Optimizing Hierarchical Valorization Pathways in Plastic Waste Reverse Logistics With Contamination-Dependent Technology Selection

Syrine Laouini, Julien Trochu, Rim Larbi, Amin Chaabane
Department of systems Engineering, École de technologie supérieure (ÉTS), Montréal, Canada.

E-mail: syrine.laouini@etsmtl.ca; julien.trochu@etsmtl.ca; rim.larbi@etsmtl.ca; Amin.Chaabane@etsmtl.ca

***Abstract*— Plastic waste reverse logistics networks under Extended Producer Responsibility (EPR) face challenges such as variable source contamination and decisions on sorting center technologies. These factors affect system costs and recycling performance. Current models often address these issues alone, limiting understanding of EPR network design. This paper presents an integrated mixed-integer linear programming (MILP) model that coordinates technology selection at sorting centers, monitors contamination levels, manages recycler flexibility, and allocates waste flows across recycling, export, and landfill options. Applied to Québec's plastic waste management system, key findings include: 1) upgrading sorting centers is economically viable only above certain contamination levels; 2) sorting center upgrades become cost-justified above a 0.5 contamination multiplier, with total system cost rising from ~45M to ~65M CAD between the lowest and highest contamination scenarios ; and 3) recycler flexibility cannot compensate for poor sorting upstream, as quality issues dominate capacity constraints. These insights offer crucial thresholds for EPR infrastructure investment planning.**

I. INTRODUCTION

Managing post-consumer plastic waste is a major challenge for a circular economy. While collection rates are increasing, global recycling rates remain below 10% in 2022, and many plastics are still exported or sent to landfills [1]. This issue stems from high variability in material streams, which affects both volume and contamination levels. This inconsistently undermines sorting facility performance, increases operational costs, and threatens the sustainability of domestic recycling networks [2, 3]. Extended Producer Responsibility (EPR) frameworks aim to tackle inefficiencies by shifting end-of-life management to producers. However, EPR implementation faces challenges in managing quality variability and making strategic infrastructure investments [4].

Material recovery facilities (MRFs) serve as essential transformation hubs where contamination levels and compositional variations directly influence sorting efficiency. Traditional MRFs often face technological limitations in handling high levels of contamination, resulting in higher rejection rates [3]. Enhanced MRFs equipped with advanced optical sorting technology can significantly enhance recovery yields and minimize contamination. However, this improvement is accompanied by notably increased capital and operational expenditures [5]. Recent research on the processing of mixed plastic waste has demonstrated that linear composition-based models can effectively predict yield outcomes. This finding supports the use of aggregate modeling approaches, which assign material properties based on feedstock composition [6]. This highlights a key trade-off between cost and valorization. While advanced technology improves material quality and recovery rates, its economic viability hinges on whether the added value surpasses the costs. Current literature provides limited quantitative insights on how different contamination levels and volumes impact this trade-off and the economic thresholds for infrastructure upgrades. Sorting operations face two main challenges: strict quality requirements and the limited capacity of local recyclers, which determine contamination thresholds and are influenced by contracts and market conditions [6]. When local quality requirements or capacity limits are exceeded, materials must be redirected to international markets with looser specifications or to landfill. This creates a hierarchical allocation problem, in which optimal distribution depends on interactions among quality levels, capacity, and transportation costs. Prior research has investigated these dimensions individually [7], [8]; however, there remains a limited understanding of the parameter combinations that influence structural transitions between valorization pathways.

To enhance network resilience, increasing recyclers' flexibility to process multiple polymer types can reduce variability in volume and composition [8]. This capability allows recyclers to handle a wide range of materials, maximizing capacity utilization. However, processing multiple materials can lower effective throughput due to changeovers and scheduling inefficiencies. Recent models show that recyclers typically operate at 70-80% capacity when handling distinct materials rather than a single type [8]. In the multi-product reverse logistics model of Yu and Solvang [8], recyclers operate at 70–80% of nominal capacity when processing multiple material types, reflecting scheduling inefficiencies from mixed-product handling. This phenomenon presents a trade-off between flexibility and capacity: greater flexibility boosts adaptability but reduces processing efficiency. While this trade-off is recognized, the acceptable limits remain unclear, and the effect of upstream sorting performance on these boundaries has not been examined.

