to TUD may have a minor effect on emissions, they can optimize operational efficiency through strategic location of the limited number of depots near sweeping zones, thus reducing unloading times.

Given these insights, our subsequent analyses will focus on optimizing truck configurations, specifically the number and payload capacity of collector trucks in the system. This focus on the truck configuration offers the most significant potential for improving resource efficiency and achieving meaningful GHG emissions reductions.

- **Distance Swept**

Truck configuration has the highest impact on the distance swept in an 8 h working shift, with an average effect of 1.63 km and a 95% confidence interval ranging from 0.84 to 2.42 km, as illustrated by the tornado plot in Figure 9. This indicates that adjustments in the number and payload capacity of trucks significantly influence the operational distance covered. The relatively wide confidence interval suggests varied outcomes with different configurations, but the impact is consistently substantial, making truck configuration a key factor for maximizing distance coverage.

CR has a moderate impact on the distance swept, with an average effect of 0.53 km and a confidence interval of ±0.16 km (ranging from 0.37 to 0.69 km). Although a higher CR would generally reduce the distance covered, the average distance in this analysis increases due to optimized operations with two trucks. Notably, the CR does not significantly affect the distance covered, likely because no correlation between speed and CR was considered. By reducing waiting times (from the availability of collector trucks), the system can maximize distance swept, resulting in a higher overall average despite the increased rate.

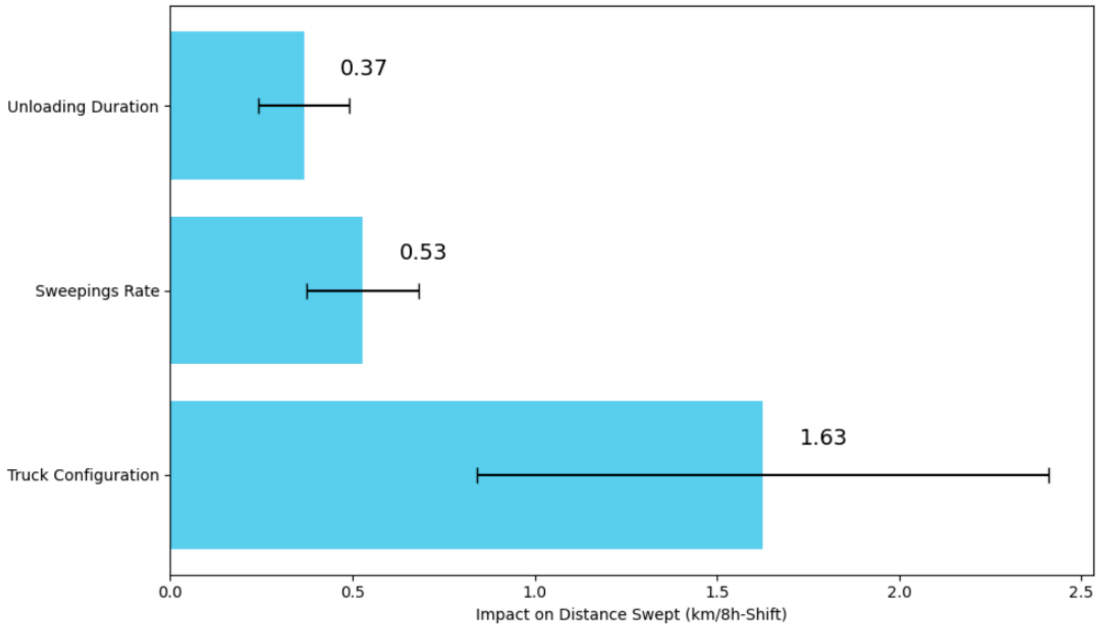


Figure 9. Factor importance influencing distance swept with 95% confidence intervals.

TUD has the smallest effect on the distance swept, with an average impact of 0.37 km and a confidence interval of ±0.12 km (ranging from 0.25 to 0.49 km). Although adjustments in TUD show limited influence on total distance, optimizing unloading times through efficient depot locations could provide minor gains in operational efficiency.

