DISCRETE-EVENT SIMULATION REVEALS COST–CARBON–SERVICE TRADE-OFFS IN REVERSE LOGISTICS

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ABSTRACT

Designing reverse logistics networks requires making cost–emissions–service trade-offs in systems where return flows are irregular and product condition is highly variable, such has circular economy (C.E) oriented business. This paper develops a discrete-event simulation model to compare centralized and localized reverse-logistics configurations for a regional bicycle supply chain. The model captures stochastic task generation, condition-dependent routing into recovery versus recycling streams, and capacity-triggered dispatching on a road-network distance representation. A factorial experiment evaluates eight scenarios with statistical validation of the results. Under the modeled assumptions and dispatch policy, the centralized configuration consistently achieves lower cost and CO_2 emissions per completed task while completing more tasks within the simulated horizon. Although the localized configuration reduces total distance traveled, it exhibits higher distance per completed task, indicating that pooling and utilization effects dominate the distance savings associated with additional hubs. These results provide comparative, mechanism-based insights into how network structure and fleet sizing interact with consolidation and dispatch rules in reverse logistics, and motivate future extensions toward adaptive control policies and higher-fidelity facility process modeling in the context of Circular Economy R-Strategies.

INTRODUCTION

Reverse logistics networks must balance consolidation benefits against responsiveness and environmental performance,fostering Circular Business Models, especially in sectors such as bicycle after-sales and repair where returned products are heterogeneous in condition. Centralized configurations can exploit economies of scale in inspection and processing, but often at the cost of longer transport distances and potentially higher emissions, whereas localized configurations may shorten lead times and reduce risk exposure but require additional facilities and more complex transport planning. Recent studies in reverse logistics and circular economy highlight that these network design choices directly affect both carbon footprint and service level [7, 8], and that experience-based common perception (e.g., "fewer facilities always means lower emissions") does not always hold once transport patterns, vehicle utilization, and return variability are accounted for. In practice, uncertainty concerns not only the quantity and timing of returns, but also return condition/quality, which can alter inspection processing times and trigger different routing (e.g., reuse vs recycling, reuse vs repair, repair vs remanufacturing, remanufacturing vs recycling, etc.), thereby reshaping cost, lead times, and transport [6, 12].

Discrete-Event simulation (DES) has become an established tool for evaluating reverse logistics concepts under operational variability, including uncertain return volumes, stochastic processing times, and condition-dependent routing. Such models allow researchers and practitioners to track system-level performance indicators such as throughput, lead time, cost, and CO_2 emissions while explicitly capturing resource utilization, bottlenecks, and queue dynamics [1]. Reverse logistics and related dynamic phenomena (e.g., the bullwhip effect) have been repeatedly highlighted as long-standing and widely studied application areas for DES in logistics and Supply Chains (SC) [4].

At the same time, broad literature-mapping and publication-trend reviews inevitably focus on patterns in the research record (e.g., themes, outlets, collaboration, and citation impact) rather than on the technical structure of individual DES models or the operational benefits they achieve in practice [4]. Recent work on

circular production systems has also studied DES to test integrated circularity frameworks. The research focuses on a De-Production model combining R-strategies and D-strategies across product and production life cycles and it was demonstrated in a remanufacturing case study of a bicycle wheel assembly [3].
In reverse SCs, DES is particularly useful for scenario-based evaluation under stochastic returns and condition-dependent routing, where capturing queues, resource constraints, and operational policies is central to the decision problem [11, 4].
This paper investigates how centralized versus localized reverse-logistics strategies and fleet size decisions jointly affect cost, CO_2 emissions, and service in a bicycle SC network. The study considers a network topology with one main warehouse and multiple retail stores, and contrasts a fully centralized strategy with a two-hub localized strategy in which stores are assigned to geographically coherent clusters. A DES model represents homogeneous bicycle components, quality-based acceptance and circular strategies (such as remanufacturing, repair, recycling), fixed routes between nodes, and event-based dispatching triggered by truck capacity thresholds, while varying fleet sizes and measuring both task completion and detailed vehicle utilization states.
The research addresses the following research question: *How do centralised vs localised reverse-logistics strategies and fleet sizes shape the trade-offs between logistics cost, CO_2 emissions, and service performance in a bicycle reverse SC network?*
The contributions are threefold. First, the paper develops a simulation-based framework for comparing centralized and localized reverse-logistics strategies with explicit tracking of transport-related CO_2 emissions and service in a bicycle context, complementing design-oriented and analytical studies on sustainable reverse logistics networks [9, 5]. Second, it quantifies the impact of fleet size on cost–emissions–service trade-offs and vehicle utilization patterns across strategies, providing scenario-based insights for transport and capacity planning. Third, it offers managerial guidance on when a localized hub configuration becomes preferable to a purely centralized solution in terms of both environmental and service performance, thus supporting circular business models for bicycles and related products.

