Supply Chain Analytics 10 (2025) 100126

Contents lists available at ScienceDirect

Supply Chain Analytics

journal homepage: www.sciencedirect.com/journal/supply-chain-analytics

Optimization-based model of a circular supply chain for coffee waste

Hanieh Zohourfazeli [a], Ali Sabaghpourfard [b], Amin Chaabane [a,*], Armin Jabbarzadeh [a]

[a] Department of Systems Engineering, École de technologie supérieure (ÉTS), Montreal, Canada
[b] Department of IT Operation, Air Canada Vacation, Montreal, Canada

ARTICLE INFO

Keywords:
Smart supply chain
Industry 4.0
Circular economy
Waste valorization
Data-driven logistics
Sustainable reverse supply chain

ABSTRACT

Spent coffee grounds (SCG) waste poses significant environmental challenges, including greenhouse gas emissions and contamination risks. However, the existing reverse logistics (RL) systems remain inefficient, costly, and prone to contamination. Although previous studies have explored RL strategies, economically viable logistics models for small-scale SCG operations remain underdeveloped. However, the role of digitalization in optimizing SCG collection has not yet been explored. This study addresses these gaps by developing and evaluating sustainable business models that integrate circular economy principles with Industry 4.0. A mixed-integer linear programming (MILP) model was formulated to optimize the location, allocation, and routing decisions for "circular coffee shops, " which serve as local collection and preprocessing nodes. Using real data from 1000 coffee shops in Montreal, three case scenarios were analyzed to assess the impact of pre-drying technologies and smart logistics on cost reduction and environmental performance. The results show that, while smart bins and real-time data analytics improve network efficiency and sustainability, the strategic placement of pre-drying technologies significantly reduces transportation and processing costs. By introducing a novel framework that integrates digitalization and collaborative waste management, this study advances SCG valorization and minimizes waste-related environmental impact. The findings offer actionable strategies for municipalities and food service stakeholders, providing a scalable, data-driven approach to promote the adoption of circular economy principles in urban organic waste management.

1. Introduction

Global coffee consumption has steadily increased in recent years, resulting in a corresponding increase in spent coffee grounds (SCG), a waste stream with significant economic and environmental implications [16]. Although SCG contains valuable organic compounds suitable for applications such as heavy metal removal, biofuel production, composting, and antioxidant extraction (T. A. [48]), these compounds are often disposed of through incineration or landfilling. These conventional methods overlook their resource potential and contribute to environmental pollution through the emission of toxic gases such as carbon monoxide (CO) and nitrogen oxides (NOx) [7].

To address these impacts, companies such as Nestlé have initiated SCG valorization efforts by using waste as a renewable energy source at several European facilities (T. A. [48]). However, most valorization initiatives operate on large industrial scales [13], whereas coffee shops, one of the primary producers of SCG, generate relatively small and scattered volumes of waste. These small and medium producers face barriers to waste recovery due to the lack of economically viable models and the high cost of collection logistics [26,33].

Comprehensive techno-economic assessments are needed to evaluate the feasibility of decentralized SCG valorization networks (T. A. [48]). Effective implementation depends on coordinated collaboration between waste generators (e.g., coffee shops) and collectors. However, uncertainty in waste generation rates and logistics constraints complicate this coordination, often resulting in inefficiencies, higher costs, and lower quality of recovered materials [53];[37].

Current SCG recovery systems suffer from fragmented decision-making, limited utilization of real-time data, and suboptimal resource allocation. Reverse logistics (RL) frameworks, which facilitate the efficient collection and transportation of waste, are essential yet underdeveloped in this context [51]. Indeed, although Industry 4.0 technologies, such as the Internet of Things (IoT), machine learning, and predictive analytics, can potentially improve logistics systems, evaluating the impact of their integration into SCG recycling remains minimal [49].

Despite growing interest in circular economy (CE) strategies and

* Corresponding author.
E-mail address: amin.chaabane@etsmtl.ca (A. Chaabane).

https://doi.org/10.1016/j.sca.2025.100126
Received 31 January 2025; Received in revised form 4 April 2025; Accepted 24 April 2025
Available online 30 April 2025

logistics optimization for SCG collection from coffee shops, essential research gaps remain. Most studies focus on centralized processing, neglecting decentralized, small-scale valorization models. Collection from dispersed coffee shops presents logistics challenges as current RL systems struggle to minimize routing costs or perform reliably under uncertainty [3]. Smart technologies, such as real-time analytics, adaptive routing, IoT infrastructure, smart bins, and automated SCG pre-drying, are rarely integrated into CE logistics models to address dynamic routing or real-time waste flows [8]. Additionally, the influence of policy, stakeholder collaboration, and governance on the effectiveness of RL systems is underexplored, hindering their practical adoption. Addressing these gaps is crucial for designing resilient, cost-effective, and sustainable systems for SCG valorization that can adapt to real-world urban and rural waste management challenges.

This study proposes a novel, data-driven, Industry 4.0-enabled framework for reverse logistics in SCG collection and valorization, integrating advanced technologies with optimization models that support decentralized recovery operations. The framework aims to convert SCG into valuable products, such as activated carbon, a high-demand material in environmental and industrial applications [37,38]. Montreal was selected as a case study due to its growing network of independent coffee shops and supportive waste management policies. Moreover, previous studies have shown that SCG collection systems in Montreal can significantly improve sustainability and resource efficiency [11]. The framework will optimize logistics decisions under operational uncertainty and variability in waste flow, including location, allocation, capacity, and routing. To guide this research, the following key questions are addressed:

1. How can Industry 4.0 technologies improve the efficiency of waste valorization within reverse logistics networks?
2. What optimization methods best balance cost reduction, waste recovery rates, and environmental impact?
3. How can the proposed framework be aligned with urban sustainability policies and principles of the circular economy?

To answer these questions, we propose a mixed-integer linear programming (MILP) model that optimizes waste collection, transportation, and processing decisions for SCG. The model is validated using municipal data from SCG collection programs in Montreal. The activated carbon valorization pathway is analyzed from both cost and environmental perspectives, as our industrial partner, the collector, focuses on this valorization pathway. Additionally, the study will assess the performance impact of integrating smart infrastructure, including IoT-based waste tracking and adaptive routing. By answering these research questions, we aim to make the following contributions:

1. From a methodological development perspective, this paper proposes a novel, Industry 4.0-enabled, data-driven decision-support framework that integrates MILP with advanced smart infrastructure, including IoT, adaptive routing, and real-time waste tracking. This framework aims to optimize decentralized SCG reverse logistics networks in the face of operational uncertainty.
2. From a practical implementation perspective, the study thoroughly analyzes the impacts of dynamic changes, uncertainty, and advanced Industry 4.0 technologies on small-scale SCG valorization through a real-world case study conducted in Montreal. This analysis provides actionable insights for urban planners, policymakers, and waste management stakeholders, facilitating the achievement of circular economy objectives and promoting sustainable urban logistics transformation.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature on reverse logistics and smart waste management. Section 3 outlines the research methodology. Section 4 presents the mathematical model and its assumptions. Section 5 applies the model to the collected data and analyzes the results. Section 6 presents a detailed sensitivity analysis regarding critical parameters. Section 7 presents the economic analysis, and Section 8 discusses the main findings and implications. Finally, Section 9 concludes the study and suggests directions for future research.

2. Literature review

2.1. Waste management in the coffee industry

The food industry is a significant contributor to global waste, with a considerable portion comprising restaurant food waste, which can lead to environmental and social problems and food safety risks [56]. This is particularly relevant for SCG because it is a common type of restaurant food waste, and more specifically, in coffee shops.

SCG, a natural byproduct of the brewing process, is rich in sugar, oil, and other energy-dense compounds with inherent value [16]. SCG is often produced in coffee shops and households, and the quantity generated depends on various factors, such as coffee consumption patterns, brewing methods, and the scale of coffee production. SCG, a wet organic waste, poses a significant threat, creating numerous adverse environmental and social impacts. Typically, SCGs are disposed of as general waste and sent to landfills, where they release methane. Potent greenhouse gases (GHG) are major contributors to global warming. Disposing of organic waste in landfills can produce hazardous gases, significantly contaminating soil and water bodies. Integrating these CE principles into SCG waste management can substantially reduce waste, lower environmental impact, and create value from recycled materials [34].

SCG can undergo various treatment processes to extract value or mitigate environmental impacts [59]. Composting is a standard method in which SCG is mixed with other organic wastes to produce nutrient-rich compost for soil amendment [59]. Additionally, SCG can generate energy through anaerobic digestion or combustion [24,58]. The production of activated carbon from SCG is one of the several products that can be obtained after treatment [38]. The process involves pretreating the SCG, activating it, washing and drying the resulting activated carbon, and then sizing and packaging it for commercial use. Activated carbon from SCG can be utilized in water treatment, air purification, environmental remediation, and industrial processes, thereby offering a sustainable solution for waste management [10] and creating valuable products with diverse applications. During the SCG collection phase, pre-drying can be performed at the local depot using modern technologies to reduce moisture content before further treatment. The equipment has various sizes, ranging from ultra-small to medium and large. Once pre-dried, SCG can be transported to a treatment facility for additional drying processes [41].

Given the increasing awareness and need for sustainable practices, there is a compelling demand to adopt innovative SCG management strategies that align with the principles of a CE [16,34]. Circularity in the coffee value chain encompasses forward logistics, which involve growing, processing, and distributing coffee, as well as reverse logistics (RL), where SCG are collected, treated, and redistributed. Initially, coffee is grown on farms, sorted, and distributed for sale in the intended markets. Subsequently, SCG is collected from waste generation sites, with coffee shops being a significant source of such waste. Owing to the realization of the effects of SCG, these coffee shops utilize diverse approaches in line with RL network designs and regulations. As an illustration, specific coffee shops can create compost from SCG on their premises, while others seek to collaborate with collectors (treatment facilities) to address challenges in coffee valorization [18]. However, various factors, including environmental conditions, market demand fluctuations, and disruptions such as the COVID-19 pandemic, contribute to these uncertainties. The coffee industry faces additional challenges, such as climate change, overproduction, price volatility, and the need for sustainable practices [4].

2.2. Industry 4.0 integration in waste management

The literature emphasizes the importance of effective waste management strategies for SCG in reducing environmental pollution and enhancing resource recovery. Integrating emerging technologies [49] and optimization techniques into reverse logistics (RL) network design presents promising opportunities for improving the collection, treatment, and valorization of SCG [39]. Key objectives include minimizing travel distances, preventing waste bin overflow and contamination, and reducing routing time, all of which contribute to improved operational efficiency [45]. Technologies such as the Internet of Things (IoT), artificial intelligence (AI), and cloud computing have demonstrated the potential to enhance operational efficiency, support circular economy (CE) principles, and advance sustainability goals [14]. Recent studies emphasize the value of I4.0 across the coffee value chain, suggesting that future research should address system uncertainties, optimize SCG treatment, evaluate social and environmental impacts, incorporate stakeholder perspectives, conduct cost-benefit analyses, and consider regulatory frameworks [60]. However, realizing the full potential of these technologies requires addressing adoption barriers and developing scalable solutions [27].

The global shift toward CE principles has driven greater interest in digital transformation within RL. Disruptive technologies, such as IoT, AI, digital twins (DT), and robotics, are being gradually implemented to modernize RL systems. Yet, Sun et al. [49] note a lack of systematic analysis of I4.0's impact on RL. To address this gap, Sun, Yu, Solvang, and Govindan [50] propose a two-level decision-support framework combining multi-objective optimization with dynamic simulation to support strategic decision-making under uncertainty [50]. To strengthen circularity in the coffee value chain, further research is needed on the impact of technological innovations on RL design and operations. A particular focus should be placed on the role of Industry 4.0 (I4.0) technologies in enabling sustainable and intelligent waste management systems despite the implementation challenges [22].

2.3. Reverse logistics network design and vehicle routing

Reverse logistics (RL) models for waste management are commonly classified into three hierarchical levels: strategic, tactical, and operational. At the strategic level, models address long-term decisions such as network design and infrastructure investment, including the optimal location of collection centers and recycling facilities. These models often integrate sustainability objectives, as seen in circular supply chain frameworks that align logistical planning with environmental goals [28].

At the tactical level, the focus shifts to medium-term planning and resource allocation. Inventory management models are employed to optimize stock levels of reusable materials, while multi-objective optimization approaches aim to balance trade-offs among cost, environmental impact, and service performance [31]. Forecasting models enhanced by artificial intelligence (AI) further support decision-making by predicting waste return flows [1].

At the operational level, models address short-term, day-to-day activities such as real-time waste collection and processing. Dynamic vehicle routing problems (DVRP) are used to optimize collection routes, while scheduling models manage sorting and processing operations [28]. These are increasingly supported by real-time decision support systems that leverage IoT and AI to adapt operations in response to fluctuations in waste volume.

Network design plays a central role across all levels, significantly influencing the efficiency, sustainability, and environmental footprint of waste management systems. Van Engeland et al. [52] conducted a comprehensive review of RL applications in waste management, with particular emphasis on strategic network design. Their work underscored the importance of integrating environmental, social, and performance indicators into multi-objective models, and highlighted the value of involving multiple stakeholders to accommodate future developments [52]. They provided an overview of existing efforts in this area, highlighting the importance of environmental, social, and performance indicators in multi-objective models. Additionally, they emphasized the potential of incorporating various stakeholders into the network design to address future developments.

RL and vehicle routing problem (VRP) models provide a robust framework for optimizing waste collection and disposal processes (A. [47]). This is particularly critical in the context of organic waste management, which presents unique logistical challenges. Organic waste is highly perishable and decomposes rapidly, necessitating frequent and timely collection. Its volume often varies seasonally, requiring adaptive routing strategies [2,21]. Additionally, specialized equipment, such as vehicles equipped with temperature control or compaction systems, is essential for managing leakage and odor.

