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Optimizing plastics recycling networks

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ABSTRACT

Plastic pollution is a serious sustainability issue facing the global community. Fragments of macroplastics and microplastics pollute terrestrial and aquatic ecosystems, while nanoplastics can also degrade air quality. The recent COVID-19 pandemic also exacerbated the problem. Large-scale commercial use of plastics recycling technologies is hindered by various socio-economic barriers. In particular, cross-contamination of mixed plastic streams is prevalent due to imperfect waste segregation. The concept of Plastics Recycling Networks is introduced to facilitate planning of reverse supply chains using optimization models. In this work, basic Linear Programming and Mixed-Integer Linear Programming models are developed for matching sources of waste plastic with plastic recycling plants within Plastics Recycling Networks. These models allocate streams while considering the ability of recycling plants to tolerate contaminants. Two illustrative case studies are analyzed to demonstrate the effectiveness of the models, and policy implications for mitigation of plastic pollution are discussed. These models enable planning of networks with some tolerance for contaminants in plastic waste, and can be the basis for developing new variants to handle additional real world aspects.

1. Introduction

Plastic pollution is serious enough to warrant a binding international agreement (Ammendolia and Walker, 2022). Macroplastics and microplastics can pollute marine and terrestrial ecosystems (Wong et al., 2020) while smaller particles of nanoplastics can degrade air quality (Prata, 2018). Ingestion or inhalation of these particles can have adverse impacts on health (Prata et al., 2020). Plastic fragments in the environment also degrade into smaller particles at varying rates (Plohl et al., 2022). There are still many barriers to the recycling of waste plastic as a key strategy for managing plastic pollution (Rudolph et al., 2020). For example, in fiber reinforced composites for high-performance applications, the separation of the polymer matrix from fibers is problematic (Cao et al., 2022). Human behavior introduces additional complications. In developing countries it remains common practice to use open burning to reduce the volume of plastic-bearing municipal solid waste (Velis, 2022), while poor segregation hinders recycling with processes that are more suited for pure polymers (Hahladakis and Iacovidou, 2019). Mixing can result in contamination of polyolefin streams with oxygen-rich polymers like polyethylene terephthalate (PET) and biodegradable plastics such as polylactic acid (PLA). Incorrect sorting of plastic waste is partly due to insufficient knowledge on the types of plastics and proper segregation practices (Nemat et al., 2022). Consumer ability to properly identify packaging materials so they can correctly dispose them is crucial to recycling, and persists to be a barrier in recycling behavior. Inconvenience or perceived difficulty in sorting also drive them away from engaging in recycling efforts (Fogt Jacobsen et al., 2022). Since the ability to correctly recognize plastics is linked to proper sorting, packaging information as well as visual cues can enhance recycling. In addition, consumer education, effective communication, label design enhancements to include sorting information, and procedural improvements to make it convenient for consumers to consistently engage in recycling are some initiatives that can be implemented (Nemat et al., 2022). Gamification also proves to be a promising tool in consumer

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engagement and behavior change with respect to environmental issues (Hsu and Chen, 2021) and specifically recycling (Hsu, 2022). Even marginal improvements in sorting efficiency can have a large effect on the profitability of plastics recycling due to the increase of output stream quality (Lim et al., 2022).

To gain insights on aggregate waste management behavior, Machine Learning (ML) techniques such as rough sets (Gue et al., 2021), hidden Markov model (Jiang and Liu, 2016), and artificial neural networks (Fan et al., 2022) have been applied to extract patterns from published government statistics. More recently, the COVID-19 pandemic compounded plastic pollution problems resulting from increased use of protective gear (e.g., face masks) and packaging for online deliveries (Klemeš et al., 2020). A producer-focused approach in plastic waste management is embedded in Extended Producer Responisbility (EPR), which shifts to producers the obligation of reducing environmental impacts in post-consumption activities (Jafari et al., 2022). EPR encourages improvement of packaging design for better recyclability. Producers can implement this scheme either individually or collectively through Producer Responsibility Organizations (PROs) that function as the implementing organization to carry out the obligation of the producers (Colelli et al., 2022). A sustainable Circular Economy (CE) framework can only be established if the interdependent choices of producers and consumers are taken into account (Grimes-Casey et al., 2007). Consumer choice is limited to the options available in the market (Klemeš et al., 2021), which suggests that manufacturers play a critical role in “choice architecture” towards sustainability goals (Chiu et al., 2020).

