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Optimal Operational Adjustments for Integrated Plastics Recycling Networks under Supply Shortage Considering Input Substitution

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ABSTRACT

Plastic pollution has become a major environmental challenge. Despite the availability of various recycling technologies, only a small proportion of plastic waste is currently recycled. Developing an Integrated Plastic Recycling Network (IPRN) offers a promising solution to tackling this issue. Facilitating the exchange of material and energy outputs among system components can enhance recycling efficiency. However, disruption in an IPRN component can trigger cascading effects that impact the whole network. This disruption may include shortages in plastic waste inputs. Thus, identifying optimal operating conditions during such disruptions is crucial. This study builds upon previously developed Mixed-Integer Linear Programming (MILP) models based on an enterprise Input-Output (IO) modelling framework to optimize IPRN operations under abnormal conditions. The model is modified to allow input substitution during shortages. The improved model incorporates user-defined substitution conditions, such as redirecting materials from mechanical recycling to pyrolysis or gasification, but not vice versa. During disruptions, rerouting some inputs to prioritize the most profitable processes can significantly improve the network's revenue. Application of the model to a case study of an IPRN demonstrates that allowing input substitution reduces the revenue drop from 9% to 2.4% under a 10% supply shortage in mixed plastic wastes. Incorporating flexible input substitution can enhance the robustness of IPRNs and ensure more effective recycling even under crisis conditions.

KEYWORDS

Plastics recycling, Input-output model, Supply-side disruption, Inoperability, Resilience.

INTRODUCTION

Plastic pollution has recently become a global environmental concern that requires a United Nations-led treaty [1]. A key contributor to this issue is the rising dependence on plastics, particularly in packaging, construction, and textiles. Global plastic demand is projected to rise from 464 Mt in 2020 to 884 Mt by 2050. This will result in a corresponding increase in plastic waste generation from 367 Mt in 2020 to 874 Mt by 2050 [2]. Unfortunately, mismanagement of these waste materials has contributed to plastic pollution in both aquatic and terrestrial

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ecosystems. This alarming trend has serious implications for Planetary Boundaries [3] and the Sustainable Development Goals [4].

Once plastics enter the ocean, they can gradually fragment into smaller particles known as microplastics [5]. These particles are persistent and can remain in the environment for centuries or even millennia [6]. Aquatic organisms exposed to these microplastics may suffer from reduced food intake, stunted growth, and lower reproductive rates [7]. These impacts can, in turn, affect the fishing industry by reducing the yields of fish and seafood [8]. Humans who consume contaminated seafood may also experience negative health effects [9]. Microplastics have also been detected in soil ecosystems, where they have been shown to disrupt the growth and photosynthesis of plants [10], as well as cause reproductive damage to small invertebrates residing in the soil [11]. Addressing the issue of plastic pollution requires a multifaceted approach with solutions targeting various aspects of the problem. These measures include reducing plastic use at the source, designing plastics to be more recyclable, enhancing waste collection and sorting processes, and advancing current recycling methods [12].

Plastic recycling plays an important role in managing plastic waste and promoting sustainable waste management [13]. Among the various recycling techniques, mechanical recycling is the most widely used. This process involves the physical conversion of plastic waste into secondary raw materials [14]. More advanced methods include pyrolysis, gasification, and solvolysis. Pyrolysis thermally breaks down plastic polymers in the absence of oxygen, yielding products that can be refined into fuels or plastic monomers [15]. Gasification partially oxidizes plastic waste to produce syngas, a versatile feedstock that can be used to produce hydrogen, methanol, and other compounds [16]. Solvolysis specifically targets condensation plastics, breaking them down into monomers that can be repolymerized into new plastics. A notable example is methanolysis, which uses methanol for decomposition [17]. Despite the availability of these technologies, global recycling rates remain low. Only 9% of plastic waste is recycled, while 12% is incinerated, 50% is sent to landfills, and 22% leaks into the environment [18]. Even achieving a 55% recycling rate by 2030 may not prevent environmental impacts from surpassing 2018 levels [19]. These statistics highlight the urgent need to enhance current recycling methods to improve recycling rates and address the growing plastic waste issue effectively.