The existing body of literature presents a significant limitation: it lacks integrated modeling frameworks that concurrently address strategic technology decisions, contamination dynamics, and outlet allocation. Most models examine volume uncertainty, quality variability, and technology investments as distinct and separate challenges [4],[9]. Furthermore, contamination is often depicted as a binary state rather than a continuously monitored variable across the network [10]. This gap hinders current models' ability to identify structural thresholds and to clarify the policy trade-offs necessary for EPR-driven decisions. To address these gaps, this paper investigates three fundamental research questions:

RQ1: Under what contamination and volume conditions does sorting center modernization become economically justified, and how does source-level variability affect the cost-valorization trade-off?

RQ2: How do quality thresholds and local recycler capacity limits jointly drive structural transitions in material flow allocation across local recycling, export, and landfilling?

RQ3: How does recycler flexibility affect effective processing capacity, and beyond what contamination threshold does upstream sorting quality become the binding constraint, rendering additional flexibility investment ineffective?

The interconnected nature of sorting technology, output quality, outlet eligibility, and recycler flexibility is crucial for optimizing reverse logistics networks under Extended Producer Responsibility (EPR) constraints. This paper presents a mixed-integer linear programming (MILP) model that addresses these elements jointly by integrating sorting center technology selection, monitoring residual contamination, and managing recycler flexibility through a capacity-penalty mechanism. The model contributes in three key ways: it links sorting performance with outlet eligibility and recycler configuration, identifies structural thresholds often overlooked by isolated models, and conducts a parametric analysis of contamination scenarios to reveal shifts in optimal flow allocations among recycling pathways. Finally, the model has been applied to Québec's EPR network, providing contamination-indexed investment thresholds to support effective infrastructure planning.

The remainder of this paper is organized as follows. Section II reviews relevant literature on quality management, contamination, technology selection, and flexibility mechanisms, and identifies the research gaps and contributions of this work. Section III presents the problem statement. Section IV describes the mathematical formulation. Section V presents the case study and computational results. Section VI concludes the paper with managerial insights, limitations, and future research directions.

II. RELATED WORK

EPR frameworks have reshaped plastic waste management by assigning end-of-life obligations to producers and driving significant investment in sorting and recycling capacity, yet quantitative models to support EPR-compliant decision-making remain underdeveloped [4]. The growing complexity of plastic waste streams, multi-polymer composition, variable contamination, and heterogeneous market outlets demands integrated frameworks that simultaneously address technology selection, flow allocation, and capacity mechanisms. This section reviews two bodies of literature that define the modeling context: quality, contamination, and technology selection in sorting operations; and flexibility, uncertainty, and capacity mechanisms in reverse logistics.

Sorting facility performance is a critical determinant of reverse logistics efficiency, as output quality governs downstream outlet eligibility and the economics of valorization. Ragaert et al. [2] establish that contamination levels directly affect processing costs and output quality, with cascading network-level consequences. Gadaleta et al. [3] corroborate this with operational data from an Italian MRF, reporting recovery rates of 80.2% (PET) and 92.8% (PE), and technology upgrades increasing overall recovery from 34.32% to 50.39%. Lubongo and Alexandridis [5] further show that advanced automated sorting systems can achieve 99.99% precision at a throughput of 10 metric tons per hour (t/h), albeit with higher capital and operating costs—implying that modernization is justified only when incremental valorization gains offset investment premiums. Despite this empirical evidence, existing optimization models treat sorting performance as a fixed parameter, decoupling technology investment from network design. Quality representation has remained largely binary: [10] model contamination as an acceptable/unacceptable state, preventing continuous tracking of residual contamination across processing stages. Genuino et al. [13] offer a methodological path forward, demonstrating that linear superposition models based on proportional composition accurately predict processing yields and enable tractable, continuous modeling of contamination within network optimization frameworks.