Managing plastic pollution requires concerted international effort comparable to that of dealing with climate change (Lau et al., 2020). While reducing plastic waste and avoiding plastic packaging are some of the top initiatives incorporated in encouraging green consumer behavior (Steinhorst and Beyerl, 2021), other measures in managing plastic waste are needed to achieve CE (Testa et al., 2022). Policy instruments such as EPR (Colelli et al., 2022), and economic interventions (incentives, subsidies, deposit-refund systems, polluter-pays-principle, etc.) have been seen to improve plastic waste management (Larrain et al., 2022). Different technologies exist for recycling polymers in plastic waste (Aziz et al., 2020). Available options are chemical (e.g., thermochemical or enzyme-based) recycling, mechanical recycling, and energy recovery via incineration (Dogu et al., 2021). The global potential reduction of plastic waste quantity using available technology is estimated at 78% by 2040, which indicates the poor state of current waste management practices (Lau et al., 2020). Optimization models using the reverse supply chain framework have been proposed to aid in planning the handling of Municipal Solid Waste (MSW) (Santibañez-Aguilar et al., 2013) and plastic waste in particular (Chaudhari et al., 2021). For instance, a model was developed to provide decision support in handling MSW; the model considered technologies available for different waste (Mohammadi et al., 2018). A Mixed Integer Linear Programming (MILP) model was developed to optimize plastic waste management networks based on cost (Castro-Amoedo et al. (2021). A P-graph model was proposed to plan MSW networks considering significant plastic content in mixed waste (Fan et al., 2020). A web-based implementation of a supply chain optimization model based on P-graph has also been demonstrated (Hu et al., 2022). An optimization model was proposed specifically for food packaging, focusing on loop-closing strategies (Accorsi et al., 2020). A CE model for plastic waste management was developed based on reverse supply chain concepts (Shetty et al., 2022). A robust optimization model was developed for planning global reverse logistics network for trade of plastic waste (Xu et al., 2021); increased network robustness was found to reduce costs but incurs an emissions penalty. A model was proposed to optimize reverse logistics for the removal of plastic waste from seas and oceans (Van Giezen and Wiegmans, 2020). A multi-stage optimization framework was proposed that allocates plastic streams in a reverse supply chain considering transport routes, and applied to an India case study (Sheriff et al., 2017). An MILP model for optimizing agricultural waste plastic recycling networks based on pyrolysis was developed for Scottish scenario (Rentizelas et al., 2018). An MINLP model to optimize sorting strategy in plastics recycling networks based on profit was proposed, considering different sorting technologies with chemical and thermal recycling pathways (Lim et al., 2023). Case studies based on scenarios in Korea and Japan show marked improvement over current industry practices. Conventional and fuzzy optimization models were developed for MSW management in China based on cost and carbon footprint (Li et al., 2022).