Each recycling method is developed to handle specific types of plastic waste input. Combining these technologies is crucial for maximizing recycling efficiency [20]. These technologies can achieve a 78% reduction in total plastic waste by 2040 when deployed optimally [21]. A promising solution is to incorporate these technologies into an Integrated Plastics Recycling Network (IPRN). An IPRN is a system of interconnected plastic recycling facilities that synergistically share material and energy flows to optimize resource use and improve economic performance. This approach adopts the concept of industrial symbiosis [22], similar to the frameworks applied in integrated product biorefineries [23], integrated energy systems [24], and eco-industrial parks [25]. Mathematical programming is often used for the optimal synthesis of such systems [26]. Despite its potential, only two studies have been published on optimizing IPRNs to date. Tan et al. [27] proposed an approach using Pinch Analysis (PA) to optimize the matching of plastic waste with appropriate recycling technologies, while Aviso et al. [28] employed Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) models to achieve similar objectives. However, these approaches do not consider the potential impact of disruptions and the subsequent adjustments needed within the network to mitigate such effects.

Interdependencies resulting from the tight integration of different technologies can lead to increased network vulnerability. A disruption in one unit, such as a reduction in its input, can cascade and affect other parts of the system [29]. This high interconnectivity and resulting supply (or demand) uncertainties have been identified as key factors contributing to failures in many eco-industrial parks [30]. Managing these risks is therefore essential for ensuring the robustness and resilience of such systems. Leontief [31] developed the Input-Output (IO) model to mathematically represent this interdependence using a system of linear equations. Haimes and Jiang [32] extended the IO model to create the Inoperability Input-Output Model (IIM), which analyzes the cascading failures in a highly integrated system. In this model, inoperability is a measure of a system's inability to perform its intended function that ranges in value from 0 (normal state) to 1 (total failure). The IIM framework provides insights that support the development of risk mitigation strategies [33]. For instance, Kasivisvanathan et al. [29] developed an MILP model that optimizes operational adjustments to maximize revenue in multi-functional energy systems under partial inoperability. Tan et al. [34] introduced an equivalent approach using P-graph methodology as an alternative to MILP. Tan et al. [35] applied Fuzzy Linear Programming (FLP) to find optimal production adjustments for industrial complexes during crises caused by resource scarcity, considering the self-interest of each plant.

Supply shortages can significantly impact the operation of a plastic recycling plant, leading to increased operational costs or even temporary shutdowns [36]. In an IPRN, such disruptions can cascade throughout the network, leading to further losses. However, these financial impacts can be mitigated through the strategic optimization of IPRN operations. This work develops a novel optimization model designed to support operational adjustments during supply-related inoperability. Unlike previous works, this model considers partial input substitution during abnormal operations. The models discussed earlier rely on the Leontief production function assumption that inputs cannot be substituted. This assumption can be too restrictive since partial substitution is possible in IPRNs. For example, mechanically recyclable plastic waste can also be processed through pyrolysis or gasification, although this flexibility does not apply in reverse. Relaxing the Leontief assumption by allowing input substitution enables the model to identify less conservative strategies to minimize losses from supply disruptions. Insights gained from this model can enhance the robustness of future commercial plastic recycling operations.

The rest of this paper is organized as follows: The next section presents the formal problem statement, followed by the formulation of the optimization model. A case study is then presented, examining an IPRN under supply shortages and analyzing the impact of allowing versus restricting input substitution. Finally, the conclusions and recommendations for future research are discussed.