SIMULATION-BASED METHODOLOGY

To compare centralized and localized reverse-logistics strategies under uncertain returns and operational constraints, a simulation-based methodology was adopted. DES is well suited to this setting because it captures event-driven flows, limited resources, consolidation and dispatch policies, and stochastic variability, enabling consistent what-if experimentation across alternative network configurations and fleet sizes. In this work, considering the main charateristics of the reverse logistic SC, Flexsim simulation engine was chosen.The FlexSim model was developed as a flexible, parameterisable representation compatible with several SC types, allowing it to be adapted to alternative SC instances with minimal structural changes.
The SC network is implemented directly within the Geographic Information System (GIS)-based modelling environment, while scenario-specific behavior is controlled through parameter tuning, enabling consistent and repeatable experimentation across multiple network configurations. Figure 1 summarizes the methodological workflow implemented in FlexSim for scenario-based evaluation of the SC system. The process begins with the SC Analyst selecting the scenario to be investigated and configuring the simulation model through sequential model-building steps, namely SC network design (implemented in the GIS-based model), definition of the initial delivery tasks (operational task logic) and definition of the model parameters. After the model setup, a validation run is executed to debug the model and calibrate its behavior. During this run, the scenario is simulated and the resulting KPIs are monitored via the KPI dashboard. The dashboard-based validation acts as a decision gate: if the model is considered validated, the workflow proceeds; otherwise, deviations trigger iterative refinement of the model logic/assumptions and re-tuning of parameters (and, if needed, adjustments to scenario definitions) until satisfactory validation is achieved.
Once validated, Flexsim's Experimenter is used to perform automated runs across the full scenario set. The Experimenter job is configured to import scenarios and execute a fixed number of replications per scenario using distinct random seeds to account for stochastic variability. For each scenario–replication combination, the simulation is executed and the results are recorded in the results database file, producing a structured dataset suitable for comparative evaluation. Finally, the stored experiment results are analyzed to quantify scenario tradeoffs and performance differences. This analysis provides the evidence base for deriving decision-making policies, with emphasis on SC design choices and transportation dispatching rules, including fleet sizing decisions.

Flexsim Model Implementation Strategy

The model is implemented using a modular and complementary logic that separates (i) scenario configuration, (ii) control logic for task creation and dispatching, and (iii) operational execution by vehicles and nodes. The main logic is encoded in Process Flow module, which coordinate event-driven behavior such as return arrivals, load formation, task creation, dispatch triggers, and task finalization. This structure ensures that the decision logic is explicit and traceable, while remaining parameterisable for systematic scenario experimentation. A key implementation principle is the explicit represen-

