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Determining Optimal Crisis Operation for Integrated Plastics Recycling Network Using Fuzzy Linear Programming

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Plastic pollution has become a major global issue, as large amounts of waste leak into the environment and cause significant ecological harm. Tackling this issue requires improvement in current recycling rates, which can be achieved through the development of Integrated Plastics Recycling Network (IPRN). IPRN combines various recycling technologies to be able to utilize resources and energy more effectively than standalone systems. However, the interconnected nature of such networks presents challenges, as disruptions in one unit can create cascading effects throughout the system. This study proposes a fuzzy linear programming enterprise input-output model to determine the optimal production adjustments across different recycling facilities during crises caused by reduced resource inputs. The model ensures a balanced and equitable solution that considers the self-interest of various decision-makers by maximizing the overall satisfaction of fuzzy goals. A case study of an IPRN facing a shortage of plastic waste inputs shows that allowing input substitution can significantly improve the overall satisfaction level. This improvement shows the model's ability to guide operations under uncertainty and strengthen the robustness of IPRNs.

1. Introduction

Plastic pollution has emerged as a serious global environmental concern in recent years. Microplastics (MPs) are pervasive contaminants that can threaten ecosystems and undermine the progress of several Sustainable Development Goals (SDGs) (Walker, 2021). In response, UN member states are working on a legally binding treaty to end plastic pollution (UNEP, 2024). Tackling this challenge requires coordinated action across its lifecycle (Cottom et al., 2024), particularly in recycling. Mechanical recycling is the most widely used method, while chemical approaches like pyrolysis, gasification, and solvolysis are gaining attention (Jiang et al., 2022). However, the global recycling rate remains low at 9 %, with 12 % of plastic waste incinerated and nearly half ending up in landfills. The remaining 22 % is either dumped in uncontrolled sites or leaks into the environment (OECD, 2022). These figures, however, vary significantly by region. For instance, the European Union's recycling rate is around 30 %, notably higher than most other countries (Plastics Europe, 2024). Lower income nations often lack formal waste management systems, leading to higher rates of environmental leakage.

An Integrated Plastics Recycling Network (IPRN) is a system of interlinked recycling facilities that exchange materials and energy to boost efficiency and flexibility. These systems can improve current rates of plastic recycling. This process integration is similar to those found in integrated energy systems (Wu et al., 2022) and eco-industrial parks (Misrol et al., 2022). IPRNs can also enable treatment of diverse types of plastic waste even if each component process can only handle a specific type of waste. Despite its potential, research on IPRNs remains limited, with only two studies currently available. Tan et al. (2022) used Pinch Analysis (PA) to match plastic waste inputs with suitable recycling techniques, while Aviso et al. (2023) used Linear Programming (LP) and Mixed-Integer Linear Programming (MILP) for similar optimization.

The integrated nature of this system can make IPRN vulnerable to cascading failures. Jiang and Haimes (2004) introduced the Inoperability Input-Output Model (IIM) to assess the propagation of disruptions. Building on this, Kasivisvanathan et al. (2013) introduced an MILP model designed to optimize operational changes that

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maximize profit during process disruption. Tan et al. (2016) developed a fuzzy linear programming enterprise input-output (FLP-EIO) model to optimize adjustments on industrial complexes during input shortages considering the competing interest of each plant. It uses fuzzy set theory to identify the best compromise among conflicting goals through the max-min aggregation developed by Zimmermann (1978).

Supply shortages can severely impact plastic recycling plants, leading to higher operating costs or shutdowns (Nixon et al., 2024). In an IPRN, these disruptions can ripple throughout the network. While the discussed models address these impacts, they assume no substitution between inputs. This limitation is addressed in the present study by extending the FLP-EIO model to allow partial input substitutability. For instance, plastic wastes for mechanical recycling can also be processed via pyrolysis or gasification, though not vice versa. The proposed model determines the optimal adjustments by maximizing overall satisfaction with fuzzy targets. These adjustments aim to balance competing interests of various decision-makers during supply disruptions. Ultimately, this model can support development of more robust and efficient plastic recycling networks.

The rest of this paper is organized as follows: Section 2 presents the formal problem statement, while Section 3 discusses the formulation of the optimization model. Section 4 presents a case study on IPRN performance under supply shortages. Finally, Section 5 provides the conclusions and recommendations for future research.