Unlike general waste streams, organic waste is typically routed to specific facilities such as composting or anaerobic digestion plants. Therefore, routing decisions must consider both the nature of the waste and its destination. Furthermore, environmental concerns play a prominent role, with green VRP models aiming to minimize travel distances and fuel consumption, thereby reducing the environmental impact of collection activities [17].

2.4. Modeling the reverse logistics network design and vehicle routing problem

Location Routing Problem (LRP) models, as extensions of the Vehicle Routing Problem (VRP), optimize vehicle routes and facility locations under constraints such as capacity, time windows, and environmental considerations [32]. Recent reviews, such as Sar and Ghadimi [45], highlight trends in VRP applications within reverse logistics (RL), emphasizing the growing role of Industry 4.0 (I4.0) technologies in enabling data-driven and adaptive solutions [45].

Smart features like intelligent bins provide real-time data critical to operational efficiency. Ramos et al. [42] demonstrated that integrating sensor data with optimization algorithms improves waste collection by enabling dynamic route planning based on bin fill levels. They advocate for models that jointly consider location and routing decisions [42].

Various VRP variants have been applied in RL contexts to address complex waste management scenarios. These include the Capacitated VRP (CVRP) [40], Periodic LRP (PLRP) [20], Capacitated LRP (CLRP) [30], and Time-Dependent LRP (TD-LRP). Recent contributions also explore multi-level models, such as the multi-level capacitated arc routing problem with intermediate facilities (MLCARPIF), which optimizes routing and facility use in hierarchical waste systems [55], as well as cost-efficient CVRP models that incorporate real-time constraints and depot positioning.

A recent study presents an optimized vehicle routing model for efficient waste collection, focusing on the CVRP. This model optimizes service costs and total travel distance, highlighting the benefits of real-time cost considerations and strategic depot positioning in waste management [44]. Another study examines the MLCARPIF in the context of waste collection. It focuses on optimizing routes and facilities such as waste collection huts and transfer stations, demonstrating substantial cost savings and improved efficiency through integrated optimization in multi-level waste collection systems [55]. In the coffee sector, integrating circular economy principles into SCG management has drawn attention. Digital technologies support traceability and decision-making, particularly when routing waste between circular coffeeshops (CCs) equipped with pre-drying technologies and smart bins. However, optimization models tailored to these systems remain underdeveloped.

Based on these studies, future research should take into account the unique characteristics of each network, which are shaped by the diversity of stakeholders, their specific objectives, and relevant environmental, social, and economic factors. This perspective highlights the

Table 1
Summary of VRP Applications in Reverse Logistics for Waste Management.

Authors	Problem type	Facilities in routing	Objective type	Decisions	Technology integration	Case Study	Waste type
Giasoumi et al., [19]	multi-trip VRP	Waste generation points and disposal sites	Total travelled distance minimization	Road selection and Routing	IoT-equipped bins	Netherland	Municipal solid waste
Rekabi et al., [43]	Multi-depot LRP	Waste generation points, Depot, and Recycling Centers	Cost and Job Opportunities	Recycling Facilities Location and Routing	IoT at recycling facilities	Numerical example	Solid Waste
Salawudeen et al., [44]	CVRP	Depots and waste collection points	Minimize service cost and total travel distance	Routing, depot positioning, truck allocation	Global Positioning System (GPS)	Nigeria	Solid waste
Wei et al., [55]	MLCARPIF	Waste collection huts and transfer stations	Minimize total cost	Routing, intermediate facility location, fleet allocation	-	China	Solid waste
Mohammadi et al., [35]	CVRP	Waste generation points and separation centers	Total cost minimization Pollution minimization	Location, allocation, routing	IoT-equipped bins	Iran	Municipal solid waste
Ma et al., [30]	CLRP	Waste generation points and recycling centers	1) Recycling center obnoxious effects minimization 2) Logistics cost minimization	Location and scale, allocation, routing	-	China	Municipal solid waste
Flores-Carrasco et al., [15]	PLRP	Waste generation points and collection centers	Logistics cost minimization	Location, allocation, day of collection. routing	-	Chile	Glass, batteries, cardboard and paper, plastic, wood, organic and electronic waste
Chaabane et al., [12]	VRP	Dealers and broker	Total cost minimization	Routing	-	North America	End-of-Life Vehicles
Qiao et al., [40]	CVRP	Disposal center and smart bins	1) Vehicle cost minimization 2) Carbon emission cost minimization	Routing	Smart bins	China	Wet waste
Qiao et al., [40]	CVRP	Disposal center and waste bins	Total cost minimization	Routing	-	China	Municipal solid waste
Lu et al., [29]	CVRP	Disposal center, transfer stations and smart bins	1) Transportation cost minimization 2) Carbon tax cost minimization	Assignment of bins to transfer stations and routing	ICT, IoT, Smart bins	China	Recyclable and non-recyclable waste, hazardous waste
Wu et al., [57]	CVRP	Disposal center and smart bins	1) Total cost minimization 2) GHG emission minimization 3) Total distance minimization	Routing and amount of	Smart bins with different priorities	China	Municipal solid waste
Bottani et al., [9]	CVRP	Vending machines companies and pellet production plant	Logistics cost minimization	Routing and vehicle type	ICT tool	Italy	SCG to produce combustible pellets
Schmidt et al., [46]	TD-LRP	Customers and depots	Total driving time minimization	Location, allocation, period, truck load, routing	-	Canada	Urban freight
Ramos et al., [42]	CVRP	Disposal center and smart bins	1) Transportation cost minimization 2) maximization of profit	Routing and flow amount	ICT, IoT, Smart bins	Portugal	Municipal solid waste
Hemmelmayr et al., [20]	PLRP	Hunger relief agencies and recycling centers	Logistics cost minimization	Location and size, allocation, schedule, routing	-	Vien-USA	Cardboard boxes
Our work	LVRP	Business model 1: CS and treatment facility Business model 2: CC and treatment facility	Business model 1: Minimization of the transportation cost Business model 2: Minimization of the transportation cost * Contamination risk minimization entails technology integration	Business model 1: Routing Business model 2: CC Location, pre-drying equipment capacity, allocation of CS to CC, routing	Smart bins, pre-drying technology equipment, Electric Vehicle (EV)	Canada	SCG to produce activated carbon

need for a more comprehensive understanding of network-specific challenges and the development of targeted solutions. Furthermore, the literature highlights the critical role of technological advancements and the transition toward sustainability through intelligent systems. Recent studies highlight the benefits of integrating smart technologies in waste management, particularly in enhancing collection efficiency. These insights indicate a promising direction for future research to explore the application of intelligent solutions in this domain.

2.5. *Literature gaps*

Despite growing interest in circular applications for SCG, significant research gaps remain, particularly concerning their integration into reverse logistics and supply chain systems. Existing studies largely overlook the logistical complexities that hinder large-scale SCG recovery. First, SCG is generated in small, dispersed quantities across decentralized sources such as cafés, households, and offices, increasing collection complexity and cost. Second, its high moisture content (60–80 %) leads to rapid degradation, necessitating timely collection or pre-treatment to maintain material quality. Third, contamination and variability—due to mixing with filters, stirrers, and food waste, as well as inconsistent grind sizes and moisture levels—pose challenges for standardization and downstream processing. Fourth, economic viability remains a major obstacle, as SCG has low intrinsic value and high logistics costs, often making recovery economically unfeasible without government subsidies or innovative business models. Finally, the integration of digital technologies (e.g., IoT, mobile apps, real-time tracking, and smart routing) into SCG logistics is underexplored, limiting opportunities for data-driven optimization. These gaps highlight the need for research into tailored, scalable, and technology-enabled reverse logistics models that address the specific characteristics of SCG and support its effective valorization within circular supply chains. Therefore, this paper aims to fill the following three gaps:

1. From a modeling perspective, no existing research proposes or evaluates logistical business models designed explicitly for SCG. A comparative analysis of their feasibility under different conditions is also lacking.
2. From a methodological perspective, no studies have addressed the location-routing problem for SCG reverse logistics, particularly from geographically dispersed and small-scale generators such as coffee shops.
3. From a decision-support perspective, there is a lack of decision-making models and managerial insights based on real cases that consider the role of Industry 4.0 in SCG reverse logistics network design.

3. Research framework

We aim to develop a decision support system (DSS) specifically designed to address the challenge of optimizing a circular supply chain for coffee waste, thereby addressing the associated business challenge. To achieve this, we adhere to a methodology centered on the "Data First / Model Second" (Fig. 1). By applying this method to our problem, we emphasize a systematic approach that prioritizes understanding and preparing data before developing the appropriate analytical model to manage the reverse logistics for waste management. The step-by-step methodology involves framing the business problem, defining the analytics problem domain, collecting and understanding data, selecting a methodology, building models, deploying models, and managing the model lifecycle [23].

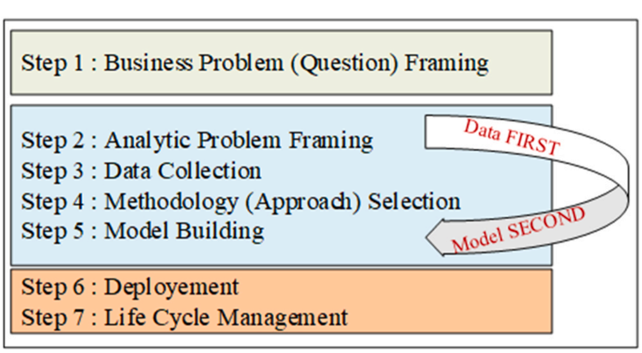

Fig. 1. Research Design Process (Adapted from [23]).

3.1. Business problem description and analytical problem framing

Our study evaluates various RL network configurations as business models supporting SCG collection and valorization. Within these networks, coffee shops generate SCG daily, which must be collected and transported to a treatment center to produce activated carbon. The treatment company is responsible for collecting and processing SCG and preparing it for sale in target markets for water purification and air filtration applications. The treatment process involves drying and activating the SCG at elevated temperatures.

This problem involves determining the most efficient strategy for collecting SCG. This can be approached from two economic perspectives: minimizing total cost and maximizing total profit. Our study tackled this problem from a cost-minimization perspective, as our primary interest lies in examining cost efficiency. To develop a realistic case study, we collaborated with a company in Montreal that specializes in collecting and treating SCG. Our objective was to explore various configurations of the SCG reverse logistic network. These configurations provide decision-makers with a spectrum of potential business model options. Consequently, we identified two primary business models for SCG collection. The first model assumes no collaboration between coffee shops, requiring the collection process to visit each location where SCG is generated individually. In contrast, the second model is based on cooperation among coffee shops, allowing SCG to be aggregated at strategically selected sites. These designated collection points, referred to as Circular Coffee Shops (CCs), serve as hubs where SCG from nearby shops is consolidated for more efficient pickup.

In the current logistics model (Baseline), trucks are scheduled to visit all coffee shops to collect SCG, as illustrated in Fig. 2(a). In this baseline scenario (Case 1), the network does not include any pre-drying equipment at the coffee shop locations. As a result, the SCG is collected in its wet state and transported directly to the treatment center. All subsequent processing steps—namely drying and activation—are carried out exclusively at the treatment facility. In Business Model 1 (Case 2), we propose integrating ultrasmall pre-drying equipment, each equipped with an IoT system, at individual coffee shops. The collector provides this equipment, enabling partial drying of the SCG on-site before collection. As shown in Fig. 2(b), this configuration reduces the moisture content—and consequently, the weight—of the SCG before transportation to the treatment center. This can lead to lower transportation costs and minimize the risk of contamination during transit. However, it is essential to consider the additional investment and operational costs associated with deploying and maintaining the pre-drying equipment.

In Business Model 2 (Case 3), SCG are first transported to CC equipped with a pre-drying system. This model introduces financial incentives and government subsidies to encourage participation from city-based delivery drivers. Within this setup, smart bins at the CC are equipped with sensors that enable waste segregation, enhancing the quality of the final product. These sensors also collect valuable data on the type and quantity of SCG, as well as other parameters such as moisture content and temperature. The CC serves several functions: it consolidates SCG from multiple coffee shops into larger, more economical batches for transportation; removes non-organic contaminants, such as plastics and metals; and provides temporary storage before the SCG is sent to the treatment facility. After dehydration and compaction at the CC, the SCG is transported to the processing facility, where it is transformed into activated carbon for use across various industries. Fig. 3 illustrates the configuration of Business Model 2 under Case 3. The decisions stemming from this business model aim to determine the optimal location for the CC and efficiently allocate coffee shops to it. This optimization seeks to minimize transportation costs, mitigate environmental risks, and minimize contamination.

3.2. Data collection

This section presents the data required to solve the proposed business

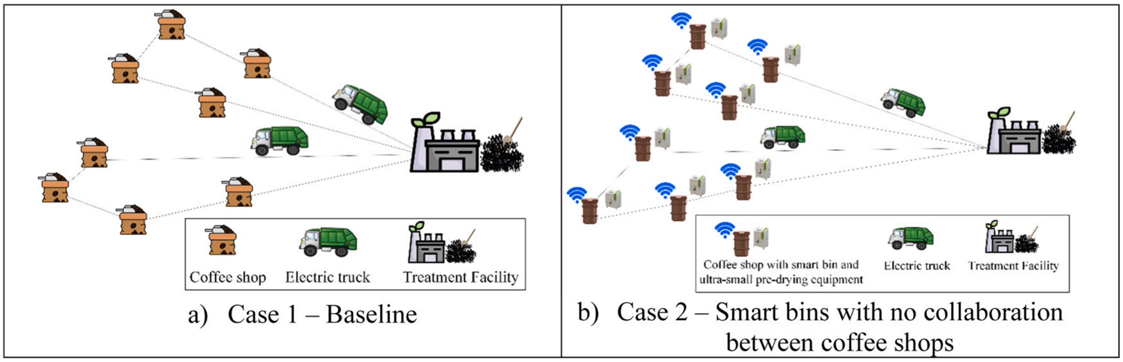

Fig. 2. Business Logistics Model 1: No Collaboration Between Coffee Shops.