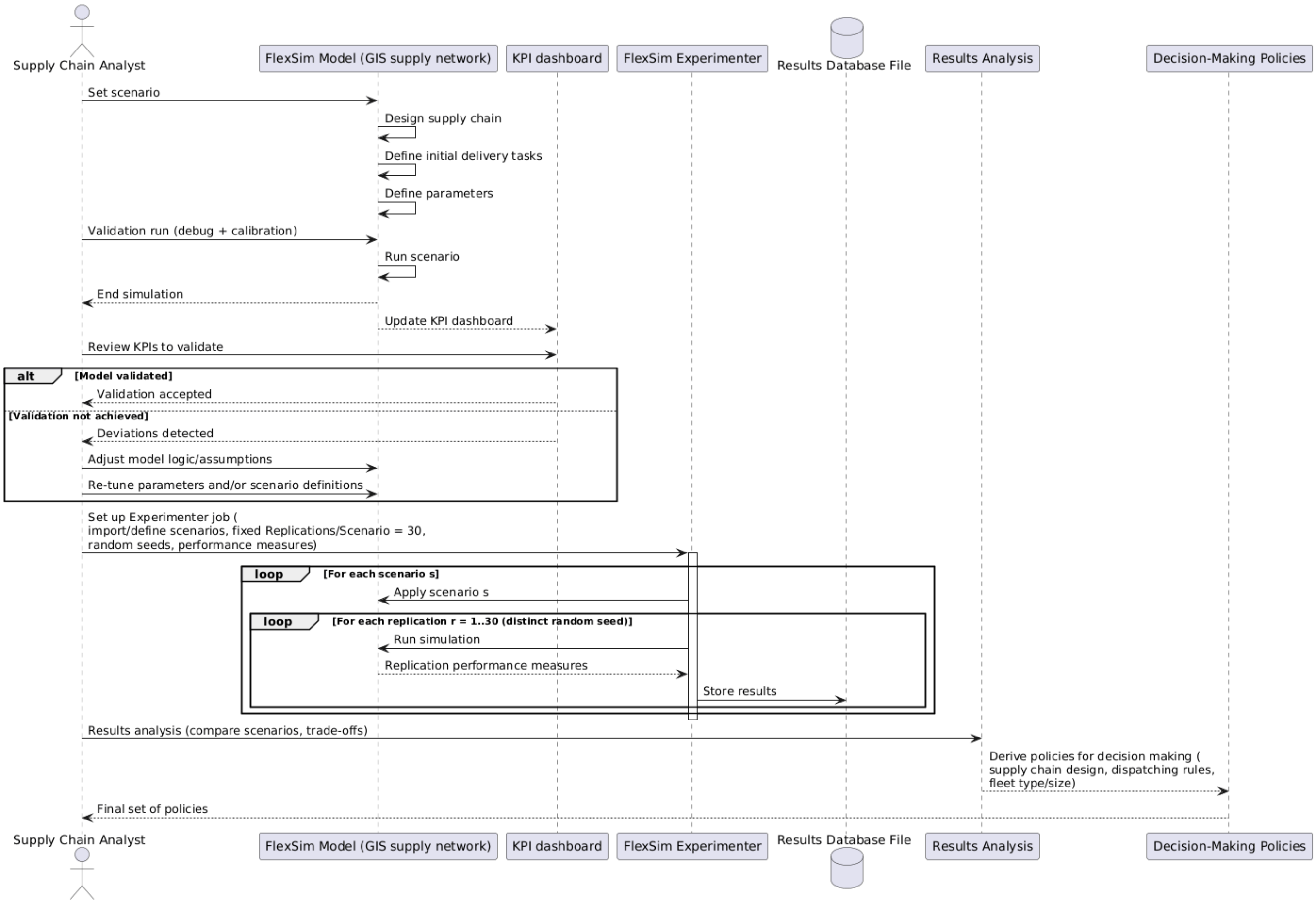

Figure 1: Methodology - Sequence Diagram

tation of decision states through Lists and Zones. Lists are used to store and manage dynamic sets of entities and tasks (e.g., newly created tasks, ready-to-dispatch loads, available vehicles, and pending requests). Zones define spatial and logical areas (e.g., store clusters, hub catchments, and vehicle assignment regions) and are used to enforce strategy-specific rules such as centralized versus localized allocation and cluster-consistent routing. To support logic that is difficult to express through standard blocks alone, the model uses custom code activities within Process Flow to implement parameter-driven selection rules, conditional branching (e.g., strategy and fleet-type logic), and scenario-dependent task generation. This combination of lists, zones, and custom code yields a compact control layer that can be extended without altering the underlying network representation. To ensure scalability and future extensibility, each supply chain node (e.g., stores, hubs, and sinks) is implemented as an Object Process Flow (OPF) that encapsulates its local behavior, including load reception, condition assessment, batching/consolidation, and downstream task generation. This object-oriented decomposition allows additional nodes, new circular pathways, or alternative processing rules to be introduced by adding or modifying OPFs, rather than restructuring a monolithic control flow. As a result, the model supports incremental expansion (e.g., additional hubs, new inspection categories, or alternative dispatch heuristics) while preserving consistent interfaces between objects. Finally, a dashboard is implemented for user interaction and experimental reproducibility. The dashboard provides scenario selection controls (e.g., scenario type, fleet type, strategy, and stochastic or deterministic load quantity settings) and applies the chosen parameters by enabling or disabling relevant parts of the Process Flow logic. This mechanism operationalizes scenario definition as a controlled configuration step, ensuring that the correct processes are activated for a given experiment while maintaining a single unified model. The dashboard-based configuration also supports non-expert use, reduces manual editing errors, and facilitates repeatable what-if analysis across alternative network configurations and policy settings.