2. Problem Statement

The formal problem statement is given as follows:

- An IPRN is comprised of multiple plants k that process raw plastic waste i into products l. At standard conditions, the IPRN functions with predefined production capacities and net product flow rates. The component plants also operate under fixed input-to-output ratio regardless of scale.
- A supply disruption is assumed, reducing the availability of certain plastic waste inputs. Additionally, the IPRN is expected to operate at a different steady-state for an extended period.
- It is also assumed that there is a fuzzy target for production level for each plant and a fuzzy target for net flow rates for each product. Both can be described by a linear membership function.
- Substitution involving various types of raw plastic waste i is permitted under specific conditions, resulting in input j. Such substitutions are allowed only if they meet unit specifications based on manufacturer guidelines, experimental data, or engineering judgement. Substitution within these limits is assumed to cause negligible changes in process performance and product quality.
- The objective of the model is to determine the operational changes (e.g. production capacity, stream allocation) that would maximize the satisfaction of all fuzzy targets during supply disruption.

3. Model Formulation

The optimization model presented here extends the FLP-EIO model proposed by Tan et al. (2016) by incorporating partial input substitution. Its objective is to maximize the overall satisfaction of the fuzzy constraint, λ, within the network during abnormal condition. This objective can be expressed as follows:

$$\max \lambda \tag{1}$$

The value of λ is limited in range as follows:

$$\lambda \in [0,1] \tag{2}$$

A λ value of 1 indicates full satisfaction, values between 0 and 1 indicate partial satisfaction, and 0 denotes non-satisfaction of the fuzzy constraint. The IPRN is modelled using the following material and energy balances:

$$\textstyle\sum_k \mathrm{A}_{lk}\mathrm{x}_k = \mathrm{y}_l \quad \forall l \tag{3}$$

$$\textstyle\sum_k \mathrm{B}_{jk}\mathrm{x}_k = \mathrm{z}_{\mathrm{input},j} \quad \forall j \tag{4}$$

$$\mathrm{z}_{ij} \le \mathrm{S}_{ij}\mathrm{M} \quad \forall i \ \forall j \tag{5}$$

$$\textstyle\sum_i \mathrm{z}_{ij} = \mathrm{z}_{\mathrm{input},j} \quad \forall i \tag{6}$$

$$\textstyle\sum_j \mathrm{z}_{ij} \le \mathrm{z}_{\mathrm{raw},i} \quad \forall j \tag{7}$$

The process coefficient A_{kl} indicates how much material l is consumed or produced per unit of component unit k's main product. Similarly, the resource coefficient B_{jk} represents the amount of plastic waste input j used by unit k to produce the same product. The variable x_k represents the production level of unit k, y_l is the net flow rate of product l, $\mathrm{z}_{\mathrm{input},j}$ is the amount of plastic waste used in a particular component unit, and $\mathrm{z}_{\mathrm{raw},i}$ is the usage of raw plastic waste i. The term z_{ij} denotes the amount of raw waste i used for input j, with $\mathrm{i} = \mathrm{j}$ indicating intended use, and $\mathrm{i} \neq \mathrm{j}$ indicating substitution. The substitutability parameter S_{ij} is a binary value set to 1 if substitution is permitted and 0 if not. By definition, S_{ii} is always 1. M is an arbitrarily large constant used in Eq(5) to force z_{ij} to zero if raw waste i cannot be used to substitute to waste j. Eq(6) defines the total amount of input for a component unit, while Eq(7) restricts raw material use based on availability. To ensure that the quantity and quality of the products remain consistent, the substitution is restricted according to:

$$\mathrm{z}_{jj} \geq \left(1 - \mathrm{S}_{\mathrm{max},j}\right) \mathrm{z}_{\mathrm{input},j} \quad \forall j \tag{8}$$

where $\mathrm{S}_{\mathrm{max},j}$ indicates the maximum allowable substitution fraction for component j.
The fuzzy target for production levels and net output flow rates are given by the following equations:

$$\mathrm{x}_k \geq \lambda\left(\mathrm{x}_k^{\mathrm{U}} - \mathrm{x}_k^{\mathrm{L}}\right) + \mathrm{x}_k^{\mathrm{L}} \quad \forall k \tag{9}$$

$$\mathrm{y}_l \geq \lambda\left(\mathrm{y}_l^{\mathrm{U}} - \mathrm{y}_l^{\mathrm{L}}\right) + \mathrm{x}_l^{\mathrm{L}} \quad \forall l \tag{10}$$