PROBLEM STATEMENT

The problem addressed by the proposed model may be formally stated as follows:

- Consider an Integrated Plastic Recycling Network (IPRN) consisting of multiple component plants k, transforming various types of raw plastic waste i into a range of products l. Under normal conditions, each plant operates at its baseline production capacity and product net flow rates. Material and energy balances are assumed to be scale-invariant for each unit.
- In certain limited cases, substitution between the different types of raw plastic waste i is allowed, resulting in the plastic waste input j, provided that the requirements of the component units are met. However, the extent of substitution is restricted to avoid significantly altering each component unit's product quantity and quality.
- It is further assumed that the material and energy balances remain consistent for all allowed substitution scenarios. Process yields thus remain unchanged for these substitutions.
- An external disruption is assumed to occur that affects the supply of one or more types of plastic waste inputs. This disruption is assumed to be prolonged enough to require planning for a temporary, off-design, steady-state operation deviating from the IPRN's baseline design state.
- The objective of the model is to determine the optimal operational adjustments that will maximize the overall operating revenue of the IPRN during the supply disruption.

Variable operating costs, such as inputs to each component unit, heat, and electricity, are explicitly included in the model. On the other hand, fixed operating costs, such as labor and administrative expenses, are assumed to remain constant during the temporary disruption. As a result, maximizing revenue effectively corresponds to maximizing profit under these conditions.

MODEL FORMULATION

The optimization model developed here extends the frameworks proposed by Kasivisvanathan et al. [29] and Tan et al. [35] by relaxing the assumption that the system components have Leontief production functions. The objective of this model is to maximize the overall operating revenue under off-design crisis conditions. It can be expressed as follows:

$$\max \sum_{l} c_l y_l \tag{1}$$

Here, c_l represents the unit price while y_l denotes the net output of the product stream l. The energy and material balances for the IPRN are assumed to be linear and can be represented by the following input-output model:

$$\sum_{k} A_{lk}\, x_k = y_l \quad \forall l \tag{2}$$

$$\sum_{k} B_{jk}\, x_k = z_{input,j} \quad \forall j \tag{3}$$

$$x_k, y_l, z_{input,j} \geq 0 \quad \forall j \ \forall k \ \forall l \tag{4}$$

where the process coefficient A_{lk} indicates the amount of material l either consumed or produced per unit of the main product of the component unit k. A positive value of A_{lk} indicates that the material is produced, while a negative value means it is consumed as an input. Similarly, the resource coefficient B_{jk} denotes the amount of plastic waste input j required to produce one unit of the main product in component unit k. The variable x_k refers to the production level of component unit k, while y_l represents the net output flow rate of material l. The term $z_{input,j}$ represents the quantity of plastic waste used as an input to a certain component unit. The values of x_k and $z_{input,j}$ are constrained to be non-negative. Although y_l can theoretically take negative values if there is an option to import materials that are normally outputs, but it is restricted to non-negative values in this study.

The substitutability of inputs can then be expressed by the following equations:

$$z_{ij} \leq S_{ij} M \quad \forall i \ \forall j \tag{5}$$

$$\sum_{i} z_{ij} = z_{input,j} \quad \forall i \tag{6}$$

$$\sum_{j} z_{ij} \leq z_{raw,i} \quad \forall j \tag{7}$$

In these expressions, $z_{raw,i}$ denotes the availability of each raw plastic wastes i, while z_{ij} represents the amount of raw plastic waste i used for plastic waste input j. When $i = j$, z_{ii} corresponds to the use of plastic waste i for its intended purpose. When $i \neq j$, z_{ij} reflects substitution of raw plastic waste i for input j. The substitutability parameter S_{ij} is a binary value that determines whether raw plastic waste i can replace plastic waste input j ($S_{ij} = 1$) or not ($S_{ij} = 0$). For all i, S_{ii} is set to 1 to allow each raw plastic waste to be used for its original intended purpose. The term M is an arbitrarily large number used in **Eq. (5),** ensuring z_{ij} is zero if plastic waste input i cannot substitute plastic waste input j. **Eq. (6)** indicates the total amount of input for the component unit, while **Eq. (7)** limits the total amount of each raw material used to match its availability.