Process Integration (PI) was developed in the 1970s to provide a rigorous approach to improve industrial plant energy efficiency through optimized heat recovery. In PI, Pinch Analysis (PA) aids in the design of Heat Exchanger Networks (HENs) based on rigorous thermodynamic principles (Linnhoff et al., 1982). Mathematical Programming (MP) is an alternative approach for designing such systems. PA and MP are mathematically equivalent (Bandyopadhyay, 2015) and are now regarded as complementary rather than competing approaches to PI, each with its own advantages and drawbacks (Klemeš and Kravanja, 2013). The initial focus on HEN synthesis has also been extended to a wide range of applications involving the efficient use of different resources and reduction of environmental footprints (Klemeš, 2013). Key developments in PI research spanning half a century are surveyed comprehensively by Klemeš et al. (2018). The scale of PI applications has also increased, from single process plants in early works, to Total Sites (clusters of plants), and more recently, to large-scale systems such as supply chains, cities, or even countries (Walmsley et al., 2019). This trend suggests the potential to use PI for plastic waste management, where its advantages as a decision support framework can be used to great effect, as recently demonstrated using a graphical PA approach (Tan et al., 2022). However, the corresponding MP formulation based on PI principles has not yet been developed to overcome the main limitation of the previous PA approach, which can only deal with simple problems involving single-contaminant systems. For source-sink mapping and CE implementations in plastics management, Chin et al. (2022) formulated a data-driven PA approach to evaluate plastic waste recycling potential. That work defines concepts and a method for targeting the possible performance of PRNs, leaving the network design to future extensions.

To address this research gap, MP models are developed here for optimizing Plastics Recycling Networks (PRNs) based on the PI framework. The models are formulated based on the structural similarity of the PRN planning problem to Resource Conservation Network (RCN) synthesis (Foo, 2012). The key feature of the PRN synthesis problem is that the quality of streams is considered in the allocation. It is given by the fraction or percentage of contaminant that hinders recycling. It is also assumed that a high quality waste plastic stream with zero or very low contaminant level (e.g., from sorting plants) is available but at a relatively high cost. The goal is to maximize the amount of plastic waste recycled, while minimizing the requirement for pre-sorted plastic waste, as well as the amount of plastic waste sent to landfill (Tian et al., 2023). The succeeding sections of this article are as follows: Section 2 gives the formal problem statement. Section 3 discusses the basic Linear Programming (LP) model formulation and then its MILP extension. Section 4 presents two illustrative PRN case studies. Section 5 provides some consideration for policy implications related to plastic recycling networks and its applications. Finally, Section 6 gives the conclusions and recommends future research directions.

2. Problem statement

The formal statement of the PRN planning problem is as follows. Given:

- A system with a single type or class of plastic waste;
- A set of contaminants in the plastic waste that limit recycling options;

- A set of sources, each of which generates plastic waste at an annual flowrate of S_i and with quality q_{ik} (expressed in terms of fraction or percentage of every contaminant k);
- A set of sinks (i.e., recycling or disposal plants), each of which has an annual capacity D_j and a feed quality specification c_{jk};
- A supplementary source of high quality (zero- or low-contaminant) but high-cost plastic waste (e.g., a sorting plant) that supplies an annual flowrate F_j to each sink;
- A final sink that can tolerate high levels of contaminants (e.g., a landfill), for the disposal of unrecyclable plastic waste from each source, W_i.

The problem allocates plastic waste optimally between the sources and sinks, r_{ij}, so that both the total amount of high quality plastic needed by the sinks, $\sum_j F_j$, and the total amount on unrecycled plastic waste sent to the final sink, $\sum_i W_i$, are minimised, while all flowrate and quality limits are satisfied. The problem can be visualized with the PRN superstructure in Fig. 1. The model formulation is discussed in the next section.

3. Modeling framework

This section describes the PI-based LP and MILP models for PRN synthesis.

3.1. Model I

The basic LP model for PRN planning is as follows:

$$\min \sum_i W_i \tag{1}$$

Subject to:

$$\sum_j r_{ij} + W_i = S_i, \ \forall i \tag{2}$$

$$F_j + \sum_i r_{ij} = D_j, \ \forall j \tag{3}$$

$$Q_k^{ext} F_j + \sum_i q_{ik} r_{ij} \leq c_{jk} D_j, \ \forall j, \forall k \tag{4}$$

