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Total Capital Investment of plastic recycling plants correlates with energy losses and capacity

Jacopo De Tommaso,[a] Federico Galli,[b] Robert Weber,[c] Jean-Luc Dubois,[d] and Gregory S. Patience*[a]

Plastic pollution is a generational problem, and stakeholders are turning to chemical recycling as a potential solution. However, decision-makers necessitate quick and reliable capital investment estimations to evaluate innovative technologies, especially in the early project stage, when limited historical data are available. To address this need, we built a database of 160+ chemical recycling plants, querying for nominal capacity, year and place of construction, total capital investment (TCI), number of long-term jobs and opportunity of subsidies. Then, we compared conventional association of the advancement of cost engineering AACE class 5 estimation methods, with literature estimates, and commercial capital expenditure confidence intervals for pyrolysis, gasification, solvolysis, and selective dissolution. We demonstrate the unreliability of classic methods, and we propose ballpark correlations based on the plant capacity, or the energy loss. Chemical recycling plants suffer from poor economy of scale (with current technologies), and capacity is not always the best indicator for TCI estimation. Pyrolysis and gasification are energy-driven technologies, and their TCI correlates very well ($R^2 = 0.91–0.92$) with the total energy losses. Solvolysis and selective dissolution, instead, are at an earlier development stage, so cost engineers or researchers will have to accept less certain TCI vs capacity ($R^2 = 0.60$).

Introduction

Plastics are valuable and versatile materials, with more than 450 millions of tons produced worldwide in 2019, and applications in packaging, construction, textiles, transportations and electronics.[1] The European circular economy action plan,[2] Canada's zero plastic waste strategy,[3] and finally the UN 2022 resolution to a "internationally legally binding instrument",[4] demonstrates national and international commitments to curb plastic pollution and improve its end-of-life.

However, the OECD (Organization for Economic Co-operation and Development) reports that in 2019 only 9 wt% of the world plastic was collected for recycling, with the rest landfilled (49 wt%), littered or mismanaged (22 wt%), or incinerated (19 wt%).[1] In the same series of reports, the OECD states that the amount of waste generated is still "very much linked to economic growth".[5] When the GDP (Gross domestic product) of a country increases, people have higher salaries, access to better food, and they spend more. This turns into a higher per capita waste produced, especially plastic waste.[6]

GDP is not the sole (or the best) predictor for plastic waste. Additional soft and hard indicators such as level of education,[7] density of population,[8] land use, level of infrastructures and even nightlight population concentration in a certain area, factor in when predicting the plastic waste management and production.[9] Nevertheless, more developed economies (i.e., higher GDP per capita), have access to more advanced and effective waste treatment processes.[10]

When not littered, countries manage plastic waste in 4 ways: landfilling, incineration, mechanical recycling, and chemical recycling. Landfilling is still the preferred handling method for waste in the majority of the world, excluding OECD Asian and EU members.[1] However, it breaks the carbon cycle, poses threats for areas and wildlife, and it is ultimately unsustainable.[11] Incineration is the preferred method in large urban areas where land is lacking and landfilling is publicly opposed, because it reduces the volume of solid waste up to 90 wt%..[12] Incineration (for energy recovery) has been consistently replacing landfilling in the last 10 years in EU,[13] but in July 2022 the European Commission included waste-to-energy plants in the list of activities "considered to do significant harm to the circular economy, including waste prevention and recycling".[14] Therefore they are now excluded from subsidies and financial support.[15] Mechanical recycling is the preferred recycling choice for most plastic (all thermoplastic in theory[16]), and it is the most convenient recycling method in terms of

[a] J. De Tommaso, Prof. G. S. Patience
Polytechnique Montrèal, 2500 ch. de polytechnique
Montréal, Québec, Canada
E-mail: gregory-s.patience@polymtl.ca

[b] Prof. F. Galli
Genie Chimique et biotechnologique
University of Sherbrooke
2500 Bd. De l'Université, J1K 2R1
Sherbrooke, Québec, Canada

[c] Dr. R. Weber
Physical and Computational Sciences Directorate
Pacific Northwest National Laboratory
Richland, WA 99352 USA

[d] Dr. J.-L. Dubois
Altuglas International/Trinseo,
Innovatieweg 14, 4542 NH Hoek, The Netherland.

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time, economic viability,[17] and environmental footprint.[18] However, mechanical recycling affects mechanical and optical properties of the material over the cycles, it is susceptible to additives and inhibitors, as well as polymer blends,[18] and it is for this reason prone to downcycling with time (e.g. the Sprite's case[19]). On the other hand, chemical recycling (reversion to monomer) is more versatile because it is not bound to a limited number of cycles, and degradation of plastic properties,[20] therefore being the ideal solution for "difficult to (mechanically) recycle" plastic waste. Pyrolysis, gasification, solvolysis break down plastic on a molecular level to produce (depending on the technology-feedstock coupling) monomers, syngas, a broad range of liquids (from waxes to diesel substitutes), or char.

Selective dissolution bridges chemical and mechanical recycling, because it requires the use of solvents, but does not break the chemical bonds of the material (which would classify it as a mechanical recycling solution).

A comprehensive review of the chemistry and engineering of pyrolysis, gasification, solvolysis and selective dissolution is outside the scope of this work, and we note recent detailed reviews.[20–22]

Despite the advantages and the government commitments, chemical recycling contributes still marginally (e.g. <1 wt.% in EU)[23] to the total recycled volumes. There are several reasons including but not limited to, from a macro to micro scale:

- conflict between government policies and directives;[23–25]
- fragmented or nonexistent literature on regulatory issues on the recycling chain (e.g. US does not have a federal mandate to ban brominated flame retardants that are banned in EU);[23,26] and
- scattered (and weak) quantitative analysis of the most common technologies (what can be treated, how much investment is required, where plants be located).

These factors reinforce a limited interest from the chemical industry to take risks and be the first to invest. Here we analyze chemical recycling technologies and provide early-stage capital investment estimation correlations for pyrolysis, gasification, solvolysis, and selective dissolution. Our goal is to reply to the research question: "How much does it cost to build a chemical recycling plant?", and in doing so offer policy makers, public bodies, private investors, and researchers, a tool to assess with high(er) accuracy total capital investments (TCI) of new recycling plants, based on individual technologies, type of feedstocks, products and utilities. The estimated CAPEX is essential to feed a first economic evaluation of the cost of production.

First, we benchmarked representative early-stage capital cost estimation correlations from selected academic publications on chemical recycling. Then, we compared the results of the benchmarks with a database of 169 chemical recycling plants (built or planned) to draw probabilistic conclusions. From this analysis, we propose new plug-in correlations to estimate the total capital investment of a new plant for a given technology starting from plant capacity, or total energy losses, demonstrating how the latter is statistically more significant for selected technologies. Finally, we show how researchers and cost engineers can use the database and the correlations drawn from it.

Methods

To address the research question, we consider:

1. What are the essential elements of total capital investment?
2. How does we attribute a cost to each of these elements and their uncertainty
3. How to validate established estimation methods versus historical data?

In this section, we provide the tools to navigate through these questions: what is the TCI, which families of estimation methods exist, and which of those are more pertinent in the framework of chemical recycling of plastic.

Then, we explain how the database for this work was constructed, how how the models compare with the published data on plant cost, and finally how to leverage on the database benchmark to develop novel regression models and draw conclusions on chemical recycling at large.

Definition of Capital Cost

The top 10 chemical companies by sales represent around 10% of the total revenue of the chemical industry (360 billion USD in 2019 out of 3.6 trillion USD).[27] All of these companies made claims or commitment to sustainability. However, only three (Ineos, ExxonMobil, with Mitsubishi ranked 11th) own chemical recycling plants, while the others outsourced the risk and are either external investors or final users. Capital cost in the chemical industry in general,[28] and in particular in chemical recycling,[29–34] is among the variables with highest impact on net present value (NPV). Chemical recycling is capital-intensive (especially compared to mechanical recycling), and economic viability is often the reason why projects fail,[35,36] or disappear altogether.[37] Although the technologies date back to 1980 (Figure 1), commercial interest has only picked up in the last 10–20 years.

Relying on start-up or early stage companies to develop technologies and prove it, it is beneficial on the short term for the individual investor but it is shortsighted for the ecosystem. Start-ups rely mostly on external funds to survive, pay high insurance fees due to the frequency of accidents in the field,[39] and they have higher failure rates (for multiple reasons not necessarily related to the

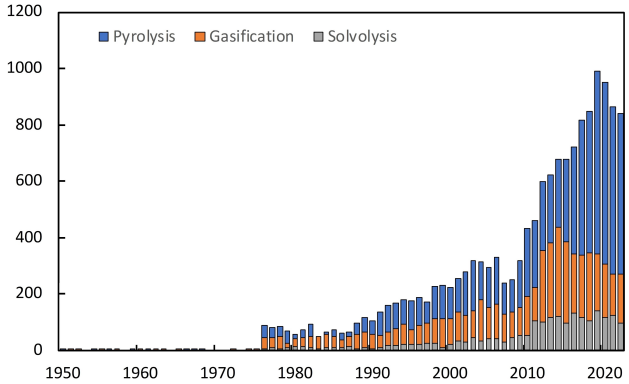

Figure 1. Granted patents for pyrolysis, gasification and solvolysis of plastic, from the Lens database.[38]

technology itself) so that it is hard even for governments to rationalize the investment.