To ensure the amount and quality of the resulting products do not significantly change despite substitutions, the substitution amount is limited according to:

$$z_{jj} \geq \left(1 - \sigma_{max,j}\right) z_{input,j} \quad \forall j \tag{8}$$

where $\sigma_{max,j}$ indicates the maximum allowable fractional substitution for component j. This parameter represents the limit at which process performance shows a negligible drop. In practice, this threshold can be set based on a combination of factors, such as equipment specifications, experiments, and the expert judgement of the process engineers. Additional constraints to ensure the feasible operating range of each component unit's production level are given by:

$$x_k^L t_k \leq x_k \leq x_k^U t_k \quad \forall k \tag{9}$$

$$t_k \in \{0,1\} \quad \forall k \tag{10}$$

where x_k^L and x_k^U denote the lower and upper limits of the feasible operating range for the production level of component unit k. t_k is a binary variable indicating whether the component unit k is operating ($t_k = 1$) or not ($t_k = 0$). **Eq. (9)** ensures that the component units only operate within their feasible ranges.

This formulation is a MILP model, for which globally optimal solutions can be readily found for problems on the scale expected in practice. The next section provides a case study to illustrate the application of this model.

CASE STUDY

The proposed model is implemented using the commercial optimization software LINGO v20.0 **[37]** on a laptop equipped with an i7 CPU and 16 GB of RAM. Solutions for various case study scenarios were obtained in less than one second each. The LINGO model is available upon reasonable request.

The model is illustrated through a case study of an IPRN shown in **Figure 1.** This network processes four types of plastic waste inputs: sorted polyethylene terephthalate (PET) plastics, single sorted plastics (SSP), mixed plastic waste containing oxygen (MPWcO), and mixed plastic waste without oxygen (MPWwO). Sorted PET wastes undergo methanolysis to chemically recycle them back into PET, while SSP is sent for mechanical recycling to recover usable plastics. MPWcO is processed through gasification, producing syngas that can be converted into methanol, hydrogen, and electricity. A portion of this syngas output is diverted to methanolysis and mechanical recycling processes as an alternative to natural gas for heating. MPWwO is processed via pyrolysis and hydrotreatment, yielding ethylene, propylene, and hydrocarbon (HC) fuels. The HC fuel is subsequently burned in a boiler to produce steam.

Table 1 outlines the IPRN's overall material and energy balances, net product output flow rates, and product prices. Product prices are based on published prices at the time of this study. The process and resource coefficients used in this study are based on data from existing techno-economic analyses, also listed in **Table 1**.

Table 1. Process Data for the baseline case of the IPRN

	Methanolysis	Meth – Elec Gen	Mech Recy	Hyd – Elec Gen	Gasi	Pyro	Boiler	Net Flow Rate	Price [USD/kg or kWh]
Inputs									
Chem recycled PET [kg/h]	1							833	1.4
Methanol [kg/h]	−0.18	1						4,843	0.4
Recycled Plastics [kg/h]			1					6,667	0.2
Hydrogen [kg/h]				1		−0.029		500	3.5
Syngas [kg/h]	−0.51	−2.4	−0.035	−14	1			0	-
HC fuel [kg/h]						1	−0.08	748	1.4
Ethylene [kg/h]						0.35		660	1.06
Propylene [kg/h]						0.25		472	1.21
Steam [kg/h]	−10.4			−6	−0.11		1	0	-
Electricity [kW]	−0.79	1.9	−0.45	7.5	−0.21	−0.14	−0.01	5297	0.15
Outputs									
Sorted PET [kg/h]	1.2							1,000	-
SSP [kg/h]			1.2					8,000	-
MPWcO [kg/h]					0.49			10,000	-
MPWwO [kg/h]						5.3		10,000	-
References	[38]	[39]	[38]	[39]	[39]	[40]			