The ability to adapt network operations in reverse logistics is essential. Flexibility involves adjustments in temporal capacity, product portfolio breadth, and technological versatility. Solvang and Yu [9] developed a stochastic bi-objective mixed-integer programming model for multi-product reverse logistics, showing that multi-type processing can lower costs under high variability but may lead to inefficiencies beyond 25%. This research highlights the flexibility-efficiency trade-off, though fixed input quality in single-period models misses interactions between sorting technology and flexibility. De Rosa et al. [10] introduced a robust bidirectional logistics network design that addresses capacity variations but treats flexibility variations as exogenous, thereby limiting the identification of unviable flexibility levels. Rahimi and Ghezavati [11] presented a stochastic model for the reverse logistics of construction waste, demonstrating that capacity expansion under uncertainty can reduce worst-case costs by 15–30% but overlooks multi-product flexibility. Overall, these studies emphasize the importance of capacity flexibility and uncertainty management in reverse logistics but often treat them as isolated factors rather than as interdependent variables. The role of improvements in sorting technology in enhancing flexible configurations remains unexplored.

Three cumulative gaps motivate this work. First, no existing model jointly addresses quality-constrained allocation, technology selection, and recycler flexibility within a single EPR-compliant framework — Govindan et al. [10] treat quality as a binary state, Solvang and Yu [8] fix input quality exogenously, and Rahimi and Ghezavati [9] abstract flexibility as a scalar capacity parameter. Second, the contamination thresholds at which sorting infrastructure upgrades become economically justified and remain unquantified across network configurations. Third, a deterministic formulation is a necessary precursor to stochastic extensions: scenario-averaging in robust models obscures the structural thresholds and cause-effect relationships that govern investment decisions under EPR constraints. This paper addresses these gaps through an integrated MILP that endogenizes technology selection, tracks contamination continuously per polymer type, and models recycler flexibility via an explicit capacity-penalty mechanism. The model is calibrated on Québec's EPR network to identify contamination-indexed investment thresholds for infrastructure planning.

III. PROBLEM STATEMENT

We design a reverse logistics network for post-consumer plastics in Québec under EPR, encompassing Municipal Regional Counties (MRCs) for collection, sorting centers (CTs) for separation, and downstream outlets (recyclers, landfills). Key interdependent decisions involve CT technology upgrades, MRC flow allocation, and bale routing, as sorting technology directly affects recovery yields, contamination, and outlet eligibility. Downstream valorization depends on quality thresholds: local recyclers impose contamination limits, exports serve as overflow, and landfilling handles residues and non-compliant bales. Recycler flexibility—accepting multiple polymer types—expands routing options but reduces operational efficiency, as reflected in a declining effective capacity ratio. The model configures a network that is cost-efficient, operationally feasible, and EPR-compliant, addressing the optimal level of quality improvement through CT modernization, the effect of quality and capacity constraints on flow allocation, and whether recycler flexibility can offset upstream quality deficiencies. Four assumptions apply: (1) all MRC material must transit through a CT; (2) quality is managed at the CT-polymer aggregate level; (3) each CT operates in a single mode (standard or upgraded); (4) flexibility costs are captured solely through effective capacity reduction.

IV. MATHEMATICAL MODEL

We formulate the problem as a Mixed-Integer Linear Program (MILP). The MILP notation used throughout the formulation is summarized in Tables II and III.