$$F_j \geq 0, \ \forall j \tag{5}$$

$$r_{ij} \geq 0, \ \forall i, \forall j \tag{6}$$

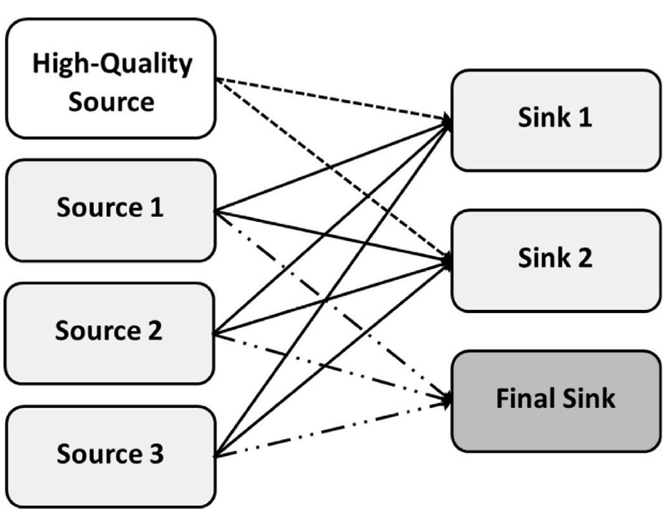

Fig. 1. PRN superstructure.

$$W_i \geq 0, \ \forall i \tag{7}$$

The over-all objective is to minimize the total unallocated plastic waste as defined in Eq. (1). Each plastic source, i, can be allocated to a sink, j, at a rate of r_{ij} while any unallocated plastic, W_i, is sent to a final sink (Eq. (2). The demand for sink j is satisfied by plastic waste from sources, i, and a low-contaminant plastic source, F_j (Eq. (3) while maintaining contaminant limits at sink j (Eq. (4) where Q^{ext} is the contaminant present in the low-contaminant plastic source; q_{ik} is the contaminant in plastic source i, and c_{jk} is the acceptable contaminant level at sink j. In the extreme case, the low-contaminant plastic source may be completely free of contaminant. The flowrate of the low-contaminant source, allocation streams, and unallocated waste streams should be non-zero (Eq. (5)–(7)). This LP model can be easily solved to global optimality without any computational difficulties. However, multiple alternative solutions may exist that cannot be readily enumerated with the simplex algorithm, nor does this model allow PRN topology to be controlled explicitly.

3.2. Model II

Model I can be extended into a MILP formulation as follows:

$$\min \sum_i W_i \tag{8}$$

Subject to:

$$\sum_j r_{ij} + W_i = S_i, \ \forall i \tag{9}$$

$$F_j + \sum_i r_{ij} = D_j, \ \forall j \tag{10}$$

$$Q_k^{ext} F_j + \sum_i q_{ik} r_{ij} \leq c_{jk} D_j, \ \forall j, \forall k \tag{11}$$

$$F_j \geq 0, \ \forall j \tag{12}$$

$$r_{ij} \geq 0, \ \forall i, \forall j \tag{13}$$

$$W_i \geq 0, \ \forall i \tag{14}$$

$$\mathrm{b_{ij}} \in \{0, 1\}, \forall i, \forall j \tag{15}$$

$$\mathrm{r_{ij}} \leq \mathrm{b_{ij}M}, \ \forall i, \forall j \tag{16}$$

As shown in Eqs (8-16), the extended model is similar to the original LP, except for the introduction of a binary variable, b_{ij} (Eq. (15) that takes a value of 1 when the link between source i and sink j is activated, and takes a value of 0 otherwise, where M is any arbitrary large number (Eq. (16). With this MILP formulation, it is possible to accommodate any additional user-defined topological constraints based on practical engineering considerations (Poplewski et al., 2010). Examples include limits on network complexity (i.e., number of source-sink matches) or the specification of forbidden and compulsory source-sink matches. This MILP model can be solved to global optimality using the standard branch-and-bound algorithm; promising near-optimal solutions can also be identified using integer cuts (Voll et al., 2015). Two case studies are shown in the succeeding sections to illustrate these models. The models are implemented using the MP software LINGO (Schrage, 1999). Solutions to both cases were determined with negligible computing time.