The Total Capital investment of a plant (TCI) is comprised of:[28]

$$TCI = Startup + WC + DCC + ICC \#(1)$$

That is:

- Start-Up costs such as raw material and products inventory, spare parts inventory, cash in hands and so on.
- Working Capital WC, that is the money to meet short-term obligations (e.g. temporary jobs for construction); and
- Direct Capital Cost DCC (Inside and Outside battery limit ISBL + OSBL), including everything that is physically built onsite;
- Indirect Capital Cost ICC (Engineering, Procurement and Construction);

In layman's term, the TCI of a plant is what companies have to spend before any operation commences. This is what the management must justify to investors or shareholders. On average, large plant projects in the process industry (oil, gas, chemicals, metal, etc.) overrun their budget estimate by 20%, with a 10% probability of 70% overrun.[40] The spread between plan and reality increases when the capital cost estimation maturity level is below 30%.[40] A scope definition maturity of 30% is equivalent to something as detailed as a preliminary engineering design for budget authorization. The AACE (Association for the Advancement of Cost Engineering) divides capital cost estimation into 5 categories, corresponding to different maturity levels of a project, and the expected accuracy of different estimation methods (Table 1[56]). While other classifications are common in the process industry as well, like the TRL concept,[41] or the UK association of cost engineers ACostE, we will refer only to the AACE to avoid confusion.

Once a project passes the AACE class 3 equivalent milestone, any modification on the design, such as reactor type or purification strategies, has a huge impact on the capital cost.[43,44]

When a project is still at class 4 or 5 level, it is still possible to investigate a lot of possible alternative processes, catalysts, feedstocks, purifications… and it is wise to spend money in research to pick the best alternative. But there might be a lot of possible options. So that's at this time that a ranking of all of the alternatives should be done, in order to prioritize the R&D activities.

When chemical companies, local bodies, governments, or supranational unions want to finance new programs, or erect new plants, they will look at the highest return on investment, the shortest payback period, and overall, the lowest probability to lose money over time. This translates into the necessity to provide the most reliable estimate at the earliest stage possible, i.e. an AACE Class 5 or 4 estimate. AACE Class 5 or 4 methods encompass:[28]

- Power law or exponential estimating;
- Factorial estimating;
- Process steps or parametric estimating; and
- Thermodynamic estimating

These approximate methods rely on one or more of the following:

- historical data of similar plants (e.g. Power law);
- a preliminary block or process flow diagram (e.g. process step);
- some preliminary process data such as maximum pressure, temperature, yield, etc. (e.g. process step methods);
- preliminary list of process equipment and their cost information – either as a vendor quote, or from similar plants built in the past (e.g. factorial methods); and
- expert judgment (process step methods).

Still considered AACE class 5, but under a different approach, are the thermodynamic methods for example adopted by Jean-Paul Lange in 2001,[45] that builds on the idea that the TCI is correlated with the energy lost or exchanged in a plant. For a more detailed review of each family of methods we suggest Tsagkari,[28] Chauvel[46], or Gerrard.[42] Here we briefly explain the rationale of each group, and its pros and cons in the framework of capital estimation for chemical recycling plants.

Capital cost estimation: Power law methods

Power law methods adjust the cost (TCI in our case) of a new plant (or piece of equipment) based on an empirical statistical similarity with a similar kind of plant but processing different capacities, as:

$$\frac{TCI_1}{TCI_2} = \left(\frac{S_1}{S_2}\right)^f \cdot F_t F_l \#(2)$$

Where S are the sizes or scale of the two plants, *f* is the scaling factor, and F_tF_l are actualization factors for time and location respectively. Traditionally, in the chemical industry *f* varies average to 0.6 (0.7 for piece of equipment), so this equation is referred at the "six-tenths rule".

Time actualization factors adjust the cost based on:[47]

- inflation and deflation over time;
- state of technological and industrial progress; and
- relative level of wages and work conditions.

Table 1. AACE estimating classes.

Class	Project maturity level	Engineering Milestone Reached	Method accuracy	Cost of the method as % of TCI[42]
Class 5	0 to 2%	Block Flow Diagram	L: −20 to 50% H: 30 to 100%	0 to 0.1
Class 4	1 to 15%	Process Flow Diagram	L: −15 to −30% H: 20 to 50%	0.1 to 0.2
Class 3	10 to 40%	Piping and instrumentation diagram issued for design	L: −10 to −20% H: 20 to 50%	0.4 to 0.8
Class 2	30 to 75%	Engineering deliverables issued for construction	L: −15 to −5% H: 5 to 20%	1 to 3
Class 1	65 to 100%	All deliverables complete	L: −3 to −10% H: 4 to 15%	4 to 10

There are multiple time actualization factors: some are regional, like the R. Boulitrop's index (Techniques de l'ingénieur) in France, the WEBCI index in the Netherlands,[48] or the NAPPCI, the PEP published by IHS; others are specific for a branch of the process industry (e.g. Oil and petrochemical[49]). In general, the chemical industry relies mostly on the M&S (Marshall and Swift), and the CEPCI (*Chemical Engineering* plant cost index) published by the Chemical Engineering online journal.[50] These factors are compounded factor with mechanical, electrical, civil, site, overhead, and labor contributions. For instance, the CEPCI comes from the compounding of :

- equipment;
- construction labor;
- buildings; and
- engineering and supervision indexes.

It is good practice to choose an index aligned with the purpose and location of the cost study.[51] because more US centered indexes like CEPCI or NAPCCI have up to a 20% spread compared to EU based factors (e.g. WEBCI). Although time adjustment factors differ among different contractors and service operators in the world, globalization is shrinking this difference.

Location adjustment factors quantify how much it would cost to build a plant with similar (but not necessarily identical) function and envelope, in a different region/country, at a given time and a given currency exchange rate.[42] They are only pertinent in AACE class 4 and 5 estimations, when quotes for labor, material and equipment are nonexistent or cumbersome to obtain.[52] Within a country, a rule of thumb is to add 10% to the cost for every 1000 miles to the nearest industrial center.[53] When comparing different countries, location factors account for currency exchange rates, materials and labor, productivity, contingency costs, feedstocks and consumable prices, and ambient conditions.[51] The most reliable source for location factors to/from US is *Richardson International Construction Factors*, that is now inside a paywall at www.costdataonline.com (after being for several years part of the Aspen capital cost estimator suite). In this work we adopted the last available open access version of the data from 2007,[54] that we then updated at today as:[42,55]

$$F_{l,a,2} = F_{l,a,1} \cdot \frac{USD/\$_{a,2}}{USD/\$_{a,1}} \#(3)$$

That is basically multiplying the location factor of 2007 (1) of a given country (a) to the ratio of the currency exchange ratio of that country in 2020 (2) to 2007 (1) compared to US dollars.

Capital cost estimation: Factorial Methods

Factorial methods build on equipment costs, factoring in one (Lang-like) or multiple factors (Hand-like).[56] Lang-derived factorial methods originate from the series of paper of Lang in 1947,[57–59] where the TCI is equal to the sum of all the equipment cost E_k times a factor (F) depending on the nature of the process (solid, liquid, solid-liquid), plus the working capital WC (Eq. 4).

$$TCI = F \cdot \sum E_k + WC \#(4)$$

Instead, in 1958 Hand assigned factors for equipment type,[60] rather than process type, to construct a correlation for the inside battery limits investment ISBL (Eq. 5):

$$ISBL = \sum F_k \cdot E_k \#(5)$$

More recent correlations are from Peter and Timmerhaus,[61] or Sinnot and Towel,[55] built on Lang's and Hand's hypothesis.

Factorial methods highly rely on the accuracy and the scope of the database, which are rarely specified.[56] These methods can be used for Class 5 estimations, but they usually require equipment list and specifications, that are unavailable at the early stage of the project.

Capital cost estimation: Process step methods

Process step methods postulate the TCI as a function of the main process steps and parameters, such as temperature, pressure, capacity and construction materials.[28] They follow the general formula:[56]

$$TCI = K \cdot C \cdot N \#(6)$$

Where K is a numerical constant, C is one of more factors accounting for the main process parameters, and N the number of process steps (or units).

Tsagkari pointed out how the main disadvantage is the loose definition of "process step", that can vary by author, and the "lack of historical data for regression analysis" . For this reason, Gerrard suggests that "collect[ing] data … for the process of interests" is more reliable than "us[ing] the standard correlations" (i.e. those from the literature), because, once again, the scope of the published equations is limited to the database from which they are drawn.[42]

Compared to the factorial methods, here the cost engineer only needs the number of units and some general information about the plant, that are available at the maturity level equivalent to a Class 4 or 5 AACE. This approach, in theory, makes the process step methods appropriate for an early-stage estimation. The IFP's Functional modules method and Petley's[46,62] correlation are the most recent examples of this group, although their application increased only after Tsagari's review of 2016.