TABLE II: Model sets and parameters

Symbol	Description
I	Set of MRCs (waste sources), indexed by i
C	Set of sorting centers (CTs), indexed by c
R	Set of local recycling facilities (CRs), indexed by r
L	Set of landfill sites, indexed by l
T	Set of polymer types $\{PET, PEHD, PVC, PEBD, PP, PS, else\}$
O	Set of number of polymer types processed by a recycler, $O = \{0,1,...,\lvert T \rvert\}$ indexed by o
F	International export outlet (singleton)
G_i	Annual plastic waste generated by MRC $i \in I$
p_i^t	Proportion of polymer type t from MRC $i \in I$
q_i	Mean contamination rate of MRC $i \in I$
c_{ic}^{tr}	Transportation cost from MRC $i \in I$ to sorting center $c \in C$
c_{cr}^{tr}	Transportation cost from CT $c \in C$ to recycler $r \in R$
c_{cF}^{tr}	Transportation cost from CT $c \in C$ to export F
c_{cl}^{tr}	Transportation cost from CT $c \in C$ to landfill $l \in L$
C_c^{std}	Variable processing cost at CT $c \in C$ under standard configuration
C_c^{up}	Variable processing cost at CT $c \in C$ under upgraded configuration
F_c^{up}	Fixed upgrade cost for sorting center $c \in C$
C_r^R	Unit treatment cost at recycler $r \in R$
C_l^L	Unit landfill disposal cost at site $l \in L$
P_{bale}	Penalty per ton of non-compliant bales sent to landfill
Z_c^S	Processing capacity of sorting center $c \in C$
Z_r^R	Processing capacity of recycler $r \in R$
Z_l^L	Capacity of landfill site $l \in L$
H_{rt}	Maximum demand of recycler $r \in R$ for polymer type $t \in T$
D_r^{min}	Minimum guaranteed volume contractually owed to recycler $r \in R$
C_{rt}^{max}	Maximum allowable contamination fraction for recycler $r \in R$, polymer type $t \in T$
C_{Ft}^{max}	Max allowable contamination fraction for export outlet F for polymer type $t \in T$
ρ_{ct}^{std}	Plastic recovery yield for polymer type $t \in T$ at sorting center $c \in C$ (standard mode)
ρ_{ct}^{up}	Plastic recovery yield for polymer type $t \in T$ at sorting center $c \in C$ (upgraded mode)
α_c^{std}	Contaminant removal efficiency at sorting center $c \in C$ (standard mode)
α_c^{up}	Contaminant removal efficiency at sorting center $c \in C$ (upgraded mode)
λ_{ro}	Effective capacity ratio of recycler $r \in R$ when processing $o \in O$ polymer types
M	Large constant (Big-M) for linearization

TABLE III Decision variables (all quantities are in tons)

Symbol	Description
z_c	Equals 1 if CT $c \in C$ is upgraded, 0 otherwise
β_{rt}	Equals 1 if recycler $r \in R$ accepts polymer type $t \in T$
u_{ro}	Equals 1 if recycler $r \in R$ processes $o \in O$ polymer
γ_{ctr}	Equals 1 if CT $c \in C$ is authorized to deliver polymer type t to recycler $r \in R$
γ_{ctF}	Equals 1 if CT $c \in C$ is authorized to export polymer type $t \in T$ to outlet F
φ_r	Number of polymers processed by recycler $r \in R$
x_{ic}	Quantity routed from MRC $i \in I$ to CT $c \in C$
y_{ctr}	Quantity delivered from CT $c \in C$ to recycler $r \in R$ for polymer type $t \in T$
y_{ctF}	Quantity delivered from CT $c \in C$ to export outlet F for polymer type $t \in T$

y_{ctl}	Quantity of non-compliant bales from CT $c\in C$ sent to landfill $l\in L$ for polymer type $t\in T$
R_{ctl}	Quantity of sorting residues from CT $c\in C$ sent to landfill $l\in L$ for polymer type $t\in T$
R_{cl}	Sorting residues from CT $c\in C$ sent to landfill $l\in L$
S_{ct}	Quantity of useful plastic of polymer type $t\in T$ entering CT $c\in C$
U_{ct}^{in}	Quantity of contaminants of polymer type t entering CT $c\in C$
P_{ct}^{out}	Quantity of plastic type $t\in T$ recovered in output bales at CT $c\in C$
U_{ct}^{out}	Quantity of contaminants in output bales of type $t\in T$ at CT $c\in C$
X_c	Total plastic waste inflow to sorting center $c\in C$
X_c^{up}	Auxiliary variable linearizing z_c
Ratio$_r$	Capacity ratio of recycler $r\in R$ determined by flexibility level $o\in O$

D. Objective Function

The objective function minimizes total system cost, including fixed fixed investments, MRC-to-CT transportation, CT processing, local recycler treatment, export transportation, and landfill disposal of non-compliant bales and sorting residues.