However, syngas was used to substitute for natural gas to meet heating demands. A substantially larger quantity of syngas was used since it has a lower heating value when compared to natural gas. **Table 2** presents the baseline production levels and the feasible operating ranges for each component unit, which are assumed values for modelling purposes due to limited available data on precise operational limits. Under baseline conditions, the system processes 1,000 kg/h of sorted PET, 8,000 kg/h of SSP, 10,000 kg/h of MPWcO, and 10,000 kg/h of MPWwO, resulting in an operating revenue of 9,299 USD/h.

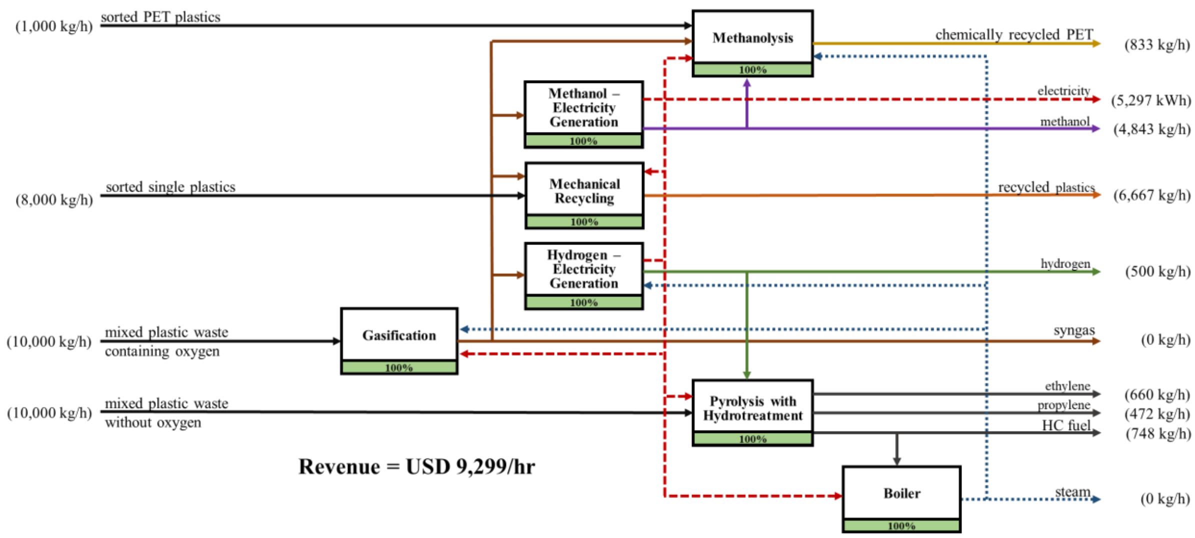

Figure 1. IPRN baseline case

Table 2. Baseline and feasible operating ranges of the component units of IPRN

Component Unit	Baseline Operating Range [kg/h]	Feasible Operating Ranges [kg/h]
Methanolysis	833	667 – 833 (80%-100%)
Methanol – Electricity Generation	4,993	2,996 – 4,993 (60%-100%)
Mechanical Recycling	6,667	5,333 – 6,667 (80%-100%)
Hydrogen – Electricity Generation	555	444 – 555 (80%-100%)
Gasification	20,408	12,245 – 20,408 (60%-100%)
Pyrolysis with Hydrotreatment	1,887	1,509 – 1,887 (80%-100%)
Boiler	14,240	8,544 – 14,240 (60%-100%)

Disruptions in plastic waste supply can occur due to various reasons. Supply chain issues like transportation delays can create these supply shortages. Consumer waste generation can also fluctuate due to seasonal changes, which further affect supply availability. Additionally, high levels of contamination in the collected plastic waste can even further reduce the usable supply **[36]**. This case study examines a disruption scenario where both MPWcO and MPWwO supplies decrease by 10%, dropping from 10,000 kg/h to 9,000 kg/h. An operational strategy is needed to maximize the operating profit despite the constraints imposed by this disruption. The initial analysis considers a scenario without input substitution. This is modelled by assigning the substitutability parameter S_{ij} to 1 when $i = j$ and 0 if $i \neq j$.