Capital cost estimation: Thermodynamic methods

Thermodynamic methods take a different, indirect approach. In 2001, Lange demonstrated that for fully optimized (design-wise) chemical and petrochemical plants, the DCC (or sum of ISBL and OSBL) of a plant correlates with the energy lost, and the ISBL with the energy transferred in the process.[45] Based on the underlying assumption that the energy lost or exchanged is proportional to the area of the heat exchangers, which is in turn a component of the DCC. To test his hypothesis he compiled a database made of internal Shell data of fuel plants, and an overall review data of representative technologies between 1960–1986 calculated by Chauvel and Lefebvre.[47] In his formulation:

$$DCC = 3 \cdot (\text{Energy losses/MW})^{0.84} \#(7)$$

With the DCC expressed in million USD of 1993. The energy losses are calculated multiplying the global inlet and outlet of a plant's streams for their lower heating values (LHV), as:

$$\text{Energy losses/MW} = \sum LHV_{in} - \sum LHV_{out} \#(8)$$

Where LHV_i is the flowrate multiplied for the LHV. Similarly, the ISBL cost (in 1993 million USD) correlates with the global energy transferred as:

$$\text{ISBL} = 2.9 \cdot (\text{Energy transfer/MW})^{0.55} \#(9)$$

Both equations are valid for energy (lost or transferred) higher than 10 MW, because they deviate for small or energy neutral plants.

Moreover, the original dataset comprises data from big (compared to plastic recycling) industrial scale facilities, built by the same company with similar standards as nth of a kind (NOAK). Conversely, chemical recycling plants are mostly at the pilot or demo scale (sole-of-a-kind or first-of-a-kind at best), with expected fully operational industrial plants with a capacity of 40–50 kt/year. We postulate that this scale involved smaller energy loss, and therefore the original model (Eq. 7) was valid in the form, but not in the substance.

More recently,[63] Lange revised the heat transfer equation when applied to the estimation of a distillation train, and he found, conveniently, that the exponent of the energy transfer-cost correlation became 0.65, which is what is usually encountered in capacity-cost scale-up curves.

Lange's models claim an accuracy equivalent to an AACE class 5 [−50, +100%], but in fact only the energy loss model (Eq. 7) is suitable for a AACE class 5 estimation. To calculate the energy losses, we would only need a block flow diagram knowing "what comes in" and "what goes out" of the plant, or the energy content of feed, products, waste, fuel, as well as the global electricity input, which are available at the very early stage (Table 1) of a project. To calculate the energy transfer, namely as heat (reactors, heat exchangers network) or mechanical (rotative equipment or electricity) transfer duty one would need a detailed process flow diagram, which is something available later on (AACE 3 or 4 equivalent).This correlation when based on full scale plants, also integrates all the energy recovery options which would have been put in place at higher Capex, and which might not be justified for a pilot or demonstration unit.

Capital cost estimation: Process build-up method

The "process build-up" estimation rationale, an early estimation (AACE Class 5) method for biorefineries beyond the state of the art,[64] combines power-law and process step estimation in a probabilistic fashion assisted by a database of 300 existing or announced plants. Although this method requires low-maturity level project information, it is specific for biorefineries projects, and it is only appropriate to estimate similar projects".[64] The authors identified common "process blocks" across the biorefinery technologies, so that new projects (within or beyond the state of the art) are series of process blocks. Then, one can calculate the cost of each block, adjusting the block reference cost from the database, by an efficiency factor that varies by the kind of block. The efficiencies are the process variables available at 0–2% maturity level: yields, product purity, flowrates, etc.

The process-build up method is a useful approach, but it is based on a database unfit for chemical recycling plants of plastic, so outside the scope of this work.

Database construction and statistical analysis

Several techno-economic assessments in the academic literature indirectly already address the research question "How much does it cost to build a chemical recycling plant?". Some of them rely on process simulators (e.g. APEA – Aspen Process Economic Analyzer[31]), others on vendor quotes,[65,66] estimation methods,[67] or follow a hybrid approach.[30,68] In 2011 Feng tested 5 process simulators on the same set of equipment and found that there is up to a 200% variability between cost estimated by different simulators. Estimation of the cost of power machines is consistent among software, but the estimate of the cost of shell equipment is not.

When testing Class 3 or Class 4 factorial methods, a more detailed scope than the one proposed here (Class 5), Van Amsterdam[56] demonstrated that half the time the methods he selected were wrong, that is they yielded a 43% absolute average error instead of the "−25%–+35%" he was targeting. Class 3 or 4 methods already require up to 10 times more preparation effort than class 5 methods, and more advanced process deliverables. He also pointed out how the database on which the models relied has the biggest impact on the difference among methods, rather than the structure of the equations itself.

Similarly, cost estimations accuracies decrease by 20 to 30% if they are not backed by pre-commercial or commercial demonstrations, or if they do not include any site-specific data .[69] This is even more relevant when paired with upper management requests for reduced estimates, which results in technologies pushed too fast, with minimal process validation. Additionally, process estimates come in ranges (e.g. Table 1), but experience teaches how ultimately the final figures are always close to the maximum amount allocated in the budget,[69] i.e. the upper range of the estimation, in a sort of "self-fulfilling prophecy".

We then concluded that to answer the question we needed to build a database tailored to chemical recycling, then test conventional methods, and finally decide which approach (exponential, thermodynamical, etc.) is the most appropriate for our scope.

In more detail, in this work we:

- Queried the open literature for press releases, white papers, newspapers articles, journal articles, government grants, environmental assessments, technical reports, companies' websites, investor presentations, conference presentations, academic literature, congress hearings or any other governmental required interaction or document, in over 15 languages;
- Mined the sources for information on plant technology, capacity (intented as waste fed to the plant), year of real or expected construction, geographical site, total capital investment;
- Updated the plants TCI to pre-covid 2020 US with a CEPCI factor for the time, and *Richardson International Construction Factor* for the location;
- Divided the data per technology clusters, and correlated the total plant capacity in terms of feedstock (or treated plastic), with the TCI;
- Regressed a linear, log-log fit, and calculated confidence and prediction intervals of the sets; and
- Fit TCI probabilities with a statistical distribution to validate the collected data relevance, because we know that total capital investment probability generally follows a log-normal distribution.[40,69–71]

At this point, we had a database of over 169 chemical recycling plants (**Supporting Information**):

- Pyrolysis (107);
- Gasification plants (32);
- Solvolysis plants (18); and
- Selective dissolution (10).

On this set, we adopted a three step approach first **(i)** we tested some "conventional" capital estimation methods to see how they would compare with the real data and their confidence interval.

Table 2. Selected project for benchmark (PtF is plastic to diesel fuel; PtO to naphtha oil).

Technology	Capacity (kt/year)	TCI M USD, 2020 US	Capital cost source	Base of Reference
Pyrolysis – PtF Fivga[45]	80	16	Vendor quotes + power law estimation	UK, 2013
Pyrolysis- PtF Ghodrat[66]	13	6	Vendor quotes + Factorial methods	Australia, 2017
Pyrolysis – PtF Riedewald[65]	40	28	Vendor quotes on detailed design	Belgium, 2020
Pyrolysis – PtO Gouzhan[68]	16	6	Hybrid: – Vendor quotes – Simulators – Technical reports	UK, 2018
Pyrolysis – PtO Volk[72]	65	70	Technical report	Germany, 2021
Gasification – NREL[73]	79	111	Internal Reference	US, 2021
Gasification – Lan[74]	655	980	Hybrid: – Vendor quotes – Technical reports	US, 2021

To compare conventional AACE class 5 estimation models (Sec. 2.2.4) we selected representative projects from highly cited papers in the literature where the capital cost was claimed to come from either engineering detailed designs by third parties, internal references, or directly from vendor quotes on the detailed flowsheet (Table 2).

We selected those projects to represent pyrolysis and gasification state-of-the art plants. For selective dissolution and solvolysis the database is so sparse, and the technologies so diverse, that we decided not to benchmark those two families for capital cost estimation models.

Among pyrolysis plants, there are facilities producing a diesel-like fuel (PtF), and ones aiming at naphtha-like oil (PtO) to be sold as a feedstock for steam crackers in the petrochemical industry (to ultimately produce virgin plastic). We therefore had two subclusters for pyrolysis, and one for gasification.

Then, **(ii)** we verified the accuracy of the reference project selected with the total plant database, to draw capacity vs TCI linear regressions with statistical significance. Here we verified whether or not the plant capacity is an appropriate indicator for TCI, and what is the probabilistic distribution of TCI based on the interval of prediction build on the historical plant database.

After that, **(iii)** when possible, we regressed the heat and mass balance of each pyrolysis and gasification plant, under the hypothesis that energy lost is a better indicator than capacity for TCI. In fact, when we calculate the theoretical energy of pyrolysis for selected plastics as contribution of sensitive heat, depolymerization, heat of fusion (in case of crystalline polymers), and vaporization, we realize that even assuming a 100% wt. polymer to monomer yield, polyolefins are the most energy-intensive plastics to depolymerize (Figure 2). And yet, they are the preferred feedstock for these technologies, which suggests that capital investment has to be related with the way energy is input or withdraw in the process, especially if such a process is highly exothermic or endothermic.