CASE STUDY AND MODEL INSTANCE

The case study is grounded in the mobility remanufacturing vision of the Horizon Europe RENÉE[1] project, which targets circular value chains by enabling flexible, human-centric remanufacturing supported by advanced robotics and AI. Within RENÉE, a key need has been identified for systematic and standardized evaluation of used products and improved component traceability, since these capabilities constitute the operational foundation required to enable remanufacturing activities closer to the point of return (e.g., within or near stores). The case study considers a bicycle reverse-logistics network in Northern Italy with 29 retail stores acting as return generation points and a main consolidation/processing site at Basiano. Two alternative network configurations are evaluated. In the centralized configuration, all stores ship returns to Basiano. In the localized configuration, an additional consolidation node at Cremona is introduced and stores are assigned to two geographically coherent clusters, forming two regional collection systems. The model represents the operational layer of reverse logistics, capturing collection from stores, consolidation at hubs, and routing to recovery or recycling streams following inspection/condition assessment. Detailed shop-floor remanufacturing is abstracted into task completion events, allowing the analysis to focus on transport capacity, dispatch dynamics, and their implications for responsiveness. The decision space includes the network strategy (centralized vs localized) and fleet size under an event-driven dispatch policy triggered by consolidation thresholds. Fleet size is varied across four levels (5/10/15/20 trucks) to expose how transport capacity interacts with network structure to influence consolidation speed, empty repositioning, and service completion. Parameterization relies on node locations with GIS-derived road distances, identical truck capacities, and stochastic characterization of return tasks (quantities) and condition distributions. Condition heterogeneity captures the fact that returned items may be routed differently (recovery vs recycling), affecting accumulation rates and dispatch timing. Performance is evaluated through total transport cost, transport-related CO_2 emissions, and service measured as the proportion of tasks completed within the fixed horizon, complemented by truck-state utilization (idle, traveling empty, traveling loaded) to explain observed trade-offs.

Simulation Model and Experiment Design

The resulted DES model (Figure 2) developed in FlexSim captures reverse flows, transport sizing policies, and responsiveness under uncertainty in the bicycle SC network. As mentioned in the case study section, the model focuses on reverse flows from the 29 stores to the processing facilities, including collection and transport, condition assessment, consolidation, and dispatch. Forward logistics and detailed remanufacturing operations are excluded. The evaluation is restricted to transportation-related cost and tailpipe CO_2 emissions. Accordingly, fixed facility costs, labor costs, and detailed processing costs are not modeled. Each replication is simulated over a horizon comprising a one-day warm-up period followed by seven operational days, and all performance indicators are computed over the seven-day operational period.

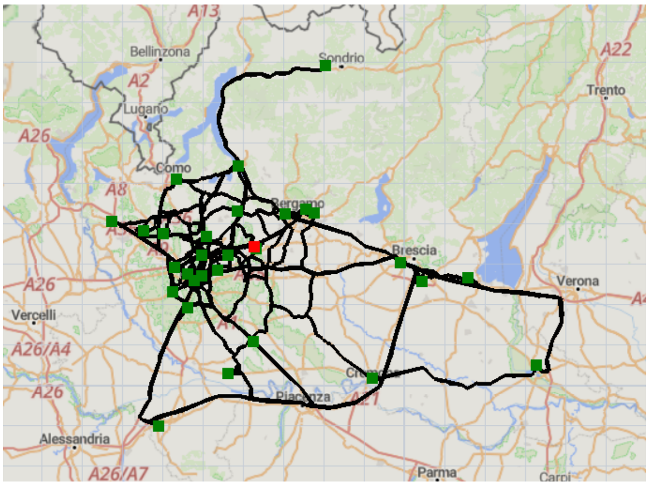

Figure 2: SC Network on FlexSim Simulation Model

The model represents two bicycle product types, while treating returned components as homogeneous units for transport and consolidation purposes. The simulation is initialized with six predefined transportation tasks (randomly chosen and present in Table 1) to provide a consistent, non-empty starting state that seeds the task-generation and dispatch mechanisms, reduces start-up bias from empty queues and idle fleets, and ensures that early dynamics are comparable across strategies and fleet-size scenarios. The total six initial transportation tasks comprise a total of 135 components, where the number of components associated with each task is sampled from a truncated normal distribution $N(10, 2)$, support restricted to non-negative values. Each component is assigned a condition score drawn from a uniform distribution $U(1, 5)$. Components with condition scores higher than 3 are classified as recoverable and are eligible to generate downstream transport tasks, while the remaining ones are routed directly to recycling. Downstream dispatch tasks are released through an event-based consolidation rule: whenever the number of recoverable components available for shipment reaches 400 units (the truck capacity), a new task is generated to trigger vehicle dispatch. Two reverse-logistics strategies are considered. In the centralized strategy, all stores are served by a single hub and returns are routed to the