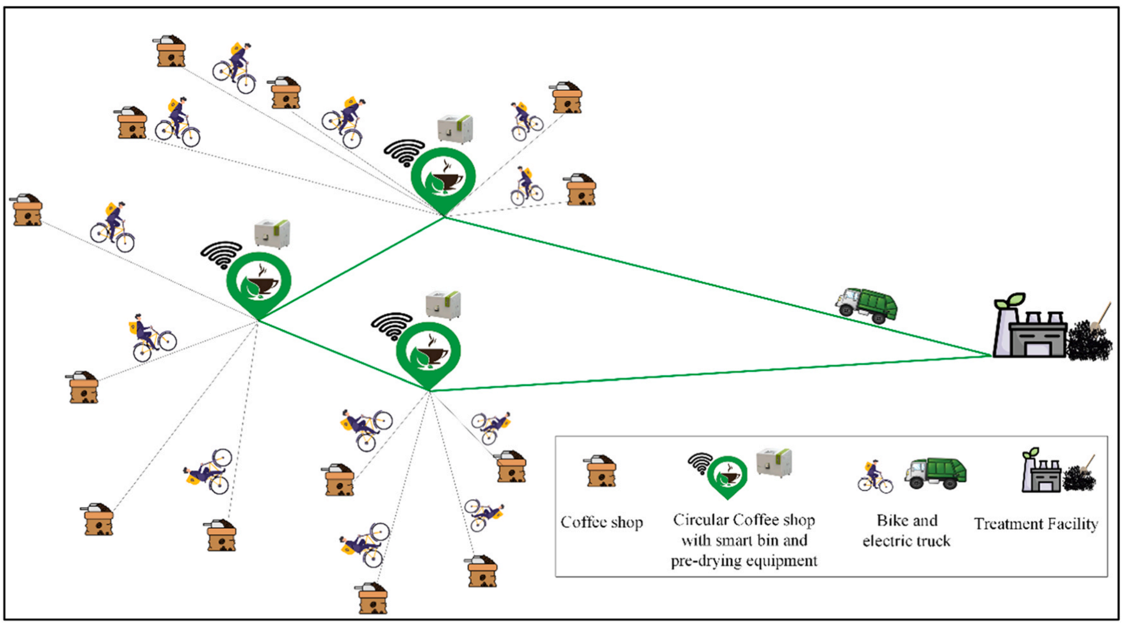

Fig. 3. Business Logistics Model 2: Collaboration Between Coffee Shops.

problem. We can classify data into three categories.

- **Data related to coffee shops**, including location and the amount of SCG generated in these establishments.
- **Data related to transportation**: Capacity of EV, Maximum distance an EV can travel (in kilometers), fixed cost of route, electricity consumption rate per unit time while EV is idle, electricity consumption rate per unit distance while the EV is moving, price of electricity per unit consumption, and the cost of transferring SCG from coffee shops to CC.
- **Data related to circular coffee shops**: Capacity of pre-drying technologies installed at CC, fixed installation cost, service time in CC to collect SCG, the amount of dehydrated SCG collected from CC, and the yield factor at CC.

3.3. Methodology selection

For each business model, we identified the problem's assumptions, utilizing insights from the literature review and information gathered about the coffee industry. In Business Model 1, since we focus on designing a collection route from a wide range of coffee shops, it is essential to solve the VRP efficiently. Different resolution methods can be used [25]. In our case, we employ a two-phase heuristic approach, where the first phase involves clustering, and the second phase requires routing. This approach is widely used to solve complex routing problems, such as the Electric Vehicle Routing Problem (eVRP) [5]. This method offers several advantages, particularly for large-scale or computationally intensive issues, such as those involving a significant number of coffee shops [6]. Therefore, the significance of clustering is evident in its ability to effectively address VRP models [54]. The methodology employed to solve the VRP in the first phase is a hierarchical clustering approach, which benefits from the required properties. Unlike other clustering methods such as k-means clustering, hierarchical clustering does not require the specification of the number of clusters in advance [54]. This makes it worthwhile because we only need the final clusters to be less than a specific amount. This clustering phase is composed of five steps: 1) Initial clustering, 2) Cluster center and service aggregation, 3) Distance estimation, 4) VRP with cluster centers, and 5) Sub-VRP within clusters and recursive clustering. The algorithm developed in this study can be summarized as follows. The algorithm begins by clustering points and estimating the routing distances within each cluster. It iterates, refines the clusters until it reaches a target number, and saves the subclusters into a tree structure. Routes are then generated by solving the VRP using an exact method (CPLEX solver) for each cluster. For each vehicle, the algorithm optimizes the route from the depot to the cluster points. It continues the VRP process until a specified stopping condition is satisfied, ultimately producing the final optimized routes.

For the second business model, a Location-Routing Problem (LRP) was formulated to identify the most cost-effective logistical configuration. Potential CC sites were selected from among the existing coffee shops already participating in the program. To generate the list of candidate CC locations, the partnering company employed a multi-criteria decision-making (MCDM) approach. Each coffee shop was evaluated and assigned a score based on several criteria, including the potential volume of SCG, proximity to the treatment center and other clusters, infrastructure readiness, willingness to participate in the program, and the associated environmental benefits. These scores informed the potential CC sites, ensuring that both logistical efficiency and sustainability objectives were considered in the configuration process.

Next, we developed a location-routing optimization model by defining the objectives, constraints, and relevant parameters for which we gathered the data. The objective function represents the goal we aim to achieve, while the constraints represent the limitations and requirements that the solution must adhere to. To solve the LRP model within the Python programming environment, we utilized exact optimization solvers, specifically Gurobi.

3.4. Deployment and life-cycle management

To address our research questions, we developed a decision support system (DSS) framework as depicted in Fig. 4. The framework consists of three modules: the Data Management module, the Optimization module, and the Evaluation module. The "data management" module is responsible for managing and validating data to construct the case study. We gathered essential data using available databases from Montreal coffee shops, the case company, and other related projects. The optimization module is developed to solve the optimization models developed for each business model and case. The evaluation module is used to analyze results. Following the resolution of the mathematical model, the focus shifts towards evaluating its performance metrics and analyzing the obtained results to gain valuable insights to inform decision-making, refine strategies, and optimize implementations. To assess the robustness of our model under varying conditions and understand its behavior under uncertainty, we conducted a sensitivity analysis using parameter variation and created different scenarios.

4. Optimization models

4.1. Assumptions

The development of mathematical models (VRP and LRP) is based on the following assumptions:

- The number and location of coffee shops are known.
- Distances were calculated based on address and postal codes.
- All the coffee shops' demands should be collected.
- The network has only one treatment facility, and its location is known.
- The quantity of SCG in the coffee shops was estimated and determined. We assumed that this was calculated by assessing the size of the coffee shop. This assessment considers average coffee sales data, which include information on the number of coffee cups sold, the volume of those cups, and a conversion factor for the weight of the generated SCG.
- The transportation costs of using EVs were estimated and determined.
- The electricity consumption rates of EVs vary and are determined for different operating modes.
- The service time is estimated and determined based on observations.
- Each EV had a predefined capacity, weight, and maximum allowable crossing length.
- The velocity of each EV is estimated based on the urban area context of the study.
- The fixed cost of each route is estimated and determined.

Additionally, several specific assumptions are considered for Business Model 2 (Case 3):

- A limited amount of SCG regarding capacity issues can be allocated to each coffee shop.
- The coffee shop has an intelligent bin with notification capabilities.
- Following the pre-drying treatment in the CC, the amount of SCG decreased due to dehydration and compaction.
- The inflow into the CC was equal to the outflow, accounting for the determined dehydration rate.
- The establishment costs of CC equipped with pre-drying technology were estimated and determined based on its capacity features, spread over the initial five years of use.
- An innovative financial mechanism estimates and determines the transportation costs between coffee shops and CC.
- Candidate locations for setting up CC were selected from the available coffee shop sites through an integrated selection process.
- The estimated establishment costs of smart bins amounted to 30 % of the costs of CC equipped with pre-drying technology.

The mathematical model for Business Model 1 (VRP) is described in the Appendix.

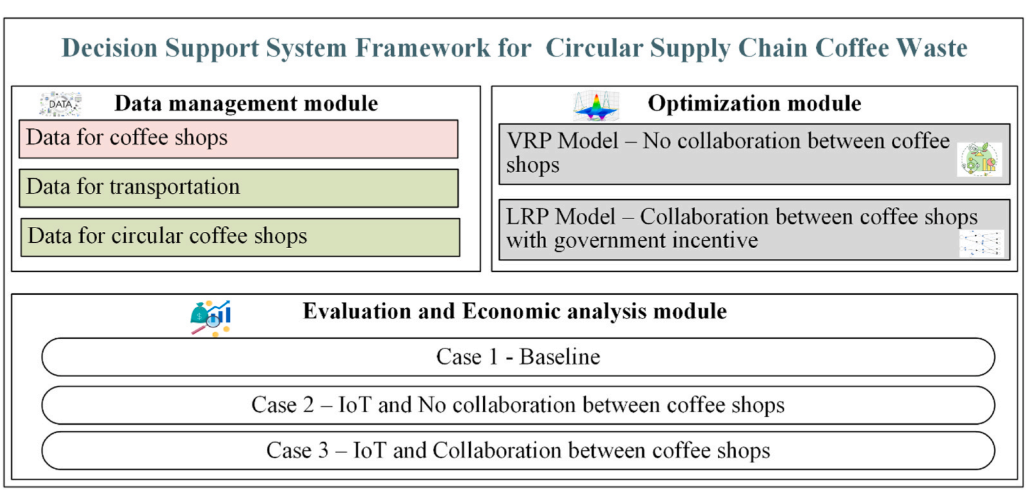

Fig. 4. DSS Framework for a Circular SCG Reverse Logistics Network.

4.2. Mathematical formulation for business model 2

To address this problem, we developed a mathematical model to minimize the total cost of the SCG collection network. We chose cost minimization over profit maximization to analyze the route costs and cost per kilogram of SCG. This approach enabled us to determine the most efficient and cost-effective method for collecting SCG. The mathematical model for Business Model 2– Cases 3 and 4 includes sets, parameters, decision variables, an objective function, and constraints, as outlined below:

4.2.1. Sets and indices

i Index of coffee shops as the SCG generation point

j, h Index of potential sites for CC equipped with pre-drying technology.

k Index of routes

c Index of capacity of CC (e.g., small =1, or large = 2)

4.2.2. Decision variables

y_{hc} If CC h with the capacity level of c is established in the location of an existing coffee shops

z_{hi} If CS i is allocated to CC h

x_{hjk} If a route k exists when transporting from CC h to CC j

4.2.3. Parameters

w_i Amount of SCG generated in coffee shops i (kg)

Q Capacity of EV (kg)

L Maximum length that an EV can traverse (km)

Q_{hc} Capacity of CC h with a capacity level of c (kg)

F_k Fixed cost of route k ($)

F_{hc} Fixed cost of establishing CC h with a capacity level of c ($)

d_{hj} Distance between CC h and CC j (km)

t_j Service time in CC j (min)

ρ_{idle} Electricity consumption rate per unit time while EV is idle (L/min)

ρ_{hj} Electricity consumption rate per unit distance while the EV is moving (kWh/km)

ρ Price of per unit electricity consumption ($/kWh)

α_{ih} Cost of transferring SCG from coffee shops i to CC h ($)

q_h The amount of dehydrated SCG that is collected from CC h (kg)

β yield factor for the dehydration process at CC.

γ yield factor for the activation carbon process at the treatment center (collector)

4.2.4. Objective function

Objective Function (1) aims to minimize the total cost associated with designing and operating a reverse logistics network for managing SCG. The function integrates five key cost components, each representing a real-world operational element:

1. Fixed cost of vehicles: This term represents the cost incurred for making transportation vehicles available within the network, regardless of usage. It includes leasing, insurance, and depreciation costs.
2. Variable transportation cost Between CC: This cost encompasses electricity consumption, maintenance, and driver wages necessary for transporting SCG between CC. It depends on the distance or time traveled and models the operational flow of materials between intermediate facilities.
3. In-Service time cost at CC: This accounts for the time-based processing cost of SCG at each CC, including labor, sorting, temporary storage, and material handling. It reflects the efficiency and capacity constraints of each coffee shop acting as a circular node.
4. Establishment Cost of CCs: This fixed cost captures the investment required to set up and operate each CC as a collection or processing point in the circular supply chain. It includes infrastructure, utilities, and administrative overhead.
5. Transportation cost of SCG from coffee shops to CCs: This represents the cost of collecting SCG from individual coffee shops and delivering it to the assigned CCs. It represents first-mile reverse logistics and varies based on location, frequency, and quantity transported.

$$MinF = \sum_{k=1}^{K}\sum_{j=0}^{N}(x_{0jk} * F_k) + \sum_{h=0}^{N}\sum_{j=0}^{N}(x_{hjk} * d_{hj} * \rho_{hj} * \rho) + \sum_{j=1}^{N}(x_{hjk} * t_j * \rho_{idle} * \rho) + \sum_{h=0}^{N}\sum_{c=1}^{2}(F_{hc} * y_{hc}) + \sum_{i=1}^{N}\sum_{h=1}^{N}(\alpha_{ih} * z_{ih}) \tag{1}$$