Adopting a black box perspective, we computed the overall energy loss across the plant using Equation 10. This calculation involves the sum of the product of flow rate and lower heating value (LHV) of all input streams (inclusive of fuel and electricity), subtracted by the equivalent sum of all output streams. Essentially, if by-products are combusted on-site for energy recovery (a common practice for light incondensable fractions in pyrolysis), they aren't included in the output streams, as they technically do not exit the plant.

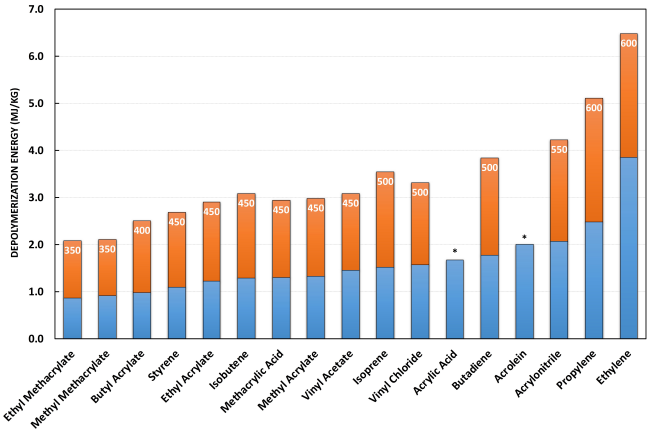

Figure 2. Energy Intensity (MJ/kg) in Pyrolysis - Polymer to Monomer (assuming 100% yield, depolymerization). Depolymerization in MJ/kg expressed as sensitive heat (orange) + heat of depolymerization and vaporization (blue), at its temperature (°C) of depolymerization (white). The sensitive heat is calculated as cpdT with data from,[75] and the depolymerization and vaporization values are taken from the literature and the NIST WebBook.[76,77]

Selected estimation methods for benchmark

Power-law, process step and thermodynamic methods are the most suited for the benchmark. They need minimal effort and low-level detail project deliverables. We selected Petley's, Wilson's, Bridgwater's, Lange's and Zvenik & Buchanan methods (Table 3). The original equations are for ISBL, OSBL or their sum, for the sake of clarity, we directly report the correlations for the TCI, and in million USD of 2020 in US. Chemical engineering handbooks like Sinnot & Towel and Perry's suggest (at least) the following compounding to transform ISBL into TCI:[55]

- OSBL + ISBL = 1.4*ISBL = DCC;
- ICC + DCC = 1.3*DCC; and
- TCI = WC + Start-Up + DCC = 1.15*DCC;

Table 3. Selected methods for deterministic and probabilistic benchmark.

Method	Ref	Relation for TCI/M USD	Description
Petley	[62]	$TCI = 1.4 \cdot 55882 \cdot P^{0.44} \cdot N^{0.486} \cdot T_{max}{}^{0.038} \cdot P_{max}{}^{-0.02} \bullet Fm^{0.341} \bullet \frac{CEPCI_{2020}}{CEPCI_{1998}}$ #(10)	T_{max} is the maximum temperature in the process P_{max} is the maximum pressure in the process P is the plant capacity expressed as "what is leaving the plant" Fm is the material factor N is the number of functional units
Wilson	[80]	$TCI = 1.4 \cdot f_i \cdot N \cdot (AUC) \cdot Fm \cdot Fp \cdot Ft \cdot \frac{CEPCI_{2020}}{CEPCI_{1971}}$ #(11) $AUC = V^{0.675}$ #(12)	AUC is average unit cost of main plant items, proportional to the plant capacity V (what is fed to the process), f_i is the investment factor, a tabulated value depending on AUC and the kind of process (Fluid, liquid, gas), Fm is the material factor, from 1 (mild steel) to 2 (titanium) Fp is the design pressure factor, Ft is the design temperature factor, N is the number of functional units.
Bridgwater A	[81]	$TCI = 1.4 \cdot 0.000489 \cdot N \cdot \left(\frac{Q}{s^{0.5}}\right)^{0.85} \cdot \left(\frac{n\, T_{max}}{N}\right)^{-0.17} \cdot \left(\frac{n'\, P_{max}}{N}\right)^{0.14} \cdot \frac{CEPCI_{2020}}{CEPCI_{1976}}$ #(13)	N number of functional units, s conversion, Q the capacity in ton/y, expressed as what is fed to the process n number of units whose temperature is higher than $\frac{T_{max}}{2}$, n' number of units whose pressure is higher than $\frac{P_{max}}{2}$, 1.4 is to transpose the original ISBL correlation to TCI. Reported accuracy is [−20%, +20%]
Bridgwater B	[82]	$TCI = 1.4 \cdot 0.001 \cdot N \cdot \left(\frac{Q}{s}\right)^{0.675} \frac{CEPCI_{2020}}{CEPCI_{1981}}$ if $\left(\frac{Q}{s}\right) > 60000$ #(14) $TCI = 1.4 \cdot 0.103 \cdot N \cdot \left(\frac{Q}{s}\right)^{0.3} \frac{CEPCI_{2020}}{CEPCI_{1981}}$ if $\left(\frac{Q}{s}\right) < 60000$ #(15)	
Bridgwater C	[82]	$TCI = 1.4 \cdot \left[3 + 9.7 \cdot 10^{-6} \cdot \left(\frac{Q}{s}\right)\right]^{*} \cdot N \cdot \frac{CEPCI_{2020}}{CEPCI_{1981}}$ #(16)	
Bridgwater D	[82]	$TCI = 1.4 \cdot 0.0014 \cdot \left(\frac{Q}{s}\right)^{0.655} \cdot e^{Q \cdot 2.58\ 10^{-7}} \cdot T_{max}{}^{-0.022} \cdot P_{max}{}^{-0.064} \cdot \frac{CEPCI_{2020}}{CEPCI_{1981}}$ #(17)	
Taylor	[83]	$TCI = 1.4 \cdot k_T \cdot \sum_1^N (1.3)^{CS} \cdot Q^{0.39} \cdot \frac{CEPCI_{2020}}{CEPCI_{1977}}$ #(18)	k_T is a constant, CS is the complexity index for each functional unit N, Q the capacity in ton/y, expressed as what is fed to the process
Lange A	[45]	$TCI = 3 \cdot (\text{Energy losses MW})^{0.84} \cdot \frac{CEPCI_{2020}}{CEPCI_{2001}}$ #(7)	Details in Section 2.2.4
Lange B	[45]	$TCI = 1.4 \cdot 2.9 \cdot (\text{Energy transfer MW})^{0.55} \cdot \frac{CEPCI_{2020}}{CEPCI_{2001}}$ #(9)	Details in Section 2.2.4
Zevnik & Buchanan	[84]	$TCI = 1.4 \cdot 7470 \cdot Q^{0.6} \cdot 10^{\left[(0.1\ \log P_{max}) + \left(1.8 \cdot 10^{-4}(T_{max} - 300)\right) + Fm\right]} \cdot \frac{CEPCI_{2020}}{CEPCI_{2000}}$ #(19)	T_{max} is the maximum temperature in the process (K) P_{max} is the maximum pressure in the process (atm) Q the capacity in ton/y, expressed as what is fed to the process Fm the material factor (0.1 aluminum to 0.4 for precious metals) N is the number of functional units

which means that the TCI is roughly twice the ISBL. The manuals suggest these factors as the lower-end for "a typical petrochemical plant", which would not be representative for our case studies. One approach would be to analyze the projects (Table 2) case by case and select the compounding factors on a "best-educated guess" rationale. However, given that we know the real TCI, this approach could be biased, because the criteria for the selection of the factors are "large and small projects", or "technological uncertainty" which are hard to quantify.

Ideally, estimation methods would benchmark selected projects in a database built on TCI values.

The key hypothesis in the TCI collected is that companies release the best figures they have at the time. Whenever possible, we considered the most recent communications, to reflect any possible cost increase over time. However, companies are both reluctant to divulge details, and their TCI figures follow a log-normal distribution with a p50 of +30%.[40] Nevertheless, at the time of release, most of the work has already been done, and quotations from key suppliers have been obtained, so that a database built on this information cannot be more accurate than that.

At the same time, detailed estimations like the ones released to the investors, often include some contingencies, which we cannot access. Moreover, the investment data are primarily disseminated to attract funding, which may result in a tendency towards over-optimism, as well as the simplification of the plant design and dependence on existing assets. We assumed that these two aspects ultimately even out, which substanciate the hypothesis that the cost announced is as close as it gets to the real TCI.