4. Case study

Two illustrative case studies are solved in this section to demonstrate the features and capabilities of the models described previously.

Table 1
Plastic waste sources in Case Study 1.

	Flowrate (t/y)	PET content (%)	PET load (t/y)
Source 1	20,000	5	1000
Source 2	10,000	10	1000
Source 3	50,000	20	10,000
Source 4	30,000	40	12,000

Table 2
Plastic waste sinks in Case Study 1.

	Description	Capacity (kt/y)	Limiting PET content (%)	Limiting PET load (kt/y)
Sink 1	Pyrolysis plant	30,000	10	3000
Sink 2	Gasification plant	40,000	15	6000
Sink 3	Waste-to-energy plant	40,000	35	14,000
Final Sink	Landfill	No limit	100	No limit

4.1. Case study 1

In this illustrative case study, the main concern is to recycle polyolefins, namely polyethylene (PE) and polypropylene (PP). Polyolefins have low oxygen content (<3%) which makes waste PE and PP well-suited to thermochemical processing (i.e., pyrolysis or gasification) to yield simple hydrocarbons. These organic chemicals can then be used for various applications, including as monomers for closed-loop plastic production. Their high calorific value (>40 MJ/kg) also makes them suitable for use as fuel in incinerator systems with energy recovery, so that the chemical energy content is converted into electricity. Due to poor segregation, the mixed waste plastic is assumed to be contaminated with significant amounts of polyethylene terephthalate (PET), which is widely used for packaging liquid products. PET has high oxygen content (>30%) which can create difficulties in thermochemical recycling (Dai et al., 2022), while its low calorific value (<25 MJ/kg) is not favorable for energy recovery systems (Dogu et al., 2021). As a result, recycling plants designed for polyolefins cannot tolerate excessive amounts of PET. This tolerance is assumed to be specified as an upper limit for the fraction or percentage of PET in the mixed plastic waste.

Source data are given in Table 1 while sink data are given in Table 2. The sources generate a total of 110,000 t/y of mixed plastic waste. It is also possible to import high-quality plastic waste which has been previously sorted to remove PET, but this option is not prioritized due to its high cost. The pyrolysis plant, gasification plant, and waste-to-energy plant have a combined recycling capacity of 110,000 t/y. These plants also have specified PET content limits, and may not be able to use all of the mixed plastic waste from the three sinks. Any excess waste is sent to a landfill, but only as a last resort. This option does not recover value from the waste streams and has the lowest priority in the waste management hierarchy. The problem is to determine the PRN that matches the sources and sinks optimally.

Solving the LP model in the previous section gives an optimal PRN that requires 5000 t/y of supplementary PET-free plastic waste and that sends 5000 t/y of low-quality plastic waste to the landfill. Table 3 shows the allocation of plastic waste in the PRN, where 105,000 t/y is recycled. This solution is a global optimum but is not necessarily unique. Alternative PRNs can be found using the MILP model by specifying additional topological constraints, such as limits on the total number of source-sink matches or forbidden matches between specific sources and sinks. Such constraints can be specified by the user to reflect practical considerations (Poplewski et al., 2010). For example, setting an upper limit of six recycle streams in this case gives the alternative optimal PRN in Table 4.

There may also be practical engineering interest in alternative solutions with good performance, even if these are not mathematically optimal (Voll et al., 2015). For example, a near-optimal PRN is shown in Table 5. This solution requires 10,000 t/y of PET-free plastic waste, and sends 10,000 t/y of low-grade plastic waste to the landfill. A total of 100,000 t/y of the plastic waste from the four internal sources in the system is recycled, which is only slightly worse that the 105,000 t/y achieved by the optimal PRN. Note that this solution has a simpler PRN topology, with just five source-sink matches. This simplification may have operational or logitistical advantages that can offset the slight reduction in the amount of recycled plastic waste.