[1] https://renee-project.eu/

ID	Origin	Destination	Type
1	Corsico	CAR Basiano	S to W
2	Rozzano	Lissone	S to S
3	Lissone	Corsico	S to S
4	Portello	Gallarate	S to S
5	CAR Basiano	Lissone	W to S
6	Gallarate	Portello	S to S

Table 1: Initial tasks (S - Store and W - Warehouse)

Basiano warehouse using the predefined store to warehouse and store to store connections. In the localized strategy, stores are partitioned into two geographically coherent clusters served by two hubs: Basiano (Milan north-east and the Bergamo, Lecco, Como area) and Cremona (southern and eastern sites). Transport tasks are restricted to intra-cluster movements.

Baseline for Costs and Emissions

The performance evaluation focuses primarily on transportation cost and CO_2 emissions, which constitute the core criteria for comparing the alternative network strategies and fleet-sizing scenarios. We model total transportation cost as the sum of (i) distance-proportional costs when driving loaded, (ii) distance-proportional costs when driving empty, and (iii) time-proportional costs when the vehicle is idle (parked, engine-off):

$$C = c_\mathrm{L}\, d_\mathrm{L} + c_\mathrm{E}\, d_\mathrm{E} + c_\mathrm{I}\, t_\mathrm{I}, \qquad [€], \tag{1}$$

where d_L and d_E are distances in kilometers traveled loaded and empty, respectively, and t_I is the idle time in minutes. For the baseline scenario, it was set $c_\mathrm{L} = 1.40$ €/km, $c_\mathrm{E} = 1.12$ €/km, $c_\mathrm{I} = 1.25$ €/min, so that (1) becomes

$$C = 1.40\, d_\mathrm{L} + 1.12\, d_\mathrm{E} + 1.25\, t_\mathrm{I}, \qquad [€]. \tag{2}$$

It is distinguished three mutually exclusive truck states: (i) travelling while carrying cargo (loaded), (ii) travelling without cargo (empty), and (iii) idle (parked, engine-off). As a baseline operating-cost proxy, we adopt the American Transportation Research Institute (ATRI) industry-average cost of operating a truck in 2024 of \$2.260 per mile [2]. Using 1 mile = 1.609 km, we obtain

$$c_\mathrm{L} = \frac{2.260}{1.609} \approx 1.40 \text{ €/km}, \tag{3}$$

where we report results in euros and treat USD≈EUR as a simplifying assumption for this illustrative calculation. Since empty operation typically incurs lower variable costs than loaded operation, we assume the empty-kilometre cost is a fraction $\alpha \in (0,1)$ of the loaded-kilometre cost:

$$c_\mathrm{E} = \alpha\, c_\mathrm{L}. \tag{4}$$

For the baseline scenario we set $\alpha = 0.8$, giving $c_\mathrm{E} \approx 1.12$ €/km. During idle periods the vehicle does not move; we therefore model idle cost as a time-based penalty capturing fixed ownership/overhead costs and the opportunity cost of unproductive time. We adopt a baseline idle cost of

$$c_\mathrm{I,h} = 75 \text{ €/h},$$

as a baseline modelling parameter for unproductive vehicle availability. For convenience, we also express this as cost per minute:

$$c_\mathrm{I} = \frac{c_\mathrm{I,h}}{60} = 1.25 \text{ €/min}.$$

Total tailpipe CO_2 emissions are computed using a distance-based factor model that distinguishes loaded and empty travel:

