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# Techno-Economic Assessment of Industrial Hydrometallurgical Recycling of Li-Ion Battery Black Mass

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# Abstract

This thesis presents a techno-economic assessment of an industrial hydrometallurgical process for the recovery of valuable metals from lithium-ion battery black mass. With the growing number of spent lithium-ion batteries due to the fast-growing demand for electric mobility and energy storage systems, recycling technologies need to be assessed not only from a technical and environmental point of view, but also from an economic perspective. Although there is a broad range of studies on process efficiency and environmental aspects in the literature, there is a lack of transparent and structured economic models for industrial-scale black mass refining. This thesis fills this research gap by providing a process-costing framework that combines capital expenditure (CAPEX), operating expenditure (OPEX), and financial performance indicators in a techno-economic model. The study defines a gate-to-gate system boundary starting from black mass feed and ending with battery-grade metal products. The adopted approach is hybrid, combining process-based costing with selected activity-based drivers for indirect cost allocation. The model evaluates economic feasibility under multiple scenarios, including variations in plant scale and metal price assumptions, providing a transparent and scalable tool for assessing the industrial viability of hydrometallurgical black mass recycling and supports decision-making in the context of a rapidly evolving battery value chain.

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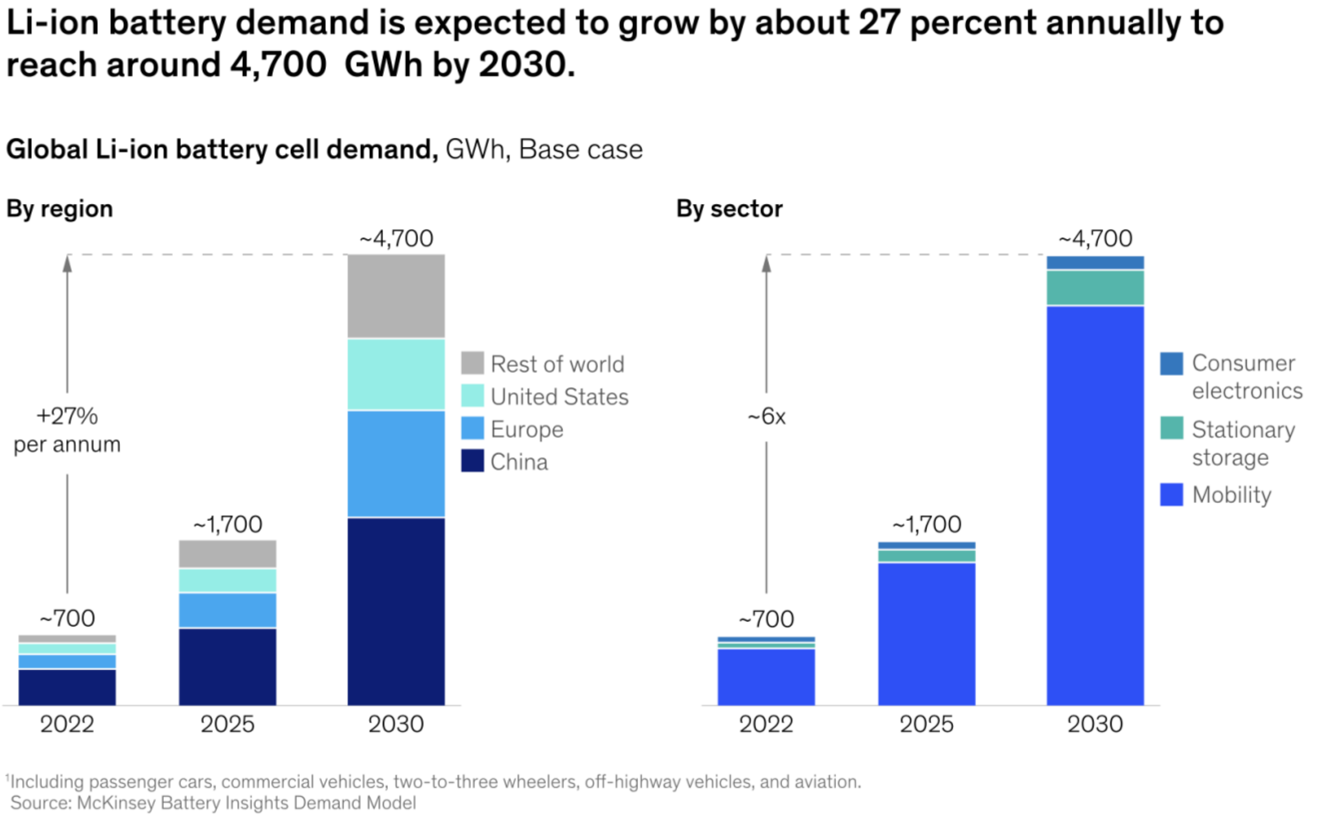
# 1. Introduction

The rapid growth of lithium-ion battery (LIB) technologies has become a key enabler of the global transition toward low-carbon energy systems. In particular, the large-scale deployment of electric vehicles (EVs), stationary energy storage systems, and portable electronic devices has significantly increased the global demand for lithium-ion batteries over the past decade. Projections from international energy agencies indicate that this demand is expected to continue rising sharply in the coming years as electrification expands across multiple sectors of the economy (Abdelbaky *et al.*, 2020; *Global EV Outlook*, 2024).


**Li-ion battery demand is expected to grow by about 27 percent annually to reach around 4,700 GWh by 2030.**

**Global Li-ion battery cell demand,** GWh, Base case

[1]Including passenger cars, commercial vehicles, two-to-three wheelers, off-highway vehicles, and aviation.
Source: McKinsey Battery Insights Demand Model

*Fig. 1: Global lithium-ion battery demand by region and sector (2022-2030). Source:(*Battery 2030: Resilient, sustainable and circular*, 2023)*

While lithium-ion batteries play a central role in decarbonization strategies, their rapid diffusion also raises important challenges related to resource availability and end-of-life management. LIBs contain several critical raw materials, including lithium, nickel, cobalt, and manganese, whose supply is geographically concentrated and often associated with environmental, economic, and geopolitical risks. Ensuring secure and sustainable access to these materials has therefore become a strategic priority for both industry and policymakers (IEA, 2024; European Commission, 2023).

In this context, recycling is increasingly recognized as a key component of a circular battery value chain. By recovering valuable metals from end-of-life batteries, recycling can reduce dependence on primary mining, mitigate environmental impacts associated with raw material extraction, and contribute to the long-term stability of critical material supply chains. For these reasons, several regulatory initiatives have been introduced to promote the development of an industrial battery recycling sector. In the European Union, the new Battery Regulation establishes ambitious targets for collection efficiency, recycling efficiency, and the recovery of critical materials from spent batteries (European Commission, 2023).

Within the battery recycling chain, mechanical pre-treatment processes are typically used to dismantle, shred, and separate battery components. These operations generate an intermediate material commonly referred to as black mass, a fine powder containing graphite and cathode active materials enriched in valuable metals such as lithium, nickel, cobalt, and manganese. Because black mass concentrates the economically valuable elements of the battery, it is widely considered the primary feedstock for downstream metallurgical refining processes (Woeste et al., 2024; Neumann et al., 2022).

Among the available recycling technologies, hydrometallurgical processes have gained increasing attention due to their ability to selectively recover multiple metals with high purity. These processes typically involve a sequence of chemical operations, including leaching, purification, separation, and precipitation, aimed at transforming the heterogeneous black mass feedstock into marketable metal compounds such as lithium carbonate and transition metal sulphates (Neumann et al., 2022; Dai et al., 2019). As industrial interest in battery recycling continues to grow, evaluating the economic feasibility of these processes at industrial scale becomes a critical research and investment challenge.

## 1.1 Research Motivation

The academic literature has made substantial progress in characterizing the technical foundations of lithium-ion battery (LIB) recycling. High-citation reviews synthesize industrial routes, classify unit operations, and compare outputs in terms of recovery efficiency and product quality, thereby clarifying the process steps that shape technological performance (Li *et al.*, 2018; Harper *et al.*, 2019). For instance, Latini et al. analyse recycling technologies through a unit-operation perspective and highlight product purity as a key factor for enabling closed-loop battery material cycles (Latini et al., 2022). Complementary studies comparing metallurgical routes show that pyrometallurgical and hydrometallurgical processes differ significantly in robustness, recovery scope, and operational requirements, while also recognizing that economic considerations play a central role in route selection (Brückner, Frank and Elwert, 2020).

Recent research has also highlighted the growing importance of feedstock complexity. In industrial practice, black mass streams are often processed without perfect pre-sorting, and mixed cathode active material (CAM) inputs may affect both process performance and separation efficiency. Petzold et al. show that variations in feedstock composition can materially influence recovery outcomes and economic drivers, reinforcing the need to consider realistic industrial conditions when evaluating recycling technologies (Petzold et al., 2025).

Although the technical basis of hydrometallurgical recycling is increasingly well understood, translating these process configurations into reliable economic assessments remains a more challenging task. Capital investment requirements, operating expenditures, and project bankability depend on whether process flowsheets can be translated into transparent and replicable cost structures under realistic market conditions (Zeng, 2025). Techno-economic assessment (TEA) has therefore emerged as a key methodological bridge between laboratory-scale research and industrial deployment. Zeng emphasizes that laboratory studies often underrepresent economic constraints, highlighting the need for TEA approaches based on detailed mass and energy balances across unit operations (Zeng, 2025).

Existing TEA studies for black-mass recycling provide useful insights but also reveal methodological limitations. Comparative analyses such as the work of Woeste et al. demonstrate how economic results depend strongly on system boundaries, cost assumptions, and the level of detail used in capital cost estimation (Woeste et al., 2024). Similarly, Petzold et al. show that the economic performance of recycling systems depends on feedstock characteristics and sorting strategies, indicating that recycling processes cannot be treated as homogeneous "black boxes" when evaluating profitability under different industrial conditions (Petzold et al., 2025).

Another important challenge concerns the economic treatment of black mass itself. As black mass increasingly becomes a traded intermediate material, the profitability of refining operations depends not only on internal processing costs and recovery yields but also on feedstock pricing mechanisms and payable-metal assumptions. Studies on battery recycling supply chains highlight that black-mass valuation and upstream supply configurations can significantly influence the economic competitiveness of recycling plants (Wesselkaemper et al., 2025).

At the same time, regulatory frameworks are progressively introducing stricter requirements for recycling efficiency and material recovery verification. The European Battery Regulation establishes standardized methodologies for calculating recovery rates and recycling efficiencies, reinforcing the need for transparent and auditable process models capable of linking material balances with economic performance (European Union, 2023).

Taken together, these developments indicate that the economic viability of hydrometallurgical black-mass refining is becoming as important as its technical feasibility. While the technical processes for recovering metals from black mass are well documented, the literature still provides limited availability of structured and transparent economic models capable of linking process parameters, cost structures, and financial performance under realistic industrial scenarios (Yu *et al.*, 2022).

This thesis addresses this gap by developing a process-based techno-economic model for the hydrometallurgical recycling of lithium-ion battery black mass. The model aims to provide a transparent framework for estimating capital and operating costs, linking them to process parameters and material balances, and evaluating economic feasibility through scenario analysis under evolving market and regulatory conditions.

## 1.2 Thesis Objectives

The primary objective of this thesis is to assess the economic feasibility of a hydrometallurgical process for the recovery of valuable metals from lithium-ion battery black mass.

Specifically, the thesis aims to:

1. Define the system boundaries for an industrial hydrometallurgical black mass refinery under a gate-to-gate perspective.
2. Develop a transparent CAPEX model distinguishing direct costs, indirect costs, contingency and working capital.

3. Develop a detailed OPEX structure separating variable and fixed cost components.
4. Implement an Excel-based techno-economic model capable of generating annual cash flows and financial indicators.
5. Evaluate economic performance under alternative scenarios including variations in scale and metal prices.
6. Identify key sensitivity drivers influencing profitability.

## 1.3 Thesis Structure

The remainder of this thesis is organized to progressively move from the technical background of lithium-ion battery recycling to the techno-economic assessment developed in this study.

Chapter 2 reviews the industrial and technological context of lithium-ion battery recycling, with particular attention to hydrometallurgical refining processes for black mass. The chapter describes the main unit operations involved in hydrometallurgical recycling and discusses the key process parameters that influence metal recovery and process performance. It also reviews techno-economic assessment approaches adopted in the literature and identifies the main economic drivers and research gaps related to black mass recycling.

Chapter 3 introduces the methodological framework used for the techno-economic analysis. The chapter discusses the costing methodologies applied in industrial TEA studies and presents the approach adopted in this thesis to estimate capital and operating costs. It also defines the economic performance indicators used to evaluate the profitability of the recycling process.

Chapter 4 defines the system boundaries and modelling assumptions of the case study. The chapter describes the hydrometallurgical refining process considered in the analysis, specifies the system inputs and outputs, and clarifies which process stages are included within the scope of the assessment. It also presents the structure of the techno-economic model and the main scenario assumptions used in the analysis.

Chapter 5 presents and discusses the results of the techno-economic assessment. The chapter analyses the cost structure of the recycling process, evaluates the effect of key technical and economic parameters on economic performance, and identifies the main drivers influencing the profitability of hydrometallurgical black mass refining.

The annex provides supplementary material supporting the analysis, including additional methodological details and Excel model parameters.

# 2. Literature Review on Black Mass Recycling and Economic Analysis

The increasing demand for lithium-ion batteries (LIBs) in electric vehicles and consumer electronics is leading to an exponentially growing number of end-of-life LIBs. By 2030, an estimated 2 million metric tons of spent LIBs per year will need to be processed globally. Yet currently only a small fraction of LIB waste (on the order of 5% or less) is being recycled (Woeste *et al.*, 2024).

This has serious implications in terms of the potential for environmental contamination (toxic metals and electrolytes leaking into soil or water) and the loss of valuable critical materials. Closed-loop recycling is therefore essential to recycle metals such as cobalt, nickel, and lithium, thus reducing the dependence on mining and the environmental impact of battery supply chains (Kemperdick *et al.*, 2025).

In response, researchers and industry are developing efficient recycling strategies. The two primary approaches are pyrometallurgical (high-temperature smelting) and hydrometallurgical (wet-chemical processing) recycling, alongside emerging direct recycling methods. This review focuses on the hydrometallurgical route, which processes the intermediate black mass powder obtained from spent LIBs, to recover valuable metals for reintegration into new batteries (Zanoletti *et al.*, 2024).