A summary of the trade-off between the number of source-sink matches and PRN performance is shown in Table 6.

Table 3
Initial optimal PRN for Case Study 1 (with flowrates in t/y).

	Pyrolysis Plant	Gasification plant	Waste-to-energy plant	Landfill
PET-free source	0	5000	0	0
Source 1	13,333	6667	0	0
Source 2	10,000	0	0	0
Source 3	6667	28,333	11,428	3572
Source 4	0	0	28,572	1428

Table 4
Alternative optimal PRN for Case Study 1 (with flowrates in t/y).

	Pyrolysis Plant	Gasification plant	Waste-to-energy plant	Landfill
PET-free source	0	5000	0	0
Source 1	20,000	0	0	0
Source 2	0	10,000	0	0
Source 3	10,000	25,000	15,000	0
Source 4	0	0	25,000	5000

Table 5
Near-optimal PRN for Case Study 1 (with flowrates in t/y).

	Pyrolysis Plant	Gasification plant	Waste-to-energy plant	Landfill
PET-free source	0	10,000	0	0
Source 1	20,000	0	0	0
Source 2	10,000	0	0	0
Source 3	0	30,000	11,428	8572
Source 4	0	0	28,572	1428

4.2. Case study 2

This illustrative case study considers two oxygen-rich polymers, PET and PLA, as contaminants of a predominantly polyolefin plastic waste stream. The use of plastic waste as an additional mechanical recycling pathway is also considered (Almohana et al., 2022). Note that the latter technique has a higher tolerance for contaminants than thermochemical processing and energy recovery options. The limiting data are indicated

Table 6
Tradeoff between number of source-sink matches and PRN performance in Case Study 1.

Number of source-sink matches	PET-free plastic waste input (t/y)	Unrecycled plastic waste (t/y)	Recycled plastic waste (t/y)
6	5000	5000	105,000
5	10,000	10,000	100,000
4	20,000	20,000	90,000
3	30,000	30,000	80,000
2	50,000	50,000	60,000
1	70,000	70,000	40,000

Table 7
Plastic waste sources in Case Study 2.

	Flowrate (t/y)	PET content (%)	PET load (t/y)	PLA content (%)	PLA load (t/y)
Source 1	20,000	5	1000	0	0
Source 2	10,000	10	1000	0	0
Source 3	50,000	20	10,000	2	1000
Source 4	30,000	40	12,000	3	900
Source 5	60,000	10	6000	3	1800
Source 6	10,000	20	2000	4	400
Source 7	100,000	25	25,000	5	5000
Source 8	20,000	25	5000	10	2000

in Table 7 for the plastic waste sources and in Table 8 for the plastic waste sinks. The total amount of available plastic waste is 300,000 t/y while the total recycling capacity is 240,000 t/y. As in the previous case study, supplementary contaminant-free plastic waste is available from a sorting facility that separates the PET and PLA from polyolefins.

The optimal solution requires no supplementary contaminant-free source, recycles 240,000 t/y of plastic waste, and sends 60,000 t/y of low-quality plastic waste to the landfill. Two alternative optimal PRNs with six and seven source-sink matches (recycle streams) are shown in Tables 9 and 10. A near-optimal network that has only five recycle streams is also shown in Table 11. This solution recycles 230,000 t/y of plastic waste and sends 70,000 t/y to the landfill. A summary of the trade-off between the number of source-sink matches and PRN performance is shown in Table 12.

5. Policy implications

The MP models can provide insights that can be translated into practical solutions (Geoffrion, 1976). The PI-based models developed here provide a framework for allocating the capacity of different available plastic waste recycling and disposal options. These technologies fit a hierarchy where mechanical and chemical recycling take priority over energy recovery, with landfill disposal being the least desirable alternative (Tian et al., 2023). Emerging technologies such as biodegradation can also be included in the portfolio of recycling options (Dailin et al., 2022). The two case studies demonstrate how it is possible to plan PRNs that can tolerate some degree of contamination in plastic waste streams. This tolerance reduces the need for costly sorting of plastic waste to remove contaminants. The PRNs capitalize on the limiting contaminant levels that recycling processes can tolerate, and meet these limits by blending streams of mixed qualities. Both models are also simple enough to be easily implemented and solved even with spreadsheet software.