$$E = e_L\, d_L + e_E\, d_E, \tag{5}$$

where d_L and d_E denote the loaded and empty vehicle-kilometers, respectively, and e_L and e_E are the corresponding emission factors ($kgCO_2$/km).
As a baseline, we adopt the regional-delivery (4-RD) CO_2 intensity reported for EU heavy-duty vehicles, $e_\mathrm{RD} = 627.0$ gCO_2/km (i.e., 0.627 $kgCO_2$/km) [10]. We further assume a constant loaded-to-empty ratio $r = e_L/e_E = 1.44$, consistent with reported differences between loaded and unloaded heavy-duty diesel trucks [13]. The scenario-specific share of loaded distance is computed as

$$p_L = \frac{d_L}{d_L + d_E}. \tag{6}$$

To ensure consistency with the baseline average factor e_RD, we derive

$$e_E = \frac{e_\mathrm{RD}}{p_L r + (1 - p_L)}, \qquad e_L = r\, e_E. \tag{7}$$

RESULTS ANALYSIS

Results are presented for eight scenarios defined by the factorial combination of two network strategies and four fleet sizes. Each scenario is evaluated using 30 independent replications, and performance is summarized by the sample mean together with its 95% confidence interval (CI). The analysis considers four key performance indicators: (i) transportation cost, (ii) tailpipe CO_2 emissions, (iii) the total number of completed tasks, and (iv) total travel distance. Because tasks are generated stochastically and the number of tasks varies across replications and scenarios, cost and emissions are reported on a per-task basis by normalizing total values by the number of completed tasks. Tables 2, 3, 4 and 5 summarize the results.
In terms of the cost per task, across all fleet sizes (Table 2), the centralized strategy yields a lower mean cost

Table 2: Total cost per task (mean ± 95% CI) and sample standard deviation.

Scenario	Cost [€/task]	s
Localized 5	321.41 ± 19.33	51.76
Centralized 5	178.89 ± 3.09	8.28
Localized 10	509.65 ± 24.36	65.24
Centralized 10	233.33 ± 6.16	16.51
Localized 15	313.20 ± 13.94	37.33
Centralized 15	194.52 ± 1.58	4.24
Localized 20	384.11 ± 11.89	31.84
Centralized 20	249.31 ± 5.78	15.48

Table 3: Transport-related emissions per task (mean ± 95% CI) and sample standard deviation.

Scenario	Emissions [kgCO_2/task]	s
Localized 5	76.720 ± 1.130	3.026
Centralized 5	75.081 ± 1.294	3.465
Localized 10	77.352 ± 1.322	3.540
Centralized 10	75.237 ± 1.021	2.733
Localized 15	84.223 ± 0.806	2.158
Centralized 15	81.494 ± 0.787	2.108
Localized 20	78.188 ± 0.695	1.862
Centralized 20	75.577 ± 0.666	1.783

per task than the localized strategy. The cost advantage is strongest for small fleets (≈ 44% lower) and remains substantial at larger fleets (≈ 35% lower). Cost dispersion is also strategy-dependent: localized scenarios show substantially larger sample standard deviations than centralized ones, suggesting localized scenarios are more sensitive to stochastic variability and/or congestion effects under the current dispatch policy.

In terms of the emissions per task, in most cases (Table 3), centralization achieves slightly lower mean emissions per task than localization. At 10 trucks, the difference is smaller, but still favors the centralized configuration, indicating that the emissions response is weaker than the cost response and likely depends on the balance between consolidation, empty repositioning, and throughput. Across fleet sizes, emissions exhibit a non-monotonic pattern (peaking around 15 trucks in both strategies and then decreasing at 20 trucks).

Service performance is measured as the number of tasks finalized within the simulation horizon (Table 4). For both strategies, the mean number of finalized tasks increases monotonically with fleet size, which is consistent with the model's task-generation and dispatch design where additional fleet capacity enables more tasks to be executed within the fixed horizon. At each fleet size, the centralized strategy finalizes more tasks than the localized strategy, with a relative gap of ≈ 5.82% (5 trucks), ≈ 16.24% (10 trucks), ≈ 10.69% (15 trucks), and ≈ 15.30% (20 trucks).

Relatively to travel distance analysis, Table 5 reports total, empty, and loaded travel distances. Across all fleet sizes, the centralized strategy yields higher total distance than the localized strategy, with relative increases of approximately 3.79% (5 trucks), 13.91% (10 trucks), 7.83% (15 trucks), and 12.21% (20 trucks). Emissions per task are better explained by distance per task than by the empty–loaded split: the empty-distance share is essentially constant across all scenarios (empty/total ≈ 48.7–49.2%), whereas total distance per finalized task increases with fleet size and is consistently higher for localized operation than for centralized operation. Consequently, a local peak in emissions per task around 15 trucks can be interpreted as a temporary reduction in operational efficiency (higher distance per task) rather than a marked increase in the fraction of empty travel.