*Fig. 2: Black mass obtained from mechanical processing of spent lithium-ion batteries. Source: ISPI.*

## 2.1 Industrial Recycling Routes for LIB

This process can be interpreted as a sequence involving three steps: pre-treatment, black mass concentration and chemical/metallurgical recovery, with variants differing in industrial maturity, recovery selectivity and feed quality requirements (Zhou *et al.*, 2020). Pre-treatment activities typically include safety, disassembly at the pack/module/cell level, and mechanical treatments (shredding, grinding, screening, magnetic and densiometric separations) aimed at separating coarse fractions (steels, plastics) and collector metals (Cu/Al) from the fine fraction (black mass) (Sommerville *et al.*, 2020; Neumann *et al.*, 2022). The variability of battery pack design and assembly makes disassembly a non-negligible and highly product-dependent operational driver (Lander *et al.*, 2021).

In the industrial domain, attention to black mass is also motivated by the fact that it represents a substantial share of the cell mass and concentrates the metallurgical value: in recent techno-economic analyses it is assumed to be in the order of ~50% of the cell mass as a fraction recovered downstream of crushing and screening, making it plausible to treat it as a dedicated feedstock for "refinery-type" plants (Petzold *et al.*, 2025). Process and impact models also show that the quality of the black mass (in particular the residual Al/Cu content and the presence of electrolyte species) is a determinant of both the complexity of the hydrometallurgical circuits and the wastewater treatment load (Brückner, Frank and Elwert, 2020; Woeste *et al.*, 2024).

Within this framework, established industrial pathways can be distinguished into: pyrometallurgy (smelting), often followed by hydrometallurgical refining of the matte/alloy; black mass hydrometallurgy (with variable thermal pre-treatments and upstream physical separations); and direct recycling (recovery and regeneration of the cathode powder), which is even less mature and strongly constrained by the purity and homogeneity of the feed (Dai *et al.*, 2019; Brückner, Frank and Elwert, 2020; Neumann *et al.*, 2022; Lin, Li and Chen, 2025).

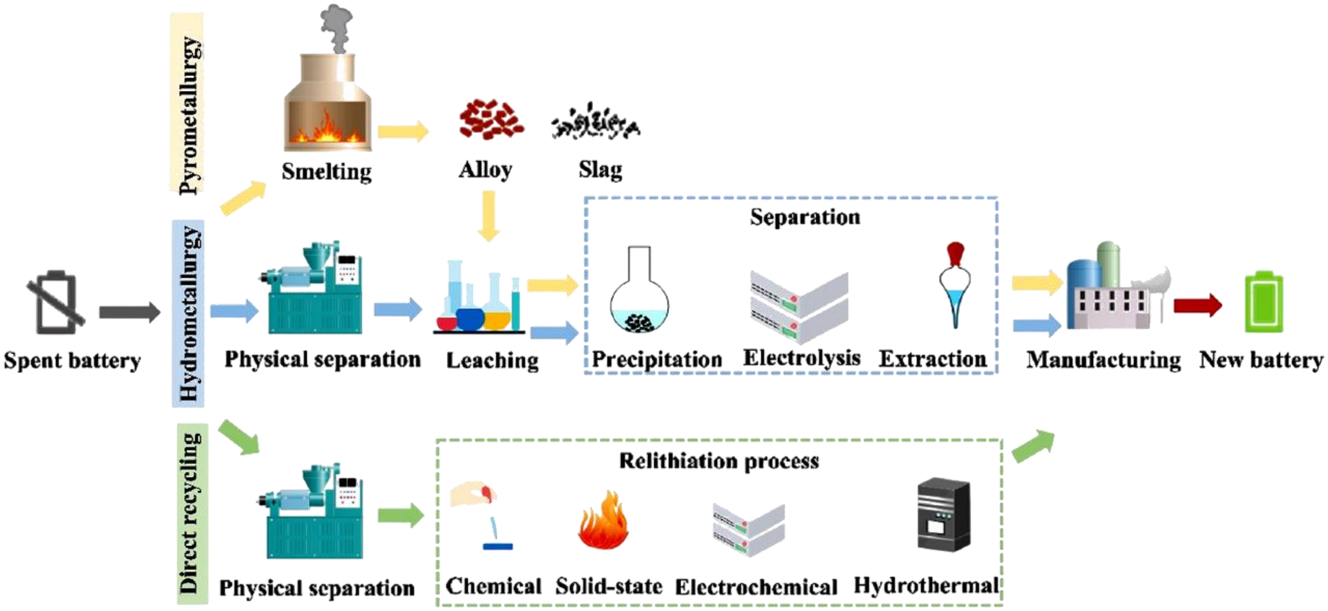


*Fig. 3: Typical LIBs recycling routes of pyrometallurgy, hydrometallurgy, and direct recycling. Source: (Zhao* et al.*, 2024).*

Pyrometallurgy is generally described as robust to feed variability and operationally compatible with heterogeneous mixtures, but tends to favour the recovery of Co/Ni/Cu in a matte/alloy with lower selectivity , often requiring a complementary hydrometallurgical step to obtain salable salts or metals; Lithium recovery is less systematic and partly associated with slag/dust, with economic and environmental implications (Dai *et al.*, 2019; Brückner, Frank and Elwert, 2020).

Black mass hydrometallurgy is instead positioned in the literature as the most suitable route for the production of high purity products (sulphates, carbonates/hydroxides) and for lithium recovery; however, it requires a more stringent control on impurities and management of aqueous flows, and incorporates significant chemical consumption (acids, bases, extractants) (Neumann *et al.*, 2022; Rinne *et al.*, 2024).

Consistent with the transition towards "Co-lean" cathodes (NMC Ni-rich and increasing LFP share), TEA studies focused on black mass indicate that hydrometallurgical routes are more resilient to chemistry and price variations, at the same scale and configuration, while pyrometallurgical routes strongly linked to the Co value show greater exposure to market dynamics (Wang *et al.*, 2024; Woeste *et al.*, 2024).

Direct recycling is discussed as a potentially superior alternative in terms of cathode value retention, as it aims to directly recover and regenerate the cathode powder rather than decomposing it into metals and reconstructing the active material. In a comparison based on cost-process and LCA models, direct regeneration can be economically competitive and more efficient from an energy and emission point of view, especially for low metallurgical value chemistries (e.g. LFP), provided that the yield and quality of the regenerated powder are guaranteed (Ciez and Whitacre, 2019; Zhao *et al.*, 2024).

However, the same literature highlights that industrial maturity is lower and that the variability of the feed (mixture of CAM, contamination from collectors, binder and electrolyte) makes standardization more complex, making the industrial adoption of hydro/pyro routes as workhorse solutions frequent in the short term (Neumann *et al.*, 2022; Das *et al.*, 2025).

## 2.2 Hydrometallurgical Recycling Process Description

Hydrometallurgical recycling of black mass typically follows a sequence of interconnected unit operations aimed at dissolving valuable metals and subsequently recovering them in purified form. In general terms, the process begins with the leaching stage, in which the active materials contained in the black mass are chemically dissolved into an aqueous solution. The resulting slurry is then subjected to solid–liquid separation to remove insoluble residues, while the liquid phase retains the dissolved metal species (Davis and Demopoulos, 2023).

The metal-bearing solution is subsequently treated through purification and separation steps designed to selectively recover transition metals such as nickel, cobalt and manganese, either as individual high-purity products or as mixed precursor materials (Dutta *et al.*, 2011; Dunn, Kendall and Slattery, 2022). Once transition metals have been recovered, lithium is typically extracted from the remaining solution through precipitation reactions. Finally, the process is complemented by wastewater treatment and residue management operations, which ensure the neutralization of effluent streams and the safe handling of process residues (Rossi *et al.*, 2024).

The following subsections describe these stages in greater detail, focusing on the main technical characteristics of each unit operation and their implications for industrial process design.

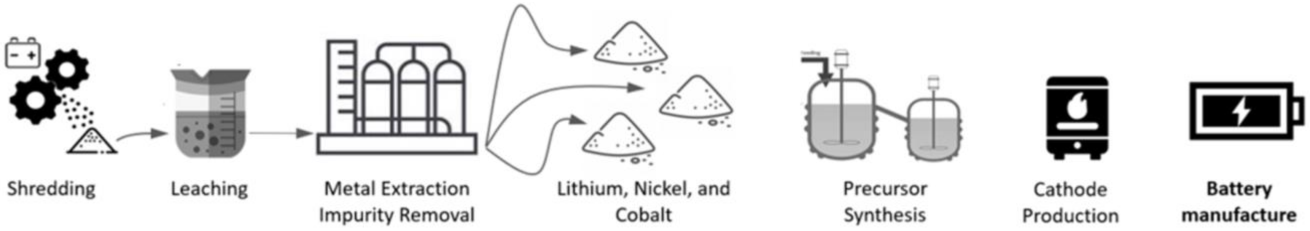


*Fig. 4: Simplified representation of the hydrometallurgical recycling process for lithium-ion batteries. Source: (Rossi* et al.*, 2024).*

### 2.2.1 Leaching

Leaching converts valuable metals from the solid phase into an aqueous "pregnant leach solution" (PLS), leaving an insoluble residue. Industrial and near-industrial descriptions commonly use sulfuric-acid-based leaching, often with a reductant depending on feed characteristics, operated at atmospheric pressure over moderate temperatures. Reported patented process conditions span from room temperature to around 80 °C, with solid-to-liquid ratios and acid concentrations varying widely across routes; this variability is consistent with feed heterogeneity and different separation philosophies downstream (Rossi *et al.*, 2024).

For economic modelling, leaching is not only a chemical step but a major "cost formation" point: it sets the solution volume to be treated downstream, the reactor sizing (and therefore a portion of CAPEX), and the baseline consumption of the most expensive bulk reagents (acid and reductant). Simulation-based studies explicitly identify leaching as acid-consuming, with sulfuric acid demand scaling with the amount of active material dissolved (Rinne *et al.*, 2024).

### 2.2.2 Solid–Liquid Separation and Residue Washing

After leaching, solid–liquid separation removes the leach residue from the PLS. This residue is frequently graphite-rich (originating from the anode and residual carbonaceous materials), while the liquid phase contains dissolved transition metals and lithium in sulphate form (for sulphate leaching routes). Industrial routes typically employ filtration (e.g., filter press) or, in some configurations, centrifugation, followed by washing to recover entrained solution and to control downstream impurity carryover (Rossi *et al.*, 2024).

Two economic considerations are central here. First, solid–liquid separation capacity (filtration area, cycle times, wash ratios) can become a throughput bottleneck and often drives equipment sizing and redundancy. Second, washing generates additional aqueous streams that later appear as wastewater volumes or internal recycle loads, affecting both utilities and effluent treatment duty (Rossi *et al.*, 2024).

### 2.2.3 Metal Purification and Separation

Purification and separation transform the multi-metal PLS into either individual metal products (high purity salts/solutions for Ni, Co, Mn) or mixed precursor products (e.g., mixed hydroxide/carbonate), depending on the chosen flowsheet.

Two broad industrial families are repeatedly distinguished in refinery-oriented reviews and industrial flowsheet discussions:

- Complete separation: sequential separation of individual metals through solvent extraction (SX), ion exchange, electrowinning, and/or crystallization. This approach produces discrete product streams (e.g., nickel sulphate, cobalt sulphate, manganese carbonate/dioxide) and requires multiple circuits with associated control complexity (Verbaan and Naidoo, 2023).
- Direct precursor production (mixed precipitation): precipitation of a mixed Ni–Co–Mn hydroxide/carbonate (a "CAM cake" or precursor) with fewer separation steps, often followed by lithium recovery from the remaining solution. This route can reduce separation complexity but

ties the output to specific downstream battery precursor uses and can be sensitive to feed chemistry variation (Rossi *et al.*, 2024).

Across both families, impurity management is a recurring unit-operation block. Typical impurities include Al and Cu from current collectors and additional elements introduced by feed diversity (e.g., F and P from electrolyte and cathode chemistry). Common strategies include pH-controlled precipitation (hydroxide removal of Fe/Al), copper recovery via cementation, sulphide precipitation, or solvent extraction, and, in some configurations, the formation of gypsum and $CaF_2$ when calcium-based reagents are used (Verbaan and Naidoo, 2023).

Operationally, purification stages determine downstream product quality and therefore revenue assumptions (battery-grade vs technical-grade), while also contributing to consumables (alkali usage, extractant losses) and residue disposal volumes. Reviews of industrial routes emphasize that handling organic and halogen-containing components contributes disproportionately to technical difficulty and cost, reinforcing why impurity control cannot be treated as a peripheral activity (Brückner, Frank and Elwert, 2020).

### 2.2.4 Lithium Recovery

Lithium recovery is commonly implemented after transition-metal recovery, when the raffinate contains lithium as the principal remaining valuable element. A frequent route is precipitation as lithium carbonate using sodium carbonate, with pH adjustment and subsequent solid separation, washing, and drying. Due to lithium carbonate solubility constraints, evaporation/concentration may be needed to achieve crystallization targets, making the lithium section potentially energy intensive (Rinne *et al.*, 2024).