4.2.5. Constraints

$$\sum_{k=1}^{K}\sum_{h=0}^{N} x_{hjk} = 1, \quad \forall j = 1, \dots, N \tag{2}$$

$$\sum_{k=1}\sum_{j=0} x_{hjk} = 1, \ \forall h = 1, \dots, N \tag{3}$$

$$\sum_{h=0}^{N} x_{hjk} = \sum_{h=0}^{N} x_{jhk} = 1, \forall j = 1, \dots, N; k = 1, 2, \dots, K \tag{4}$$

$$\sum_{j=1}^{N} x_{hjk} * q_h \le Q, \ \forall h = 0, 1, \dots, H \tag{5}$$

$$q_h = \left(1 - \beta\right) * \left[\sum_{i=1}^{N} z_{ih} * w_i\right] \forall h = 0, 1, \dots, H \tag{6}$$

$$\sum_{h=0}^{N}\sum_{j=0}^{N} d_{hj} * x_{hjk} \le L, \quad \forall k = 1, 2, \dots, K, \quad h \ne j \tag{7}$$

$$\sum_{h=0}^{N}\sum_{j=0}^{N} x_{hjk} \le |S| - 1, \quad S \subseteq \{1, 2, \dots, N\}, \quad \forall k = 1, 2, \dots, K \tag{8}$$

$$\sum_{h=0}^{N} z_{ih} = 1, \quad \forall i = 1, 2, \dots, I \tag{9}$$

$$\sum_{c=1}^{C=2} y_{hc} = 1, \quad \forall h = 1, 2, \dots, H \tag{10}$$

$$\sum_{i=1}^{N} z_{ih} * w_i \le Q_{hc} * y_{hc} \quad \forall h = 1, 2, \dots, H, \forall c = 1, 2 \tag{11}$$

$$x_{hjk}, y_{hc}, z_{ih} = \{0, 1\} \tag{12}$$

Constraint (2) ensures each CC is visited exactly once, guaranteeing timely SCG collection and preventing material buildup. It mirrors real-world policies where every collection point must be serviced during the planning period. Constraints (3) and (4) define the start and end points of vehicle routes. Each vehicle departs from the central depot (Constraint 3) and returns to the treatment facility after servicing its assigned CCs (Constraint 4), reflecting a closed-loop reverse logistics system. Constraint (5) limits the amount of SCG on each route to the vehicle's maximum load, ensuring safety, compliance with legal weight limits, and operational feasibility. Constraint (6) models the transformation of wet SCG to dehydrated SCG at CCs. It enforces mass balance by applying a fixed yield factor, based on moisture content, to avoid overestimating usable output. Constraint (7) limits each vehicle's total travel distance to a predetermined maximum, reflecting physical, regulatory, or operational limitations (e.g., driver hours, urban constraints), thereby ensuring practical and efficient routing. Constraint (8) prevents subtours, ensuring that all routes form a single, connected path from the depot through assigned CCs to the treatment facility, avoiding isolated loops that disrupt SCG consolidation. Constraint (9) assigns each coffee shop to exactly one CC to simplify logistics, reduce handling complexity, and ensure efficient routing and scheduling. Constraint (10) enforces a single capacity type (e.g., small, medium, large) per CC, supporting infrastructure planning and ensuring operational consistency. Constraint (11) ensures that the SCG assigned to each CC does not exceed its processing capacity, aligning shop assignments with CC capabilities and thereby avoiding bottlenecks. Constraint (12) defines binary decision variables for routing, facility setup, and assignments, capturing essential yes/no decisions within the reverse logistics network.

5. Experimentation, results, and insights

5.1. Case study: data collection

The proposed approach for creating a smart and sustainable RL network for SCG valorization was implemented in a case study in Montreal, Canada. With a population exceeding 1.7 million, Montreal produces considerable SCG daily, demanding significant attention. To evaluate the applicability of this research, 1000 CS in Montreal that are potentially willing to participate in collaborative SCG collection and treatment are considered as waste generation points. This list was obtained from our industrial partner and represents the list of coffee shops that confirmed their voluntary participation in this pilot project. To ensure data accuracy, we validated available datasets using Google Maps. Finally, the dataset was cleaned by standardizing variables (e.g., shop names, addresses, categories), geocoding location data, and filtering out incomplete or irrelevant entries.

For SCG generation rates, these were derived from actual data obtained through our partner and supplemented with estimates based on average coffee sales volumes from selected coffee shop chains. Each coffee shop typically sells between 4000 and 10,000 cups of coffee per week, resulting in daily outputs of 5–7 kg of SCG. For 1000 coffee shops participating in this program, 6271 kg of SCG were generated daily.

For the transportation data, a hybrid approach was employed. Real-world cost parameters were collected from local logistics providers and government databases. Routing distances were simulated using GIS-based tools to model various collection scenarios. Additionally, according to our observations, servicing each coffee shop takes approximately 3–5 minutes. Finally, based on the company's data for the EV, the values are as follows: $Q = 2,000Kg, L = 150km$, and $F_k = 300\$$.

In our analysis, we considered the fixed costs associated with establishing pre-drying capabilities at coffee shops and CCs by assuming specific capacities and cost parameters for different types of pre-drying machines. For the ultra-small pre-drying machine, which has a capacity of 40 kg, we assumed a capital cost of $10,000. This machine is deployed in Model 1 – Case 2, and a daily operational cost of $13 was considered in the model to represent its amortized fixed cost over time. For CC in Model 2 – Case 3, we examined two types of pre-drying equipment based on their capacity levels. The small pre-drying machine, with a capacity of 100 kg, was assumed to cost $16,000, and its daily fixed cost was set at $36 per day. Similarly, the medium-sized pre-drying machine, capable of handling 300 kg, was estimated at $20,000, with a corresponding daily fixed cost of $45. These daily costs were incorporated into the models to reflect the fixed costs of establishing CCs with different pre-drying capacity levels, thereby enabling a comparative evaluation of the investment requirements and economic performance across the various business models and scenarios. The computational experiments were conducted on a workstation equipped with an Intel Core i7–1165G7 processor operating at 2.80 GHz, 16 GB of RAM, and running a 64-bit version of Windows 11 Pro. The implementation was conducted using Python 3.10, with optimization tasks managed by CPLEX and Gurobi solvers. Performance metrics of the proposed system were computed and analyzed to evaluate its efficiency. Most of the VRP instances were successfully solved by CPLEX within one hour. For the LRP model, Gurobi was able to solve most instances within an average computation time of 20 minutes.

5.2. Results for Case 1

To manage the complexity of the routing problem in Case 1, we began by clustering the 1000 participating coffee shops into 12 manageable groups, referred to as efficient points (EF), using a customized hierarchical clustering approach based on geographical distribution. The decision to use 12 clusters strikes a balance between geographical accuracy and computational efficiency. This configuration represents a trade-off between granularity, problem manageability, and computational tractability. Specifically, our system's computational capabilities enable the solution of the VRP for 12 clusters within a reasonable timeframe, making the optimization process both feasible and effective. Each cluster is represented by a virtual center, as illustrated in Fig. 5. These virtual centers do not necessarily correspond to the location of a specific coffee shop but instead serve as aggregated representations of all shops within the cluster. For each virtual center, we aggregated the total service time and the total amount SCG generated by the coffee shops in that cluster. These virtual centers then served as single nodes in the initial routing computations, significantly simplifying the problem size and structure. Since the exact distances between coffee shops within a cluster were unknown before solving the full VRP, we estimated initial distances for the preliminary calculations. This estimation involved calculating the average distance from all coffee shops in a cluster to the cluster's virtual center and applying necessary adjustments to improve approximation accuracy. Using this approach, we conducted a preliminary VRP, treating the treatment facility and the 12 cluster centers as nodes, as shown in Fig. 6. The actual and estimated distances from the treatment facility to each virtual cluster center were calculated to determine the optimal number of routes and the optimal sequence for visiting these clusters. This method enabled a rapid and efficient estimation of routing logistics, facilitating subsequent, more detailed VRP solutions within each cluster.

After solving the VRP for the cluster centers, we proceeded to optimize the routes within each cluster through a secondary VRP. This step aimed to determine the most efficient path for visiting all the coffee shops associated with each cluster. For clusters containing more than ten coffee shops, a recursive subdivision method was implemented, dividing them into smaller subclusters with no more than ten coffee shops each. This hierarchical approach significantly enhances computational

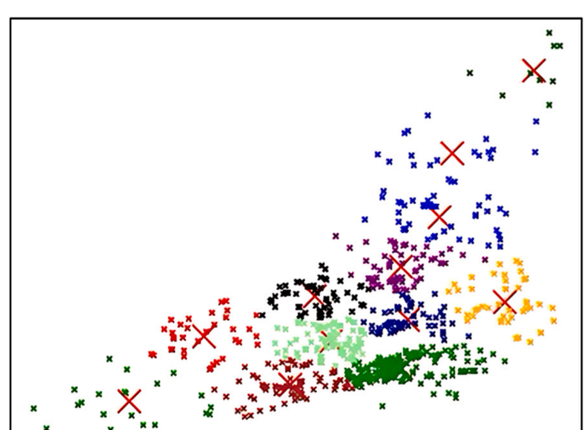

Fig. 5. Creation of Clusters of Coffee Shops.

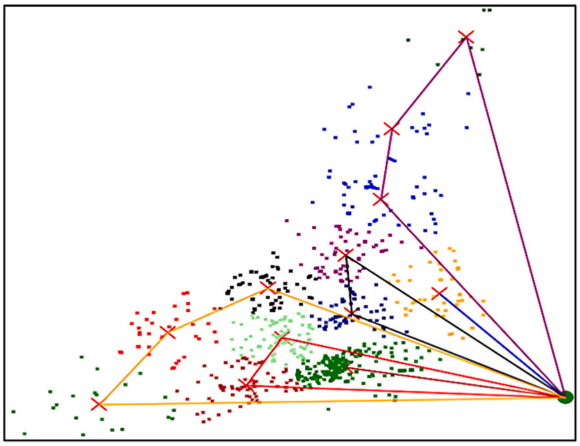

Fig. 6. VRP Solution Based on 12 Cluster Centers.

efficiency, ensuring that each VRP instance can be solved within a practical timeframe. Fig. 7 illustrates the outcome of applying the recursive clustering technique to Business Model 1 in our case study. The figure highlights the six optimized routes required to collect all spent coffee SCG.

In Case 1, as illustrated in Fig. 7, the collection of 6271 kg of SCG per day required six routes, covering a combined distance of 611 km. The entire collection process took approximately 65.25 hours, including 24 hours of transportation time and 41 hours of service time at the coffee shops (CS). The total transportation cost was $1835.73, comprising $1800 for routing operations and $35.73 for the energy consumption of EVs. This results in a unit transportation cost of $0.29 per kilogram of SCG. With a two-shift daily operation, consisting of 10-hour shifts, it was feasible to schedule the SCG collection process over three days to complete all six routes. Adhering to this timeline is crucial, as exceeding it significantly increases the risk of SCG contamination. Table 2 presents detailed metrics for each of the six routes. It is essential to note that no investment costs were incurred in this scenario, as neither smart bins nor pre-drying equipment were implemented.

5.3. Results for Case 2

In Business Model 1 – Case 2, each coffee shop is equipped with IoT-

Table 2
Detailed Information on the VRP Plan in Case 1.

Route	SCG amount (kg)	Number of coffee shops	Distance (km)	Time (h)
1	800	120	53.59	4.89
2	1462	230	96.65	10.61
3	447	100	117.70	13.91
4	1288	150	124.00	9.10
5	1258	170	81.23	14.14
6	1016	230	138.11	12.60
Total	**6271**	**1000**	**611**	**65.25**

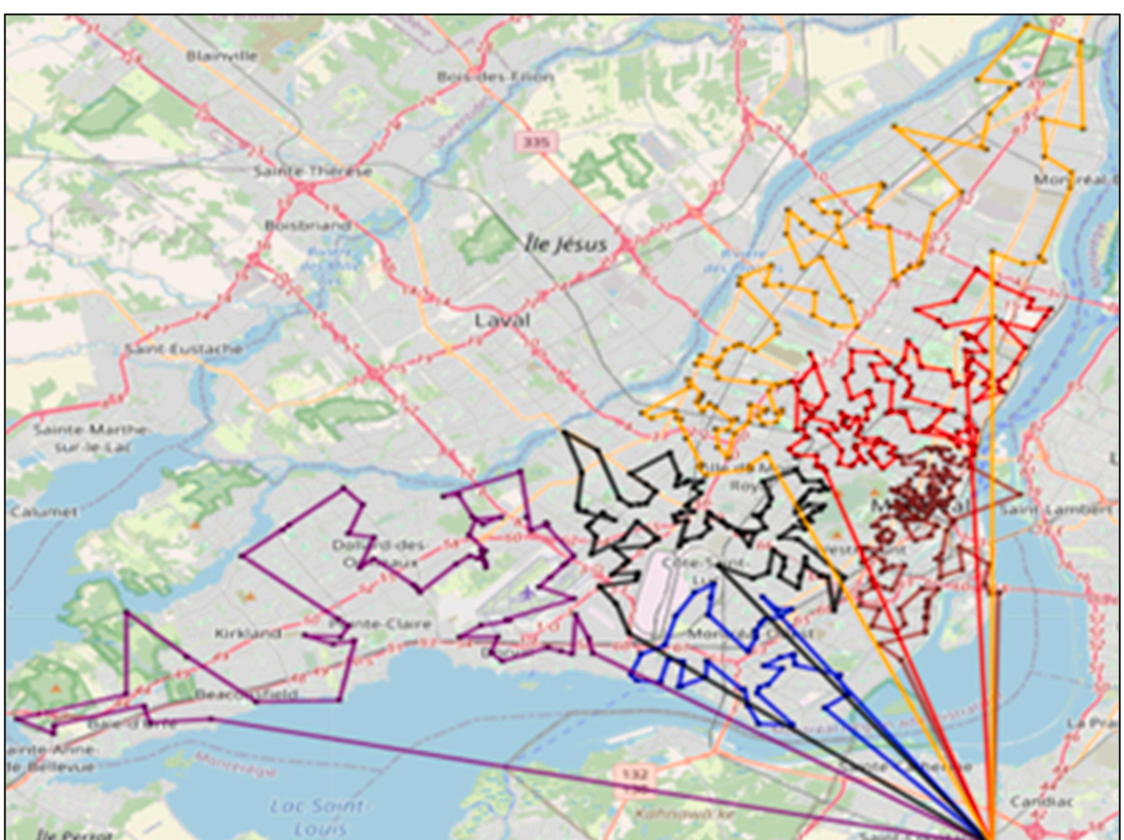

Fig. 7. Optimal Route Configuration – Business Model 1, Case 1.

enabled smart bins and ultra-small pre-drying technology. This configuration allows for the safe storage of pre-dried SCG on-site for up to one week, eliminating the need for daily collection. The pre-dried SCG produced under this model maintains a quality suitable for activated carbon production, with no risk of contamination at the source. However, the incorporation of these advanced technologies results in higher costs compared to Case 1. Specifically, an annual investment of $10 million (10,000 $ * 1000) is required over five years to deploy the intelligent bins and ultra-small pre-drying units across participating coffee shops.