Here, $\mathrm{x}_k^{\mathrm{U}}$ and $\mathrm{y}_l^{\mathrm{U}}$ are the upper limits for the production level of unit k and net flow rate of product l, respectively. These values are obtained from baseline operating conditions. The lower bound values $\mathrm{x}_k^{\mathrm{L}}$ and $\mathrm{y}_l^{\mathrm{L}}$ are set by the individuals in charge of each unit. Input shortages can significantly reduce the achievable x_k and y_l values. Since units may compete for limited inputs, increasing the output of one can reduce the output of another. The model is designed to find a balanced solution for these competing interests. Note that the objective function Eq(1) maximizes the degree of satisfaction of the least satisfied constraint (Zimmermann, 1978). The resulting LP model allows the globally optimal solution to be found without significant computational difficulties. A case study in the next section demonstrates the model's application.

4. Case Study

The model was implemented in LINGO v20.0 (Schrage, 2006) on a laptop with i7 CPU and 16 GB RAM. Each case study scenario was solved in under a second. The LINGO model is available upon request. Figure 1 shows the IPRN used to demonstrate the model, which features various technologies for treating different plastic waste types. Pyrolysis with hydrotreatment converts mixed plastic waste without oxygen (MPWwO) into olefins and hydrocarbon (HC) fuels. Gasification breaks down mixed plastic waste containing oxygen (MPWcO) into syngas used for methanol and hydrogen generation. Tail gases for these processes can be used to generate electricity. Mechanical recycling physically processes sorted single plastics (SSP) for reuse, while methanolysis uses chemically recovers PET. A boiler supplies the steam needed for various operations. Table 1 provides the material and energy balances with data sourced from techno-economic studies. It also presents the baseline and minimum allowable production levels for each unit and net flow rates for each product. Composition of the plastic waste inputs are also based on these studies. SSP and PET wastes have 90 % quality. Elemental analysis of MPWwO is 86 % C and 14 % H, while MPWcO contains 70 % C, 15 % H, and 11 % O.