$$\min \sum_{c\in C} F_c^{up} z_c + \sum_{i\in I}\sum_{c\in C} c_{ic}^{tr} x_{ic} + \sum_{c\in C}\left[C_c^{std} X_c + \left(C_c^{up} - C_c^{std}\right) X_c^{up}\right] + \sum_{c\in C}\sum_{t\in T}\sum_{r\in R}\left(c_{cr}^{tr} + C_r^{R}\right) y_{ctr} + \sum_{c\in C}\sum_{t\in T} c_{cF}^{tr} y_{ctF} + \sum_{c\in C}\sum_{t\in T}\sum_{l\in L}\left(c_{cl}^{tr} + C_l^{L} + P_{bale}\right) y_{ctl} + \sum_{c\in C}\sum_{l\in L}\left(c_{cl}^{tr} + C_l^{L}\right) R_{cl} \tag{1}$$

E. Constraints

Flow routing and CT capacity: All MRC flows must be routed to a sorting center and respect its maximum capacity.

$$\sum_{c\in C} x_{ic} = G_i \qquad \forall i \in I \tag{2}$$

$$\sum_{i\in I} x_{ic} \le Z_c^S \qquad \forall c \in C \tag{3}$$

Material balance at CT: Inputs at each CT are decomposed into useful plastic and contaminants per polymer type.

$$S_{ct} = \sum_{i\in I} x_{ic}\, p_i^t (1 - q_i) \qquad \forall c \in C,\ \forall t \in T \tag{4}$$

$$U_{ct}^{in} = \sum_{i\in I} x_{ic}\, p_i^t q_i \qquad \forall c \in C,\ \forall t \in T \tag{5}$$

CT output quality and technology selection constraints (6)–9): $\forall c \in C,\ \forall t \in T$ *we have*:

$$\rho_{ct}^{std} S_{ct} - M z_c \le P_{ct}^{out} \le \rho_{ct}^{std} S_{ct} + M z_c \tag{6}$$

$$\rho_{ct}^{up} S_{ct} - M(1 - z_c) \le P_{ct}^{out} \le \rho_{ct}^{up} S_{ct} + M(1 - z_c) \tag{7}$$

$$(1 - \alpha_c^{std}) U_{ct}^{in} - M z_c \le U_{ct}^{out} \le (1 - \alpha_c^{std}) U_{ct}^{in} + M z_c \tag{8}$$

$$(1 - \alpha_c^{up}) U_{ct}^{in} - M(1 - z_c) \le U_{ct}^{out} \le (1 - \alpha_c^{up}) U_{ct}^{in} + M(1 - z_c) \tag{9}$$

Bale conservation and flow routing: Output bales are fully allocated across outlets.

$$\sum_{r\in R} y_{ctr} + y_{ctF} + \sum_{l\in L} y_{ctl} = P_{ct}^{out} + U_{ct}^{out} \quad \forall c \in C,\ \forall t \in T \tag{10}$$

$$y_{ctr} \le M\gamma_{ctr} \qquad \forall c \in C, \forall t \in T,\ \forall r \in R \tag{11}$$

$$y_{ctF} \le M\gamma_{ctF} \qquad \forall c \in C,\ \forall t \in T \tag{12}$$

Outlet quality eligibility constraints (13)–14):

$$U_{ct}^{out} \le C_{rt}^{max}\left(P_{ct}^{out} + U_{ct}^{out}\right) + M(1 - \gamma_{ctr}) \qquad \forall c \in C,\ \forall t \in T,\ \forall r \in R \tag{13}$$

$$U_{ct}^{out} \le C_{Ft}^{max}\left(P_{ct}^{out} + U_{ct}^{out}\right) + M(1 - \gamma_{ctF}) \qquad \forall c \in C,\ \forall t \in T \tag{14}$$

Recyclers' capacity and demand.

$$\sum_{c\in C} y_{ctr} \le H_{rt} \qquad \forall r \in R,\ \forall t \in T \tag{15}$$

$$\sum_{c\in C}\sum_{t\in T} y_{ctr} \le Z_r^R \cdot \text{Ratio}_r \qquad \forall r \in R \tag{16}$$

$$y_{ctr} \le M\beta_{rt} \qquad \forall c \in C,\ \forall t \in T,\ \forall r \in R \tag{17}$$