Solving the MILP model under these conditions yields a 9% decrease in operating revenue to 8,464 USD/h. **Figure 2** illustrates the adjustments made across the system to sustain revenue as much as possible under these limitations. The figure also highlights that the reduced plastic waste inputs prevent the complete processing of all other waste materials; approximately 200 kg/h of waste PET remains unprocessed due to the constrained operating conditions.

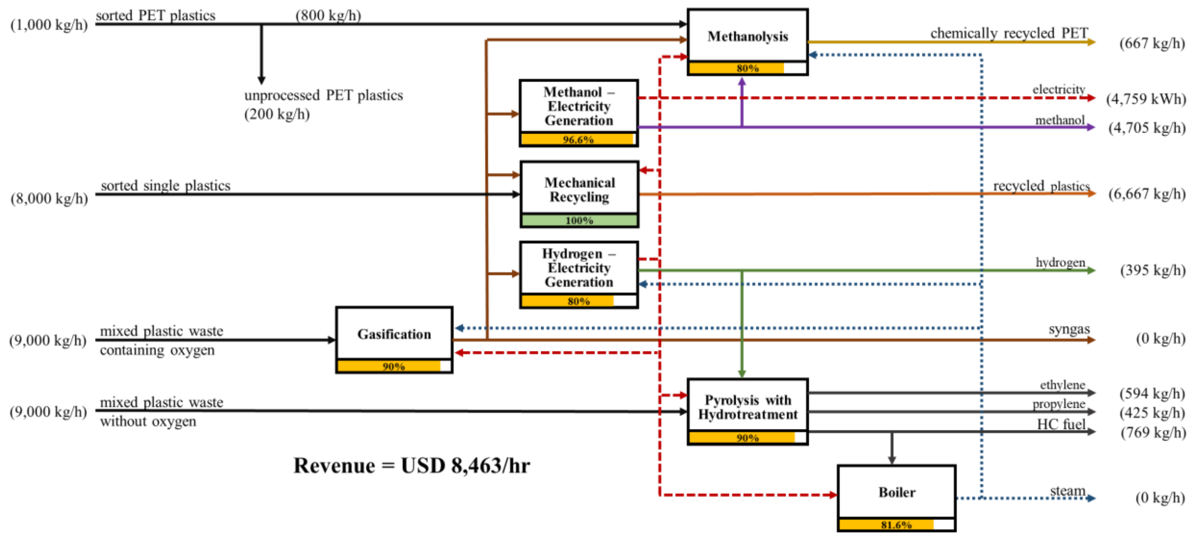

Figure 2. IPRN disrupted case without input substitution

One way to increase the operating revenue during disruption is by rerouting certain plastic waste streams. Sorted PET and SSP can be redirected as substitutes for MPWcO in the gasification process. SSP can also be a substitute for MPWwO in pyrolysis. However, the mixed plastic wastes cannot replace sorted PET in chemical recycling or SSP in mechanical recycling due to the specificity of these processes. In particular, mechanical recycling necessitates a high-quality, well-sorted, and clean single-polymer stream. Current sorting technologies can produce only limited quantities of such streams, with most waste still ending up as mixed plastic [41]. Furthermore, plastics having high contamination (e.g., with food residues) or additives (e.g., fillers or pigments) can make them unappealing for mechanical recycling [42]. Additionally, certain plastic types, such as thermosets and multi-layered plastics, cannot be mechanically recycled. For these types of plastic waste, pyrolysis or gasification can be used.