If daily collection were implemented in Case 2, the utilization rate of EVs would decrease due to underutilized truck capacity, leading to inefficiencies. In contrast, the weekly collection model proves to be more efficient and cost-effective, as it minimizes the number of trips and maximizes EV capacity utilization. This approach also reduces overall maintenance expenses, resulting in a more predictable and consistent operating cost structure. While daily collection provides greater flexibility, it introduces lower efficiency and higher maintenance costs, which may offset its perceived operational advantages in the long term. Table 3 presents a comparison of EV utilization rates for Cases 1 and 2 under daily and weekly collection scenarios, highlighting the operational benefits of the weekly collection strategy in Case 2.

5.4. Results for Case 3

In Case 3, a total of 6271 kg of SCG was transported from coffee shops to the CC. However, after applying the consolidation and pre-drying process at the CC, only 1500 kg of pre-dried SCG was ultimately collected. As shown in Fig. 8, 21 out of 28 potential sites were selected for the establishment of CC, each equipped with medium-sized pre-drying technology. Existing coffee shops were then allocated to these selected CCs. Due to the consolidation of SCG and efficient route planning, only one route—with a total travel distance of 89.5 km—was required to collect all pre-dried SCG. Moreover, the total collection time was reduced to 4.9 hours, which includes 3.5 hours of transportation and 1.4 hours of service time at the CC. This represents a significant improvement compared to the longer collection process observed in Case 1.

Additionally, Case 3 offers operational advantages, including reduced time spent on the road and lower risk of EV accidents and SCG contamination. This is made possible by the ability to safely store dehydrated SCG at the CCs for up to one week. The total transportation cost in Case 3 was $305.44, which includes $300 for routing and $5.44 for EV energy consumption. As a result, the unit cost for collecting and transporting SCG is $0.29/kg in Case 1 and significantly lower at $0.04/kg in Case 3. These costs are considered reasonable and justifiable when compared to the market value of activated carbon and its valuable byproducts, reinforcing the economic viability and sustainability of the overall process. A cost comparison between Cases 1 and 3 in Table 4 highlights the superior transportation cost-effectiveness of Business Model 2, which achieves substantial savings by leveraging centralized collection and pre-drying. In this scenario, we also assumed that transportation from coffee shops to CCs is supported through a subsidy, provided to the collector as an incentive. Since this cost is not directly compared to the fixed costs of establishing CCs, the optimization algorithm tends to reduce the total system cost by selecting fewer CCs, even if this results in longer travel distances for bikes or other local transport methods.

Table 3
Comparison of EV Utilization Rates by Route: Daily vs. Weekly Collection.

Route	EV utilization rate – Case 1 (Daily collection)	EV utilization rate – Case 2 (Weekly collection)
1	27 %	7 %
2	49 %	12 %
3	15 %	4 %
4	43 %	11 %
5	42 %	10 %
6	34 %	8 %
Average	35 %	9 %

6. Sensitivity analysis

6.1. Change in the participation rate of coffee shops in SCG generation

This analysis evaluated the impact of varying participation rates among coffee shops in the SCG collection program under both optimistic and pessimistic scenarios. Pessimistic scenarios, such as accidental disposal of SCG, were considered for the post-network establishment phase. In contrast, optimistic scenarios reflect improved participation driven by effective awareness campaigns. To capture a broad spectrum of potential outcomes, we developed scenarios by assigning participation rates ranging from 65 % to 125 %, based on realistic assumptions. A uniform distribution was used to randomly assign corresponding SCG weights, allowing for a comprehensive assessment of program performance under various participation conditions.

The sensitivity analysis results and the performance comparison between Cases 1 and 3 in terms of collection cost per unit of SCG under varying coffee shop participation rates reveal that Case 1 consistently incurs higher collection costs across the analyzed scenarios. This outcome highlights the impact of economies of scale, where increasing the volume of SCG collected results in lower unit collection costs. In pessimistic scenarios, where SCG generation is lower than anticipated, the pre-drying equipment may be underutilized, potentially rendering the investment in such technology economically unjustifiable.

In Business Model 2 – Case 3, the network was initially configured with 21 CCs. However, in the most optimistic scenario—driven by successful awareness campaigns and higher-than-expected participation at coffee shops—five additional CC were required, increasing the total to 26. This outcome highlights the importance of strategic planning in meeting future demand growth, particularly during the project extension phase. Ongoing investment in awareness initiatives is also critical to maintaining high levels of participation.

Conversely, in the most pessimistic scenario, eight CCs remained unused due to the limited volume of SCG collected, emphasizing the importance of aligning infrastructure investments with realistic participation expectations. Furthermore, the analysis reveals a clear correlation between participation rates and time-related performance metrics. As coffee shop participation increases, total transportation and service time rise proportionally. This indicates that higher engagement levels place greater operational demands on the collection system. To address this, managers should consider strategies that enhance efficiency, such as route optimization based on real-time data on participation and SCG volumes at each location. Improving scheduling and resource allocation can also reduce idle time and enhance productivity during SCG collection operations.

6.2. Change in the number of coffee shops during the program contract

Participation in the SCG collection program may fluctuate over time, as some coffee shops may exit the program while others may join. These changes can be driven by various factors, including shifts in ownership, evolving business priorities, operational challenges, increased market competition, regulatory changes, and growing interest in sustainability initiatives. The results indicate that, under the same network configuration as in Case 3, a reduction in the number of participating coffee shops led to a decrease in the total distance traveled during the collection process. However, this decrease was accompanied by a reduction in the utilization rate of EVs. This suggests that although fewer participating coffee shops can result in lower transportation distances and potential cost savings, it also reduces vehicle efficiency and resource utilization.

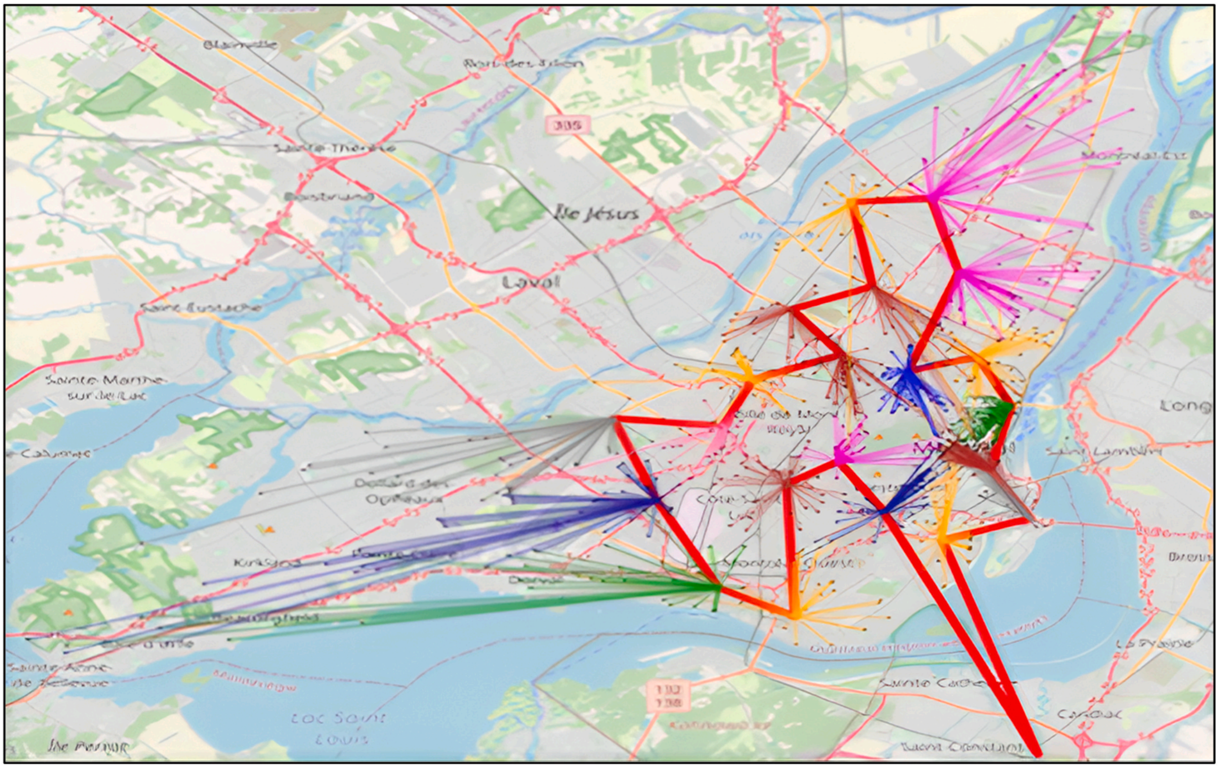

Fig. 8. Optimal Locations, Allocations, and Routes for Case 3.

Table 4
Comparative Analysis of Business Model 1 and Business Model 2.

Criteria	Case 1 (Baseline)	Case 2 (no collaboration)	Case 3 (with collaboration)
Infrastructure	-	Smart bin and ultra small pre-drying in all coffee shops	Pre-drying and smart bins in some coffee shops (CC)
Transportation Cost	1835.73 $	1829.89 $	305.44 $
Operational Efficiency	High transportation weight	Medium transportation weight	Low transportation weight
Environmental Impact	No monitoring, high contamination risk	Moderate efficiency of monitoring, medium contamination risk	High efficiency of monitoring, low contamination risk
SCG Quality for Treatment	Low	Medium	Standard

This finding highlights the interconnectedness of key operational variables in the SCG collection program. Evaluating program performance requires a holistic perspective that accounts not only for direct cost metrics but also for vehicle utilization and system adaptability in response to changing participation levels.

However, the observed decrease in EV utilization rates indicates a potential underutilization of resources, which can negatively affect overall operational efficiency. To address this, managers should prioritize building and maintaining strong relationships with participating coffee shops (and implement targeted measures to encourage their sustained involvement in the program. These measures may include providing continuous support, proactively addressing operational challenges, and offering incentives or reward systems for participation.

Equally important is balancing the recruitment of new coffee shops with strategies aimed at retaining existing participants. Ensuring program stability requires consistent engagement with current partners, which can be achieved through ongoing communication and responsiveness to their needs. Furthermore, leveraging data analytics and feedback mechanisms to monitor coffee shops' engagement and satisfaction levels can help managers quickly identify emerging issues and respond with timely interventions. This proactive approach fosters long-term commitment and contributes to the overall success and scalability of the SCG collection program.

The yield of pre-drying equipment may vary due to uncertainty factors, which can affect overall system performance. Fig. 9 illustrates the impact of fluctuations in the consolidation rate on electric EV utilization. This analysis reveals a clear trade-off between the weight reduction of SCG achieved through pre-drying and the utilization rate of EVs. Specifically, as the yield rate at the CCs decreases, meaning less effective weight reduction of SCG, the EV utilization rate increases. While higher EV utilization might appear beneficial, a lower consolidation rate undermines the purpose of pre-drying and reduces the overall efficiency of the consolidation strategy. Conversely, increasing the yield rate results in a more significant weight reduction; however, this may also lead to decreased EV utilization due to lighter loads and fewer full-capacity trips. As illustrated in Fig. 9, the EV utilization rate increases linearly with the SCG yield. This linear relationship can be explained using a single vehicle for SCG collection from CCs in Case 3. Since the quantity of SCG generated is directly proportional to the yield, and the vehicle's capacity remains constant, the utilization rate of the EV also follows a linear trend with respect to the yield. Managers must carefully navigate this trade-off to strike an optimal balance between transportation efficiency and waste processing effectiveness. Recognizing and addressing this dynamic is essential for optimizing waste management operations and maximizing the benefits of pre-drying technologies within the SCG collection network.

6.3. Business models' behavior in areas with different velocity ranges

In our analysis, we examined two distinct types of operational environments: areas with low potential for velocity and those with high

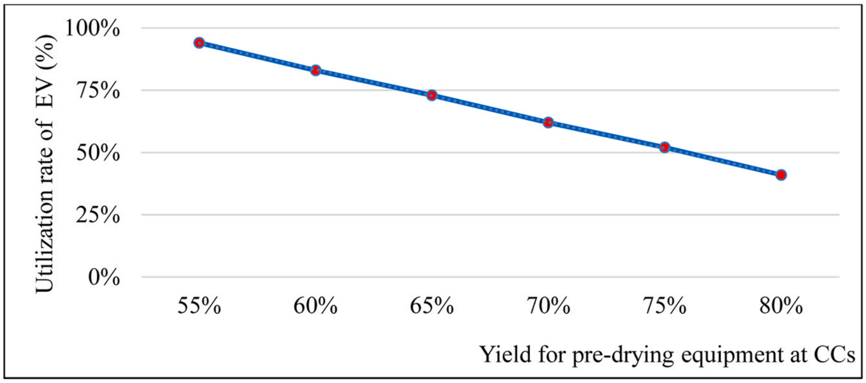

Fig. 9. Relationship Between Pre-Drying Yield Rate and EV Utilization (Case 3).

velocity potential. In regions with low-velocity zones, EVs travel at an average speed of 25 km/h, with possible fluctuations ranging from 22 to 32 km/h. These variations are influenced by factors such as traffic density, road conditions, and local speed limits. In contrast, high-velocity potential zones support higher average travel speeds, typically around 50 km/h, with variations ranging from 45 to 55 km/h. These differences are attributed to better road quality, favorable terrain conditions, and fewer regulatory speed constraints. Scenarios classified under high-velocity potential include regions such as the agricultural heartland, historic rural towns, tourist destinations, cultural heritage sites, and retirement communities. In contrast, low-velocity potential scenarios encompass settings like bustling downtown financial districts, vibrant and trendy neighborhoods, tranquil suburban residential communities, innovative tech hubs, and culturally diverse urban areas.