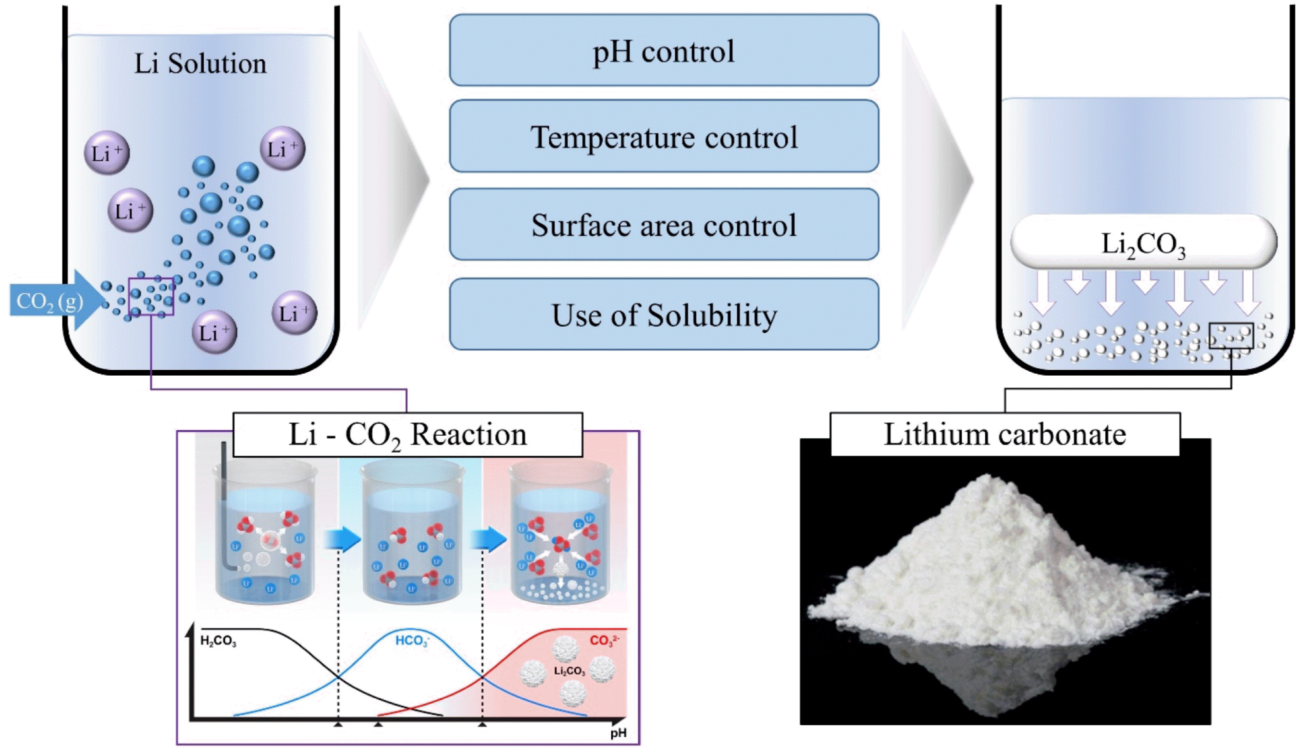


*Fig. 5: Schematic representation of lithium carbonate precipitation from lithium-bearing solutions through carbonate formation and crystallization. Source: (Kim* et al.*, 2023)*

The route selected for lithium has direct economic implications. Precipitation with soda ash can introduce significant sodium sulphate formation in sulphate-based flowsheets, increasing downstream brine management or by-product handling requirements; alternative reagent systems (e.g., ammonia-based chemistries in some proposed flowsheets) are sometimes discussed specifically to alter the by-product slate (Verbaan and Naidoo, 2023).

### 2.2.5 Wastewater Treatment and Residue Management

Wastewater treatment is structurally embedded in black mass hydromet flowsheets because multiple steps generate aqueous streams: leach residue washing, impurity precipitation filtrates, crystallization mother liquors, and general wash-down and cleaning streams. Process descriptions explicitly route mother liquors and wash waters to wastewater treatment, and gate-to-gate models treat effluent management as part of the core system rather than an externality (Rossi *et al.*, 2024).

Typical wastewater treatment logic consists of pH neutralization, precipitation of dissolved metals and fluorine-related species, solid–liquid separation for sludge removal, and controlled discharge or recycle. In simulation-based flowsheets, effluent streams are subjected to final neutralization (e.g., with lime milk), reflecting the practical necessity to stabilize dissolved species before discharge (Rinne *et al.*, 2024).

## 2.3 Techno-Economic Assessment Approaches in Battery Recycling

TEA applied to Li-ion recycling is placed between process modelling and industrial finance: it defines system boundaries, plant configuration, scale assumptions and capacity factors, and translates physical flows into cash flows through CAPEX/OPEX structures and assumptions on revenues from products and co-products (Choux *et al.*, 2024).

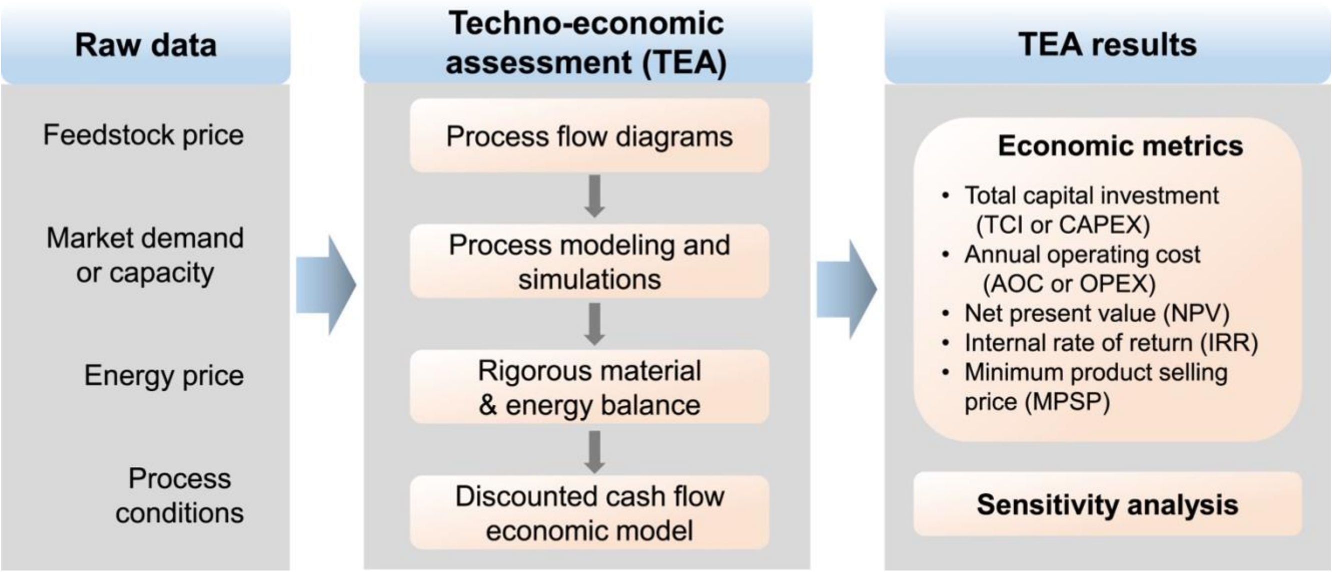


*Fig. 6: The framework of TEA. Source: (Fu* et al.*, 2023)*

In the black mass sector, the most recurring methodological issue is the choice between "gate-to-gate" boundaries (refinery that processes black mass) and "supply-chain inclusive" (collection, transport, disassembly, pre-treatment, refining), because it shifts the cost centre of gravity and modifies the interpretation of the result (cost/revenue of refining vs. cost/revenue of the entire chain) (Dai *et al.*, 2019; Lander *et al.*, 2021; Rinne *et al.*, 2024).

A first strand of TEA adopts economic models integrated with standard financial indicators (NPV, IRR, payback) and scenario/sensitivity analyses. The model by Lander et al. explicitly integrates geographical and logistical variability, highlighting that the profitability of the chain can fluctuate from loss to profit depending on transport distances, wages, pack design and the chosen recycling route; the result is expressed as profit/cost per battery energy unit (Lander *et al.*, 2021). Consistently, institutional interventions underline that the economic component of recycling critical minerals depends significantly on the regional context and economies of scale, as well as on the availability of feedstock and vertical integration (*Global EV Outlook*, 2024).

A second strand, particularly relevant for black mass, uses extended Total Cost of Ownership (TCO) approaches to include product sales revenues. Woeste et al. apply a TCO that includes cash flows associated with the operation and "internalizes" revenues; the comparison between pyrometallurgical and hydrometallurgical routes (with early lithium recovery) emphasizes the non-linearity between market conditions and economic performance and calls for scenarios on material prices and chemistry mixes (Woeste *et al.*, 2024). Similarly, Petzold et al. use a multi-year TCO to evaluate the economic effect of pre-sorting (CAM mix) before hydrometallurgy, showing that feed composition simultaneously modifies process performance and revenue/cost profile (Petzold *et al.*, 2025).

Methodological standardization is partially supported by open-model tools. EverBatt, developed by Argonne National Laboratory, provides a modular Excel model for cost-environmental comparisons along multiple stages (virgin production, collection/transport, recycling, material conversion, cathode powder production, recycled production), including pyrometallurgical, hydrometallurgical and direct recycling routes and allowing scaling-up/down via capacity curves and geographical variations on utility, labour and disposal costs. In the documented version, the recycling module works at cell level and reports the absence (or partial representation) of typical pack recycling operations such as discharging and disassembly, implicitly highlighting how boundary assumptions influence the interpretation of the results (Dai *et al.*, 2019).

Methodological differences between TEA studies, besides boundaries, concern functional unit (€/t black mass, €/t cells, $/kWh), product valorisation modalities (spot prices, discounts, payables), treatment of co-products and residues (economic allocation, avoided burden credits, or disposal costs), uncertainty modelling (discrete scenarios vs. broader parametric sensitivity) (Yazıcı *et al.*, 2025). The literature on the economics of critical mineral recycling notes that many transactions of recycled materials are indexed to market prices and that volatility may require financial robustness and the ability to absorb day-to-day variations; in the case of black mass, this translates into the need to explicitly model payables and discounts compared to battery-grade salt/metal prices (*Global EV Outlook*, 2024).

A cross-cutting element, often cited as a limitation, is data transparency: even in open access studies, industrial cost data can remain confidential, reducing replicability. Woeste et al. explicitly declare the confidential nature of the data used, an aspect that requires caution in transferring results between contexts and reinforces the need for parameterized and auditable models for theses and investment decisions (Woeste *et al.*, 2024).

## 2.4 Cost Structure and Economic Drivers of Battery Recycling

The TEA literature identifies a black mass recycling cost structure dominated by feedstock cost (when purchased), reagent and utility consumption, labour, treatment and disposal costs, as well as CAPEX for auxiliary equipment and facilities. The centrality of black mass cost becomes clear when the system is modelled as a refinery purchasing feed on the market: in an assessment based on industrial data and techno-economic modelling, black mass can represent a share close to half of the total costs of a hydrometallurgical plant, with utilities and fixed costs (including labour) as subsequent components . This implies that, in an industrial plant model, black mass cannot be treated as “zero-cost waste” without introducing a systematic bias in the estimated profitability.

CAPEX front, available models oscillate between bottom-up approaches (estimation by equipment and installation factors) and factorial/scaling approaches (cost curves and indices). EverBatt makes explicit the use of sizing/cost curves and supports scaling analyses within capacity ranges, while more targeted academic studies construct CAPEX from process layout and equipment assumptions (Dai *et al.*, 2019; Petzold *et al.*, 2025). The CAPEX component is particularly sensitive to the separation philosophy: multi-circuit SX, electrowinning and crystallization tend to require more plant complexity than flowsheet with co-precipitation and precursor production, but the latter can transfer complexity downstream (conversion to CAM) and constrain the saleability of the product (Verbaan and Naidoo, 2023).

For OPEX, black mass studies converge in placing energy and consumables among the main items, although the relative weight depends on scale and architecture. In Petzold et al., energy and materials each represent a relevant fraction of the total cost, with ranges reflecting process and feed scenarios (Petzold *et al.*, 2025). In Woeste et al., sensitivity analysis indicates that energy and material costs are determinants of the economic feasibility of both considered routes, with further dependence on the operational set-up (e.g., need for continuous operation for high temperature pyrometallurgical units) (Woeste *et al.*, 2024). Chemical input is also the main bridge between process performance and cost: reductions in acid concentration in the leaching, when technically feasible, are reflected in reductions in neutralizer requirements and effluent loads, simultaneously impacting OPEX and treatment infrastructure (Rinne *et al.*, 2024).

A critical economic driver is the feedstock composition (mix of Ni/Co/Mn/Li chemistries and concentrations) and the related value "dilution." Petzold et al. show that the presence of LFP in the black mass impacts not only the value of recoverable metals, but also the process efficiency due to impurities and chemical specificities, making it non-trivial to indiscriminately extend NMC-centric flowsheets to the treatment of phosphate-containing feeds (Petzold *et al.*, 2025). Consistently, industry reviews report that lithium recovery is in many cases less systematic than Co/Ni/Cu and that graphite and electrolyte remain technically recoverable but economically challenging components, also due to quality issues and handling of organic/halide-containing species (Brückner, Frank and Elwert, 2020). This explains why, in many TEAs, profitability is highly concentrated on Ni/Co (and partly Li), while the "low value" fractions enter as residual management costs or marginal revenues.

Plant scale produces economies of scale effects especially through the dilution of fixed costs (labour, maintenance, insurance, G&A, depreciation) and a better saturation of critical equipment. Woeste et al. explicitly discuss that an increase in throughput can improve the ratio between fixed costs and output, although proportional investments and operational constraints must be considered, especially in pyrometallurgy (Woeste *et al.*, 2024). Institutional analyses on the economics of battery recycling also highlight that regions with greater vertical integration and large volumes (e.g. contexts with strong industrialization of the supply chain) obtain more favourable cost-revenue profiles, while in emerging markets profitability is more fragile and linked to volumes and stability of the feed (*Global EV Outlook*, 2024).

Metal price volatility and the construction of black mass pricing mechanisms (payables and discounts) constitute the main source of external uncertainty in TEAs. In the case of purchased black mass, the dominant share of input cost makes refining margins sensitive to a few percentage points of variation in payables or battery-grade prices of Ni/Co/Li salts; in parallel, the decrease in Co content in EV chemistries reduces the economic "buffer" of pathways that base a large part of the value on Co, pushing the literature towards robustness assessments of the hydrometallurgical pathway and towards hypotheses of upcycling/precursor production as value capture strategies (Woeste *et al.*, 2024; Wesselkaemper *et al.*, 2025).

Cost estimation in emerging technologies remains affected by uncertainties due to non-public industrial data, non-homogeneous maturity of unit operations (particularly in direct recycling variants and innovative hydromet flowsheets), assumptions on wastewater treatment and product quality specifications, learning and scale-up effects. The combination of these factors suggests that a methodological chapter oriented to the construction of a TEA model for black mass should (a) make boundaries and functional unit explicit, (b) link mass-energy balances to reagent consumption and yields,

(c) parameterize payables/prices and allow multi-parameter sensitivity analyses on scale, chemistry mix, yields and utility costs (Dai *et al.*, 2019; Woeste *et al.*, 2024; Petzold *et al.*, 2025).

## 2.5 Key Technical Parameters Relevant for Economic Analysis

Techno-economic models of lithium-ion battery recycling rely on a set of technical parameters that link process performance to economic outcomes. In hydrometallurgical black mass refining, variables such as feed composition, operating conditions, recovery efficiencies and waste generation directly influence reagent consumption, equipment sizing, energy demand and ultimately the revenues generated by recovered products. As a result, the economic performance of a recycling process cannot be evaluated independently of its underlying technical assumptions.