For the deterministic analysis, when available, we directly compared the methods outputs (ISBL) to avoid introducing extra factors. For the probabilistic analysis we decided to adopt a fixed factor of 1.4 to convert ISBL into TCI when needed in the estimation methods, assuming that because we are looking at AACE class 5 estimation methods, they come with a [−20%, +100%] accuracy (Table 1), so we do not want to introduce new uncertainties. In this way we infer that whatever mismatch there is between what we calculate from 1.4×ISBL and the TCI of the dataset, it is within the expected range

of the estimation methods. The scope of our analysis is not to find the perfect method, but to see whether the methods fall within the interval of prediction of our dataset, or namely if they could be a good first educated guess for researchers and technology owners at the early stage of a project.

Results and Discussion

The research query identified plants mainly in three macro-regions (Figure 3):

- Australia and North America;
- Europe; and
- Eastern and South-Eastern Asia

These areas share different views on recycling, and they are at the different stages of their zero-waste journey. Europe and US are the most fertile ecosystems for new plants, with most plants in our database based there. South Korea and Japan lead the effort in Asia. The plastic waste control plan in South Korea aims to reduce plastic content of total waste to 50% and increase plastic waste recycling to 70%.[75] Japan's Resource Circulation Strategy for Plastics, instead, targets 100% of used plastic for reuse or recycling.[76] A smaller cluster of plants (mainly pyrolysis to road fuel) is in Australia, where the National Waste Policy promotes circular economy initiatives, albeit later then "other jurisdictions".[77]

The authors know by direct experience that areas not represented in the map, such as Latin America, northern Africa or India, have recycling plants as well. For cultural reasons, and the absence coordinated regulations, plant owners often prefer to trade in the local market, or they do not advertise the recycling content of their products, especially if the quality is comparable to the virgin (monomer, road fuel, naphtha oil). In fact, if the end-user does not see the difference on the final product, recyclers do not want to disclose their feedstock (i.e. plastic waste) source. With some geographical exceptions, consumers still value price and quality over environmental impact,[78] and they expect to pay a discount if the goods are made with recycled material, because they believe it to be of lower quality.[79]

Deterministic and Probabilistic benchmark for pyrolysis

We divided pyrolysis into two sub-technological clusters: Plastic to Fuel and Plastic to Naphtha oil with, respectively, three and two reference projects. Although each estimation model has its own accuracy, in general 5 AACE methods are supposed to estimate with a −50%, +100% accuracy on the median value (Table 1). From a deterministic point of view (a fixed value for the estimation), Wilson's and Bridgewater's (A and D) are the best performers for pyrolysis overall (Table 4), because their errors are within the AACE accuracy range. However, when we benchmark the methods on the historical database of plants, the majority of reference projects underestimate the TCI compared to the historical database. This underestimation suggests that techno-economic assessments require a more analytical approach, and researchers in academia need guidelines and references when estimating TCI of plastic recycling plants. At the same time, Wilson's method falls within the 95% (or 2σ) confidence interval (Figure 4) of the best-fit line only for two projects, while Bridgewater (A,D) only one (Figure 4,

Figure 3. Map of chemical recycling plants,[87] divided into gasification (yellow), pyrolysis to fuel (blue), pyrolysis to naphtha oil (red), solvolysis (light grey), and selective dissolution (dark grey).

Table 4. Deterministic comparison for pyrolysis, with absolute errors.

Method	Pyrolysis PtF[45]	Pyrolysis PtF[66]	Pyrolysis PtF[65]	Pyrolysis PtO[68]	Pyrolysis PtO[85]
Capacity/kton year^{-1}	80.0	13.2	40.0	16.0	64
Original (ISBL / TCI) M USD	16 (TCI)	6 (TCI)	28 (TCI)	4 (ISBL)	15 (ISBL)
Petley	49 (+199%)	17 (+201%)	34 (+23%)	20 (+437%)	42 (+103%)
Wilson	29 (+75%)	9 (+56%)	19(−32%)	6 (+61%)	23 (+11%)
Lange A	55 (+233%)	6 (−2%)	66 (+138%)	7 (+105%)	34 (+67%)
Lange B	20 (+24%)	15 (+161%)	15 (−46%)	11 (+196%)	19 (−8%)
Bridgwater A	27 (+68%)	9 (+49%)	15 (−46%)	7 (+102%)	34 (+65%)
Bridgwater B	13 (−21%)	18 (+217%)	15 (−46%)	12 (+235%)	20 (−5%)
Bridgwater C	22 (+36%)	28 (+375%)	20 (−29%)	19 (+430%)	33 (+63%)
Bridgwater D	15 (−10%)	9 (+58%)	10 (−65%)	7 (+86%)	25 (+20%)
Zevnik & Buchanan	178 (+992%)	76 (+1209%)	92 (+229%)	75 (+1956%)	175 (+1094%)
Taylor	22 (+34%)	9 (+56%)	5 (−80%)	9 (+160%)	13 (−36%)

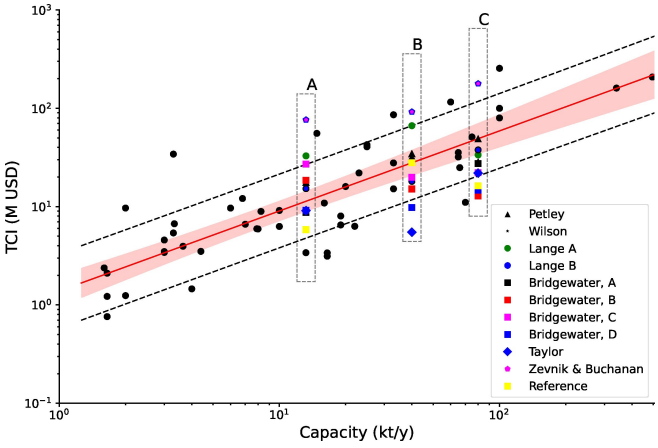

Figure 4. Pyrolysis - Plastic to Road Fuel - Probabilistic Analysis. References (in yellow) A: *Ghodrat 2017*; B: *Riedewald 2020*; C: *Figva 2013*. The capacity correlates with the TCI: log TCI $= 0.81\log(\text{Capacity}) + 0.14$ with a $R^2 = 0.75$. Dashed black lines represent 1σ prediction interval, while the red region represents the 2σ confidence interval around the best fit (red line). The black dots are the plants part of our database. Confidence interval is the one where to expect the best regression line, while prediction is the interval to be used for future observations.

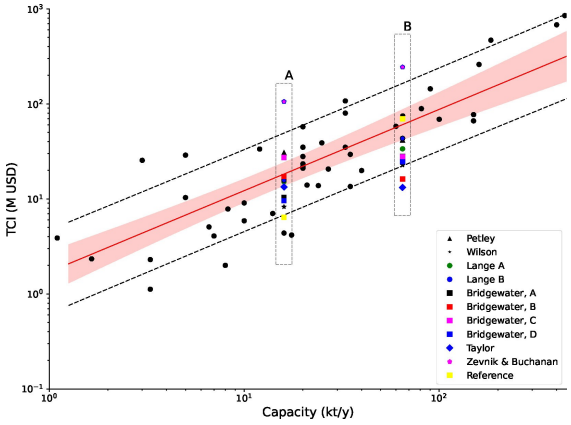

Figure 5. Pyrolysis - Plastic to Naphtha Oil - Probabilistic Analysis. References (in yellow) A: *Volk 2021*; B: *Gouzhan 2018*. The capacity correlates with the TCI: log TCI $= 0.86\log(\text{Capacity}) + 0.24$ with a $R^2 = 0.72$. Dashed black lines represent 1σ prediction interval, while the red region represents the 2σ confidence interval around the best fit (red line). The black dots are the plants part of our database. Confidence interval is the one where to expect the best regression line, while prediction is the interval to be used for future observations.

Figure 5). Overall, the family of methods that show that the thermodynamic group (Lange A, B) are the most accurate; they estimate within the 95% confidence interval four out of five times. However, Lange B models rely on the energy exchanged in a process, which we calculated from the detailed process flowsheets in the academic papers. At the very early stage, we may have partial access to this information, for instance we might be able to roughly estimate the heat of reaction and/or purification, but not the energy for rotary equipment. For this reason, Lange B, which is the top performer among the ones we tested, is not always usable. If we consider the other best methods, Petley, Wilson, Lange A, no method is clearly better than the others. Wilson and Bridgewater (A and D), the top methods in the deterministic analysis, fall within the 95% confidence interval 0 and 1 times respective.

The probabilistic analysis also gives insights on plastic pyrolysis as a whole:

- Recyclers are migrating from a business model that converts waste plastic to diesel fuel to one that converts waste plastic to naphtha oil.
- The technology suffers from a poor economy of scale, because TCI scales up with capacity$^{0.81}$ to capacity$^{0.86}$ for PtF and PtO respectively, which hints that they are based on unit parallelization principles rather than size scale up. However, capacity is not the ideal indicator to estimate TCI, given that the $R^2 = 0.71$–0.75 for the predictions.
- Recyclers choose a standard plant size, on the order of 35–45 kton/year of capacity.
- The TCI for the plants follows a log-normal distribution for a given capacity.