Fig. 10 illustrates the collection time associated with each scenario, considering the distinct velocity characteristics of the respective environments for Case 1 (baseline) and Case 3 (with CC). The results clearly show that collection times are consistently longer in low-velocity potential areas. This disparity is primarily due to factors commonly found in urban environments, such as higher traffic volumes, congestion, frequent stops, and shorter distances between collection points, which collectively slow down the collection process. Conversely, high-velocity potential areas enable faster and more efficient SCG collection. The reduced traffic, fewer interruptions, and more fluid traffic flow, combined with longer distances between stops, contribute to shorter and more consistent collection times. The contrast in operational performance between these two types of environments underlines the importance of incorporating environmental and contextual factors into the planning and optimization of EV-based SCG collection systems.

6.4. Business models' behavior in rural and urban areas

We further extended our evaluation by comparing the effectiveness of Business Model 1 – Case 1 (Baseline) and Business Model 2 – Case 3 in collecting SCG from 40 coffee shops located in rural areas, specifically in the cities of Drummondville and Victoriaville, near Montreal. Table 5 presents a comparative analysis of the performance of both models in rural versus urban settings. The results reveal that Business Model 1 – Case 1 outperformed Business Model 2 – Case 3 in rural areas, particularly in terms of cost per collection, demonstrating greater cost-effectiveness in low-density regions. This suggests that the use of centralized pre-drying equipment at CCs, as proposed in Case 3, may be less suitable or economically viable in rural contexts where the distances between coffee shops are more significant and the volume of collected SCG is relatively low.

These findings emphasize the need for further research and the development of tailored strategies to optimize SCG collection in rural areas, where logistical and economic considerations differ significantly

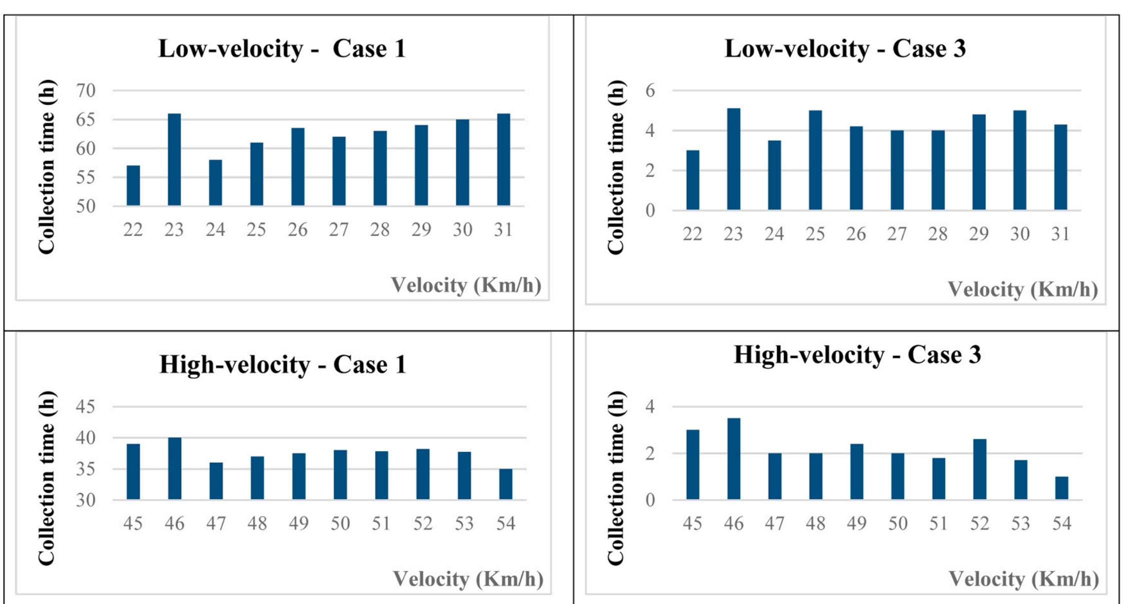

Fig. 10. Impact of Vehicle Velocity on SCG Collection Time.

Table 5
Comparative Analysis of Business Model Behavior in Urban and Rural Areas.

Business model	Urban		Rural	
	1 (Baseline)	**2 (case3)**	**1**	**2**
Number of coffee shops	1000	1000	40	40
Number of routes	6	1	1	1
Number of CC	0	21	0	3
Distance (km)	611	89.5	319.51	305.73
Time (h)Time (h)Time (h)Time (h) Time (h)Time (h)Time (h)	65.25	4.9	8.80	6.35
Total transportation cost ($)Total transportation cost ($)	1835.73	305.44	316.70	313.86
Cost of collection per unit ($ per kg)Cost of collection per unit ($ per kg)	0.29	0.04	3.73	3.69

from those in urban environments.

Table 5 compares the performance of Business Model 1 – Case 1 and Business Model 2 – Case 3 across both high- and low-density scenarios. In rural areas, the difference in cost per unit between the two business models was relatively small, amounting to only $0.04 per kg. This marginal difference suggests that, in low-density regions, the choice between Business Models 1 and 2 has minimal impact on the cost of SCG collection per unit. As a result, managers operating in rural settings may prioritize other decision-making factors, such as operational efficiency, equipment availability, and community engagement levels, when selecting the appropriate model. This indicates that either business model could be considered viable for rural applications, depending on local context and strategic objectives.

In contrast, the cost differential in urban areas is significantly more pronounced, with Business Model 2 offering a $0.25 lower cost per unit compared to Business Model 1. This substantial gap highlights the importance of selecting the most cost-effective model in high-density environments, where optimized logistics can lead to significant financial savings and enhanced overall profitability. Therefore, in urban settings, decision-makers should conduct detailed cost-benefit analyses that incorporate factors such as route optimization, vehicle utilization, and labor allocation to inform the selection of the optimal business model.

7. Economic analysis

The results from the optimization model provide estimates of operational expenses (OPEX); however, capital expenditures (CAPEX) are also critical for evaluating the project's overall feasibility. A comprehensive financial analysis includes a five-year cash flow projection, encompassing both costs and revenues, to assess the economic viability of the proposed solution. It is assumed that 6271 kg of SCG are generated daily across the 1000 coffee shops. Therefore, on an annual basis, this results in a total of 2288,915 kg of SCG (6271 kg/day × 365 days), which must be collected under both models. In Model 1, the daily cost of SCG collection is approximately $1836. In contrast, Model 2 presents a significantly lower daily collection cost of roughly $305. Revenue is assumed to be generated from the sale of activated carbon, which is produced by treating SCG. To estimate revenue, we use a conversion efficiency (yield rate), which reflects the percentage of activated carbon obtained from SCG after the activation process is complete. For this analysis, a yield rate of 0.22 is assumed for Case 1, while a higher yield rate of 0.25 is applied to Case 3. The improved yield in Case 3 is attributed to the pre-drying process conducted at CCs, which enhances the quality of SCG for activation. Operating costs are assumed to remain constant over the five years, while capital expenditures are incurred entirely at the start of the project (Year 0). Table 6 presents a summary of the cost and revenue estimates for both business models.

Based on the five-year cash flow projections presented in Table 6,

Table 6
Cost and Revenue Summary for Business Models (Case 1 and Case 3).

	Business model 1 - Case 1 (Baseline)	Business model 2 - Case 3
Annual SCG collected (kg)	2 288 915	2 288 915
Yield factor (γ)	0.22	0.25
Annual activated carbon (kg)	503 561	572 228
Price of Activated carbon ($/ kg)	80	80
Annual Collection Cost ($)	670 140	111 325
Investment Cost ($)	-	2 100 000
Annual Revenue ($)	40 284 904	45 778 300
Annual Profit ($)	39 614 764	43 566 975

Business Model 2 – Case 3 demonstrates a more favorable financial outlook compared to *Business Model 1 – Case 1*, despite requiring a higher initial investment. While the upfront capital cost for installing equipment at CCs may seem substantial at the project's outset, it is essential to recognize that this investment is a one-time expense typically incurred in the early stages and amortized over the project's lifespan. Unlike recurring operational costs such as transportation and routine maintenance, this capital expenditure represents a long-term asset that contributes to improved yield and overall efficiency in the reverse logistics network.

Fig. 11 presents a comparison of the discounted cumulative cash flows for two business models, Case 1 (Baseline) and Case 3 (Business Model 2), over a five-year period, using a discount rate of 5 %. Case 1 starts without any initial investment, resulting in a neutral cash flow position at year zero. In contrast, Case 3 requires a one-time upfront investment of $2.1 million, leading to a negative starting cash flow.

Over the five-year horizon, both models generate consistent annual profits. Case 1 yields a yearly profit of approximately $39.6 million, whereas Case 3 achieves a higher annual profit of $43.6 million. This difference of nearly $4 million in additional yearly profit gives Case 3 a substantial financial advantage.

Despite the initial investment cost, Case 3 quickly surpasses Case 1 in cumulative discounted cash flow before the end of the first year. This early crossover point indicates a remarkably short payback period, demonstrating the exceptional profitability of Case 3. As time progresses, the financial gap between the two models continues to widen. By the end of the five-year period, Case 3 significantly outperforms Case 1, with its higher profit margin compounding over time. The discounting effect at 5 % has minimal impact given the scale of the returns. In summary, although Case 3 involves a substantial initial investment, it proves to be financially superior in the medium term. Its rapid payback, higher recurring profits, and stronger overall financial performance make it a more attractive and strategically beneficial business model over the five-year timeframe.

Interest rate fluctuations can significantly impact project valuation, making the financial outlook a critical consideration. Fig. 12 illustrates that *Business Model 2* consistently yields a higher net present value (NPV) than *Business Model 1* across a range of interest rates. This trend highlights the financial robustness of Business Model 2 under varying economic conditions. Moreover, the figure shows that as the interest rate increases, the NPV of both projects declines, reflecting the more significant discounting effect on future cash flows. This underlines the importance for decision-makers to carefully evaluate both short-term and long-term financial implications when selecting a business model. It also calls for the development of contingency plans to address risks arising from uncertain economic variables such as interest rate volatility.

8. Discussion and managerial implications

Following a thorough analysis of the three case studies within the

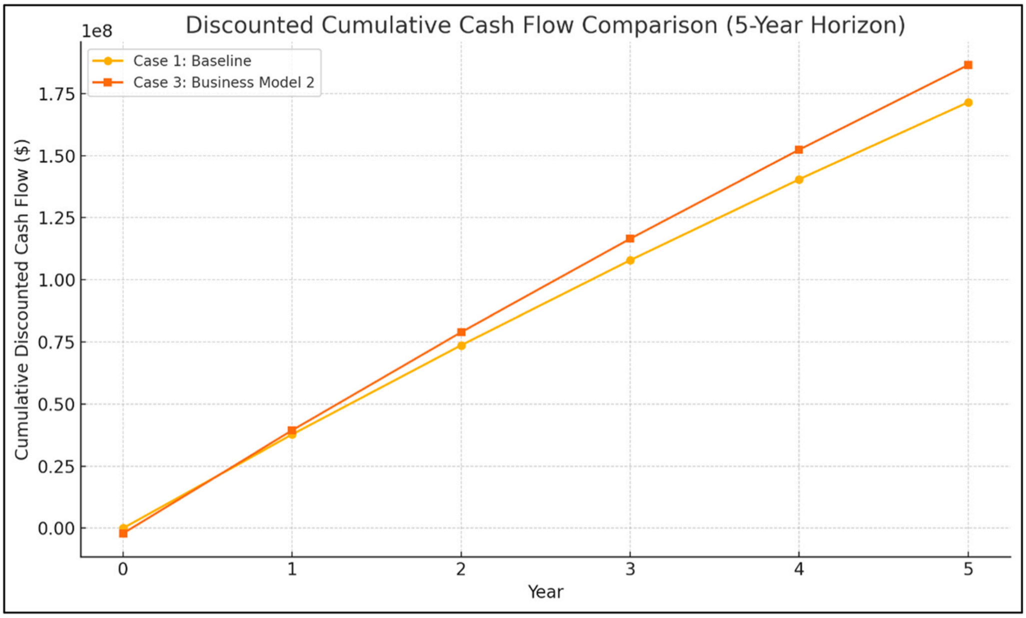

Fig. 11. Cash Flow Analysis: Business Model Comparison Over 5 Years.

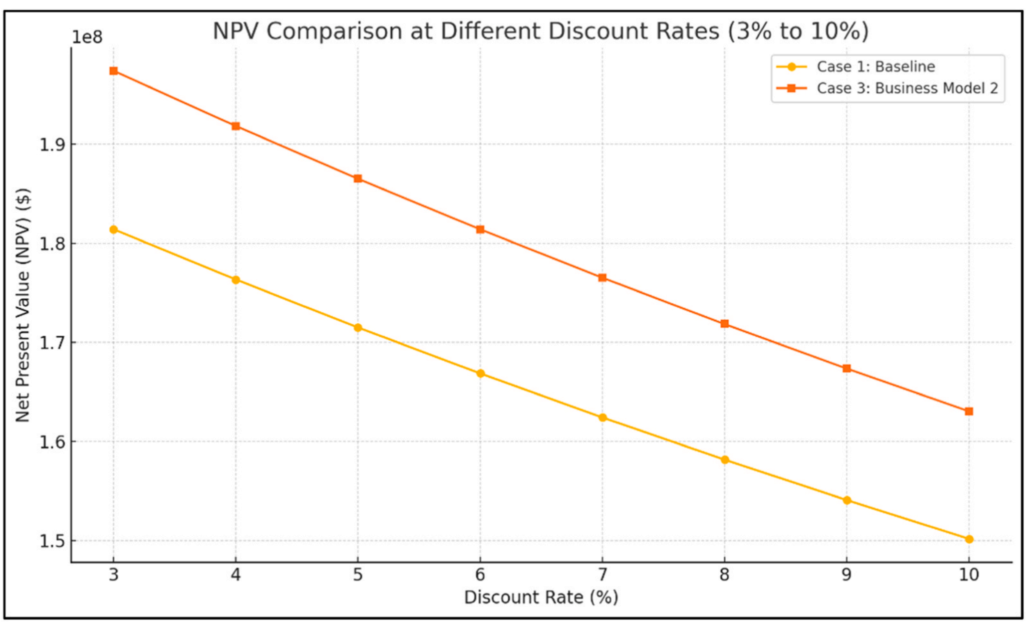

Fig. 12. NPV Comparison at Different Discount Rates (3–10 %).

framework of the two distinct business models, we will outline the ensuing discussion and managerial implications that emerge from our findings. This exploration aims to underscore the key insights gleaned from the cases, offering a comprehensive framework for grasping the operational dynamics and strategic opportunities present in each model. Throughout this dialogue, we will present actionable recommendations for managers eager to leverage these insights to improve organizational effectiveness and foster sustainable growth.