In summary, optimizing truck configuration remains the most effective strategy for enhancing distance coverage in an 8 h working shift. Additional, moderate gains are also achievable through adjustments to the TUD.

- **Impact of Truck Configuration**

Figure 10 displays the impact of truck configurations on GHG emissions (kg CO_2-eq/ton) and distance covered (km), with each subplot representing one of four possible configurations per system—using either one or two trucks with payload capacities of 16t or 24t. The colors in the figure correspond to the 95% confidence intervals, providing a clear visual representation of the uncertainty in the indicators. This structure provides a clear comparison of how each configuration influences emissions per ton collected and distance swept, highlighting the effects of truck number and payload capacity on both environmental and operational performance across the two systems (ISS and CSS).

- **GHG Emissions**
    - **Single vs. Dual Trucks:** Across both the ISS and CSS, configurations with two trucks consistently produce higher GHG emissions compared to configurations with one truck. This trend is expected, as doubling the number of trucks naturally increases fuel consumption and emissions.
    - **Payload Capacity (16t vs. 24t):** Among configurations with the same number of trucks, those with a higher payload capacity (24t) tend to have slightly elevated emissions compared to the 16t configurations.
    - **ISS vs. CSS Comparison:** Overall, the CSS system shows higher GHG emissions across configurations than the ISS system, particularly for the two-truck setups. This indicates that ISS may operate more efficiently, even under similar configurations.
- **Distance Covered**
    - **Effect of Payload Capacity:** Configurations with higher payload capacity (24t) typically cover a slightly greater distance than their 16t counterparts, especially in single-truck configurations. This suggests that trucks with larger payloads

may be able to travel further before requiring unloading, potentially optimizing operational efficiency in terms of coverage.

- **Single vs. Dual Trucks:** Two-truck configurations generally cover a greater distance than single-truck setups. However, this increase in coverage comes at a cost of higher emissions. This trade-off implies that while adding more trucks boosts coverage, it also raises environmental impact.
- **TUD's Impact:** In various configurations, longer TUDs tend to correlate with higher GHG emissions and also impact the distance covered. This suggests that the proximity and accessibility of depots, which affect unloading time, could contribute to emission reduction and improve operational reach.