These results find practical implications with what we observe in the industry. Theoretically, the main contributor to the TCI (on the equipment side) is the reactor. We note that the most common reactor designs are stirred tank (Plastic Energy), an auger reactor (Agylix) and a microwave reactor (Pyrowave). The first two have in common a limited wall surface to transfer heat to the plastic, so that the energy fed depends on the transfer area. This geometry suggests (on the basis of surface area per unit volume) a scaling factor of 0.5.[86] However, reactors are size-limited because in pyrolysis the heat has to be transferred through the walls, so that increasing the plant capacity necessitates numbering up rather than scaling up (which explains why there is limited economy of scale).[87] Of course, the temperature at which the process is carried out is also important, and it should not compromise the product quality. If additional reagents are used in the process, such as Steam, Hydrogen, Catalyst, they would affect the product quality and might give a better value to the product.

Microwave reactors are limited in the penetration depth of the irradiation and by the volume to be irradiated. Finally, pyrolysis in general is impeded by feedstock (waste plastic) collection. Plastic is a low-density material, which means high transport volume (i.e., trucks). Moreover, mixed waste sorting is better effected by individual households rather than in more highly populated areas, but collection volumes trend in the opposite direction.[88,89]

In addition, the wastes to be processed are not "uniformed" or standardized. Numbering up rationales are therefore preferred to cope with the heterogeneity of the feedstocks from batch to batch.

The dispersion on capex, whatever the correlation selected, illustrates the diversity of technologies which are possible for pyrolysis. Some technologies cannot be easily scaled up, and so require reactors numbering up. Other technologies are more appropriate for scaling up and would have a lower "power law" factor for the pyrolysis reactor. For these reasons, for plastic pyrolysis, there is an optimum plant size (35–45 kton/y range) where companies can save on the engineering costs building a "standard" kind of reactor, while allowing for the practicalities of feedstock sourcing. In the future, we foresee companies will look at a hub and spoke model to incorporate the pyrolysis plants in an existing refinery centre. Here, small, delocalized pyrolysis plants surrounding a bigger existing refinery, will receive low-density plastic waste and liquefy it into naphtha-like oil that feeds the central facility to refine or crack the output, to ultimately produce new plastics.

Where possible (40 out of 106 plants), we calculated the global mass balance and the energy loss across the plant, for the whole pyrolysis database (PtF + PtO).

The energy loss (MW) correlates linearly with the TCI (Figure 6) better than the plant capacity does ($R^2 = 0.92$, versus $R^2 = 0.76$ for capacity). This also supports the hypothesis that factors that correlate with energy input are the main contributors to the pyrolysis economics.

At low project maturity level, with this correlation (Figure 6) one can directly estimate the plant TCI with a very high confidence, and screen different technologies based on

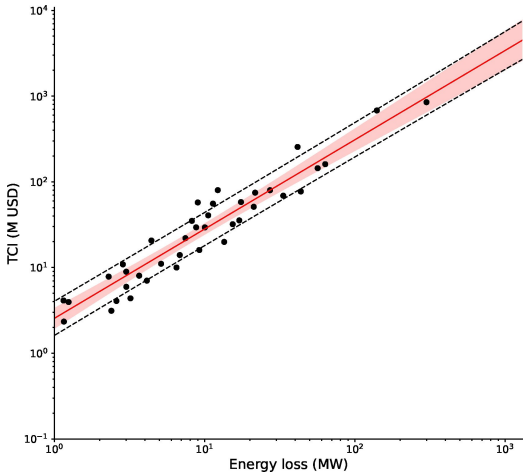

Figure 6. Pyrolysis – Probabilistic Analysis Energy loss vs TCI. The energy loss in MW correlates with the TCI: $\log \mathrm{TCI} = 1.04 \log(\mathrm{MW_{loss}}) + 0.41$ with a $R^2 = 0.92$. Dashed black lines represent 1σ prediction interval, while the red region represents the 2σ confidence interval around the best fit (red line). The black dots are the plants part of our database. Confidence interval is the one where to expect the best regression line, while prediction is the interval to be used for future observations.

estimated capital cost. To do so, researchers need to know (or calculate):

- Global plant mass balance; and
- Nature of feedstock and products which are available at the beginning of the project.

When possible, the MW lost is not just a better indicator for the TCI nominally, but it also probabilistically (Figure 7).

However, Similar to Lange A, when a project is non-thermal, or highly energy integrated, the correlation would not be as reliable. In the special case of plastic pyrolysis, it is common practice to use part of the products as fuel to make the process energy self-sufficient, which makes the calculation easier because one only needs to know (or set) the total mass yield for the process (as opposed to the utility balance). Generally, uncondensable off-gases are targets for energy recovery, and a rule of thumb for a quick estimation is to assume them as 15–30% wt. of the products.

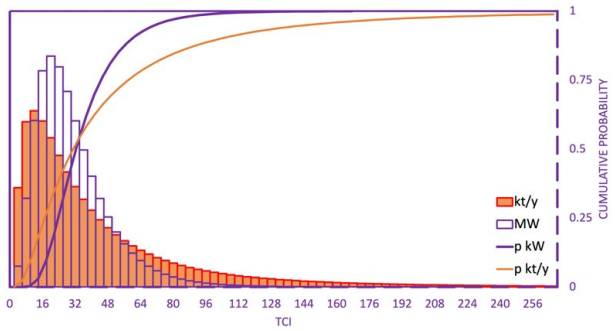

Figure 7. TCI log-normal distribution for a representative plant using the capacity (kt/y) or the energy losses (MW), and their cumulative probabilities (p).

For a typical pyrolysis plant from the database, the log-normal distribution of TCI is sharper when estimated from the MW lost compared to the capacity in kt/y, which leads to a higher level of confidence in the overall estimation.

Deterministic and Probabilistic benchmark for gasification

We selected two reference plants for gasification, one to produce H_2, and the other to produce methanol, which are representative of the technologies seen in the industry presently. Again, Wilson, Lange A, and Bridgewater (A,B,C,D) perform the best in the deterministic analysis, because they estimate with errors within the AACE class 5 boundaries in both case studies, with Lange and Bridgewater A and C being the most accurate of all (Table 5).

One reference (NREL 2020) falls in the 95% confidence interval for the probabilistic analysis, and in this case, Bridgewater (A,C) are actually the best methods overall. The other reference (Lan 2021) falls outside the 95% confidence interval, and Bridgewater C and D are the best performers when comparing with the database (Figure 8). Bridgewater C is overall the best estimation method. However, once again one should not rely too much on the performance of the methods, because they were developed for different types of plants, and for larger-scale applications. For instance, Bridgwater developed his first method (A) using 24 plants from 16 hydrometallurgical processes,[28] and even he stopped using his methods (A–D) in favor of more specific correlations for the process at hand.[90] Once again, the problem of using methods based on process steps is that they are highly dependent on the definition of the "process steps" (N-Table 3), which are not unequivocal in the literature. Unlike with pyrolysis, gasification capacity correlates very well with TCI ($R^2 = 0.91$), and regressing energy and mass balances (when possible) did not improve the correlation taking the total plant energy losses as basis (Figure 9). Additionally, gasification facilities can run with a "flexible feed" or "clean feed" approach. Process gas or fuels in the gasifier are less problematic (i.e., cheaper) than processing waste (biomass or plastic), because the latter need additional Capex for waste residue sorting, pelletizing or pre-treatment (for plastic), additional operative costs to dispose of the residues, and present technical challenges during operation due to the presence of sticky ash prone to agglomeration in the reactor. Conversely, plants designed to use clean fuel and handle only pre-sorted plastics would incur costs for their feedstocks. Although the projects populating the database claim to be plastic gasifiers, we can assume that this is completely true only for new or under-construction projects; existing projects are likely to operate in flexible feed mode,[91] which was more attractive in the recent past.

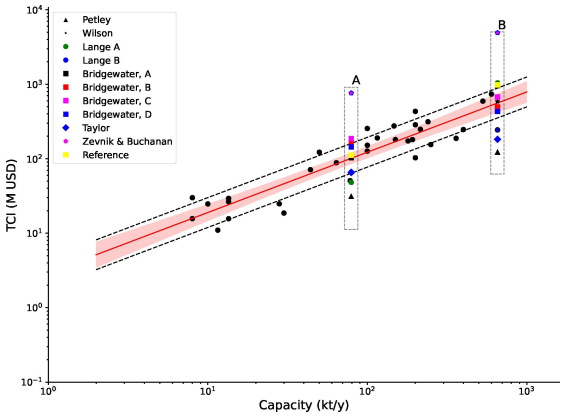

Figure 8. Gasification - Probabilistic Analysis. References (in yellow) A: *NREL 2021*; B: *Lan 2021*. The capacity correlates with the TCI: $\log \mathrm{TCI} = 0.81 \log(\mathrm{Capacity}) + 0.47$ with a $R^2 = 0.91$. Dashed black lines represent 1σ prediction interval, while the red region represents the 2σ confidence interval around the best fit (red line). The black dots are the plants part of our database. Confidence interval is the one where to expect the best regression line, while prediction is the interval to be used for future observations.