The literature therefore identifies several categories of parameters that are particularly relevant for techno-economic analysis. These include feed-related characteristics of the black mass, operational variables governing leaching and downstream separation processes, lithium recovery conditions, and overall recovery yields for valuable metals. In addition, waste generation and treatment requirements represent an important component because they affect both operating costs and environmental management obligations. The following subsections summarize the key technical parameters commonly reported in the literature and discuss their relevance for economic modelling of black mass recycling processes.

### 2.5.1 Feed-Related Parameters

Black mass grade and impurity profile determine the maximum achievable revenues and the intensity of purification. Industrial data show black mass categories typically described as “high cobalt” vs “high nickel” (reflecting cathode chemistry mix), with illustrative ranges for Co and Ni mass fractions and lithium content in a few percent range; moisture and particle size ranges are also reported. These parameters influence throughput economics (metal units per tonne), reagent requirements per tonne, and waste generation (Verbaan and Naidoo, 2023).

Market-linked black mass pricing (payables) is a pivotal economic input: when the feed purchase cost is indexed to payable metal value, profitability becomes highly sensitive to metal prices and payables assumptions, and the refinery’s value-add is measured against this market baseline rather than against “zero-cost waste” (*Recycling of Critical Minerals*, 2023).

### 2.5.2 Leaching Parameters

Solid-to-liquid ratio (S/L) and solution volume govern reactor sizing, pumping, filtration duty, and (downstream) separation circuit loading. Industrial patents and assessments report S/L choices spanning roughly 10% solids (≈1:10) down to more concentrated regimes in certain contexts, while also noting practical constraints for downstream separations at higher concentrations. Acid consumption is often the dominant bulk chemical consumption term. Simulation-based studies provide order-of-magnitude indications of sulfuric acid demand scaling with dissolved active material and explicitly identify acid consumption optimization as a major lever because leaching is inherently acid-consuming (Rossi *et al.*, 2024).

Reductant requirement (where needed) affects variable OPEX and, in some flowsheets, can be partially substituted by "self-reducing" impurities such as Fe/Cu-bearing fractions in the feed. This concept is used in gate-to-gate flowsheet modelling, and it is economically relevant because reductants can be significant consumables (Rinne *et al.*, 2024).

Residence time and temperature influence vessel volume (CAPEX) and thermal energy demand (OPEX). Industrial conditions reported in high-TRL descriptions span moderate temperatures up to ~80 °C at atmospheric pressure, supporting the view that energy duty is non-trivial but typically lower than pyro-based routes, while chemical costs remain prominent (Rossi *et al.*, 2024).

### 2.5.3. Separation and Purification Parameters

Choice of separation route (mixed precipitation vs SX-based complete separation) is a first-order structural parameter in the cost model. Mixed precipitation typically has fewer unit operations and can reduce chemical diversity, while SX-based routes increase circuit count, require organic chemicals, and introduce additional equipment and control complexity. Agency and industrial sources explicitly separate these approaches and relate them to product flexibility and process complexity (Rossi *et al.*, 2024).

Solvent extraction reagent consumption and losses should be represented even when organics are largely recycled. Simulation-based analysis shows that SX chemicals can be a meaningful contributor and should not be omitted simply because they circulate; extractants such as Cyanex 272 are explicitly referenced in modelled flowsheets and industrial practice discussions (Rinne *et al.*, 2021).

Impurity precipitation dosage and sludge formation affect both reagent cost and disposal cost. Calcium-based impurity control can form gypsum and improve fluoride removal via $CaF_2$ formation, altering residue mass and handling requirements; such trade-offs are highlighted in industrial flowsheet reviews (Verbaan and Naidoo, 2023).

### 2.5.4 Lithium Recovery Parameters

Lithium recovery yield and product form ($Li_2CO_3$ vs alternative products) affect revenue and downstream utility demands. Reviews of industrial routes underscore that lithium recovery has historically been less consistently achieved than Ni/Co/Cu recovery, and that full lithium recovery often requires dedicated hydromet circuits (Brückner, Frank and Elwert, 2020).

Energy intensity of concentration/crystallization can be material in lithium carbonate production because evaporation may be required to overcome solubility constraints (Ding *et al.*, 2025). Gate-to-gate flowsheet descriptions explicitly note the need for water evaporation in lithium carbonate crystallization conditions (Rinne *et al.*, 2024).

### 2.5.5 Recovery Yields as Economic Multipliers

Recovery yields act as multipliers on revenue and also affect metal inventory circulating in the plant (and therefore recycle loads and reagent intensity). Example modelled scenarios illustrate that reduced-acid operation can materially lower recoveries (illustrative recoveries in the ~80–86% range for Li/Co/Ni/Mn under a low-acid scenario) compared to baseline conditions, demonstrating the trade space between reagent savings and revenue loss (Rinne *et al.*, 2024).

For cost modelling, it is useful to treat yields at two levels:

- Stage extraction efficiencies (e.g., leaching dissolution fraction; SX distribution performance; precipitation yield) for mass balance closure and equipment sizing (Rinne *et al.*, 2024).
- Overall recovery to final products (per metal), used for revenue calculation and for sensitivity analysis. Industrial-economic frameworks repeatedly emphasize that profitability sensitivity to yields is high because product prices and payables are volatile, while many operating costs scale with throughput regardless of yield (Lander *et al.*, 2021; Seo *et al.*, 2025).

### 2.5.6 Waste Generation and Treatment Loads

Waste generation metrics that affect OPEX (treatment, disposal) and sometimes CAPEX (treatment plant sizing) include:

- Mass of leach residue (often graphite-rich) and its potential upgrading vs disposal route. Industrial descriptions note filtration-based removal and optional purification steps for graphite product generation (Rossi *et al.*, 2024).
- Mass of hydroxide/gypsum sludges and metal-bearing precipitates from impurity removal and wastewater treatment (Verbaan and Naidoo, 2023).
- Volume of wastewater and mother liquors requiring treatment and/or recycle, explicitly present in industrial flow diagrams (Rossi *et al.*, 2024).

## 2.6 Research Gaps and Limitations

Despite the growing body of work on LIB recycling economics, there are clear methodological gaps and limitations in the existing studies. These gaps motivate the need for a more structured, transparent, and scalable economic model for hydrometallurgical black mass recovery. Key limitations identified in the literature include:

- **Non-Transparent and Simplified Cost Assumptions:** Many studies rely on proprietary or opaque data for costs, making it difficult to scrutinize or reproduce their results. For instance, Woeste *et al.* (2024) noted that the detailed cost data feeding their TCO model were confidential. Similarly, Petzold *et al.* (2025) only provide aggregate cost breakdowns in their publication, with granular data available upon request. This lack of transparency means readers cannot always tell what specific unit costs (e.g. price of sulfuric acid per ton, labour rates, etc.) were assumed. Moreover, some analyses use oversimplified costing methods (for example, applying a flat cost per kg for processing or using a generalized scale-up factor) without detailing the engineering basis. While such methods can give a rough estimate, they hide key assumptions. Equipment cost models are often based on scaled estimates from other industries (using the six-tenths rule, etc.), which may not accurately reflect novel battery recycling systems. In short, the literature would benefit from more open-data approaches where assumptions and cost models are explicitly stated or shared. The lack of standardized cost parameters leads to disparate results and difficulty in comparing studies.

- **Limited Process Flexibility and Modular Scaling:** A recurrent critique is that existing economic models are too case-specific and not easily adaptable. As one recent study observes, "recycling spent LIBs faces numerous economic challenges due to the low process flexibility, imperfect parameter system, and lacking quantitative approaches" (Li *et al.*, 2025). In other words, many models examine one fixed process at one scale, with a fixed input assumption, and do not readily allow modifications. For example, a model built around recovering Ni, Co, Mn via solvent extraction might not accommodate a different flowsheet that uses selective precipitation, or a combined pyro+hydro ("hybrid") process, without essentially being rebuilt (Ramasubramanian *et al.*, 2024). Likewise, most published analyses focus on a single plant size (often arbitrarily chosen, e.g. 10,000 tonnes/year) and do not illustrate how CAPEX/OPEX would scale up or down for a smaller or larger facility. This is a gap because industry planners might want to evaluate a modular 2,000 t/yr plant vs. a large 30,000 t/yr plant, but the literature seldom provides formulas or models for scaling beyond simple economy-of-scale factors. A related issue is lack of geographic or scenario modularity: cost models are often calibrated to one region's conditions (e.g. China in Xiong et al. 2020, or Germany in Woeste/Petzold's case) and don't allow easy swapping in of another region's data (energy price, wages, etc.). Only a few tools (like Argonne's EverBatt) support such flexibility, and even those require careful input updating for a new scenario (Almahri and An, 2025). Overall, the literature lacks open, modular frameworks where users can plug in different process configurations, scales, and locations to get tailored economic outputs. Each study tends to build its own model from scratch, which is inefficient and limits cross-comparison (Roy *et al.*, 2024).

- **Inadequate Sensitivity Analysis and Scenario Coverage:** Many economic studies for battery recycling analyse a very narrow set of scenarios, often just a optimistic/base/pessimistic metal price case. Few perform comprehensive sensitivity analyses varying multiple parameters. For instance, metal prices are usually recognized as critical (and indeed some papers do vary metal prices or perform scenario analysis on cobalt price trajectories (Woeste *et al.*, 2024; Petzold *et al.*, 2025). However, other uncertain factors – like future automation levels, energy prices, regulatory fees, or material recovery rates – are often held constant. This is a limitation because the profitability of recycling can pivot not only on commodity prices but on policy (carbon price, subsidies), technology improvements (automation reducing labour needs), and feedstock changes (e.g. more LFP batteries in the mix). The absence of sensitivity or Monte Carlo analysis means we don't know how robust a given business case is to changes in these parameters. For example, if a study reports an IRR of 20% assuming current labour costs, what happens if wages double? Or if the acid consumption is 10% higher than assumed? Such questions are not routinely explored. A 2025 multi-objective assessment by Zheng *et al.* explicitly points out that *"the efficiency of recycling LIBs has been severely limited by a lack of multi-dimensional economic analysis"*, and that more work is needed to examine varying future supply chain scenarios (Li *et al.*, 2025). Their study responded by modelling different market scenarios up to 2040 (varying metal prices, battery supply, etc.), which is an approach still rare in this field. In summary, the current literature sometimes gives a false sense of precision (a single NPV value or cost/kg value) without conveying the uncertainty bands around those estimates. This undermines the usefulness of the studies for decision-making, since investors and policymakers need to understand risk and best/worst-case outcomes. The gap here is the need for robust scenario and sensitivity analysis in economic models – e.g. built-in sensitivity modules or at least systematic variation of key inputs (metal prices, feed composition, plant uptime, etc.) to identify break-even conditions (Almahri and An, 2025; Petzold *et al.*, 2025).

- **Weak Integration of Process Parameters with Cost Models:** Several studies do not fully integrate the process simulation/flowsheet with the cost estimation. By "process–cost integration," we mean that changes in the process (yields, purities, energy usage of equipment, etc.) should automatically reflect in the cost outputs. In practice, many TEA papers separate these steps: first performing a chemical process analysis (to get recovery rates, material balances) and then plugging those results into a static cost spreadsheet. This approach can miss feedback loops and can oversimplify the relationship between process performance and economics. For instance, if a leaching step's efficiency drops, it might not only reduce revenues (less metal recovered) but also increase costs (more residue waste to treat, or more reagents used to achieve the same extraction). A tightly integrated model would capture that, but a static model might not. Some publications hint at this gap, e.g. Petzold *et al.* (2025) discuss how the presence of LFP causes more impurities and reagent consumption in the process, but their economic model had to manually account for that by adjusting the material cost input. A truly integrated model might simulate the impurity removal steps and calculate the additional chemical costs directly. Another aspect is dynamic vs. static costing: most studies use static, point-in-time costs and do not link them to a time-phased cash flow except to compute NPV. This means they often ignore ramp-up periods, potential learning curve effects (cost reductions over time), or commodity price projections year-by-year. These factors matter, e.g. initial years of operation might have lower efficiency and higher unit costs until the process optimizes (Pražanová *et al.*, 2024). No reviewed study provided a fully dynamic process–cost integration with such temporal considerations. The absence of open-source, process-level economic models is notable, and researchers and industry often cannot tinker with the published models to test new process innovations. This methodological gap points to the need for reproducible models (e.g. open simulation tools or at least detailed model documentation) that marry the process engineering and economics in one platform.

- **Lack of Open-Access, Reproducible Tools:** As alluded to above, there is a dearth of publicly available, validated models or datasets for LIB recycling economics. EverBatt is a positive exception – it is open-access and has been used in multiple studies (Almahri and An, 2025). However, EverBatt is a high-level tool (Excel-based) with a pre-defined process flow; it is not fully transparent in terms of its internal assumptions without digging into the spreadsheets, and it may not capture novel hydrometallurgical techniques outside the scope of its default scenarios. Beyond EverBatt, most academic models are custom-built and not shared. This is evident from the literature: papers present their results and perhaps a diagram of the cost breakdown, but do not provide the reader with the actual model. Without access to the model, one cannot easily adjust assumptions or explore new cases. This limits reproducibility and means each new study must re-gather data and rebuild the analysis framework. It also hinders peer verification of results. From an industrial perspective, the lack of a standard modelling framework means that feasibility studies might use inconsistent methods or cost basis, complicating comparisons. There is also no open library of cost benchmarks (for equipment or reagents) specific to battery recycling – authors often borrow from analogies (mining, chemical industry) or use proprietary quotes. All this points to a need for a structured, shareable economic model where assumptions are documented and users can input their own parameters (plant size, feed composition, recovery yields, country, etc.) to get customized outputs. Such a model would greatly enhance the ability of researchers to build on each other's work and of decision-makers to test scenarios. At present, knowledge transfer is hampered by every study's model being effectively a "black box" to others (aside from qualitative descriptions in the text).

- **Insufficient Support for Decision-Making:** The usefulness of techno-economic studies lies in informing real-world decisions, whether an investor should fund a recycling plant, whether a policymaker should set certain incentives, or how a process engineer might improve a flowsheet to reduce costs. The current literature, however, often stops short of delivering actionable insights for these stakeholders. For example, relatively few studies report investor-oriented metrics like Internal Rate of Return (IRR) or payback period explicitly, even though they do compute NPVs (Woeste *et al.*, 2024). This can make it harder for an investor audience to interpret the attractiveness of a project. Additionally, many analyses do not consider financing structure (they assume all equity financing and neglect how loans, interest, or depreciation might affect economics in practice). From a policy standpoint, while several papers (e.g. Das *et al.*, 2025, Ciez and Whitacre, 2019) mention that subsidies or credits could improve viability, they usually don't model specific policy scenarios (such as a \$50/ton carbon price or a subsidy of \$X per kg of material recycled). This leaves a gap in understanding how policy levers would change the outcomes. Moreover, there is a process–policy disconnect: e.g. no study has integrated the upcoming EU Battery Regulation's requirements (such as mandated recycling efficiencies or content quotas) into a cost model to see how compliance might impact profitability. Sensitivity analyses on regulatory or market changes (like a scenario with a 50% drop in cobalt price due to new mining, or a scenario with higher collection costs due to stricter transport rules) are generally missing. All these omissions mean that existing work, while academically rigorous, may not fully answer the practical questions of "Is this investment a good idea under plausible future conditions?" or "What policy support is needed to make this technology profitable?".