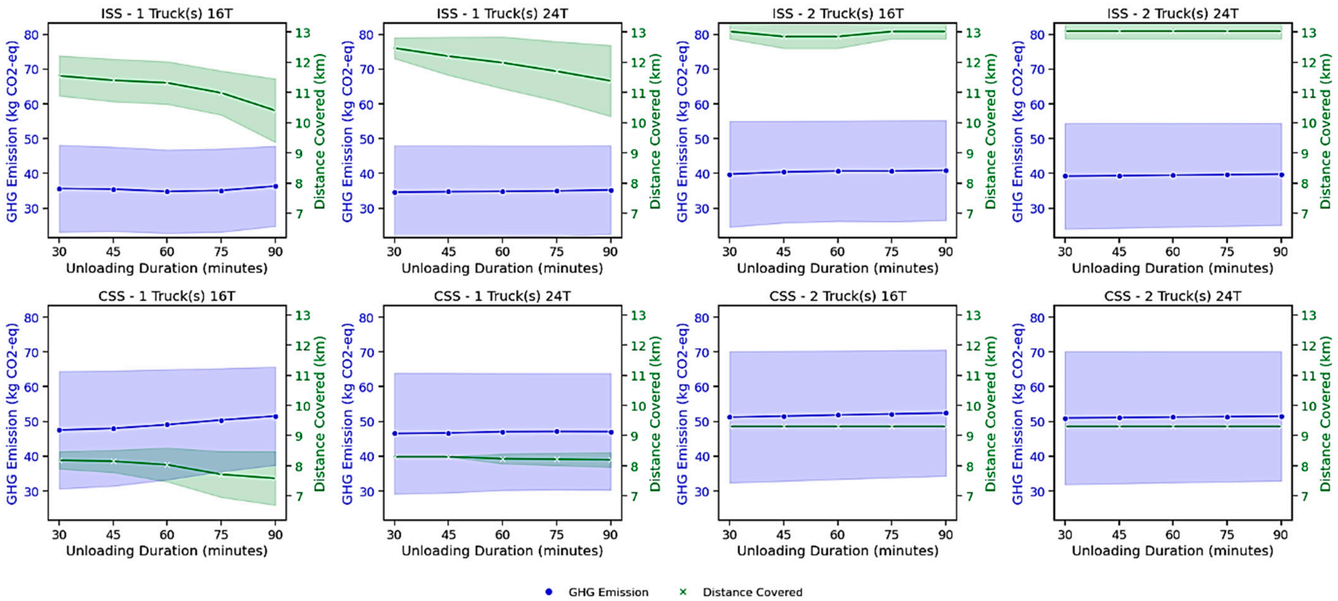


Figure 10. Impact of truck configuration on performance indicators for ISS and CSS with 95% confidence intervals.

This analysis shows that truck configuration—specifically single vs. dual truck setups and payload capacity—significantly affects both GHG emissions and distance covered. Further analysis could help optimize truck deployment for specific goals, such as minimizing emissions per swept kilometer.

- **Performance Functional Unit**

According to ISO 14040 standards for life cycle assessment [28], defining a functional unit is crucial for comparing the environmental impact of different systems providing the same service. For the sweeping systems under study, the chosen functional unit is one kilometer of road swept. This unit allows for a direct comparison of the environmental performance of the ISS and CSS by normalizing results to assess their efficiency relative to the same service rendered. It is also essential in sensitivity analyses, where it enables measurement of the impact of parameters (such as truck configuration) on emissions per kilometer swept, facilitating the identification of optimal configurations. Additionally, this unit allows for comparisons with other systems and studies on sweeping operations. Figure 11 illustrates the functional unit across various contexts (i.e., four truck configurations and five TUDs) for both systems, highlighting performance differences under different setups.

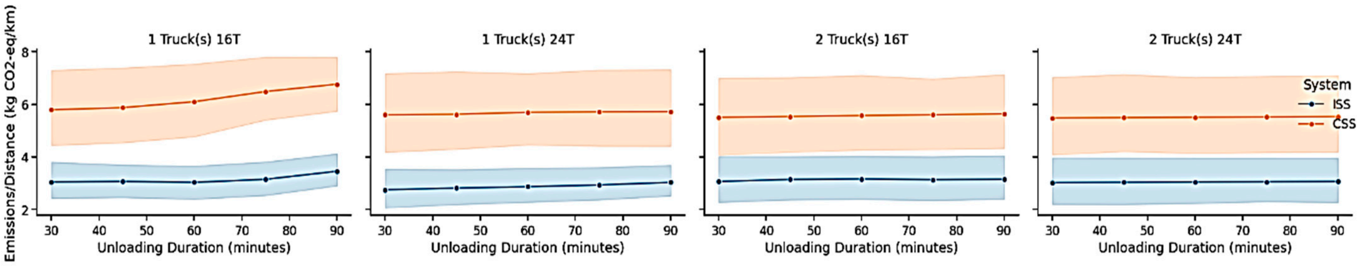


Figure 11. Comparison of emissions per km by truck configuration and system over TUD with 95% confidence intervals.