Table 5. Deterministic comparison for gasification, with absolute errors.

Method	Gasification H_2[74]	Gasification MeOH[73]
Capacity (kton/year)	656	79
Original (ISBL/TCI) M USD	580 (ISBL)	75 (ISBL)
Petley	88 (−85%)	49 (−35%)
Wilson	419 (−28%)	131 (+74%)
Lange A	744 (+28%)	63 (−16%)
Lange B	174 (−70%)	Insufficient data
Bridgwater A	686 (+18%)	86 (+15%)
Bridgwater B	354 (−39%)	46 (−38%)
Bridgwater C	480 (−17%)	65 (−14%)
Bridgwater D	307 (−47%)	41 (−45%)
Zevnik & Buchanan	3607 (+505%)	800 (+987%)
Taylor	130 (−78%)	47 (−38%)

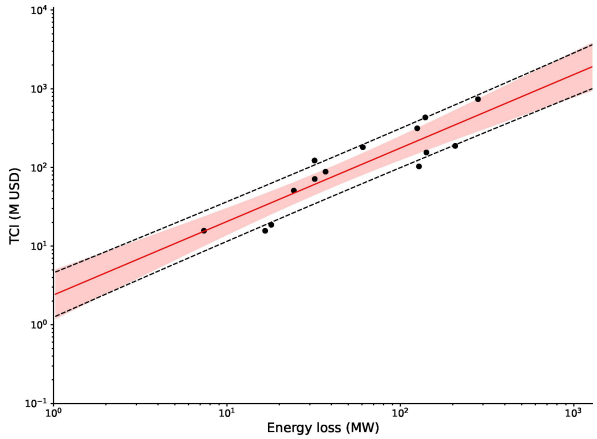

Figure 9. Gasification - Probabilistic Analysis Energy loss vs TCI. The energy loss in MW correlates with the TCI: $\log TCI = 0.93\log(MW_{loss}) + 0.37$ with a $R^2 = 0.91$. Dashed black lines represent 1σ prediction interval, while the red region represents the 2σ confidence interval around the best fit (red line). The black dots are the plants part of our database. Confidence interval is the one where to expect the best regression line, while prediction is the interval to be used for future observations.

Because the plants are not so well defined, we therefore must accept an uncertainty in TCI, and also contend with a variability in the feedstocks and products.

The probabilistic analysis for gasification suggests that:

- Capacity (expressed in terms of kton/year) is a sufficient basis for estimating the TCI. It is as accurate as total energy loss through the plant;
- Gasification, like pyrolysis, suffers from poor economy of scale, and it scales up with as capacity$^{0.81}$.
- The average plant size of the database is 145 kton/year, and 2016 is the average year of construction, similar to pyrolysis to diesel fuel. This observation supports the hypothesis that some of the bigger size plants might be multipurpose facilities.

Additionally, because of its multipurpose nature, gasification may be better suited for municipalities, because the sorting and/or waste pretreatment can be outsourced, as suggested by the early experience of Enerkem.[92]

Deterministic and Probabilistic benchmark for solvolysis and selective dissolution

Solvolysis and selective dissolution are similar in many ways, for instance both employ a solvent and must be tuned for the specific polymer (depolymerized or dissolved respectively). The difference is that selective dissolution is more flexible in terms of waste feedstock. Both technologies are newer compared to pyrolysis or gasification, and data are mostly limited at pilot or demo scale, with few industrial-scale plants. Solvolysis projects mainly target PET (in different alternatives – Glycolysis, methanolysis, hydrolysis), polycarbonate and foam polyurethanes (more recently). Selective dissolution is appropriate for polyolefins, polystyrene, polycarbonate and mixed plastics which are difficult to recycle mechanically, such as multilayers films.

Patent and academic literature is ample, but the low maturity level of existing projects increases the uncertainties in the estimation. Similarly, the variability (chemical or technical) of the process within this cluster, is an additional source of dispersion in the data. For instance, in hydrolysis, methanolysis or glycolysis, PET depolymerizes respectively to terephthalic acid, dimethyl terephthalate, or PET glycolates (e.g., bis-2-hydroxyethyl terephthalate). Hydrolysis produces an easier to sell but difficult to purify product, dimethyl terephthalate is in turn easier to purify but has a smaller market, and glycolysis requires a catalyst for a real plastic to plastic (PET) recycling.[20] The database includes diverse processes, such as Gr3n, which uses a microwave reactor, Carbios, which used enzymatic hydrolysis, or Ioniqua's catalytic glycolysis with magnetic separation for catalyst recovery. The technology spread causes the total capital cost to be only poorly related to feedstock capacity (Figure 10, Figure 11), with selective dissolution having a better economy of scale compared to solvolysis. Theoretically, scale up for solvolysis and selective dissolution is correlated to the volume, and it is limited by the productivity. Dissolution and solvolysis require several hours (if not days) of residence time. So that when one wants to increase the capacity, numbering up rationales are employed on the reactors to increase the flexibility.

However, estimation for new plants relies on scarce full scale data, and therefore must accept higher uncertainties. At the same time, the investor should not be lured with promises of low capex and production costs, so that's especially where it is important to be able to estimate as early as possible the full production cost.

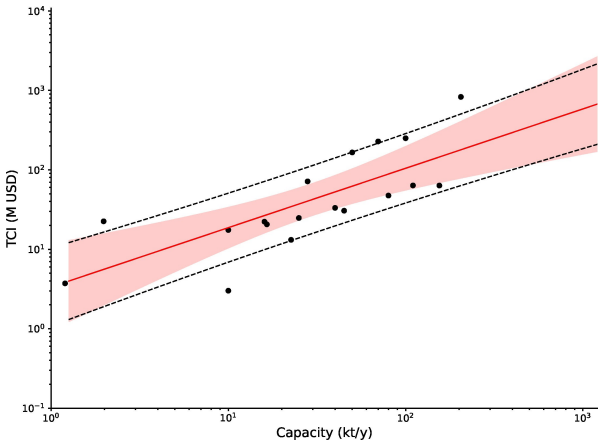

Figure 10. Solvolysis - Probabilistic Analysis. The capacity correlates with the TCI: $\log TCI = 0.75\log(Capacity) + 0.52$ with a $R^2 = 0.61$. Dashed black lines represent 1σ prediction interval, while the red region represents the 2σ confidence interval around the best fit (red line). The black dots are the plants part of our database. Confidence interval is the one where to expect the best regression line, while prediction is the interval to be used for future observations.

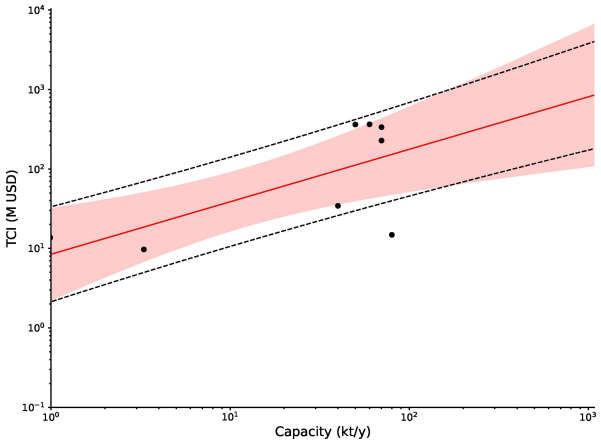

Figure 11. Selective Dissolution - Probabilistic Analysis. The capacity correlates with the TCI: log TCI $= 0.66\log(\text{Capacity}) + 0.93$ with a $R^2 = 0.63$. Dashed black lines represent 1σ prediction interval, while the red region represents the 2σ confidence interval around the best fit (red line). The black dots are the plants part of our database. Confidence interval is the one where to expect the best regression line, while prediction is the interval to be used for future observations.

How to use the database

Researchers have to convince either their company, investors or funding agency that the technology they promote is the future "block buster". In order to do so they have to demonstrate that the technology will have superior economic and technologic advantages to compensate for the risk of investing in a new (unproven) technology. This has to be done at a time when no or nearly no pilot results are available yet. At best, one has to convince the funding agencies when a Technology Readiness Level (TRL) of 3–4 has been reached, and within the companies even at lower TRL to get the money to start the preliminary research. It is then particularly important to be able to give some numbers at low TRL levels, when a lot of issues are not solved yet. Of course, these numbers come with a lot of uncertainty or dispersion. But as we have seen earlier, even a Class 5 estimate is given at +100%/−50% level. For that level of precision, process engineers need already a good definition of how the plant would look like, and it might take them several months and a few 100 k€ to give a value. So, what is needed is a method which might have a larger dispersion, but is be faster and cheaper.

Once a capital cost has been calculated, it would be fed in the production cost model. It has multiple impacts: as depreciation cost first; but also on maintenance, insurance, property taxes which are factored from the capital cost. There is also a correlation between the capital cost and the labor cost. Here also it can be related to the number of processing steps, whether the process is operated in batch or continuous mode, the plant capacity… and to the wages. Indeed, in countries with low labor costs, it might be better to reduce the Capital cost and increase the labor cost.