8.1. Discussion

First, it is recommended that Business Model 2 be adopted in urban settings. Given the substantial cost differences observed in such environments, Case 3—which incorporates SCG consolidation at Circular Coffee Shops (CCs) along with pre-drying technology—proves to be both more cost-effective and environmentally advantageous (reduced SCG contamination) [36]. Urban areas, with their higher volumes of SCG, benefit from economies of scale in both transportation and processing, resulting in significantly lower unit costs compared to Business Model 1. Second, it is advisable to implement Smart Bins selectively in high-volume or strategically located coffee shops. Although Case 3 (business model 2 with coffee shop collaboration) requires a higher upfront investment due to smart bin deployment, its use in targeted areas enhances data-driven decision-making [37]. By collecting real-time data on SCG quality, quantity, and contamination risk directly at the source, smart bins support more efficient route planning and improve the overall quality of SCG. This justifies their deployment in locations with frequent or high-volume SCG generation, where the operational benefits outweigh the additional capital costs.

At the operational level, implementing weekly collection improves cost efficiency (Case 2). Weekly collection of pre-dried SCG from coffee shops allows for greater truck capacity utilization, lower operational costs, and reduced wear on the EV fleet. This approach is particularly suitable for cases with stable and predictable SCG volumes, helping avoid underutilization and unnecessary trips [28]. The focus on Quality Control measures in the processing stages across the collection and processing stages (Case 3) enhanced the SCG yield for activated carbon. This focus on quality throughout the collection and pre-drying stages can minimize contamination and boost yield, thereby increasing the profitability of the processed SCG. For areas with widely spaced coffee shops, adjusting transportation cost weighting in routing algorithms can balance cost efficiency and distance, ensuring that remote locations are integrated without excessive costs to the network.

8.2. Managerial implications

The experimental results for the three cases highlight several key managerial implications. Strategic investment in high-cost infrastructure is crucial for long-term returns. Business Model 2, which requires intensive collaboration between coffee shops, despite its higher initial capital expenditure, offers substantial financial advantages in urban contexts. Prioritizing this model in high-density areas enables managers to capitalize on economies of scale, reduce transportation costs, and improve operational efficiency. Additionally, enhanced data utilization is crucial for informed operational decision-making. The use of smart bins, as demonstrated in Cases 2 and 3, allows for data-driven optimization of collection routes, transportation scheduling, and SCG management. By capturing real-time data on SCG quality, quantity, and contamination risk, managers can make informed adjustments to improve collection strategies and processing outcomes.

Balancing environmental impact with operational efficiency is another critical consideration. Pre-drying technology, introduced in Cases 2 and 3, reduces SCG weight and contamination risk, which not only lowers transportation costs but also aligns with environmental goals by minimizing emissions and resource use. This ensures higher-quality SCG for downstream processing. Scenario-based planning is also recommended for resource allocation and network design. Sensitivity analysis reveals that variables such as SCG participation rates, yield rates, and quality have a significant impact on overall program performance. Adopting flexible, scenario-based strategies allows managers to respond to these uncertainties and maintain system resilience.

Furthermore, building strong relationships with coffee shops is vital to mitigating participation-related risks. Reliable partnerships can prevent disruptions, especially in areas with fluctuating engagement. Offering incentives, maintaining consistent communication, and addressing concerns can foster trust and sustained participation. Lastly, optimizing routes according to area-specific factors such as traffic conditions and velocity potential enhances efficiency. Comparisons between urban and rural contexts indicate that tailored route planning improves electric vehicle utilization, reduces delays in low-velocity zones, and maximizes collection performance in both densely populated and sparsely populated regions.

9. Conclusion

This paper presents a digital intelligence framework for developing a sustainable SCG recovery system in Montreal, leveraging Industry 4.0 technologies to optimize a reverse logistics network. The proposed business models improve economic viability by consolidating SCG at Circular Coffee Shops and incorporating pre-drying processes to reduce weight, thereby significantly lowering transportation costs. These findings underscore the importance of circular economy principles in SCG recovery and highlight the transformative potential of intelligent technologies in advancing efficient and sustainable waste management.

The integration of Industry 4.0 tools—such as smart bins, pre-drying equipment, and electric vehicles demonstrates how technological innovation can reduce contamination risks, maintain SCG quality, and improve operational efficiency across the coffee value chain. Applying the customized reverse logistics model to 1000 coffee shops in Montreal, the study shows how Circular Coffee Shops' infrastructure can streamline collection logistics, reduce transportation frequency, and enhance overall network performance. Key strategic and operational decisions—including the location of Circular Coffee Shops, the allocation of coffee shops within Circular Coffee Shops, and route optimization—demonstrate the critical role of digital intelligence in enhancing RL efficiency.

However, the study acknowledges certain limitations. The financial analysis may overestimate returns by assuming that transportation costs between coffee shops and Circular Coffee Shops are fully offset through incentives. Additionally, the use of specific assumptions and static data may limit the model's generalizability and applicability in varied real-world contexts. Future research should investigate financial mechanisms to support SCG transport, explore diversified value-added products from SCG treatment, and assess system performance under dynamic, real-time data conditions. Moreover, introducing flexibility into the circular coffee shops' infrastructure—such as selectively deploying smart bins and pre-drying technologies—could enhance the model's adaptability to fluctuating SCG volumes and site-specific characteristics.

Finally, as we observe a low rate of EV capacity utilization in current transportation systems, future research should explore the integration of EV charging possibilities directly into the VRP models. The underutilization of EV capacity is often linked to the limited driving range, lack of real-time charging infrastructure planning, and suboptimal routing decisions that fail to account for energy constraints and recharging opportunities. This would enable more realistic and operationally viable routing solutions, particularly for urban waste collection and reverse logistics operations. Integrating real-time data, including traffic, battery status, and dynamic energy prices, can further enhance the responsiveness and efficiency of routing decisions.

Overall, this study lays the groundwork for establishing an intelligent, economically viable, and sustainable SCG recovery network. By combining digital intelligence with circular economy principles, it offers a promising pathway toward more efficient urban waste management and greater environmental responsibility.

Ethical approval and consent to participate

This article does not contain any studies involving human participants or animals performed by any of the authors.

Consent for publication

All the authors have agreed to publish this study.

Funding

Québec Circular Economy Research Network (RRECQ) - Fonds de recherche du Québec – Société et culture (FRQSC).

CRediT authorship contribution statement

Chaabane Amin: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jabbarzadeh Armin:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sabaghpourfard Ali:** Writing – review & editing, Visualization, Software, Formal analysis. **Zohourfazeli Hanieh:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no conflicts of interest.

Acknowledgements

The authors gratefully acknowledge the support provided by Afmerica for this work.

Appendix

Mathematical model formulation for Business Model 1 (VRP)

The mathematical formulation of Business Model 1 includes sets, parameters, decision variables, an objective function, and constraints, as detailed below.

Sets and indices.

i, j Index of coffee shops as the SCG generation point

k Index of routes

Decision variables

x_{ijk}If a route k exists when transporting from a coffee shop$i$ to a coffee shop j

Parameters

QCapacity of EV (kg)

LMaximum length that an EV can traverse (km)

F_kFixed cost of route k ($)

d_{ij}Distance between coffee shop i and coffee shop j (km)

t_jService time in CC j (min)

ρ_{idle}Electricity consumption rate per unit time while EV is idle (L/min)

ρ_{ij}Electricity consumption rate per unit distance while EV is moving (kWh/km)

ρPrice of per unit electricity consumption ($/kWh)

q_jAmount of SCG collected from each coffee shop j(kg)

Objective function

$$MinF = \sum_{k=1}^{K}\sum_{j=0}^{N}(x_{0jk} * F_k) + \sum_{i=0}^{N}\sum_{j=0}^{N}(x_{ijk} * d_{ij} * \rho_{ij} * \rho) + \sum_{j=1}^{N}(x_{ijk} * t_j * \rho_{idle} * \rho) \tag{0.1}$$

Constraints

$$\sum\nolimits_{k=1}^{K}\sum\nolimits_{i=0}^{N} x_{ijk} = 1, \forall j = 1, ..., N \tag{0.2}$$

$$\sum_{k=1}\sum_{j=0} x_{ijk} = 1, \forall i = 1, ..., N \tag{0.3}$$

$$\sum_{i=0}^{N} x_{ijk} = \sum_{i=0}^{N} x_{jik} = 1, \quad \forall j = 1, ..., N \quad ; k = 1, 2, ..., K \tag{0.4}$$

$$\sum_{j=1}^{N} x_{ijk} * q_j \le Q, \quad \forall i = 0, 1, ..., I \quad ; k = 1, 2, ..., K \tag{0.5}$$

$$\sum_{i=0}^{N}\sum_{j=0}^{N} d_{ij} * x_{ijk} \le L, \forall k = 1, 2, ..., K, i \ne j \tag{0.6}$$

$$\sum_{i=0}^{N}\sum_{j=0}^{N} x_{ijk} \le |S| - 1, S \subseteq \{1, 2, ..., N\} \forall k = 1, 2, ..., K \tag{0.7}$$

$$x_{ijk} = \{0, 1\} \tag{0.8}$$

The objective function (0.1) calculates the total cost, which includes both the fixed costs associated with route selection and the variable costs related to electric vehicle (EV) operations. The latter accounts for energy consumption while traveling between coffee shops and service time at each location, with electricity costs estimated based on values from the literature. Constraint (0.2) ensures that each coffee shop is visited exactly once by a vehicle. Constraints (0.3) and (0.4) specify that each vehicle route begins at the depot and ends at the treatment facility after visiting the last coffee shop. Equation (0.5) enforces the vehicle capacity constraint, stating that the quantity of SCG collected on each route must not exceed the vehicle's maximum load. Constraint (0.6) limits the total length of each route, ensuring it does not surpass the maximum allowable travel distance. Constraint (0.7) eliminates subtours to maintain route feasibility. Finally, constraint (0.8) defines the nature of the decision variables.

References

[1] M. Abdallah, M. Abu Talib, S. Feroz, Q. Nasir, H. Abdalla, B. Mahfood, Artificial intelligence applications in solid waste management: a systematic research review, Waste Manag. 109 (2020) 231–246, https://doi.org/10.1016/j.wasman.2020.04.057.

[2] A.I. Adetunji, P.J. Oberholster, M. Erasmus, From garbage to treasure: a review on biorefinery of organic solid wastes into valuable biobased products, Bioresour. Technol. Rep. 24 (2023) 101610, https://doi.org/10.1016/j.biteb.2023.101610.

[3] H. Ahmed, R.S. Abolore, S. Jaiswal, A.K. Jaiswal, Toward circular economy: potentials of spent coffee grounds in bioproducts and chemical production, Biomass 4 (2) (2024) 286–312. Retrieved from ⟨https://www.mdpi.com/2673-8783/4/2/14⟩.

[4] A. Alamsyah, S. Widiyanesti, P. Wulansari, E. Nurhazizah, A.S. Dewi, D. Rahadian, P. Tyasamesi, Blockchain traceability model in the coffee industry, J. Open Innov.: Technol., Mark., Complex. 9 (1) (2023) 100008, https://doi.org/10.1016/j.joitmc.2023.100008.

[5] M. Amine Masmoudi, L.C. Coelho, E. Demir, Plug-in hybrid electric refuse vehicle routing problem for waste collection, Transp. Res. Part E: Logist. Transp. Rev. 166 (2022) 102875, https://doi.org/10.1016/j.tre.2022.102875.

[6] A. Amini, M. Haughton, A mathematical optimization model for cluster-based single-depot location-routing e-commerce logistics problems, Supply Chain Anal. 3 (2023) 100019, https://doi.org/10.1016/j.sca.2023.100019.

[7] A.E. Atabani, I. Ali, S.R. Naqvi, I.A. Badruddin, M. Aslam, E. Mahmoud, T.M. Y. Khan, A state-of-the-art review on spent coffee ground (SCG) pyrolysis for future biorefinery, Chemosphere 286 (2022), https://doi.org/10.1016/j.chemosphere.2021.131730.

[8] H. Baziyad, V. Kayvanfar, A. Kinra, A bibliometric analysis of data-driven technologies in digital supply chains, Supply Chain Anal. 6 (2024) 100067, https://doi.org/10.1016/j.sca.2024.100067.

[9] E. Bottani, L. Tebaldi, A. Volpi, The Role of ICT in Supporting Spent Coffee Grounds Collection and Valorization: A Quantitative Assessment, Sustain. (Switz.) 11 (23) (2019) 6572, https://doi.org/10.3390/su11236572.

[10] R. Campbell, B. Xiao, C. Mangwandi, Production of activated carbon from spent coffee grounds (SCG) for removal of hexavalent chromium from synthetic wastewater solutions, J. Environ. Manag. 366 (2024) 121682, https://doi.org/10.1016/j.jenvman.2024.121682.