Considering the above limitations, there is a compelling justification for developing a new, structured, and scalable economic model for hydrometallurgical black mass recovery. Such a model would aim to address the gaps by being transparent (clearly stating cost assumptions or allowing user input), modular (able to simulate different process configurations and scales), and integrated (linking process parameters with cost outcomes in a dynamic way). It would also incorporate robust scenario and sensitivity analysis capabilities, enabling users to explore how outcomes change with fluctuations in key factors (metal prices, feed composition, plant automation, energy costs, etc.). The need for this has been echoed in recent literature – researchers have called for more comprehensive, multi-dimensional economic evaluations of LIB recycling (Li *et al.*, 2025). By filling this gap, the new model would improve decision support for stakeholders: an investor could obtain not just a single NPV, but a range of possible NPVs with associated probabilities or conditions; a policymaker could see, for example, how a subsidy of \$x per kg affects the IRR of a recycling project; an engineer could pinpoint which process step contributes the most to cost and target it for innovation. Existing studies provide valuable point estimates and isolated analyses, but they lack the holistic, flexible framework needed for rigorous decision-making in a rapidly evolving battery recycling landscape. This shortcoming in the state-of-the-art justifies the development of a more advanced techno-economic model that can be scaled and adapted.

# 3. Economic Sustainability Analysis Methodology

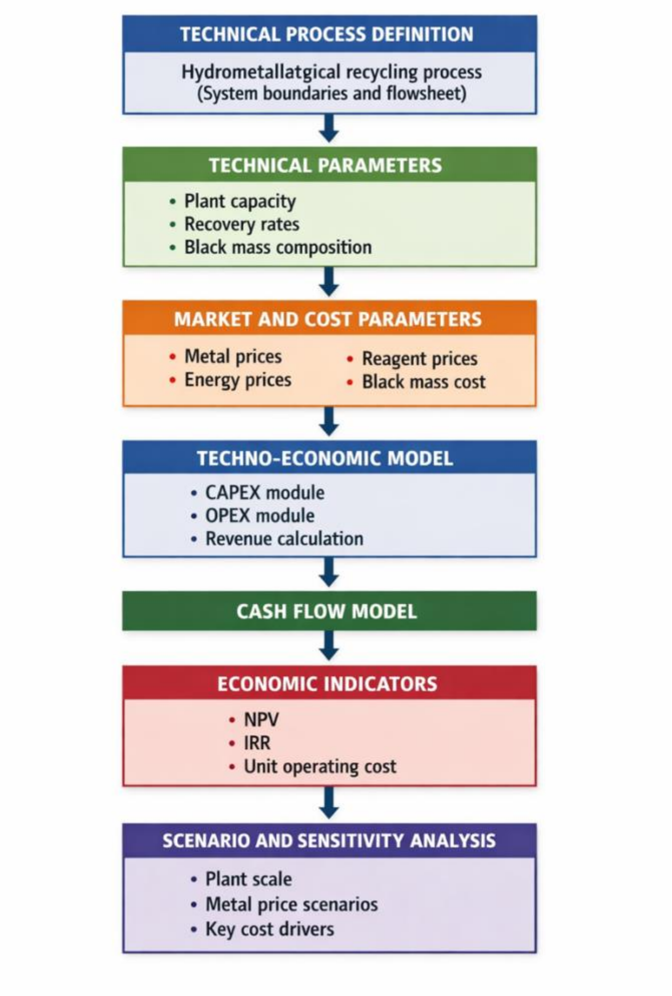


*Fig. 7: Methodological framework of the techno-economic assessment developed in this study.*

Within industrial process development, techno-economic assessment is routinely framed as an engineering-economic decision tool used to prioritize R&D options, test scale-up plausibility, and support investment narratives under incomplete information. This chapter defines the techno-economic methodology adopted in this thesis to evaluate the economic feasibility of hydrometallurgical recycling of lithium-ion battery black mass. The methodological framework builds on established techno-economic assessment (TEA) practices developed for process industries and adapts them to the specific characteristics of battery recycling systems. In particular, the methodology proposed in this thesis integrates process parameterization, structured cost modelling (CAPEX and OPEX), scenario analysis, and discounted cash flow evaluation within a modular techno-economic framework implemented in Excel. This structure allows technical assumptions, cost drivers, and financial outcomes to be explicitly linked and transparently evaluated.

A recurring methodological implication is that TEA is not a single calculation template but an iterative workflow in which the depth of process definition co-evolves with the economic questions asked. In the

TRL-based framework by Buchner *et al.* (2018), early-stage TEA is discussed as fundamentally constrained by the absence of process concepts robust enough to justify equipment-based cost estimates, and the paper explicitly cautions against "forced detail" assumptions introduced merely to enable a particular costing method (Buchner et al., 2018). In parallel, guidelines developed for $CO_2$ utilization TEA identify structural comparability issues ("apples vs. oranges") as a central motivation for methodological standardization, placing transparency of assumptions and intermediate results on the same level of importance as the choice of indicators (Zimmermann *et al.*, 2020). In line with these methodological considerations, the present study adopts a simplified but transparent techno-economic modelling approach suitable for early-stage evaluation of hydrometallurgical recycling processes.

Across chemical, metallurgical, and recycling TEAs, the process first logic is consistent: process design defines mass and energy balances; balances determine equipment sizing and utility demands; these technical quantities become the dominant explanatory variables for CAPEX and OPEX. A representative articulation is provided in a National Renewable Energy Laboratory report that explicitly sequences (i) a flowsheet, (ii) rigorous material and energy balances via process simulation (Aspen Plus), (iii) capital/project cost estimation via equipment lists and scaling, and (iv) a discounted-cash-flow economic model to compute a plant-gate price consistent with a target return (Davis *et al.*, 2015). The same source details a pragmatic cost data strategy typical of TEA: equipment baseline costs are assembled from vendor budgetary quotes where relevant and from historical cost databases for "secondary" equipment, then adjusted automatically as flows and sizing parameters change through scaling relationships (Davis *et al.*, 2015). This process-to-economics logic forms the conceptual basis of the modelling framework developed in this thesis, where process parameters such as feed composition, recovery rates, and reagent consumption are translated into cost structures and financial indicators through a structured techno-economic model.

Institutional TEA guidelines also emphasize the importance of structured capital cost definitions that clearly distinguish equipment costs, installation, engineering services, and contingencies, ensuring transparency and comparability across technological alternatives (NETL, 2021).

The strongest evidence that TEA is fundamentally inventory-driven also appears in bottom-up cost modelling traditions beyond classical chemical plants. Nelson et al. (2019), in an Argonne National Laboratory manual for the BatPaC model, define their approach as a cost calculation that accounts for "every step" of a manufacturing process, documenting equations and assumptions so that users can reproduce calculations and identify cost-driving mechanisms (Nelson et al., 2019). While the object is battery manufacturing rather than hydrometallurgical recycling, the methodological parallel is direct: costs are functions of process-step resource requirements (materials, labour, equipment) under an explicit production scale assumption (Nelson et al., 2019). This bottom-up logic also underpins the modelling approach adopted in this thesis, where costs are derived from process parameters and scaled according to plant capacity and operational assumptions.

## 3.1 Objectives and Assumptions

Techno-economic assessment (TEA) is widely used to evaluate the feasibility of emerging industrial processes by linking technical process characteristics with economic performance indicators. Across chemical, metallurgical, and recycling applications, TEA studies typically pursue three main objectives: first, to characterize the cost structure of a process, including capital intensity and operating cost levels; second, to evaluate the financial attractiveness of potential investments through discounted economic indicators; and third, to compare alternative technological or market scenarios in order to identify the key drivers of economic feasibility.

In the context of lithium-ion battery recycling, these objectives are particularly relevant because the economic performance of recycling systems depends on both technological parameters and highly uncertain market conditions. The techno-economic framework developed in this thesis is designed to evaluate the economic viability of hydrometallurgical black mass refining by explicitly linking process assumptions, cost structures, and financial outcomes within a structured modelling environment.

The methodological approach adopted in this work follows a modular techno-economic modelling logic implemented in an Excel-based framework. The model combines technical process parameterization, structured CAPEX and OPEX estimation, and discounted cash flow analysis. This structure allows technical inputs such as feed composition, recovery rates, and process intensities to be translated into cost drivers and ultimately into financial performance indicators. In addition, the modular structure of the model enables scenario-based analysis in which key parameters—such as plant scale and market prices—can be varied systematically.

Methodological guidance in the TEA literature highlights that the selection of economic indicators should be consistent with the maturity of the technology and the level of process definition. In the TRL-oriented framework proposed by Buchner et al. (2018), early-stage techno-economic assessments typically rely on simplified cost indicators, while more detailed investment metrics become appropriate once scenario assumptions and technical parameters are sufficiently defined (Buchner et al., 2018). Similarly, Zimmermann et al. (2020) emphasize that dynamic indicators such as net present value (NPV) should only be applied when the scenario description and financial assumptions are clearly specified, particularly with respect to discount rates and project risk profiles (Zimmermann et al., 2020). Following these recommendations, the present analysis combines both static and dynamic indicators in order to characterize cost intensity while also evaluating investment performance.

A critical methodological choice in techno-economic modelling concerns the definition of system boundaries. Boundary selection determines which process stages are included in the analysis and directly affects the interpretation of economic indicators. Zimmermann et al. (2020) distinguish between gate-to-gate system boundaries, which focus on a specific industrial process, and broader value-chain perspectives that include upstream and downstream stages (Zimmermann et al., 2020). Given the objective of evaluating the economic performance of the refining stage of lithium-ion battery recycling, this study adopts a gate-to-gate perspective in which black mass is treated as the primary input and the hydrometallurgical refining process represents the system under analysis.

Another important methodological aspect concerns the treatment of assumptions. Techno-economic models necessarily rely on numerous technical, financial, and market assumptions, and the resulting economic indicators should therefore be interpreted within the context of these assumptions. Davis et al. (2015) emphasize that TEA is particularly useful as a comparative tool for evaluating alternative technological configurations rather than as a precise forecasting instrument (Davis et al., 2015). In addition, many techno-economic studies adopt so-called “nth-plant” assumptions, which represent a mature industrial configuration rather than a first-of-a-kind facility, thereby avoiding distortions associated with early-stage deployment costs and financing risks (Davis et al., 2015). Consistent with this convention, the model developed in this thesis represents a hypothetical mature industrial facility rather than a pioneer plant.

Scenario analysis plays a central role in addressing uncertainty in techno-economic studies. In battery recycling systems, economic outcomes are strongly influenced by external drivers such as metal prices, energy costs, and technological performance parameters. For example, Woeste et al. (2024) structure their techno-economic evaluation around long-term scenarios for material price development and battery chemistry distribution, highlighting the importance of sensitivity analysis in recycling economics (Woeste et al., 2024). Following a similar approach, the techno-economic model developed in this thesis evaluates multiple scenarios in which key parameters—such as plant scale and market price conditions—are varied systematically to identify the principal drivers of economic feasibility.

## 3.2 Costing Methodologies in Techno-Economic Studies

Cost estimation represents a central component of techno-economic assessment because it provides the link between technical process assumptions and economic performance indicators. In industrial TEA practice, several costing approaches are used to translate process parameters into capital and operating cost estimates. Among these, process-based costing represents the most widely adopted framework for evaluating emerging technologies in chemical and metallurgical industries, while alternative methods such as Activity-Based Costing (ABC) may provide complementary insights in specific contexts (Harris, Grim and Tao, 2021).

The methodology adopted in this thesis builds on these established approaches but adapts them to the specific requirements of techno-economic modelling for lithium-ion battery recycling. In particular, the model developed in this study combines a process-based costing backbone with selected driver-based allocations for indirect operating costs, resulting in a hybrid costing framework suitable for early-stage industrial evaluation.

### 3.2.1 Process-Based Costing in Industrial TEA

In techno-economic assessments of chemical, metallurgical, and recycling processes, cost estimation is commonly implemented through process-based costing. In this approach, costs are derived from the physical structure of the process, meaning that the economic model is built upon technical process parameters such as material flows, recovery rates, reagent consumption, and plant capacity (Sakti *et al.*, 2015).

Process-based costing typically follows a bottom-up logic in which process modelling provides the basis for estimating both capital expenditure (CAPEX) and operating expenditure (OPEX). For example, Davis et al. (2015) describe a canonical TEA workflow in which process simulation first generates material and energy balances, which are then used to determine equipment sizing, estimate capital costs, and calculate operating costs based on resource consumption. These cost structures are subsequently integrated into a discounted cash-flow model to evaluate economic feasibility (Davis et al., 2015).

Institutional TEA guidelines further emphasize the importance of structured capital cost definitions in process-based assessments. The NETL costing framework, for example, defines successive layers of capital investment, ranging from equipment installation costs to broader engineering, procurement, construction, and contingency components—allowing transparent and comparable estimation of total plant investment (NETL, 2021). Similar structured cost architectures are widely adopted in techno-economic models for emerging industrial technologies (Alipanah *et al.*, 2023; Al-Sharrah and Marafi, 2024).

The same bottom-up logic is visible in publicly available cost models designed to improve transparency and interpretability of cost drivers. The BatPaC model developed by Argonne National Laboratory, for instance, calculates manufacturing costs by explicitly modelling each process step and linking resource requirements to production scale (Rachmadhani and Priyono, 2023). Similarly, Sakti et al. (2015) propose a process-based cost modelling framework in which machine-level parameters, labour requirements, and operational characteristics are specified for individual process steps in order to estimate resource consumption and associated costs.

Following this process-based logic, the techno-economic model developed in this thesis derives cost structures directly from technical process parameters. In the model implementation, process characteristics such as feed composition, metal recovery rates, reagent consumption, and energy demand are first defined in the technical process module. These parameters are then translated into operating costs and production outputs within the economic model, ensuring that economic results remain directly traceable to underlying process assumptions.