Table 4: Delivery tasks finalized (mean ± 95% CI) and sample standard deviation.

Scenario	Tasks finalized	s
Localized 5	403.87 ± 5.62	15.04
Centralized 5	428.83 ± 6.94	18.58
Localized 10	691.03 ± 11.47	30.72
Centralized 10	824.97 ± 9.92	26.56
Localized 15	1137.70 ± 14.58	39.04
Centralized 15	1273.87 ± 9.91	26.55
Localized 20	1316.50 ± 18.54	49.65
Centralized 20	1554.40 ± 16.50	44.20

In summary, the fleet size primarily acts as a capacity driver: increasing the fleet increases the number of finalized tasks and, correspondingly, increases total travel distance over the horizon. Across fleet sizes, the strategy choice mainly shifts per-task efficiency: the centralized strategy finalizes more tasks while maintaining a lower distance per finalized task, which is consistent with better matching and/or reduced unproductive movement. This efficiency advantage aligns with the economic results, where scenarios with lower distance-per-task tend to exhibit lower cost per task. Finally, because emissions are computed from loaded and empty vehicle-kilometers, the emissions intensity per task is expected to be mainly governed by the weighted travel distance per task. Therefore, improvements in distance-per-task efficiency should translate into lower emissions per task.

CONCLUSION AND FUTURE RESEARCH

This paper presented a discrete-event simulation model in FlexSim to assess how reverse-logistics network configuration (centralized vs. localized) and fleet sizing jointly influence transportation cost, CO_2 emissions, and service under stochastic task generation, condition-dependent routing, and capacity-triggered dispatch in a context of C.E. R-Strategies for product life-cycle extension. Across eight scenarios (two strategies and four fleet sizes) and 30 replications per scenario, the central-

Table 5: Travel distance results (mean ± 95% CI over 30 replications) and sample standard deviation s.

	Total distance [km]		Empty distance [km]		Loaded distance [km]	
Scenario	Mean ± CI	s	Mean ± CI	s	Mean ± CI	s
Localized 5	58047 ± 481	1289	28431 ± 245	657	29616 ± 297	795
Centralized 5	60332 ± 210	561	29709 ± 234	626	30622 ± 163	435
Localized 10	100126 ± 1677	4490	48726 ± 773	2071	51400 ± 929	2487
Centralized 10	116310 ± 472	1264	57029 ± 331	886	59281 ± 323	864
Localized 15	166569 ± 2262	6057	81558 ± 1123	3008	85010 ± 1186	3176
Centralized 15	180719 ± 418	1120	88847 ± 282	755	91872 ± 323	866
Localized 20	193406 ± 2755	7379	94700 ± 1352	3621	98706 ± 1431	3834
Centralized 20	220312 ± 1534	4110	108132 ± 787	2109	112180 ± 813	2177

ized strategy consistently achieved lower cost and CO_2 emissions per completed task while completing more tasks within the one-week horizon. Although the localized strategy reduced total travel distance, it exhibited higher distance per completed task, indicating that pooling and utilization effects under the modeled dispatch policy outweighed distance savings from an additional hub. Future work will investigate adaptive control using reinforcement learning to learn dispatch and assignment policies from system state, and will extend the model with a higher-fidelity warehouse/processing simulation to explicitly represent receiving, inspection, sorting, batching, and internal resource constraints. Additionally, it may investigate how RENÉE's inspection technologies influence the effective condition-score distribution, particularly in terms of reducing uncertainty and misclassifications in recovery decisions.

Limitations

This exploratory study provides comparative insights under the modeled assumptions rather than externally validated performance estimates. Results are based on a one-week simulation horizon (with a one-day warm-up) and may therefore depend on horizon length, warm-up choice, and initial conditions. The localized strategy is modeled as two independent clusters with no cross-serving, whereas the centralized strategy pools resources; observed differences thus reflect pooling effects under the specific task-generation and dispatch rules and may change under alternative operational policies. Emissions are estimated using a distance-based loaded/empty factor model, which is consistent at first order but does not capture second-order effects such as speed variability, congestion, stop–go dynamics, or idling emissions.

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