It is also important to note that sorted PET and MPWcO are not viable substitutes for MPWwO in pyrolysis, as the presence of oxygen in plastic waste inputs can reduce pyrolysis product yields [43]. In contrast, MPWwO can replace MPWcO in gasification. Nevertheless, the extent of substitution is limited to avoid significantly altering the quantity and quality of each component's products. Table 3 shows the substitutability parameters S_{ij} and the maximum fractional substitution limits $\sigma_{max,j}$.

Table 3. Substitutability Parameters (S_{ij}) and maximum fractional substitution limits ($\sigma_{max,j}$)

	Sorted PET	SSP	MPWcO	MPWwO
Sorted PET	1	0	1	0
SSP	0	1	1	1
MPWcO	0	0	1	0
MPWwO	0	0	1	1
$\sigma_{max,j}$	10%	10%	10%	10%

The solution of the MILP model considering input substitution resulted in an operating revenue of 9,074 USD/h. This represents a significant improvement over the 8,464 USD/h revenue achieved without substitution. Figure 3 shows the operational adjustments under the disrupted conditions. This revenue increase is mainly attributed to rerouting Sorted PET and SSP to more profitable processes. The solution deprioritizes methanolysis which requires significant material input and mechanical recycling which produces lower-value products. Instead, it focuses on the more profitable operations including methanol generation, hydrogen generation, and pyrolysis. By strategically redirecting sorted PET and SSP to these high-value processes, the system achieves robust profitability even during supply shortage. Additionally, it enables complete processing of all plastic waste. This is unlike the previous scenario where some materials remained unused when input substitution is not considered.

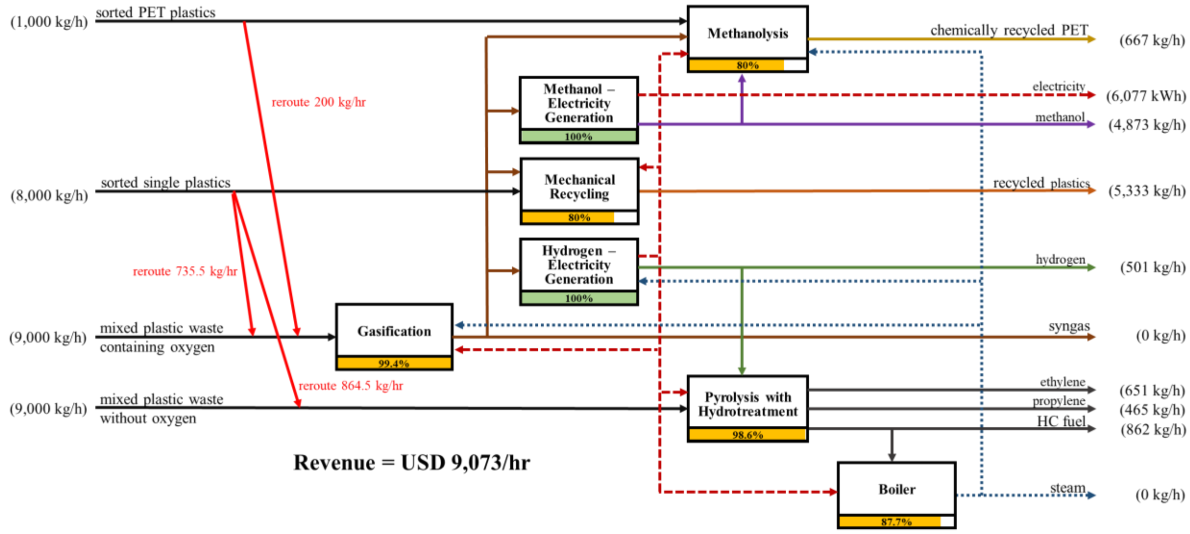

Figure 3. IPRN disrupted case with input substitution

Table 4 summarizes the results of the case study. The supply of both MPWcO and MPWwO is assumed to drop by 10% under both disrupted conditions. Without input substitution, this disruption leads to a 9% decline in revenue. When input substitution is allowed, the decline is limited to only 2.4%. These findings demonstrate that rerouting certain waste streams can help IPRN minimize revenue losses when facing disruption from plastic waste supply shortages. The strategic rerouting identified by the MILP model, particularly diverting Sorted PET and SSP into gasification and pyrolysis, yielded a 6.6 percentage points of recovery in revenue.