The analysis of GHG emissions per kilometer swept indicates that the ISS system consistently outperforms the CSS system in all configurations, with confidence intervals (CI) reinforcing the reliability of these results. For the single-truck 16t configuration, ISS averages 3.15 kg CO_2-eq per km (95% CI: ±0.30), significantly lower than CSS at 6.20 kg CO_2-eq per km (95% CI: ±0.50), underscoring a nearly 50% reduction with a tight interval, indicating stable performance. In the single-truck 24t setup, ISS achieves 2.88 kg CO_2-eq per km (95% CI: ±0.25), while CSS records 5.67 kg CO_2-eq per km (95% CI: ±0.45), reflecting a 49% reduction with limited variability. The dual 16t truck configuration shows ISS emissions of 3.14 kg CO_2-eq per km (95% CI: ±0.28) versus CSS at 5.57 kg CO_2-eq per km (95% CI: ±0.48), with consistent performance across setups. The dual 24t configuration further confirms ISS's advantage with 3.05 kg CO_2-eq per km (95% CI: ±0.27) compared to CSS's 5.51 kg CO_2-eq per km (95% CI: ±0.47). These confidence intervals demonstrate not only lower emissions but also stable performance for ISS, making it a more reliable and environmentally efficient choice across configurations. Figure 12 illustrates this analysis.

4.2.4. Discussion of Results and Limitations

- **Model Assumptions, Limitations, and Performance**

The comparative study presented in this paper is built upon models developed using real-world data. Its limitations are tied to the data collection conditions, data processing methods, and model validation. The performance indicators used are calculated based on the duration of a working shift, excluding travel to and from the work site to ensure consistency in assessing on-site operational and environmental performance, as travel times can vary significantly and are not directly related to the efficiency being measured.

The data were collected over two spring seasons, considering the previous winter's meteorological conditions, which affect the amount of abrasive spread, and in turn, influences the rate of material collection. The data were cleaned, outliers were removed, and then primarily processed using supervised dual multi-classification algorithms with an average accuracy of 87%, further improved to 94% through heuristics, according to the supervised ML multi-classification models in [24]. As shown in Figure 1, the collected data fall into two categories: the first captures sweeping behavior through GPS data recorded every second, and the second includes fuel consumption data alongside GPS information. Fuel consumption was calculated using a microscopic model that measures consumption every 5 s, based on the power exerted by the truck and the innovative broom engines. Since the onboard system for measuring fuel consumption was not installed on the conventional broom due to technical reasons, fuel consumption for the conventional broom was estimated based on the novel broom's data, proportional to the engine displacement. The conventional broom has a 6.7 L engine, while the front broom is equipped with an 8.3 L engine. Therefore, fuel consumption for the conventional broom was estimated to be 6.7/8.3 (approximately 80.7%) of the fuel consumption of the innovative broom.

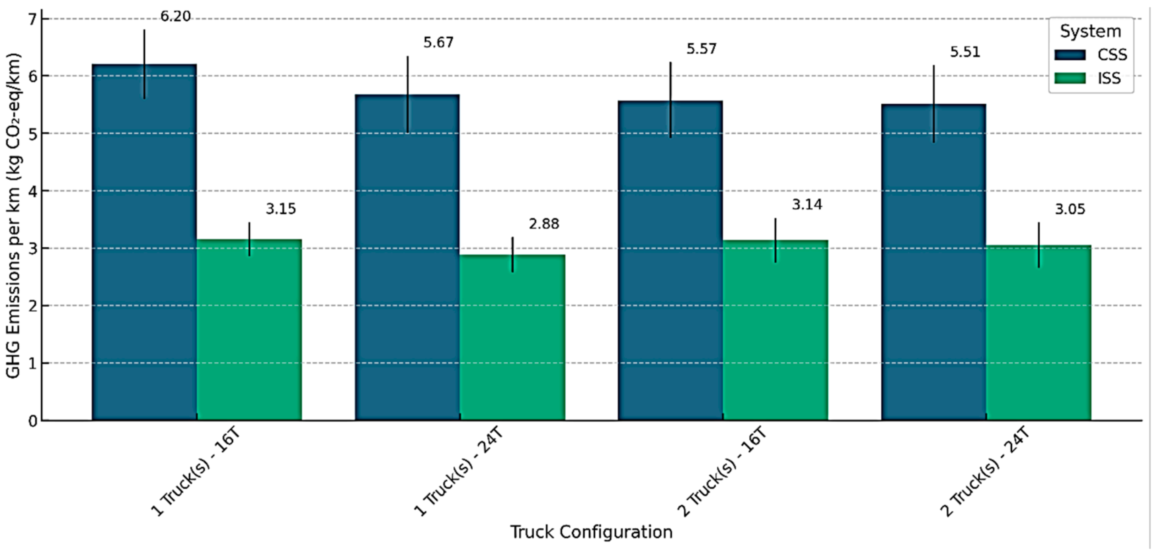


Figure 12. GHG emissions per km swept by system and truck configuration with 95% confidence intervals.