### 3.2.2 Activity-Based Costing

Activity-Based Costing (ABC) represents an alternative approach to cost allocation that originates in management accounting. In ABC systems, indirect and overhead costs are assigned to cost objects through activities and cost drivers, with the objective of improving the accuracy of cost attribution when indirect costs represent a significant share of total expenditure (Shields, 1995; Gosselin, 1997).

Although ABC provides a powerful framework for analysing cost behaviour within operating organizations, the empirical literature highlights several challenges associated with its implementation. Studies in management accounting show that the success of ABC systems often depends on organizational and behavioural factors such as managerial commitment, employee training, and integration into performance management systems (Shields, 1995). Other case-based analyses also document implementation difficulties and resistance to ABC adoption within decentralized organizations (Malmi, 1997). More broadly, Gosselin (1997) emphasizes that organizational structure and strategic orientation play a significant role in determining whether ABC systems move beyond initial adoption to full operational implementation.

These characteristics explain why full ABC approaches are rarely used as the primary costing framework in techno-economic assessments of emerging industrial technologies. TEA models are typically developed for technologies that are still under development or for industrial systems that are not yet operating at scale. As a result, the detailed activity-level operational data required for full ABC implementation—such as time allocations, process-level overhead structures, and detailed cost driver measurements—are generally unavailable.

Methodological guidance in TEA literature therefore suggests that costing methods should be consistent with the level of available data and technological maturity. Buchner et al. (2018) caution that introducing excessive modelling detail in early-stage techno-economic studies may lead to misleading conclusions if the required empirical data are not available (Buchner et al., 2018). Similarly, Zimmermann et al. (2020) emphasize that transparency and comparability across scenarios are often more important than the adoption of highly detailed accounting frameworks in early-stage assessments.

### 3.2.3 Hybrid Costing Framework

Although full Activity-Based Costing is rarely applied in techno-economic studies, simplified driver-based allocations are often combined with process-based costing in order to represent selected indirect cost components. In practice, many TEA models adopt a hybrid approach in which the core cost structure is derived from process inventories, while certain cost elements are estimated using simplified cost drivers.

For example, Woeste et al. (2024) implement a techno-economic model for lithium-ion battery recycling in which variable operating costs are calculated from material and energy flows, while fixed costs such as maintenance and insurance are estimated as proportions of plant investment. In this framework, variable costs are directly linked to process resource consumption, whereas fixed costs are determined by broader capacity-related drivers such as installed capital or staffing levels (Woeste et al., 2024).

A similar hybrid logic appears in institutional TEA guidelines. The NETL costing framework introduces factor-based components such as project contingencies, owner costs, and working capital allowances, which are not strictly determined by material and energy balances but are nevertheless required to represent realistic project economics (NETL, 2021). These components function as simplified driver-based allocations within an otherwise process-based cost structure.

The techno-economic model developed in this thesis adopts a comparable hybrid costing approach. In the implemented model, variable operating costs are calculated directly from process parameters such as reagent consumption, electricity demand, water usage, and waste treatment requirements. These costs therefore scale proportionally with plant throughput and reflect the underlying process intensities defined in the technical model.

At the same time, several cost components are represented using simplified driver-based relationships. Fixed operating costs such as labour, maintenance, and insurance are estimated based on plant capacity or capital investment, reflecting the fact that these costs are not directly determined by material and energy balances. This hybrid structure allows the model to maintain transparency and traceability of process-related costs while avoiding unrealistic data requirements associated with full activity-based accounting systems.

Overall, this combined approach provides a practical and transparent framework for techno-economic evaluation. By using process-based costing as the structural backbone of the model while incorporating simplified driver-based allocations where appropriate, the methodology ensures that cost estimates remain consistent with both the technical process description and the level of available data (Buchner et al., 2018).

## 3.3 Capital and Operating Cost Breakdown

Techno-economic assessments of industrial processes typically rely on a structured engineering cost architecture in which capital investment and operating expenditures are modelled separately. In most process-industry TEA frameworks, capital costs are derived from plant equipment and installation requirements and then expanded through indirect project costs, contingency allowances, and working capital provisions. Operating costs, by contrast, are generally divided into variable costs linked to process flows and fixed costs associated with plant capacity and operational organization.

This cost architecture appears consistently across techno-economic design cases developed for chemical and energy technologies, including institutional frameworks from NREL and NETL, as well as battery recycling cost models such as the EverBatt model developed by Argonne National Laboratory (Dai et al., 2019). These studies emphasize that a transparent separation between CAPEX and OPEX components is essential for identifying the main economic drivers of industrial processes.

In the present study, this standard TEA architecture is implemented within an Excel-based techno-economic model that translates process assumptions into capital investment, operating costs, and financial performance indicators. The model therefore mirrors the conventional cost structure used in process-industry TEA while adapting it to the specific characteristics of hydrometallurgical recycling systems.

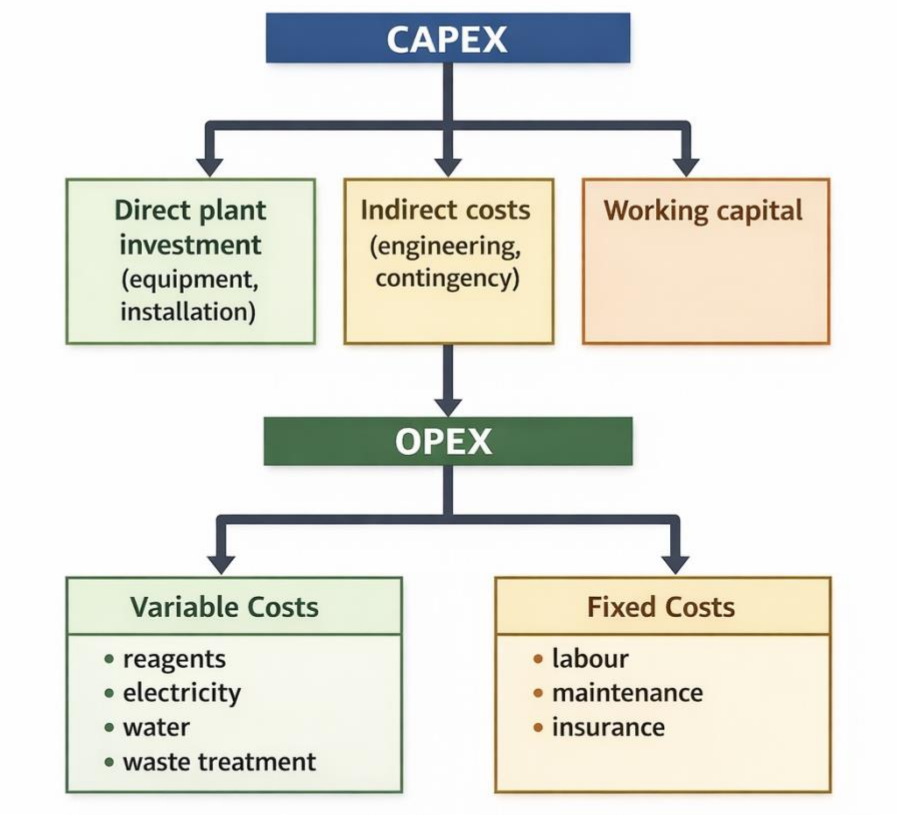


*Fig. 8: Cost structure used in the techno-economic model.*

### 3.3.1 CAPEX Structure

Capital expenditure in process-industry techno-economic studies is commonly expressed as Total Capital Investment (TCI), which combines direct equipment costs with indirect project costs and working capital requirements. In design-case analyses developed by NREL, capital investment is typically estimated through a layered structure in which purchased equipment and installation form the core of the estimate, followed by engineering services, construction management, contingency allowances, and other project-related costs (Dutta et al., 2011).

Similar approaches are adopted in techno-economic models for battery recycling systems. The EverBatt framework developed by Argonne National Laboratory represents capital investment as the sum of direct plant costs—such as equipment, instrumentation, piping, and buildings—together with indirect costs associated with engineering, construction, and contingency allowances (Dai et al., 2019). Institutional cost-estimation frameworks such as the NETL methodology further formalize this layered structure by defining successive cost levels ranging from equipment installation to total plant investment (NETL, 2021).

Following these conventions, capital investment in the techno-economic model is represented through a structured build-up including direct plant investment, indirect project costs, contingency allowances, and working capital. This structure enables the evaluation of capital intensity across alternative plant scales and scenarios while maintaining consistency with established TEA practice.

### 3.3.2 OPEX Structure

Operating expenditure in techno-economic assessments is typically divided into variable operating costs and fixed operating costs. Variable costs depend directly on process throughput and are usually derived from material and energy balances, including reagents, utilities, and waste management costs. Fixed costs, by contrast, are associated with plant capacity and organizational requirements and typically include labour, maintenance, and insurance.

This distinction is widely used in techno-economic design cases. For example, NREL studies explicitly separate variable operating costs—such as feedstock, chemicals, and utilities—from fixed costs including labour and maintenance (Dutta et al., 2011). Battery recycling techno-economic studies adopt similar structures. Woeste et al. (2024) and Petzold et al. (2025), for instance, estimate variable costs from process flows while linking fixed costs to plant investment and staffing requirements.

Within the techno-economic model developed in this thesis, variable operating costs are calculated directly from process parameters such as reagent consumption, electricity demand, water usage, and waste treatment requirements. Fixed operating costs are represented through simplified relationships linked to plant capacity and capital investment, reflecting typical industrial cost structures for chemical processing plants.

### 3.3.3 Structural Drivers of Cost Composition

The relative importance of capital and operating costs in industrial processes is strongly influenced by plant scale and process configuration. Increasing plant throughput generally reduces the relative contribution of fixed operating costs because labour and other capacity-dependent expenses are distributed across larger production volumes. Similar scale effects are observed in techno-economic analyses of battery recycling systems, where increasing processing capacity leads to lower unit costs due to the dilution of fixed expenditures (Woeste et al., 2024; Tran et al., 2020).

Process configuration also affects cost composition. Hydrometallurgical recycling routes typically involve significant consumption of chemical reagents and require wastewater treatment systems, which increases the share of operating costs associated with materials and utilities. In contrast, alternative recycling routes may involve higher energy demand or greater capital investment in thermal equipment (Woeste et al., 2024).

Finally, the maturity of the technology influences the level of detail that can be used in cost estimation. Institutional TEA guidelines emphasize that early-stage assessments often rely on factor-based cost estimation methods and contingency allowances because detailed engineering data are not yet available (Gerdes, Summers and Wimer, 2011). Transparent documentation of these assumptions therefore remains an essential component of techno-economic modelling.

## 3.4 Economic Performance Indicators

Techno-economic assessments rely on a set of economic indicators that translate cost structures and process assumptions into interpretable measures of economic performance. These indicators allow the comparison of alternative scenarios, plant scales, and technology configurations. In most TEA studies, economic performance is evaluated through a combination of static cost indicators and dynamic investment metrics, reflecting both cost structure and financial viability.

The techno-economic framework implemented in this thesis follows this dual approach. Static indicators are used to analyse cost intensity and compare alternative scenarios, while dynamic financial indicators are employed to evaluate investment attractiveness and long-term profitability.

### 3.4.1 Static Cost Indicators

Static indicators are widely used in techno-economic studies because they allow comparisons across scenarios without requiring a full financial structure to be specified in detail. In recycling systems, these indicators are typically expressed in normalized units such as cost per tonne processed, since plant throughput directly affects both operating costs and the distribution of fixed costs.

Several techno-economic studies of battery recycling adopt similar normalization approaches. Woeste et al. (2024), for example, report a Total Cost of Ownership (TCO) per tonne of recycled black mass, which is interpreted as a threshold price determining the economic feasibility of the process under given assumptions. Petzold et al. (2025) similarly evaluate recycling economics using cost indicators expressed per tonne of processed battery material.

In process-industry techno-economic analysis, other normalized indicators are also commonly used. For instance, specific CAPEX expresses capital investment relative to plant capacity and allows comparison across different plant sizes. Institutional TEA frameworks frequently rely on such normalized metrics because they facilitate the identification of structural cost drivers across alternative process configurations (NETL, 2021).

In the present analysis, static indicators are primarily used to evaluate the cost intensity of the recycling process and to compare economic outcomes across alternative scale and price scenarios.

### 3.4.2 Operational Performance Metrics

In addition to static cost indicators, techno-economic assessments often evaluate operational performance through margin-based indicators that incorporate both revenues and operating costs. This approach is particularly relevant for recycling systems, where revenues depend on the recovery and sale of valuable materials such as nickel, cobalt, and lithium.

Battery recycling techno-economic studies therefore frequently combine cost models with revenue estimation based on recovered material fractions and market price assumptions. For example, Woeste et al. (2024) incorporate revenues from recycled materials into their cost model and evaluate profitability under different market scenarios. Petzold et al. (2025) similarly model revenues from recovered materials alongside operating expenditures in order to assess economic feasibility.

Within this framework, break-even conditions provide an important interpretative metric. In several recycling TEA studies, the cost of processing material is interpreted as the maximum acceptable input price compatible with economic viability. For instance, Woeste et al. (2024) interpret the TCO per tonne of black mass as the threshold purchase price above which the recycling process becomes economically unattractive.

This break-even logic is closely related to the minimum selling price (MSP) concept commonly used in chemical-process techno-economic studies. In these analyses, the MSP corresponds to the product price required to achieve NPV = 0 at a specified target rate of return (Davis et al., 2015).

### 3.4.3 Dynamic Investment Indicators

While static indicators allow comparison of cost structures across scenarios, dynamic financial indicators are required to evaluate the long-term economic viability of a project. For this reason, techno-economic assessments frequently incorporate discounted cash-flow analysis to compute investment performance metrics such as Net Present Value (NPV), Internal Rate of Return (IRR), and payback period.

Dynamic indicators are increasingly used in techno-economic studies of battery recycling systems, where economic outcomes depend strongly on uncertain variables such as metal prices, feedstock composition, and plant scale. For example, Woeste et al. (2024) evaluate recycling economics under multiple market scenarios and report NPV as a key indicator of project feasibility. Petzold et al. (2025) similarly compute NPV based on discounted annual cash flows derived from process revenues and operating expenditures.

The values of key financial parameters such as plant lifetime and discount rate vary across techno-economic studies depending on the assumed industrial context. Design-case studies developed by NREL commonly assume plant lifetimes of approximately 30 years and discount rates around 10% in order to ensure comparability across technology assessments (Davis et al., 2015). Similar assumptions are often adopted in recycling techno-economic analyses, although alternative values may be used depending on industry-specific risk conditions.