For the investor, the Capital cost is where the risk is taken. The world is full of plants that have been built but never operated as expected. In the capital cost, there are contingencies and start-up costs included to compensate for those risks, but nevertheless plants can finally cost twice as much as initially planned or never been finally operated. Especially for a completely new technology, the investor needs to see much better economics than with alternative processes, and requests to have lower capex and production costs by 30% are not uncommon.

As explained previously, the capex (TCI) feeds in the fixed cost and labor cost. There are other costs such as R&D, Laboratory (quality control), sales and distribution that have to be added but which are usually proportional to the sales, and so to the plant capacity and product price. The variable costs will include mostly the feedstocks and utilities (gas, electricity, water…) needed for the plant. It might be also difficult to assess the variable costs initially, but again a fair percentage of the sales can give a good estimate.

What is interesting with the correlation between the TCI and the energy loss, is that it could also work in the opposite direction. If we have a fair estimate of a plant cost (TCI), we can derive a fair estimate of the energy consumption (knowing the mass balance).

All those data come with uncertainties or dispersions, and Monte-Carlo type simulations can be used to get a dispersion on production prices.[30,93] It might then be easier to convince management, shareholders, investors and funding agencies on a probability to reach a given production price. What those data usually demonstrate is where the focus should be for the improvement of the technology.

One key question that one might have at early stage of the process is: should I focus to reduce the Capex, but then buy a more expensive feedstock, or make a lower purity product (sold at lower price), or should I try to make the highest purity product, with the cheapest feedstock at the expense of the plant complexity? The answers to these questions are going to determine how the experimental work should be conducted. It would not be at all the same type of experiments if the feedstock is already very pure (for example a post-production plastic waste), of if one has to use a dirty waste (for example a post-consumer, 30 years old plastic with additives and ingredients which are no longer allowed on the market). Also, the type of purification technologies to be validated strongly depend on these assumptions. Upper managements pressure researchers and cost engineers to have the most precise estimation possible on the capital cost (at the earliest possible stage). However, Montecarlo simulations demonstrate that the TCI is only one of the three main contributors on the economic feasibility, together with product selling price, and purchasing price of feedstock (if any).[30,31,94] Let's now assume that upper management wants to build a plant to recycle 100 kt/y of waste, with no precise technology in mind yet, and they need to estimate its TCI to ultimately decide whether or not moving on with the investment. Our database demonstrates that is not the detail of the technology that makes the difference (Figure 12), because within the early-stage estimation uncertainties, all the technologies yield similar TCIs (e.g. between 55 and 215 M USD for 100 kt/y). This is why in the early stage development it is not essential to pursue higher precision on

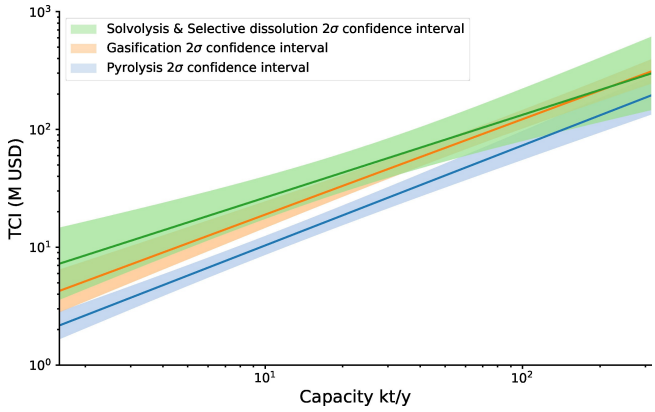

Figure 12. 2σ confidence interval around the best fit for Pyrolysis (PtF + PtO) – in blue, Gasification – in orange, and Solvolysis + Selective Dissolution – in green.

the capital investment beyond what we suggest in this study, as we would lack precision on the other two factors – purchasing and selling cost anyway.

Instead, a special attention should also be given to the mass yield of the recycling processes, especially when considering closed-loop recycling. This would justify classifying the processes based on the number of cycles the carbon can make while retaining 50% in the economy. When the polymer-to-product mass yield is 90%, it is possible to keep 50% of the carbon in the economy after $0.5 = (0.9)^6$, 6 recycling operations. Mixed plastics (polyolefins) pyrolysis would give 70% mass yield to liquid products, and only 70% of it would be directed to a steam cracker. Then, the usual yield of a steam cracker is 50% ethylene + propylene. So, only 25% of the initial mass can return in the polymer economy. Other plastics have much better mass yields, such as PMMA (polymethylmethacrylate) with more than 90% with the best quality scraps, and PS (polystyrene) with about 70%, with depolymerization via pyrolysis.[95] Therefore, from an environmental point of view, one should favor the technologies that keep the carbon longer in the economy. In that sense, mechanical recycling has a high mass yield, but suffers from down-cycling (the product often does not return to the same application in the economy). For instance, waste PVC window frames are recycled mechanically in the same market but are diluted with virgin PVC in a sandwich layout where recycled PVC containing harmful additives like Pb is at the core, and virgin PVC is on the external surface. So, the yield is high, but it is not completely closed-loop. If we project ourselves in the future, the carbon source should come from biomass, recycling, and as little as possible from fossil sources. The only way to achieve this target is to have a high recycling yield, because the amount of biomass available is limited.

An additional factor often overlooked by researchers is the use of existing assets. Again, we can take a real world example. PET recyclers have multiple options: mechanical recycling; solvolysis via glycolysis, methanolysis, hydrolysis, or ammonolysis; selective dissolution; and even (albeit more technically and economically challenging) pyrolysis or gasification. A company like SABIC tried to make a new material with added value, so they selected a type of glycolysis. Toray which is a PET producer also selected glycolysis. Eastman which is a PET producer selected methanolysis. Carbios, which develops an enzymatic hydrolysis, partnered with Indorama to adapt their process to PET. An even more self-explaining scenario is the one of mixed plastics. With exactly the same waste, Enerkem would selected gasification while others chose pyrolysis. In the first case, Enerkem gasifies to methanol or ethanol, while in the second case the target is to make a stream which can feed a steam cracker - and use that existing asset. The mass yield is poor in the case of the steam cracker, and will always be low, because of the high energy and temperature needed to depolymerize PE and PP back to the olefins (Figure 2). The mass yield could be much higher with gasification, especially with added hydrogen from electrolysis. But the assets of a steam cracker are so expensive that the petrochemical companies want to fill them as much as possible. They could have selected, with the same TCI, to invest more in waste pretreatment, sorting, washing and mechanical recycling/selective dissolution. But that does not use the steam cracker assets, and would be considered as a form of cannibalization. Similarly, smaller plants have a larger uncertanty in the TCI vs capacity (Figure 12), also because in some cases the product can be diluted in a bigger stream (like pyrolysis oil in a steam cracker), and the hydrothermal section of the plant to remove heteroatoms (e.g. N,O, or S) can be omitted. At the same time, however, smaller plants are more prone to reuse existing assets compared to bigger plants, so that albeit not always the best choice, executives are more inclined to give them the green light.

What ultimately the correlations derived in this paper teach us is that there can be a large dispersion of capital cost for the same capacity, but that for the same feedstock and same product, the energy is independent of the route. The correlation is independent here of the details of the process. The guideline for the technology developer is then to select a process which would minimize the energy losses.

For the selective dissolution and solvolysis processes, which are closer to chemical plants, there are a wide diversity of processes. That's also where it would be important to be able to select the right one as early as possible. But there is also a wide diversity of feedstocks and targeted products. For example, in the case of PET, one would not build the same plant to depolymerize bottle grade PET (transparent clear) and unsorted PET textile. In such a case, it will be necessary to have a more complete definition of the process blocks that have to be combined.

Conclusions

To guide decision makers and researchers who are tasked with screening among different chemical recycling technologies, we built a database of over 160 existing industrial facilities from several countries. The majority of our projects are in Europe and North America, with some in Eastern Asia and Australia. We demonstrated that conventional AACE class 5 capital cost

estimation methods are deterministically and/or probabilistically unreliable for chemical recycling projects. In fact, no class of method estimates correctly (and consistently) pyrolysis and gasification projects, while solvolysis and selective dissolution are so early in their technology development journey that it is currently impossible to fully validate the existing correlations.

Starting from as simple as a global plant mass balance, the new empirical equations we propose can estimate the TCI of plastic waste pyrolysis and gasification facilities both easily and accurately.

Convention wisdom[96] not withstanding, we found that plastic recycling plants do not benefit much from economies of scale.

When available, energy losses estimate the TCI way better than the plant capacity, but they are not always possible to calculate. Moreover, one-size fits all scaling factors are not appropriate, especially when the TCI accuracy plays a key role in determining whether or not a project will be profitable.

Future work should focus on expanding the database for solvent based technologies and understanding (similar to what we did for energy-based processes) which variables can correlate directly with the TCI of those processes. Similarly, continuous updates and refinements of the empirical equations proposed in this study will also contribute to improving the accuracy of TCI estimation for different chemical recycling technologies as the industry matures.

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Conflict of Interests

The authors declare no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available in the supplementary material of this article.

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