[11] F. Carassou, UNE RÉCUPÉRATION SPÉCIFIQUE DU MARC DE CAFÉ AURAIT-ELLE UNE PLUS-VALUE POUR LA COMMUNAUTÉ ? *CAS DE L'ÎLE DE MONTRÉAL*. (Master MAÎTRISE EN Environ.). Univ.É DE SHERBROOKE, Sherbrooke (2015). Retrieved from ⟨https://savoirs.usherbrooke.ca/bitstream/handle/11143/7937/Carassou_Francky_MEnv_2015.pdf?sequence=1⟩.

[12] A. Chaabane, J. Montecinos, M. Ouhimmou, A. Khabou, Vehicle routing problem for reverse logistics of End-of-Life Vehicles (ELVs), Waste Manag. 120 (2021) 209–220, https://doi.org/10.1016/j.wasman.2020.11.008.

[13] U. Choe, Valorization of spent coffee grounds and their applications in food science, Curr. Res. Food Sci. 10 (2025) 101010, https://doi.org/10.1016/j.crfs.2025.101010.

[14] Y.A. Fatimah, K. Govindan, R. Murniningsih, A. Setiawan, Industry 4.0 based sustainable circular economy approach for smart waste management system to achieve sustainable development goals: A case study of Indonesia, J. Clean. Prod. 269 (2020) 122263, https://doi.org/10.1016/j.jclepro.2020.122263.

[15] J. Flores-Carrasco, D. Morillo-Torres, J.W. Escobar, R. Linfati, G. Gatica, The Periodic Location-Routing with Selective Recycling Problem: Two Solution Approaches, IFAC-PapersOnLine 54 (1) (2021) 787–792, https://doi.org/10.1016/j.ifacol.2021.08.092.

[16] A. Forcina, A. Petrillo, M. Travaglioni, S. di Chiara, F. De Felice, A comparative life cycle assessment of different spent coffee ground reuse strategies and a sensitivity analysis for verifying the environmental convenience based on the location of sites, J. Clean. Prod. 385 (2023) 135727, https://doi.org/10.1016/j.jclepro.2022.135727.

[17] A.K. Garside, R. Ahmad, M.N.B. Muhtazaruddin, A recent review of solution approaches for green vehicle routing problem and its variants, Oper. Res. Perspect. 12 (2024) 100303, https://doi.org/10.1016/j.orp.2024.100303.

[18] G.D. Gebreeyessus, Towards the sustainable and circular bioeconomy: Insights on spent coffee grounds valorization, Sci. Total Environ. 833 (2022) 155113, https://doi.org/10.1016/j.scitotenv.2022.155113.

[19] S. Giasoumi, G.H. de Almeida Correia, M. de Bok, L. Tavasszy, J. Streng, D. van den Elzen, Optimizing demand-responsive IoT-based waste collection services: a two-step clustering technique, Res. Transp. Bus. Manag. 59 (2025) 101302, https://doi.org/10.1016/j.rtbm.2025.101302.

[20] V. Hemmelmayr, K. Smilowitz, L. De La Torre, A periodic location routing problem for collaborative recycling, IISE Trans. 49 (4) (2017) 414–428, https://doi.org/10.1080/24725854.2016.1267882.

[21] C. Hess, A.G. Dragomir, K.F. Doerner, D. Vigo, Waste collection routing: a survey on problems and methods, Cent. Eur. J. Oper. Res. 32 (2) (2024) 399–434, https://doi.org/10.1007/s10100-023-00892-y.

[22] D. Kannan, S. Khademolqorani, N. Janatyan, S. Alavi, Smart waste management 4.0: The transition from a systematic review to an integrated framework, Waste Manag. 174 (2024) 1–14, https://doi.org/10.1016/j.wasman.2023.08.041.

[23] K.G. Kempf, Getting started with analytics, *INFORMS Anal. Body Knowl.* (2018) 31–48.

[24] N. Kondamudi, S.K. Mohapatra, M. Misra, Spent coffee grounds as a versatile source of green energy, J. Agric. Food Chem. 56 (24) (2008) 11757–11760, https://doi.org/10.1021/jf802487s.

[25] G.D. Konstantakopoulos, S.P. Gayialis, E.P. Kechagias, Vehicle routing problem and related algorithms for logistics distribution: a literature review and classification, Oper. Res. 22 (3) (2022) 2033–2062, https://doi.org/10.1007/s12351-020-00600-7.

[26] I.K. Kookos, Technoeconomic and environmental assessment of a process for biodiesel production from spent coffee grounds (SCGs), Resour., Conserv. Recycl. 134 (2018) 156–164, https://doi.org/10.1016/j.resconrec.2018.02.002.

[27] A. Kumar, A novel framework for waste management in smart city transformation with industry 4.0 technologies, Res. Glob. 9 (2024) 100234, https://doi.org/10.1016/j.resglo.2024.100234.

[28] W. Li, N.T. Foo, I. Haidi, S.L. Wang, A literature review of the state of the art of sustainable waste collection and vehicle routing problem, J. Air Waste Manag. Assoc. 75 (1) (2025) 3–26, https://doi.org/10.1080/10962247.2024.2415298.

[29] X. Lu, X. Pu, X. Han, Sustainable smart waste classification and collection system: A bi-objective modeling and optimization approach, J. Clean. Prod. 276 (2020) 124183, https://doi.org/10.1016/j.jclepro.2020.124183.

[30] Y. Ma, W. Zhang, C. Feng, B. Lev, Z. Li, A bi-level multi-objective location-routing model for municipal waste management with obnoxious effects, Waste Manag. 135 (2021) 109–121, https://doi.org/10.1016/j.wasman.2021.08.034.

[31] K.T. Malladi, T. Sowlati, Sustainability aspects in Inventory Routing Problem: A review of new trends in the literature, J. Clean. Prod. 197 (2018) 804–814, https://doi.org/10.1016/j.jclepro.2018.06.224.

[32] S.T.W. Mara, R.J. Kuo, A.M.S. Asih, Location-routing problem: a classification of recent research, Int. Trans. Oper. Res. 28 (6) (2021) 2941–2983, https://doi.org/10.1111/itor.12950.

[33] J. Massaya, A. Prates Pereira, B. Mills-Lamptey, J. Benjamin, C.J. Chuck, Conceptualization of a spent coffee grounds biorefinery: a review of existing valorisation approaches, Food Bioprod. Process. 118 (2019) 149–166, https://doi.org/10.1016/j.fbp.2019.08.010.

[34] S. Mayson, I.D. Williams, Applying a circular economy approach to valorize spent coffee grounds, Resour., Conserv. Recycl. 172 (2021), https://doi.org/10.1016/j.resconrec.2021.105659.

[35] M. Mohammadi, G. Rahmanifar, M. Hajiaghaei-Keshteli, G. Fusco, C. Colombaroni, Industry 4.0 in waste management: an integrated IoT-based approach for facility location and green vehicle routing, J. Ind. Inf. Integr. 36 (2023) 100535, https://doi.org/10.1016/j.jii.2023.100535.

[36] M. Mohammadi, G. Rahmanifar, M. Hajiaghaei-Keshteli, G. Fusco, C. Colombaroni, A. Sherafat, A dynamic approach for the multi-compartment vehicle routing problem in waste management, Renew. Sustain. Energy Rev. 184 (2023) 113526, https://doi.org/10.1016/j.rser.2023.113526.

[37] A. Mukherjee, J.A. Okolie, C. Niu, A.K. Dalai, Techno – Economic analysis of activated carbon production from spent coffee grounds: Comparative evaluation of different production routes, Energy Convers. Manag.: X 14 (2022) 100218, https://doi.org/10.1016/j.ecmx.2022.100218.

[38] A. Mukherjee, B. Saha, C. Niu, A.K. Dalai, Preparation of activated carbon from spent coffee grounds and functionalization by deep eutectic solvent: Effect of textural properties and surface chemistry on CO2 capture performance, J. Environ. Chem. Eng. 10 (6) (2022) 108815, https://doi.org/10.1016/j.jece.2022.108815.

[39] L.S. Oliveira, R.L. Machado, Application of optimization methods in the closed-loop supply chain: a literature review, J. Comb. Optim. 41 (2) (2021) 357–400, https://doi.org/10.1007/s10878-020-00677-y.

[40] Q. Qiao, F. Tao, H. Wu, X. Yu, M. Zhang, Optimization of a Capacitated Vehicle Routing Problem for Sustainable Municipal Solid Waste Collection Management Using the PSO-TS Algorithm, Int. J. Environ. Res. Public Health 17 (6) (2020) 2163, https://doi.org/10.3390/ijerph17062163.

[41] J. Rajesh Banu, S. Kavitha, R. Yukesh Kannah, M. Dinesh Kumar, Preethi, A. E. Atabani, G. Kumar, Biorefinery of spent coffee grounds waste: Viable pathway towards circular bioeconomy, Bioresour. Technol. 302 (2020) 122821, https://doi.org/10.1016/j.biortech.2020.122821.

[42] T.R.P. Ramos, C.S. de Morais, A.P. Barbosa-Póvoa, The smart waste collection routing problem: Alternative operational management approaches, Expert Syst. Appl. 103 (2018) 146–158, https://doi.org/10.1016/j.eswa.2018.03.001.

[43] S. Rekabi, Z. Sazvar, F. Goodarzian, A bi-objective sustainable vehicle routing optimization model for solid waste networks with internet of things, Supply Chain Anal. 5 (2024) 100059, https://doi.org/10.1016/j.sca.2024.100059.

[44] A.T. Salawudeen, O.A. Meadows, B. Yahaya, M.B. Mu'azu, A novel solid waste instance creation for an optimized capacitated vehicle routing model using discrete smell agent optimization algorithm, Syst. Soft Comput. 6 (2024) 200099, https://doi.org/10.1016/j.sasc.2024.200099.

[45] K. Sar, P. Ghadimi, A systematic literature review of the vehicle routing problem in reverse logistics operations, Comput. Ind. Eng. 177 (2023) 109011, https://doi.org/10.1016/j.cie.2023.109011.

[46] C.E. Schmidt, A.C.L. Silva, M. Darvish, L.C. Coelho, The time-dependent location-routing problem, Transp. Res. Part E: Logist. Transp. Rev. 128 (2019) 293–315, https://doi.org/10.1016/j.tre.2019.06.015.

[47] A. Singh, Managing the uncertainty problems of municipal solid waste disposal, J. Environ. Manag. 240 (2019) 259–265, https://doi.org/10.1016/j.jenvman.2019.03.025.

[48] T.A. Singh, N. Pal, P. Sharma, A.K. Passari, Spent coffee ground: transformation from environmental burden into valuable bioactive metabolites, Rev. Environ. Sci. Bio/Technol. 22 (4) (2023) 887–898, https://doi.org/10.1007/s11157-023-09669-w.

[49] X. Sun, H. Yu, W.D. Solvang, Towards the smart and sustainable transformation of Reverse Logistics 4.0: a conceptualization and research agenda, Environ. Sci. Pollut. Res. 29 (46) (2022) 69275–69293, https://doi.org/10.1007/s11356-022-22473-3.

[50] X. Sun, H. Yu, W.D. Solvang, K. Govindan, A two-level decision-support framework for reverse logistics network design considering technology transformation in Industry 4.0: a case study in Norway, Int. J. Adv. Manuf. Technol. 134 (1) (2024) 389–413, https://doi.org/10.1007/s00170-024-14121-6.
[51] I. Usman, P.V. Nanda, Paper presented at the Journal for Global Business Advancement, Green. Bus. Oppor. Coffee Ground Waste Reverse Logist. (2017).
[52] J. Van Engeland, J. Beliën, L. De Boeck, S. De Jaeger, Literature review: Strategic network optimization models in waste reverse supply chains, Omega 91 (2020) 102012, https://doi.org/10.1016/j.omega.2018.12.001.
[53] M. van Keulen, J. Kirchherr, The implementation of the Circular Economy: Barriers and enablers in the coffee value chain, J. Clean. Prod. 281 (2021) 125033, https://doi.org/10.1016/j.jclepro.2020.125033.
[54] A. Viktorin, D. Hrabec, V. Nevrlý, R. Šomplák, R. Šenkeřík, Hierarchical clustering-based algorithms for optimal waste collection point locations in large-scale problems: A framework development and case study, Comput. Ind. Eng. 178 (2023) 109142, https://doi.org/10.1016/j.cie.2023.109142.
[55] C. Wei, S. Wøhlk, A. Che, A multi-level capacitated arc routing problem with intermediate facilities in waste collection, Comput. Oper. Res. 167 (2024) 106671, https://doi.org/10.1016/j.cor.2024.106671.
[56] Z. Wen, S. Hu, D. De Clercq, M.B. Beck, H. Zhang, H. Zhang, J. Liu, Design, implementation, and evaluation of an Internet of Things (IoT) network system for restaurant food waste management, Waste Manag. 73 (2018) 26–38, https://doi.org/10.1016/j.wasman.2017.11.054.
[57] H. Wu, F. Tao, B. Yang, Optimization of vehicle routing for waste collection and transportation, Int. J. Environ. Res. Public Health 17 (14) (2020) 4963, https://doi.org/10.3390/ijerph17144963.
[58] L. Yeoh, K.S. Ng, Future prospects of spent coffee ground valorisation using a biorefinery approach, Resour., Conserv. Recycl. 179 (2022) 106123, https://doi.org/10.1016/j.resconrec.2021.106123.
[59] A. Zabaniotou, P. Kamaterou, Food waste valorization advocating Circular Bioeconomy - A critical review of potentialities and perspectives of spent coffee grounds biorefinery, J. Clean. Prod. 211 (2019) 1553–1566, https://doi.org/10.1016/j.jclepro.2018.11.230.
[60] Zohourfazeli, H., Chaabane, A., & Jabbarzadeh, A. (2023, 2023/10//). *The Role and I4.0 Technologies in The Restaurant Food Waste Managemen.* Paper presented at the 50th International Conference on Computers and Industrial Engineering (CIE).