In addition to financial parameters, operational assumptions such as plant utilization rates also influence economic outcomes because they determine how fixed costs are distributed over production volumes. Techno-economic studies therefore typically incorporate assumptions on annual operating hours and maintenance downtime when calculating annual cash flows.

The combination of static cost indicators and dynamic investment metrics provides a comprehensive framework for evaluating the economic feasibility of recycling processes. Static indicators allow structural comparison across scenarios, while dynamic indicators provide a project-level assessment of financial performance under specified assumptions regarding plant lifetime, utilization, and discount rates.

# 4. Case Study: Industrial Hydrometallurgical Recovery of Li-ion Black Mass

Black mass is an intermediate material stream generated after the mechanical processing of lithium-ion battery cells or modules. It typically contains a mixture of cathode and anode active materials (such as NMC or LCO oxides and graphite), conductive carbon, binder residues, fragments of current collectors (aluminium and copper), and residual electrolyte compounds including lithium salts and organic solvents. The exact composition and impurity profile depend strongly on the upstream dismantling and mechanical separation processes used to generate the material (Sommerville *et al.*, 2021).

From an economic perspective, black mass is increasingly treated as a traded feedstock in the battery recycling value chain. Its market value is commonly linked to the payable content of valuable metals—particularly nickel, cobalt, and lithium—using pricing formulas indexed to battery-grade metal reference prices. As a consequence, techno-economic models typically represent black mass as a purchased input rather than as an internally generated intermediate stream, implicitly embedding upstream collection and mechanical pre-processing costs in the feedstock price (IEA, 2023).

Hydrometallurgical recycling processes aim to recover valuable metals from black mass through a sequence of chemical and physical separation steps. At an industrial level, these processes can be interpreted as a series of unit operations that convert a heterogeneous solid feed into purified metal products. Typical stages include metal dissolution through leaching, solid–liquid separation, impurity removal and selective metal separation, product recovery through precipitation or crystallization, and the treatment of process effluents and residues. This unit-operation perspective is commonly adopted in techno-economic assessments, where the focus lies on reliable material separation and scalable process configurations rather than on chemical innovation (Rossi et al., 2024).

## 4.1 Boundary Definition and Modelling Approach

The case study analysed in this thesis adopts a gate-to-gate system boundary in which black mass is treated as the main input material and the hydrometallurgical refinery represents the system under evaluation.

In process-oriented techno-economic assessments, a common boundary definition begins with the reception of black mass (or the inlet to the leaching stage) and ends with the production of purified metal products together with treated waste streams and residues. Gate-to-gate boundaries of this type are frequently used in simulation-based and techno-economic studies of battery recycling because they isolate the refining stage while excluding upstream battery dismantling and mechanical processing (Rinne et al., 2024).

Within this framework, upstream activities such as battery collection, transportation, discharging, dismantling, shredding, and mechanical separation are considered external to the analysed system. This distinction reflects the practical structure of the battery recycling value chain, where pretreatment operations responsible for generating black mass are typically separated from downstream material recovery and refining processes (IEA, 2023).

## 4.2 Processes Included

Within the defined system boundary, the hydrometallurgical recycling plant can be represented as a sequence of four operational blocks that together perform the recovery and purification of valuable metals.

1. The first stage consists of feed handling operations, including reception, storage, sampling, and potential conditioning of the black mass feed. Feed properties such as moisture content and particle size distribution can vary depending on upstream mechanical processing and may influence handling behaviour and reaction kinetics during subsequent processing steps (Verbaan and Naidoo, 2023).
2. The core of the process consists of hydrometallurgical treatment steps, including leaching, solid–liquid separation, washing, impurity removal, and selective metal separation. These operations allow valuable metals to be dissolved, separated from impurities, and recovered as purified compounds suitable for further processing (Rossi et al., 2024).
3. Additional plant operations include utility systems such as reagent preparation, water management, power distribution, heating and cooling systems, and compressed air supply. These auxiliary systems support the main chemical operations and represent an important component of both capital and operating costs in hydrometallurgical facilities (Dai et al., 2019).
4. The system includes waste and effluent management processes, such as wastewater neutralization, precipitation of dissolved contaminants, solid residue handling, and controlled discharge or disposal of process by-products. Hydrometallurgical recycling plants typically generate several liquid waste streams that must be treated before discharge or reuse (Rossi et al., 2024).

## 4.3 System Inputs

For techno-economic modelling purposes, system inputs are defined in a way that allows direct mapping to operating cost categories within the economic model. A practical categorization is:

- **Black mass** (the primary material input), characterized by its metal content, impurity levels, and physical properties such as moisture and particle size. These parameters influence both process performance and economic outcomes.
- **Chemical inputs**, including leaching reagents, typically mineral acids such as sulphuric acid and, in some process configurations, reducing agents such as hydrogen peroxide (Rossi et al., 2024). Additional reagents are required for neutralization and precipitation steps, including sodium hydroxide, sodium carbonate, lime, or other chemicals used to control solution chemistry and enable selective metal recovery (Rinne et al., 2024). Depending on the separation strategy adopted, further chemicals may be used in purification processes, including solvent extraction reagents, ion exchange resins, flocculants, and filtration aids (Verbaan and Naidoo, 2023).
- **Utility inputs**, including electricity, process heat, and water supply. Even when environmental inventories are not explicitly calculated, these utilities represent important drivers of operating costs and influence equipment sizing and plant design (Lander et al., 2021).

## 4.4 System Outputs

The outputs of the system consist of saleable metal products together with secondary streams and process residues:

- **Primary saleable products**: the main outputs of hydrometallurgical recycling plants are typically battery-grade metal compounds, such as nickel and cobalt sulphates, mixed hydroxide or carbonate intermediates used in cathode precursor production, and lithium carbonate recovered through precipitation or crystallization processes (Verbaan and Naidoo, 2023).
- **By-products and secondary streams**: depending on the process configuration and reagent selection, the process may also generate secondary streams, including sulphate-rich solutions that may produce sodium or ammonium sulphate as potential by-products.
- **Solid residues**: solid outputs include leaching residues, which may contain graphite or other undissolved components, as well as impurity precipitates generated during purification stages and wastewater treatment (Rossi et al., 2024).
- **Wastewater and off-gas**: In addition, the system generates liquid effluent streams and, in some configurations, gaseous emissions requiring treatment before discharge (Dai et al., 2019).

## 4.5 Processes Explicitly Excluded

Given the gate-to-gate system boundary adopted in this study, several activities in the battery recycling value chain are explicitly excluded from the analysis:

- Upstream operations related to battery collection, transportation, discharge, dismantling, shredding, and mechanical separation are not included, as these processes occur prior to the generation of black mass and are typically performed by specialized pretreatment facilities (IEA, 2023).
- Similarly, downstream processes related to the synthesis of cathode active materials or battery manufacturing are excluded from the system boundary. Although these stages are part of the broader battery value chain, they represent distinct industrial processes with their own capital and operating cost structures (Rossi et al., 2024).

Under this boundary definition, black mass is therefore treated as an externally sourced feedstock with a market-linked purchase price. This approach allows the techno-economic analysis to focus on the value created through hydrometallurgical refining and metal recovery rather than on the upstream costs associated with battery dismantling and mechanical processing (IEA, 2023).

## 4.6 Economic Model

The economic evaluation developed in this study is implemented through a modular Excel-based techno-economic model. The objective of the model is to translate technical process parameters and market assumptions into a financial representation of a hydrometallurgical recycling plant processing lithium-ion battery black mass.

The model is structured as a sequence of interconnected modules that progressively transform technical inputs into economic indicators. This modular architecture improves transparency and traceability, allowing each financial result to be linked back to the technical assumptions and cost drivers from which it originates. At the same time, the structure facilitates scenario analysis by enabling modifications of selected input parameters without altering the underlying calculation logic.

The model is organized into three main layers: input definition, economic calculations, and financial performance indicators. In practical terms, these layers are implemented through a series of interconnected worksheets, including scenario selection, input parameters, process basis, CAPEX estimation, OPEX estimation, revenue calculation, and financial analysis. This organization ensures a clear separation between assumptions, intermediate calculations, and final results.

The first layer contains the scenario selection and input definition modules, which collect all parameters defining the technical, financial, and market environment in which the plant operates. The scenario sheet allows the user to select combinations of plant scale, market price conditions, and process configurations, enabling the rapid generation of alternative scenarios. The Inputs Master sheet centralizes numerical assumptions used throughout the model, including financial parameters such as discount rate, plant lifetime, and tax rate, as well as industrial parameters such as labour costs, reagent prices, and energy prices.

The second layer defines the technical basis of the process. The Process Basis sheet specifies the main technical characteristics of the hydrometallurgical recycling route considered in the analysis. These include the assumed composition of the black mass feedstock, recovery rates for each target metal, and process intensities expressed per tonne of feed material. Process intensities represent the consumption of reagents, electricity, water, and other inputs required to treat one tonne of black mass. In addition, the model includes conversion factors linking recovered metal quantities to saleable chemical products. In the base configuration, lithium is recovered as lithium carbonate ($Li_2CO_3$), while nickel, cobalt, and manganese are recovered as sulphate salts, which are commonly used intermediates in cathode precursor production.

The third layer converts the technical parameters into economic quantities through the CAPEX and OPEX estimation modules. Capital expenditure is estimated using a structured cost breakdown that includes direct process equipment, indirect engineering and construction costs, contingency allowances, and working capital requirements. Cost scaling relationships are incorporated to allow capital investment to adjust when plant capacity varies across scenarios.

Operating expenditures are estimated using a hybrid costing framework that distinguishes between flow-dependent and capacity-driven costs. Variable operating costs are calculated directly from process intensities defined in the technical module, including reagent consumption, electricity demand, water usage, and waste treatment. Fixed operating costs are instead linked to plant scale or capital investment and include labour, maintenance, insurance, and general overhead costs. Maintenance and insurance are modelled as proportions of installed capital investment, while labour costs are estimated based on the number of full-time equivalent employees required to operate the facility.

The economic representation of the project is completed through the cash flow module, which combines revenues, operating costs, depreciation, and taxes to calculate annual net cash flows over the lifetime of the plant. The model explicitly accounts for the initial capital investment and working capital requirements at the beginning of the project, as well as the recovery of working capital at the end of the operating period.

The model computes the main financial indicators used to evaluate economic feasibility, including net present value (NPV), internal rate of return (IRR), break-even throughput, and unit processing cost per tonne of black mass treated. This modular structure allows the model to function as a decision-support tool for evaluating how variations in plant scale, market conditions, or process performance affect the economic viability of hydrometallurgical black mass recycling.

### 4.6.1 Scenario Definition

The techno-economic model evaluates the economic performance of the hydrometallurgical recycling process under different operating and market conditions. To capture these variations, the analysis is structured around a set of scenarios reflecting differences in plant scale, market prices, and process performance.

| **Scenario** | **Plant Scale (t/y)** | **Metal Price Set** | **Process Configuration** | **Description** |
|---|---|---|---|---|
| Base Case | 10,000 | Base | Config A | Reference plant configuration |
| Small Scale | 5,000 | Base | Config A | Reduced plant capacity |
| Large Scale | 20,000 | Base | Config A | Increased plant capacity |
| Low Metal Prices | 10,000 | Low | Config A | Downside metal price scenario |
| High Metal Prices | 10,000 | High | Config A | Upside metal price scenario |
| Configuration B | 10,000 | Base | Config B | Alternative process configuration |

*Table 1: Scenario definitions used in the techno-economic model.*

The analysis begins with a base case scenario, which represents the reference configuration of the recycling plant. This scenario assumes a representative plant capacity, baseline market prices for battery materials and energy, and a reference set of process parameters for the hydrometallurgical treatment of black mass. The base case serves as the benchmark against which all alternative scenarios are compared.

The first dimension of the scenario analysis concerns plant scale. Industrial facilities often benefit from economies of scale, as larger plants can distribute fixed costs and capital investment over higher production volumes. To capture this effect, the model evaluates different capacity levels representing small-, medium-, and large-scale plants. Changes in plant scale influence both capital costs, through equipment scaling relationships, and operating costs through variations in throughput.

The second dimension concerns market price conditions. The profitability of lithium-ion battery recycling processes is strongly influenced by the market value of recovered metals. Prices of lithium, nickel, cobalt, and manganese are subject to significant fluctuations due to changes in global demand for battery materials and variations in mining supply. For this reason, the model incorporates alternative price scenarios representing different market conditions to evaluate the sensitivity of project profitability to changes in metal prices.

A third dimension concerns process performance assumptions. Even within hydrometallurgical recycling routes, different process configurations may lead to variations in metal recovery rates and reagent consumption. The model therefore considers alternative parameter sets representing plausible variations in process efficiency and operating requirements.

By combining variations in plant scale, market price assumptions, and process performance parameters, the scenario framework allows a systematic exploration of the economic viability of hydrometallurgical black mass recycling.

### 4.6.2 Main Assumptions

The techno-economic model relies on a set of technical, financial and market assumptions. These parameters define the operating conditions of the recycling facility and provide the basis for the estimation of capital costs, operating costs and revenues. Whenever possible, assumptions are derived from industrial statistics, techno-economic studies and publicly available market data.

| **Category** | **Parameter** | **Assumption** | **Unit** | **Justification** |
|---|---|---|---|---|
| **Plant configuration** | Plant lifetime | 15 | years | Typical lifetime assumed in techno-economic assessments of chemical processing facilities (Peters, Timmerhaus & West, *Plant Design and Economics for Chemical Engineers*) |
| | Operating days | 330 | days/year | Continuous industrial operation with scheduled maintenance downtime (Towler & Sinnott, *Chemical Engineering Design*) |
| | Operating hours | 7920 | hours/year | Equivalent to 330 operating days |
| **Financial parameters** | Discount rate | 8 | % | Typical discount rate used in techno-economic analyses of industrial projects |
| | Corporate tax rate | 27 | % | Approximation of Italian corporate tax structure (IRES + IRAP) |
| | Depreciation method | Straight-line | – | Standard accounting method used in industrial financial modelling |
| **Process parameters** | Metal recovery rates | Process dependent | % | Values derived from hydrometallurgical recycling literature |
| | Reagent consumption | Process dependent | kg/t feed | Based on process intensities defined in the technical model |
| | Energy consumption | Process dependent | kWh/t feed | Typical ranges reported in recycling studies |
| **Market assumptions** | Lithium carbonate price | Market-based | €/kg | Battery material market reports (IEA, Benchmark Mineral Intelligence) |

| | | | | |
|---|---|---|---|---|
| | Nickel sulphate price | Market-based | €/kg | Battery precursor chemical market data |
| | Cobalt sulphate price | Market-based | €/kg | Critical minerals market reports |
| | Manganese sulphate price | Market-based | €/kg | Cathode precursor supply chain references |
| **Utilities and operating costs** | Electricity price | ~0.15 | €/kWh | Eurostat statistics for non-household electricity consumers in Europe |
| | Water price | 1–3 | €/m³ | Typical industrial water tariffs in Europe |
| | Maintenance factor | 3 | % of CAPEX | Standard assumption in chemical plant costing (Towler & Sinnott) |
| | Insurance factor | 1 | % of CAPEX | Typical estimate for industrial facilities |
| | Labour cost | Country dependent | €/FTE/year | Based on Eurostat labour cost statistics |

*Table 2: Techno-economic assumptions used in the economic model.*

Financial assumptions define the economic framework used to evaluate the investment. Key parameters include plant lifetime, discount rate, corporate taxation, and depreciation method. The assumed plant lifetime reflects the expected operational horizon of a chemical processing facility, while the discount rate represents the opportunity cost of capital associated with industrial investments. Corporate taxation is approximated using the current Italian corporate tax structure, and depreciation is modelled using a straight-line method, which is commonly adopted in techno-economic studies to represent the gradual allocation of capital investment over the operational life of the plant.