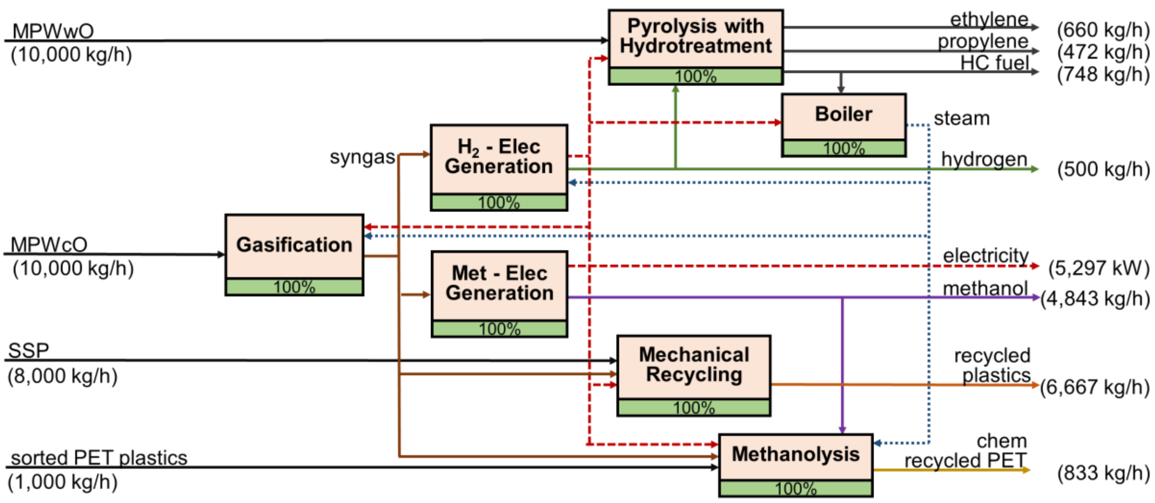

Figure 1: Baseline Condition for IPRN

Table 1: Process Data and Baseline Condition for IPRN

	Pyrolysis	Boiler	H_2-Elec Gen	Gasi	Meth-Elec Gen	Mech Recy	Methano-lysis	Net Output/ Input	Lower Limit Net Output
References	(Gracida-Alvarez et al., 2023)	–	(Wu et al., 2023)	(Wu et al., 2023)	(Wu et al., 2023)	(Uekert et al., 2023)	(Uekert et al., 2023)	–	–
Output									
HC Fuel (kg/h)	1	−0.08	0	0	0	0	0	748	598
Ethylene (kg/h)	0.35	0	0	0	0	0	0	660	528
Propylene (kg/h)	0.25	0	0	0	0	0	0	472	377
Steam (kg/h)	0	1	−6	−0.11	0	0	−10.4	0	0
Hydrogen (kg/h)	−0.029	0	1	0	0	0	0	500	400
Syngas (kg/h)	0	0	−14	1	−2.4	−0.035	−0.51	0	0
Methanol (kg/h)	0	0	0	0	1	0	−0.18	4,843	3,875
Recycled plastics (kg/h)	0	0	0	0	0	1	0	6,667	4,000
Recycled PET (kg/h)	0	0	0	0	0	0	1	833	500
Electricity (kW)	−0.14	−0.01	7.5	−0.21	1.9	−0.45	−0.79	5,297	3,178
Input									
MPWwO	5.3	0	0	0	0	0	0	10,000	–
MPWcO	0	0	0	0.49	0	0	0	10,000	–
SSP	0	0	0	0	0	1.2	0	8,000	–
Sorted PET	0	0	0	0	0	0	1.2	1,000	–
Capacity	1,886.8	14,239.9	554.7	20,408.2	4,993.2	6,666.7	833.3	–	–
Lower limit of production level	1,509.4	8,543.9	332.8	16,326.5	2,995.9	5,333.3	500.0	–	–

Plastic waste supply can be disrupted by various reasons, such as transportation delays and logistical issues, as well as seasonal changes in plastic waste consumption. In addition, contamination in collected plastic waste significantly lowers the amount that can be effectively recycled (Nixon et al., 2024). This case study analyzes the impact of 10 % supply reduction in both MPWcO and MPWwO, lowering their input rates from 10,000 kg/h to 9,000 kg/h. An operational adjustment must be identified to maximize the overall satisfaction of the fuzzy constraint λ in response to this disruption. Two scenarios are considered for this case study. The first scenario assumes that there was no substitution occurs between plastic waste inputs. The model can represent this assumption by setting the substitutability parameter S_{ij} to 1 if $i = j$, or 0 otherwise. The result for this scenario yields a low λ value of just 0.500. Figure 2 illustrates the corresponding operational adjustments that lead to this outcome.

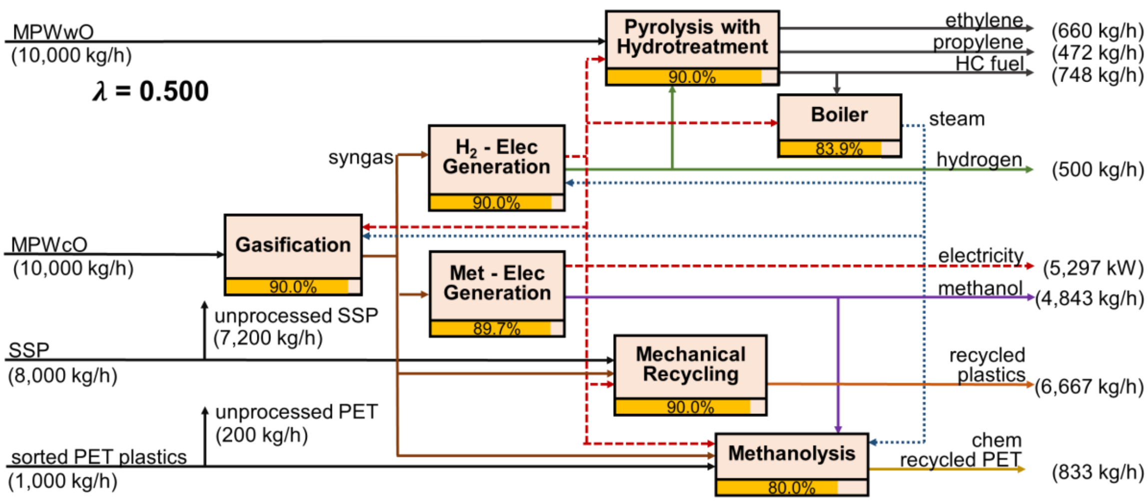

Figure 2: IPRN under supply disruption without input substitution

The reduced MPWcO and MPWwO quantities directly limit the availability of syngas and steam, both critical intermediates for many processes within IPRN. To maximize λ, these limited materials must be distributed equitably across the network. Thus, it requires all processes to lower their production levels. This includes both the mechanical recycling and methanolysis processes, leading to underutilization of their respective inputs. As illustrated in Figure 2, 800 kg/h of SSP and 200 kg/h of sorted PET remain unprocessed.