The GHG emissions models were developed from fuel consumption models using specific emission factors. FCMs were constructed with regression algorithms to estimate fuel use during both sweeping and transit phases, taking into account vehicle speed and distance traveled within the sweeping system. A probability distribution was used to model fuel consumption during the waiting state for each vehicle type, based on waiting time.

To balance bias and variance, second-degree polynomials were selected for the regression models, as shown in Figure 7. This choice addresses the limitations of simpler linear regression models, which can lead to underfitting by oversimplifying relationships and thereby increasing bias. Conversely, higher-degree polynomial models, while reducing bias, can lead to overfitting the data, capturing noise instead of true patterns and thus increasing variance. Additionally, to manage bias, the collected data were refined by removing outliers, improving the overall reliability of the models.

Over a 500 h simulation period, validation results indicate that the ISS models show an average deviation of about 2.2% compared to static models, with a standard deviation of 2%. In comparison, the CSS models exhibit an average deviation of approximately 1.2% and a standard deviation of 1.1%. These results confirm the robustness of both models in accurately replicating sweeping behavior based on real-world data parameters throughout the extended simulation duration.

Sensitivity analysis, using the same models (simulation and fuel consumption), was performed to account for the different contexts of sweeping activities, such as system configurations (number of trucks and their payload capacities), the round-trip time to a depot for unloading a truck, and variability in the rate of material collection. To ensure a fair comparison, equivalent collection rate were assumed for both systems. Key hyperparameters for scenarios testing, including the number of replications (10), warm-up time (30 h), and a 95% confidence interval, were used to ensure optimal convergence of the model parameters.

Although the results are based on specific assumptions, the methods for data collection, processing, simulation model development, and analysis of GHG emissions and operational performance can be applied to more complex logistics scenarios beyond sweeping activities.

- **Key Results and Interpretations**

The findings of this study are based on a combination of parameters derived from real-world data and simulation-based experimental scenarios used in the sensitivity analysis. These scenarios illustrate how key factors, such as CR, TUD, and resource configurations, influence the operational and environmental performance of sweeping systems. The key results are outlined below:

- **Simulation Results:** Over a simulated 500 h period, the innovative sweeping system demonstrates clear environmental and operational advantages over the conventional system in highway scenarios. In terms of GHG emissions, the innovative system using a single 16t collector truck emits 29.5 kg CO_2-eq per ton collected, notably lower than the 46.8 kg CO_2-eq for the conventional system. Even with two collector trucks, the innovative system maintains an emissions advantage, producing 32.8 kg CO_2-eq compared to 54.1 kg CO_2-eq for the conventional system. Operationally, the innovative system covers significantly more distance, reaching 715 km with one truck and 835 km with two trucks, while the conventional system covers only 545 km.
- **Sensitivity Analysis Results:** The sensitivity analysis identifies the relative importance of key factors with a 95% confidence interval—CR, truck configuration, and TUD—revealing their specific impacts on GHG emissions and distance covered in the ISS and CSS. CR has the highest impact on emissions, while truck configuration significantly affects both emissions and operational distance. Knowing that CR and TUD are exogenous factors, the primary focus for further analysis is resource configuration. In terms of truck setup, the ISS with a single 16t configuration shows the lowest emissions per ton, outperforming CSS in both environmental and operational efficiency. Two-truck configurations extend coverage but also raise emissions, highlighting the need to manage a trade-off between operational reach and environmental impact. In the ISS system, performance indicators can degrade in cases where TUD exceeds 60 min for a single 16t truck or 75 min for a single 24t truck, resulting in declines in both operational efficiency and emissions performance.
- **The establishment of a functional unit**—emissions per kilometer of road swept—supports consistent comparison of the ISS and CSS systems' environmental performance, with ISS showing a clear emissions advantage. With stable emissions at 3.15 kg CO_2-eq per km in a single-truck with 16t payload, ISS demonstrates superior efficiency over CSS, which averages 6.20 kg CO_2-eq per km in comparable configurations. On average, across all configurations, the ISS achieves an approximate 45% reduction in GHG emissions compared to CSS. This functional unit also facilitates meaningful benchmarking, providing a basis for evaluating and improving sweeping systems' environmental impact.