The primary strength of the model lies in its ability to leverage input flexibility to overcome specific input shortages. It achieves this by repurposing other available waste streams towards pathways that generate the highest revenue. In addition, it supports the full use of all available waste to produce valuable outputs, further increasing the revenue. This strategic adjustment, captured quantitatively through MILP optimization, helped turn potentially large losses into a more manageable decline in revenue. This highlights the practical value of the proposed model for enhancing operational robustness of IPRNs.

Table 4. Summary of the Results

	Baseline Condition	Disrupted without Substitution	Disrupted with Substitution
Revenue [USD/h]	9,299	8,464	9,074
%Revenue Reduction	–	9.0%	2.4%

CONCLUSION

This study developed a novel MILP-based model to determine optimal operational adjustments for an IPRN during supply-related inoperability. It expands on previous models by relaxing the rigid assumption of the Leontief production function and allowing partial input substitution. The model's effectiveness was demonstrated through a case study where a 10% reduction in MPWcO and MPWwO supplies resulted in a 9% reduction in revenue when input substitution is not considered. This loss was reduced significantly to just 2.4% when input substitution is allowed. By strategically rerouting inputs to prioritize the most profitable components, the model significantly reduces the economic impact of supply disruptions. These results highlight the model’s practical value as a decision-support tool for enhancing the operational resilience of future plastic recycling networks.

This study has several limitations that offer opportunities for further research. It assumes that material and energy balances remain fixed across all operating levels, and that product yields and qualities do not change with input substitution. Additionally, the model does not account for the time aspect of disruptions. Future work could address these limitations by exploring potential nonlinear relationships in material/energy flows, accounting for changes in the output due to substitution, and integrating dynamic modelling to capture how the network responds to disruptions over time. Advancing these areas will provide a more robust framework for adapting recycling networks to real-world fluctuations.

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AUTHOR DECLARATIONS

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NOMENCLATURE

Indices

i	raw plastic waste input prior substitution	
j	plastic waste input after substitution	
k	component unit	
l	product stream	

Parameters

A_{lk}	Process output/input of stream l for component unit k	[kg or kWh / kg or kWh]
B_{jk}	Resource input of material j for component unit k	[kg/kg]
$z_{raw,i}$	Availability of raw plastic waste i	[kg/h]
c_l	Unit price of product l	[USD/kg or kWh]
S_{ij}	Substitutability parameter of waste i with waste j	
$\sigma_{max,j}$	Maximum allowable fractional substitution for waste j	
M	Arbitrarily large number	[kg/h]
x_k^L	Lower limit of the operating range for unit k	[kg/h]
x_k^U	Upper limit of the operating range for unit k	[kg/h]

Variables

x_k	Production level of component unit k	[kg/h]

y_l	Net output flow rate of product l	[kg/h] or [kW]
$z_{input,j}$	Quantity of plastic waste j used as an input	[kg/h]
z_{ij}	Quantity of plastic waste i used as substitute for plastic waste input j	[kg/h]
t_k	Binary variable denoting if component k is operating or not	

Abbreviations

IPRN	Integrated Plastics Recycling Network
LP	Linear Programming
MILP	Mixed-Integer Linear Programming
IO	Input-Output
IIM	Inoperability Input-Output Model
FLP	Fuzzy Linear Programming
PET	Polyethylene terephthalate
MPWcO	Mixed plastic waste containing oxygen
MPWwO	Mixed plastic waste without oxygen
HC	Hydrocarbon

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