The value of λ can be improved by allowing partial substitution of unused SSP or sorted PET for mixed plastic wastes, increasing production of syngas and steam intermediates. Sorted PET and SSP can substitute for MPWcO, while SSP can replace MPWwO. PET plastics, however, cannot substitute MPwO since their oxygen content can significantly reduce pyrolysis yields (Lubongo et al., 2022). Additionally, mixed plastic wastes designated for gasification or pyrolysis are not suitable for mechanical recycling due to current sorting limitations. Multi-layer packaging and presence of pigments, additives, and contaminants further hinder their mechanical recyclability. The second scenario considered in this study incorporates partial input substitution. Table 2 presents the substitutability parameters S_{ij}. For illustrative purposes, the maximum allowable substitution fractions $S_{\max,j}$ are set at 10 across all inputs. The corresponding optimal operational adjustment for this scenario is illustrated in Figure 3.

Table 2: Substitutability parameters (S_{ij})

	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

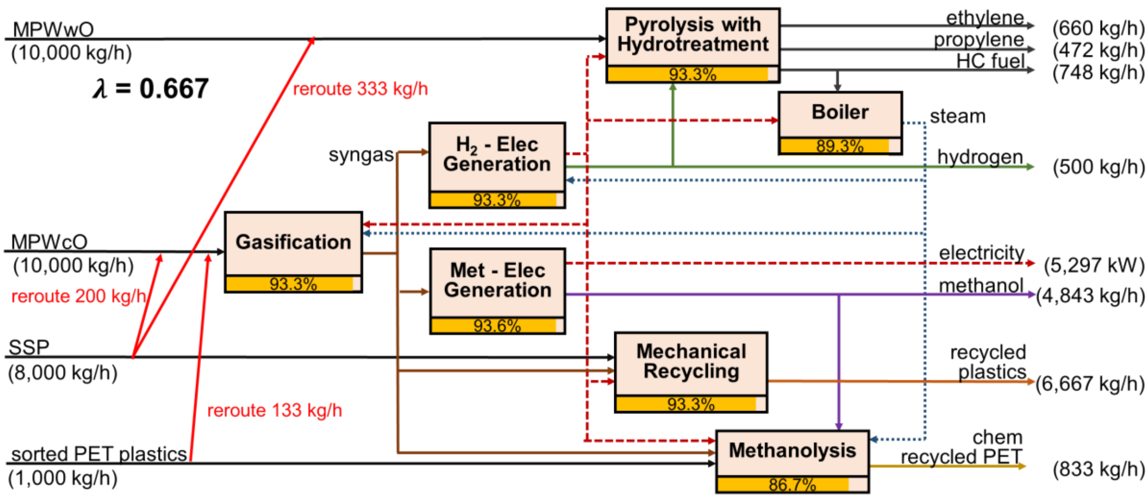

Figure 3: IPRN under supply disruption with input substitution

Allowing partial input substitution in the MILP model resulted in a higher λ value of 0.667, indicating a stronger overall satisfaction of fuzzy constraints under the same supply disruption conditions compared to the scenario without substitution. It should be noted that the substituted input mixtures maintained elemental compositions comparable to the original plastic waste streams. Specifically, inputs to pyrolysis contained around 86 % C and 14 % H, similar to that of MPWwO. Likewise, gasification inputs had around 73 % C, 15 % H, and 11 % O, closely matching MPWcO. This consistency ensures that product outputs remain comparable after substitution. The increase in λ is largely driven by increased production of key intermediates, namely syngas and steam. By enabling input substitution, the model strategically redirected previously unused plastic waste inputs toward processes that produce these intermediates. This, in turn, increased the production level of all component unit, including that of mechanical recycling and methanolysis processes. When the mechanical recycling and methanolysis processes shared their inputs with other operations, their own production level rose during the supply disruption. This also reduces underutilization of available plastic waste inputs, improving resource efficiency. This outcome demonstrates the model's success in identifying equitable and balanced solution that considers the competing objectives of various system components. These results clearly highlight the model's capability to guide decision-making and maintain robust operation of IPRNs during periods of supply disruption.