Recycler flexibility and capacity ratio constraints (18)–21):

$$\phi_r = \sum_{t\in T} \beta_{rt} \qquad \forall r \in R \tag{18}$$

$$\sum_{o\in O} u_{ro} = 1 \qquad \forall r \in R \tag{19}$$

$$\phi_r = \sum_{o\in O} o\, u_{ro} \qquad \forall r \in R \tag{20}$$

$$\text{Ratio}_r = \sum_{o\in O} \lambda_{ro} u_{ro} \qquad \forall r \in R \tag{21}$$

Sorting residues and landfill capacity. Sorting residues are computed as the difference between CT inflow and bale output:

$$\sum_{l\in L} R_{ctl} = \left(S_{ct} + U_{ct}^{in}\right) - \left(P_{ct}^{out} + U_{ct}^{out}\right) \forall c \in C,\ \forall t \in T \tag{22}$$

$$R_{cl} = \sum_{t\in T} R_{ctl} \qquad \forall c \in C,\ \forall l \in L \tag{23}$$

$$\sum_{c\in C}\sum_{t\in T}\left(y_{ctl} + R_{ctl}\right) \le Z_l^L \qquad \forall l \in L \tag{24}$$

EPR minimum demand guarantee. Each contracted recycler must receive at least its guaranteed minimum volume:

$$\sum_{c\in C}\sum_{t\in T} y_{ctr} \ge D_r^{min} \qquad \forall r \in R \tag{25}$$

V. CASE STUDY AND RESULTS

A. Case Study and Data Assumption

The case study models Québec's plastic waste management system under an EPR framework. It incorporates 82 municipal regional counties (MRCs) that supply post-consumer plastic waste through the Blue Box program, with population and waste generation data sourced from the Institut de la statistique du Québec [X] and [11]. The network comprises 26 sorting centers and 16 recycling facilities, with location, capacity, and throughput data from [11]. Materials flow from MRCs to sorting centers and subsequently to recycling facilities. Initial contamination rates at the MRC level range from 18% to 30%, consistent with reported values in Québec [12]. Sorting performance varies by technology: standard centers achieve 45%–54% contaminant removal, while upgraded facilities reach 92%–95%, directly affecting residual contamination in sorted outputs and downstream allocation decisions. Transportation flows are modeled using inter-facility distances, with capacity constraints. The MILP model was implemented in Python using Gurobi v13.0.1 and solved on an Intel Core i5 machine with 16 GB RAM. A 30-minute time limit was imposed per scenario; all instances reached optimality within this limit, with a maximum MIP gap of 2%.

B. Results and discussion

This section analyzes the impact of source contamination on system cost, flow allocation, and infrastructure decisions through parametric analysis, scaling contamination within the 18%–30% baseline range. Sorting performance is modeled via contaminant removal parameters for standard (45%–54%) and upgraded (92%–95%) centers, which directly govern residual contamination and downstream outlet eligibility under constraints (13) and (14). This structure ensures a direct link between contamination levels and flow feasibility, enabling the identification of structural thresholds and the confirmation of trend robustness across scenarios.

1) Contamination impact on system cost

As contamination q_i increases, total system cost increases significantly, from approximately 45 M CAD to over 65 M CAD, as shown in Figure1. This increase is primarily driven by higher volumes of non-compliant materials, leading to increased landfill flows y_{ctl} and sorting residues R_{ctl}. This indicates that cost escalation is primarily driven by reduced material eligibility rather than increased processing volumes.