- **Actionable Insights for Sweeping**

- **Optimizing Fleet Management for Sweeping Operations:** The configurations identified in the sensitivity analysis provide crucial guidance for optimizing fleet management. Decision-makers can leverage these configurations to balance operational needs with environmental sustainability, selecting setups that enhance efficiency while minimizing GHG emissions. This enables a more data-driven approach to fleet management within the sweeping system.
- **Aligning Operational and Environmental Goals:** Despite potential conflicts between operational efficiency and environmental objectives, this study shows that both can be jointly achieved by focusing on faster service delivery and effective delay management. Prioritizing configurations that reduce waiting time and optimize sweeping routes allows for meeting service demands while maintaining a lower environmental footprint.
- **Enhancing Conventional Sweeping System Performance:** For conventional sweeping systems, particularly on highways, reducing waiting times can significantly improve both operational and environmental outcomes. This can be achieved by coordinating the roles of the brooms—for example, alternating between primary sweeping and finishing tasks—to ensure balanced load distribution and reduce delays when one broom becomes full. This approach minimizes interruptions and boosts overall system efficiency.

– **Toward Greener Public Procurement in Road Maintenance:** This study defines the functional unit as the kilometer of road swept, establishing a basis for quantitative tools that evaluate the environmental impact of road maintenance activities and standardize comparisons across sweeping systems. This approach enables policymakers to identify and prioritize the most energy-efficient services, supporting more sustainable procurement decisions. By providing a functional unit to assess the carbon footprint of spring sweeping, this study reinforces integrating environmental criteria into procurement policies. This encourages the adoption of low-carbon technologies in road maintenance and aligns public procurement with climate goals.

- **Comparison with Other Studies**

This study encountered challenges in identifying directly comparable research on sweeping systems, as an extensive search of major databases did not yield relevant references, particularly regarding the street sweeping operations. This highlights a significant gap in the literature, especially concerning emissions from such systems. However, by referencing studies on logistics operations emissions, a partial comparison was possible, since sweeping systems rely heavily on logistics physical assets (e.g., two to four heavy trucks for unloading the collected street sweepings, highways impact mitigation, and dust control). Focusing on the transportation component, reliable sources reporting truck emissions per ton transported over one mile at an average speed of 50 km/h (31 miles/h) were utilized. The calculations derived from this work (Formula (5)) indicate emissions of 106 g/mile/ton for a 16-ton payload at this speed.

This result aligns with findings in [19], who developed a GHG model for port road transport (trucks) and reported emissions of 122 g/mile/ton for the same speed and payload. Additionally, Li et al. [29] reported emissions of 1000 g/km at a speed of 60 km/h (37.3 mph), which equates to 1610 g/mile for a 16-ton truck, resulting in 101 g/mile/ton. This value is slightly lower than the calculated emissions but remains within a comparable range, considering the different speeds and operational conditions.

A comparable activity providing valuable insights is waste collection, where trucks operate at low speeds, frequently stop, and experience extended idle times during loading and unloading. GHG emissions from waste collection trucks range between 5.08 kg and 35 kg CO_2-eq per ton, depending on the type of fuel used [30]. In the present study, emissions ranged from 29.5 kg to 54.1 kg CO_2-eq per ton, considering that the sweeping system involves multiple vehicles, including brooms and trucks.