However, there are important factors to allow model solutions to be implemented in the real world. Implications for the development of policies to mitigate plastic pollution are as follows:

Table 9
Initial optimal PRN for Case Study 2 (with flowrates in t/y).

	Pyrolysis Plant	Gasification plant	Waste-to-energy plant	Concrete mixing plant	Landfill
Contaminant-free Source	0	0	0	0	
Source 1	0	0	0	20,000	0
Source 2	0	0	0	0	10,000
Source 3	0	30,000	0	0	20,000
Source 4	0	30,000	0	0	0
Source 5	50,000	0	0	10,000	0
Source 6	0	0	0	0	10,000
Source 7	0	0	100,000	0	0
Source 8	0	0	0	0	20,000

Table 10
Alternative optimal PRN for Case Study 2 (with flowrates in t/y).

	Pyrolysis plant	Gasification plant	Waste-to-energy plant	Concrete mixing plant	Landfill
Contaminant-free source	0	0	0	0	
Source 1	0	0	0	0	20,000
Source 2	0	0	0	0	10,000
Source 3	0	50,000	0	0	0
Source 4	0	10,000	0	0	20,000
Source 5	0	0	60,000	0	0
Source 6	0	0	0	0	10,000
Source 7	30,000	0	40,000	30,000	0
Source 8	20,000	0	0	0	0

- At global, regional, and national levels, numerous public policy responses to plastic pollution have been proposed and implemented (Stegmann et al., 2022). Many national policies rely on regulatory instruments instead of economic and persuasive approaches. Bans on single-use plastic products can strengthen the CE model for plastic; additional policy instruments such as EPR on PET waste will reduce its quantity and reduce the contaminant level in the plastic waste streams. Requiring label enhancements to add visual cues on sorting information can aid in consumer education.
- The MP models have clear objectives and constraints for PRN planning. However, there is a need for reliable data on plastic waste stream quantity and quality for the MP models to be used. The local government units that are usually responsible for managing MSW should assume this data collection task. The values of these parameters can also change over time in response to real demographic or economic trends, or changes in consumer behavior. In practice, the models may need to be re-optimized periodically to determine the best allocation for a given time frame. The actual PRN to be implemented will thus vary based on the model results.
- The functionality and technologies of the treatment facilities are key enablers of functional PRNs. Knowledge transfer, green financing, and effective maintenance operations are essential managerial resources to allow model solutions to be implemented. The factors introduce the possibility of temporal changes in the PRN (e.g., due to

Table 8
Plastic waste sinks in Case Study 2.

	Description	Capacity (t/y)	Limiting PET content (%)	Limiting PET load (t/y)	Limiting PLA content (%)	Limiting PLA load (t/y)
Sink 1	Pyrolysis plant	50,000	10	5000	4	2000
Sink 2	Gasification plant	60,000	15	9000	10	6000
Sink 3	Waste-to-energy plant	100,000	35	35,000	25	25,000
Sink 4	Concrete mixing plant	30,000	100	30,000	10	3000
Final Sink	Landfill	No limit	100	No limit	100	No limit

Table 11
Near-optimal PRN for Case Study 2 (with flowrates in t/y).

	Pyrolysis plant	Gasification plant	Waste-to-energy plant	Concrete mixing plant	Landfill
Contaminant-free source	0	0	0	10,000	
Source 1	0	0	0	0	20,000
Source 2	0	0	0	0	10,000
Source 3	0	50,000	0	0	0
Source 4	0	0	0	0	30,000
Source 5	50,000	10,000	0	0	0
Source 6	0	0	0	0	10,000
Source 7	0	0	100,000	0	0
Source 8	0	0	0	20,000	0

Table 12
Tradeoff between number of source-sink matches and PRN performance in Case Study 2.