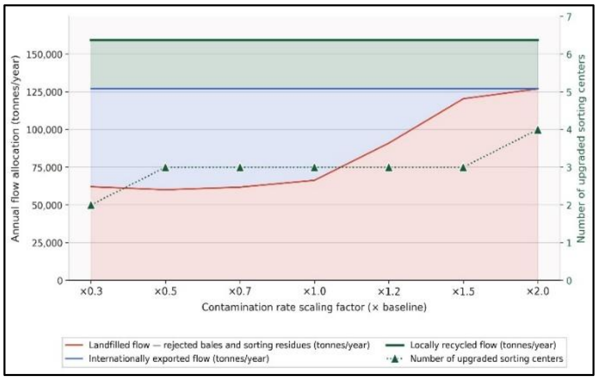

Figure 1: Impact of contamination on system costs

The model responds by activating additional upgrades, with the number of upgraded sorting centers z_c increasing from 2 to 4, as illustrated in Figure 2.

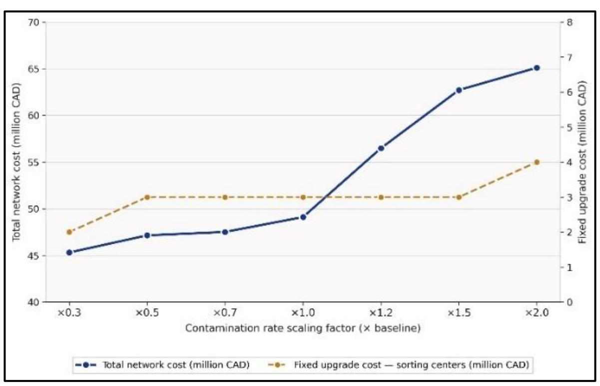

Figure 2: Impact of contamination on flow allocation and sorting center upgrade decisions.

This indicates that improvements in sorting performance α_c become economically justified only beyond certain contamination thresholds: the number of upgraded centers rises from 2 to 3 at the ×0.5 scenario (total cost: 47.2 M CAD), and reaches 4 only at the highest contamination level (×2.0, total cost: 65.1 M CAD), when export flows collapse to zero. Below the ×0.5 threshold, the fixed upgrade cost F_c^{up} and marginal gains in recovered material P_{ct}^{out}.

2) Impact of contamination on flow allocation

Increasing contamination q_i induces a significant reallocation of flows across outlets, as illustrated in Figure 3. Export flows y_{ctF} decrease from approximately 40% of the total volume to zero, as the contamination of output streams $U_{ct}^{out}/(P_{ct}^{out}+U_{ct}^{out})$ exceeds export tolerance thresholds C_{Ft}^{max}. This loss of export capacity is compensated by a strong increase in landfill flows, which rise from 40% to 80% of the total processed volume. This transition is not gradual but occurs once contamination exceeds outlet-specific quality thresholds, reflecting the hierarchical structure of outlet allocation.

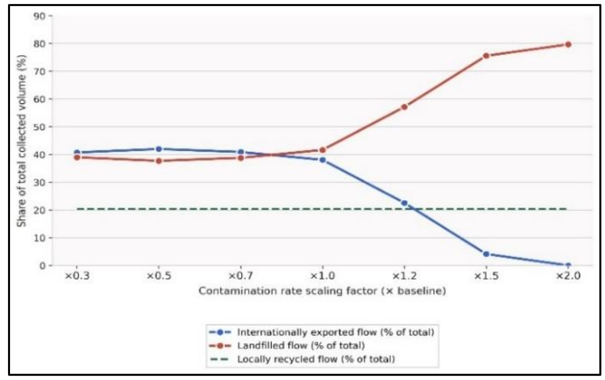

Figure 3: Impact of contamination on flow allocation across recycling, export, and landfill pathways.

This transition reflects the structure of the quality eligibility constraints (13)–(14): once residual contamination exceeds the outlet-specific threshold, the corresponding flow becomes infeasible. The shift is therefore abrupt rather than gradual, as a binary authorization variable determines eligibility. In contrast, flows to local recyclers y_{ctr} remain stable, indicating that local recycling is primarily constrained by capacity Z_r^R and demand H_{rt}, rather than by variations in quality alone. These results reveal critical quality thresholds in constraints (13) and (14), beyond which materials become ineligible for recycling or export, leading to an abrupt shift to landfill.