5. Conclusions

This study developed a novel FLP model designed to optimize operational adjustments within an IPRN during periods of supply disruption. It extends the existing FLP-EIO framework by incorporating partial input substitution, allowing for greater flexibility in resource use. The model aims to balance the self-interest of multiple decision-makers, quantified through the production levels of each component plant and net output flow rates. The model's capability is demonstrated through a case study of an IPRN that treats four different plastic waste types. Results show that allowing input substitution allows better operational strategies under crisis conditions. By enabling more adaptive planning under uncertainty, this model supports the development of more efficient and robust plastic recycling networks. Future work can consider the analysis of other disruption scenarios, such as demand-driven disruptions or reduction in the supply of water due to drought. The work may also be extended to a multi-period version to evaluate the evolution of disruptions and system responses over time.

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References

Aviso K.B., Baquillas J.C., Chiu A.S.F., Jiang P., Fan Y.V., Varbanov P.S., Klemeš J.J., Tan R.R., 2023, Optimizing plastics recycling networks. Cleaner Engineering and Technology, 14, 100632.

Jiang J., Shi K., Zhang X., Yu K., Zhang H., He J., Ju Y., Liu J., 2022, From plastic waste to wealth using chemical recycling: A review. Journal of Environmental Chemical Engineering, 10(1), 106867.

Jiang P., Haimes Y.Y., 2004, Risk Management for Leontief-Based Interdependent Systems. Risk Analysis, 24(5), 1215–1229.

Kasivisvanathan H., Barilea I.D.U., Ng D.K.S., Tan R.R., 2013, Optimal operational adjustment in multi-functional energy systems in response to process inoperability. Applied Energy, 102, 492–500.

Lubongo C., Congdon T., McWhinnie J., Alexandridis P., 2022, Economic feasibility of plastic waste conversion to fuel using pyrolysis. Sustainable Chemistry and Pharmacy, 27, 100683.

Misrol M.A., Alwi S.R.W., Lim J.S., Manan Z.A., 2022, Optimising renewable energy at the eco-industrial park: A mathematical modelling approach. Energy, 261, 125345.

Nixon K.D., Schyns Z.O.G., Luo Y., Ierapetritou M.G., Vlachos D.G., Korley L.T.J., Epps T.H. III, 2024, Analyses of circular solutions for advanced plastics waste recycling. Nature Chemical Engineering, 1(10), 615–626.

OECD, 2022, Global Plastics Outlook: Policy Scenarios to 2060. OECD Publishing, Paris, France.

Plastics Europe, 2024, The Circular Economy of Plastics – A European Analysis. Plastics Europe, <https://plasticseurope.org/knowledge-hub/the-circular-economy-for-plastics-a-european-analysis-2024/>, accessed 13.06.2025.

Schrage L., (6th Ed), 2006, Optimization Modeling with LINGO. Lindo Systems, Chicago, United States.

Tan R.R., Aviso K.B., Cayamanda C.D., Chiu A.S.F., Promentilla M.A.B., Ubando A.T., Yu K.D.S., 2016, A fuzzy linear programming enterprise input–output model for optimal crisis operations in industrial complexes. International Journal of Production Economics, 181, 410–418.

Tan R.R., Aviso K.B., Jiang P., Fan Y.V., Varbanov P.S., Klemeš J.J., 2022, Pinch-Based Synthesis of Plastics Recycling Networks. Chemical Engineering Transactions, 94, 49–54.

Uekert T., Singh A., DesVeaux J.S., Ghosh T., Bhatt A., Yadav G., Afzal S., Walzberg J., Knauer K.M., Nicholson S.R., Beckham G.T., Carpenter A.C., 2023, Technical, Economic, and Environmental Comparison of Closed-Loop Recycling Technologies for Common Plastics. ACS Sustainable Chemistry and Engineering, 11(3), 965–978.

UNEP, 2024, Compilation of draft text of the international legally binding instrument on plastic pollution, including in the marine environment. United Nations Environment Programme, <https://wedocs.unep.org/bitstream/handle/20.500.11822/45858/Compilation_Text.pdf>, accessed 13.06.2025.

Walker T.R., 2021, (Micro)plastics and the UN Sustainable Development Goals. Current Opinion in Green and Sustainable Chemistry, 30, 100497.

Wu M., Du P., Jiang M., Goh H.H., Zhu H., Zhang D., Wu T., 2022, An integrated energy system optimization strategy based on particle swarm optimization algorithm. Energy Reports, 8, 679–691.

Wu W., Xu H., Shi B., Kuo P. C., 2023, Techno-economic analysis of plastic wastes-based polygeneration processes. Chemical Engineering and Processing - Process Intensification, 184, 109297.

Zimmermann H.J., 1978, Fuzzy programming and linear programming with several objective functions. Fuzzy Sets and Systems, 1, 45–55.