In conclusion, although direct comparisons for street sweeping systems were not available, the emissions from trucks in the sweeping system under study align with findings from similar logistics operations.

5. Conclusions

This study offers a comprehensive assessment of the operational and environmental performance of two sweeping systems, using simulation models grounded in real-world data. By applying supervised machine learning techniques for dual-state multi-classification, the geolocation data gathered are converted into critical insights about system behavior, ensuring that the simulations accurately mirror historical patterns. Additionally, fuel consumption models are developed and integrated into simulation models to estimate the GHG emissions of each system.

The findings clearly demonstrate the advantages of the innovative sweeping system in both operational and environmental performance. Sensitivity analysis, focusing on key parameters such as sweepings collection rate, truck number and payload capacity, and truck unloading duration, reveals critical insights for optimizing system configurations. The analysis shows that the ISS single-truck configuration achieves the lowest emissions per ton, outperforming conventional systems in both environmental and operational metrics. Two-truck setups increase coverage but raise emissions, highlighting the need to balance reach with the environmental impact. Efficiency drops when truck unloading duration exceed certain limits, underscoring the importance of optimized resource allocation and route management.

Additionally, establishing GHG emissions per kilometer swept as a functional unit provides a consistent benchmark to compare sweeping systems, confirming the superior environmental efficiency of the innovative system. The ISS system demonstrates a significant reduction in GHG emissions per kilometer (functional unit) across all configurations compared to the CSS system, with the single-truck 16t setup showing a nearly 50% reduction (ISS: 3.15 kg CO_2-eq per km; CSS: 6.20 kg CO_2-eq per km). On average, across all configurations, the ISS achieves an approximate 45% reduction in GHG emissions compared to the CSS. This consistent advantage, supported by tight confidence intervals, highlights the ISS as a more environmentally efficient and reliable choice. The insights from this analysis offer valuable guidance for industrial and policy stakeholders, reinforcing the need to prioritize resource configurations that align environmental and operational objectives. Ultimately, these findings support a shift towards more sustainable fleet management and procurement practices, promoting low-carbon solutions in road maintenance operations.

Future research should prioritize refining these models by integrating advanced technologies such as the Internet of Things (IoT), AI-driven analytics, and digital twin systems for smart cities in order to enhance decision-making processes based on predictive models and the real-time collection and treatment of data. Moreover, combining the evaluation of environmental, economic, and social impacts through a life cycle approach will be crucial for providing more comprehensive assessment of sustainability. This will ensure the long-term viability of logistics operations and foster more sustainable practices. Together, these advancements will contribute significantly to the broader goal of reducing the carbon footprint and thus promoting greener logistics in the road network maintenance.

Author Contributions: Conceptualization, B.B.D., J.-F.A. and A.L.; methodology, B.B.D., J.-F.A. and A.L.; software, B.B.D.; validation, B.B.D. and J.-F.A.; formal analysis, B.B.D.; investigation, B.B.D.; resources, J.-F.A.; data curation, B.B.D.; writing—original draft preparation, B.B.D.; writing—review and editing, B.B.D., J.-F.A. and A.L.; visualization, B.B.D.; supervision, J.-F.A. and A.L.; project administration, J.-F.A.; funding acquisition, J.-F.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Fonds de recherche du Québec (Nature et Technologies and Société et Culture) and Fonds Vert under grant number 2019-GS-260551.

Data Availability Statement: A data processing example with real data using a multi-classification ML algorithm can be found at https://github.com/bechirbendaya/multiclass_example (accessed on 10 November 2024).

Acknowledgments: The authors acknowledges Biopterre, City of Trois-Rivières/IDETR, Innofibre, Ministère des Transports du Québec and Arseno Balayage for their involvement in the research initiative under grant number 2019-GS-260551, especially to the later their key support in this work.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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