3) Impact of contamination on the recycler's effectiveness

Despite large variations in contamination q_i, recycler utilization remains stable, with total flows $\sum_{c,t} y_{ctr}$ corresponding to 45%–50% of effective capacity $Z_r^R.Ratio_r$, as shown in Figure 4. This indicates that recycling capacity is not fully utilized due to quality constraints, as a growing share of materials becomes ineligible for recycling when contamination exceeds tolerance.

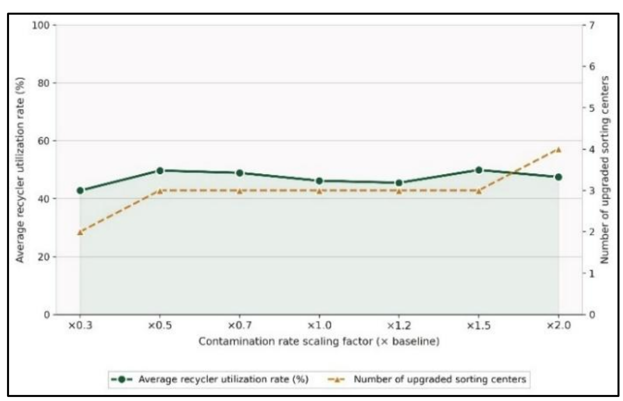

Figure 4: Impact of contamination on recycler effectiveness

Consequently, even with flexibility mechanisms modeled through λ_{ro}, recyclers cannot absorb additional flows when input quality degrades. This confirms that increasing capacity alone is insufficient to improve system performance without adequate input quality. More broadly, the results show that quality constraints dominate capacity limitations, and that recycler flexibility alone cannot offset insufficient upstream sorting performance. As shown in Figure 4, recycler utilization remains between 42.8% and 49.9% across contamination levels. In contrast, locally recycled flows remain constant at 32,400 t/year across all scenarios—equal to the minimum guaranteed demand imposed by constraint (25). This indicates that the binding constraint on local recycling is not capacity or flexibility, but material eligibility. As contamination increases, a growing share of output bales falls below recycler quality thresholds, preventing any additional flow from reaching recyclers, regardless of their flexibility. Recycler flexibility governs effective capacity allocation; it does not affect input quality requirements and cannot substitute for insufficient upstream sorting performance.

C. Key system insights

Contamination significantly impacts system performance by reducing material recovery and increasing impurities in sorted outputs, thereby limiting access to higher-value markets due to quality standards. While sorting upgrades can help, they can't fully counteract poor input quality in high-contamination situations, reducing the proportion of materials that meet quality requirements. Thus, focusing on improving material quality at the source, by better separating waste and minimizing non-target materials, yields greater benefits than relying solely on downstream upgrades or recycling capacity. Higher input quality expands access to better markets, stabilizes material flows, and reduces reliance on landfills, underscoring the importance of upstream quality control. These findings contribute to reverse logistics optimization by addressing a previously unexplored dimension. While prior studies, such as those by Govindan et al. [10] and Ghezavati [9], focus on capacity and binary contamination classifications, the current model treats contamination as a continuous variable. This impacts outlet eligibility based on residual contamination, revealing how excessive contamination can shift material from export to landfill, a nuance overlooked by earlier models.

VI. CONCLUSION

This paper presents a MILP model to optimize plastic waste reverse logistics networks under EPR. It focuses on the selection of sorting technology, material allocation, and recycling flexibility. Applied to Québec, the results show that total system costs rise from approximately 45 million CAD to 65 million CAD as contamination increases from 18% to 30%. Upgrades to sorting centers occur only at specific contamination thresholds, while export flows drop from 40% to zero when quality limits are exceeded. Recycler utilization stabilizes at 45%-50%, indicating that quality constraints are the primary bottleneck. The key insight is that improving upstream source quality provides greater network-wide benefits than investing in downstream technology or expanding capacity. The model identifies key thresholds for EPR-compliant infrastructure but relies on a deterministic, single-period approach, restricting its capacity to address contamination variability and investment dynamics. Future enhancements aim to incorporate stochastic contamination variability for risk assessment, develop a multi-period model to address timing and transition costs, and calibrate the flexibility-penalty mechanism using MRF operational data to improve realism and validate efficiency assumptions.

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