Number of source-sink matches	Contaminant-free plastic waste input (t/y)	Unrecycled plastic waste (t/y)	Recycled plastic waste (t/y)
6	0	60,000	240,000
5	10,000	70,000	230,000
4	20,000	80,000	220,000
3	40,000	100,000	200,000
2	80,000	140,000	160,000
1	140,000	200,000	100,000

plant repair or closure), which in turn will require extended model formulations.

- Reduction of the amount of plastic waste sent to landfills can be made possible by identifying the proper location of recycling facilities within proximity to corresponding sources. Geographic aspects can be integrated into decision-making along with the waste management hierarchy through user-defined topological constraints. The possibility of trading plastic waste between cities, regions, and countries should also be considered, especially if there are geographic variations in recycling capacity. Information drive will be needed for improved social acceptance of these recycling facilities to reduce the need for landfills.
- Transitioning to a CE framework for plastics requires focus on optimized use of recycling technologies, with avoidance of cross-contamination of plastic waste to minimize the need for costly sorting processes. Strenghtening consumer education, incentivizing proper segregation, and increasing consumer awareness and engagement are essential to achieving this goal.
- Two policy recommendations of the International Resource Panel (2021) are also strong enablers of the MP models developed: target indicators and unlocking resistance to change. MP models can be used to set benchmark targets, and a feedback loop can be put in place to gauge the effectiveness of PRNs in the real world. Unlocking of resistance to changes consumer behavior that affects PRN performance can allow model benchmarks to be achieved in practice.

6. Conclusion

Optimization models were developed for optimal PRN planning. The main PRN planning problem is to match system sources and sinks to maximize recycling, while minimizing low-value disposal in landfills or incineration without energy recovery. Stream quality is characterized based on the fraction or percentage of contaminants that hinder recycling. Two illustrative case studies were solved where 95.5% and 80% of the available plastic waste was recycled in the optimal PRNs. The model formulation also allows for alternative near-optimal solutions to be examined. These model capabilities enable effective decision support for planning PRNs that can tolerate some degree of contamination, and have general practical policy implications for mitigating plastic pollution.

In future work, the simple models developed here can be the basis for extended multi-objective MP models to consider additional real-world aspects of PRNs. The extended methods can benefit from combining the MP models with a performance targeting stage, fully following the proven PI approach. Economic performance can be integrated into models along with environmental footprints. Network properties such as resilience can also be used. Measures of quality based on physical properties (Chin et al., 2022) or composite metrics (Golkaram et al., 2022) can be used instead of contaminant level. Large-scale models can be developed with spatial (geographic) and temporal aspects, leading to multi-region and multi-period extensions. The interplay between government regulators and industry can also be modelled using game theory. These future variants may present additional computational challenges that will require new solution algorithms.

Author contributions

KBA: Model development, coding, analysis JCB: Analysis, writing, editing ASFC: Analysis, writing, editing PJ: Analysis, writing, editing YVF: Analysis, writing, editing PSV: Analysis, writing, editing JJK: Conceptualization RRT: Conceptualization, analysis, writing.

Declaration of competing interest

The authors declare that we have no conflicts of interest.

Data availability

Data will be made available on request.

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Nomenclature

Indices

i	Source
j	Sink
k	Contaminant

Variables

b_{ij}	Binary variable that indicates the activation
F_j	Amount of low-contaminant plastic source sent to sink j

r_{ij} Recycled plastic from source i to sink j
W_i Unallocated plastic from source i sent to final sink

Parameters
c_{jk} Quality requirement of sink j in terms of contaminant k
D_j Annual capacity of sink j
M Arbitrary large number
q_{ik} Quality of source i in terms of contaminant k
Q_k^{ext} Concentration of contaminant k in the low-contaminant source
S_i Annual flowrate of plastic waste from source i

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