Technical assumptions describe the operational characteristics of the hydrometallurgical recycling process. These include the composition of the black mass feedstock, the recovery rates of lithium, nickel, cobalt, and manganese, and the specific consumption of reagents, energy, and utilities required for processing. In the model, these parameters are represented as process intensities per tonne of feed material, allowing technical performance to be directly linked to operating costs and product output.

Market assumptions define the external economic environment in which the recycling plant operates. Revenues are generated from the sale of lithium carbonate, nickel sulphate, cobalt sulphate, and manganese sulphate. Product prices are based on benchmark values reported in battery materials market analyses and critical minerals reports. Utility costs, including electricity and water prices, are derived from publicly available statistics for industrial consumers in Europe. These assumptions provide a realistic representation of market conditions while allowing scenario analysis to capture potential variations in price dynamics.

### 4.6.4 Model Limitations

The techno-economic model developed in this study provides a structured framework for evaluating the economic feasibility of hydrometallurgical recycling of lithium-ion battery black mass. Nevertheless, several simplifying assumptions have been adopted to maintain the model tractable and consistent with the scope of an early-stage techno-economic assessment. These limitations should be considered when interpreting the results of the analysis.

First, the model follows a deterministic approach, meaning that all technical, financial and market parameters are treated as fixed values within each scenario. In practice, many of these variables are subject to uncertainty. Metal prices, electricity tariffs and reagent costs can fluctuate significantly over time, particularly in the rapidly evolving battery materials market. Rather than modelling these uncertainties through probabilistic methods, the analysis explores their impact through a set of discrete scenarios. While this approach allows for a clear comparison of alternative conditions, it does not capture the full range of possible market dynamics.

Second, the technical representation of the hydrometallurgical process is simplified. The process is described through aggregated parameters such as recovery rates and specific consumption of reagents, energy and utilities. This level of abstraction is sufficient for techno-economic modelling, but it does not reproduce the detailed behaviour of individual unit operations or chemical reactions. Factors such as reaction kinetics, impurity behaviour, equipment design and operational constraints are therefore not explicitly modelled. The technical parameters should consequently be interpreted as representative performance indicators rather than precise engineering specifications.

Another limitation concerns the capital cost estimation methodology. Capital expenditure is estimated using cost scaling relationships and cost factors commonly employed in preliminary economic assessments of chemical plants. Although this approach captures the main drivers of investment costs, it does not replace a detailed engineering design or a bottom-up equipment cost estimation. As a result, the CAPEX values obtained from the model should be interpreted as order-of-magnitude estimates rather than precise investment budgets. Similarly, operating costs are estimated using a hybrid costing framework that combines process-based and capacity-driven cost drivers. While this method provides a realistic representation of how operating costs depend on process performance and plant scale, several cost items are represented using simplified allocation factors. Maintenance, insurance and overhead costs, for example, are estimated as proportions of capital investment or labour expenditure. These approximations are widely used in techno-economic studies but inevitably introduce a degree of uncertainty into the cost estimates.

The model assumes that the recovered metals can be converted into saleable battery-grade salts and sold at prices consistent with benchmark market values. In practice, the commercial value of recovered materials depends on several factors, including product purity, quality specifications and contractual arrangements with downstream buyers. The analysis therefore represents an idealized commercial context in which the recovered products meet the required specifications of cathode precursor manufacturers.

Despite these limitations, the model provides a coherent and transparent framework for linking technical process parameters to financial performance indicators. By systematically relating process performance, cost structure and market conditions, the model allows the identification of key economic drivers and supports the evaluation of different scenarios for the industrial implementation of hydrometallurgical black mass recycling.

# 5. Results and Discussion

This chapter presents and discusses the results obtained from the techno-economic model developed in this study. The analysis focuses on the economic performance of a hydrometallurgical recycling plant processing lithium-ion battery black mass under different operational and market conditions.

First, the base case scenario is presented, providing an overview of the main technical and financial indicators of the reference plant configuration. The cost structure of the process is then analysed to identify the main components of operating expenses. Subsequently, the effects of plant scale and metal price fluctuations are examined through scenario analysis. Finally, the key economic drivers influencing the profitability of the recycling process are discussed.

Together, these results provide insights into the economic feasibility of hydrometallurgical black mass recycling and highlight the main factors that determine the viability of industrial-scale recycling facilities.

## 5.1 Base Case Results

The base case scenario represents the reference configuration of the hydrometallurgical recycling plant and assumes a nominal processing capacity of 10,000 tonnes of black mass per year. A capacity utilization rate of 90% is considered, resulting in an annual throughput of approximately 9,000 tonnes of feedstock.

Based on the process model and the assumed recovery efficiencies, the plant produces approximately 10,300 tonnes per year of battery-grade salts, including lithium carbonate, nickel sulphate, cobalt sulphate and manganese sulphate. These products represent the recovered metal value contained in the incoming black mass.

The total capital investment required for the facility is estimated at approximately 43.8 million euros. This corresponds to a specific capital intensity of about 4,385 € per tonne of installed processing capacity and roughly 4,872 € per tonne of annual throughput. These values fall within the range typically reported in techno-economic analyses of hydrometallurgical recycling plants.

Total operating costs are estimated at approximately 67.8 million euros per year. Variable costs represent the dominant component of operating expenses, accounting for the vast majority of total OPEX. This is primarily driven by the cost of the black mass feedstock, which constitutes the largest cost element in the recycling process. On a unit basis, the operating cost amounts to approximately 7,534 € per tonne of processed feedstock.

Energy and reagent consumption represent only a small share of total operating costs, accounting for roughly 1–1.5% each. This highlights that the economic performance of the process is largely driven by feedstock price and metal recovery rather than by utilities consumption.

Under the assumed product price conditions, the plant generates annual revenues of approximately 80.9 million euros, corresponding to an average revenue of around 8,986 € per tonne of processed black mass. The resulting EBITDA is about 13.1 million euros per year, corresponding to an EBITDA margin of approximately 16%. After accounting for depreciation and taxes, the project yields a positive operating margin of about 13%.

From a financial perspective, the base case scenario shows a positive economic outlook. The net present value of the project is estimated at approximately 42 million euros, while the internal rate of return reaches about 21%. These results indicate that hydrometallurgical recycling of black mass can represent an economically viable investment under the assumed technical and market conditions.

The break-even analysis indicates that the plant would reach economic viability at a throughput of approximately 1,464 tonnes per year, corresponding to about 15% of the installed capacity. This suggests that the project maintains a reasonable degree of resilience to fluctuations in plant utilization.

Overall, the base case results show that the recycling process can generate positive economic returns while remaining strongly dependent on feedstock price and metal market conditions, which remain the primary drivers of profitability in the system.

| **Study** | **Process** | **Plant Capacity** | **CAPEX (€/t capacity)** | **IRR** |
|---|---|---|---|---|
| This study | Hydro recycling | 10 kt/y | 4,385 | 21% |
| Harper et al. (2019) | Hydro recycling | ~10 kt/y | ~4,000–6,000 | n.a. |
| Neumann et al. (2022) | Hydro recycling | 10–20 kt/y | ~3,500–5,500 | ~15–25% |
| Peters et al. (2023) | Hydro recycling | 10 kt/y | ~4,000 | ~18–24% |

*Table 3: Comparison with techno-economic studies in the literature.*

| **Scenario** | **Plant Scale (t/y)** | **Revenue (M€)** | **EBITDA margin** | **NPV (M€)** | **IRR** |
|---|---|---|---|---|---|
| Small Scale | 5,000 | 40.4 | 14% | 10.8 | 13% |
| Base Scale | 10,000 | 80.9 | 16% | 42.2 | 21% |
| Large Scale | 20,000 | 161.7 | 17% | 112.8 | 29% |

*Table 4: Summary of economic performance across different scale scenarios.*

## 5.2 Cost Structure

The operating cost structure of the recycling plant is largely dominated by the cost of the black mass feedstock. In the base case scenario, total operating expenses amount to approximately 67.8 million euros per year, corresponding to a unit operating cost of about 7,534 € per tonne of processed feedstock.

Operating costs can be divided into two main categories: variable costs and fixed costs. Variable costs represent the largest share of total OPEX, accounting for more than 95% of total operating expenses. The dominant component within this category is the cost of the black mass input material, which reflects the intrinsic value of the metals contained in the feedstock.

In contrast, the contribution of process-related operating costs such as reagents, energy consumption and utilities remains relatively limited. Energy costs account for approximately 1.4% of total operating expenses, while reagent costs represent about 1.5%. These relatively small shares indicate that the process itself is not particularly energy-intensive and that the majority of economic value in the system is associated with the recovery of metals rather than the transformation process.

Fixed operating costs represent a much smaller portion of total expenses and include labour, maintenance, insurance and other plant overheads. In the base case scenario, these costs amount to roughly 2.5 million euros per year. When expressed on a per-tonne basis, fixed costs contribute only a limited fraction of the overall unit operating cost due to the relatively high throughput of the plant.

Overall, the cost structure highlights a key characteristic of black mass recycling systems: the economic performance of the process is primarily driven by feedstock price and metal recovery rather than by operational expenditures related to utilities or labour. As a result, fluctuations in black mass market prices can have a substantial impact on plant profitability.

This cost structure also explains why economies of scale have a relatively limited effect on unit operating costs. Since the majority of operating expenses scale proportionally with the quantity of feedstock processed, increases in plant size primarily affect capital intensity rather than significantly reducing operating cost per tonne.

## 5.3 Effect on Plant Scale

The impact of plant scale on economic performance was evaluated by comparing three plant capacities: 5,000, 10,000 and 20,000 tonnes of black mass processed per year. In all scenarios the same technical assumptions, metal recoveries and product prices were maintained, allowing the analysis to isolate the effect of scale on investment costs and financial performance.

As expected, increasing plant capacity leads to a substantial improvement in economic indicators. The small-scale plant, processing 5,000 tonnes per year, requires a total capital investment of approximately 28.9 million euros and generates an internal rate of return of about 13%. While the project remains economically viable, profitability is relatively limited due to the higher capital intensity of small-scale installations.

When plant capacity increases to 10,000 tonnes per year, total capital investment rises to approximately 43.8 million euros, but the specific capital cost decreases significantly. The specific CAPEX declines from about 5,786 € per tonne of capacity in the small-scale configuration to roughly 4,385 € per tonne in the base case. This reduction reflects the typical economies of scale observed in chemical processing plants, where equipment size and infrastructure costs increase less than proportionally with capacity.

At this scale, financial performance improves substantially. The internal rate of return increases to approximately 21%, while the net present value reaches about 42 million euros. The plant therefore achieves a more balanced relationship between capital investment and operating profitability.

A further increase in capacity to 20,000 tonnes per year results in additional improvements in economic performance. Although total CAPEX increases to about 66.5 million euros, the specific capital cost decreases further to roughly 3,323 € per tonne of installed capacity. This confirms the presence of strong scale effects in the capital cost structure of the recycling facility.

Operating costs per tonne remain relatively stable across the three configurations. Unit operating costs range from approximately 7,689 € per tonne in the small-scale scenario to around 7,442 € per tonne in the large-scale configuration. This limited variation reflects the fact that the majority of operating expenses are associated with the cost of black mass feedstock, which scales directly with throughput and is therefore largely independent of plant size.

Due to the reduction in capital intensity and the slight improvement in operating margins, the large-scale configuration achieves the best financial performance. The internal rate of return increases to approximately 29%, while the net present value exceeds 110 million euros.

Overall, the analysis highlights that plant scale plays a critical role in determining the economic viability of black mass recycling facilities. While smaller plants may still be economically feasible, larger installations significantly benefit from economies of scale, particularly through reductions in specific capital investment. As a result, industrial deployment of hydrometallurgical recycling technologies is likely to favour medium-to-large scale facilities capable of processing significant volumes of battery waste.

## 5.4 Sensitivity to Metal Prices

In addition to plant scale, market conditions represent one of the most critical factors affecting the economic performance of black mass recycling. In particular, the prices of recovered metals play a fundamental role in determining the profitability of the process, as revenues are directly linked to the market value of the produced metal salts.

To evaluate this effect, two additional scenarios were analysed by varying the selling prices of the recovered products while keeping all technical and operational assumptions constant. These scenarios represent a low metal price environment and a high metal price environment, reflecting the strong volatility typically observed in lithium, nickel and cobalt markets.

Under the low-price scenario, total annual revenues decrease significantly to approximately 56.6 million euros. Given that operating costs remain largely unchanged, this reduction in revenue leads to negative operating performance. The plant generates a negative EBITDA of approximately 11.2 million euros and an operating margin of around –25%. As a result, the project becomes economically unviable under these market conditions, with a strongly negative net present value of about –142 million euros and no calculable internal rate of return.

In contrast, the high price scenario leads to a substantial improvement in project economics. Annual revenues increase to approximately 105.1 million euros, resulting in an EBITDA of about 37.3 million euros and an EBITDA margin of approximately 35%. Under these favourable market conditions, the project achieves a net present value of nearly 194 million euros and an internal rate of return close to 59%.

These results highlight the strong dependence of black mass recycling economics on metal market dynamics. Since feedstock costs remain relatively stable while revenues fluctuate with metal prices, changes in commodity markets can dramatically alter project profitability.

The sensitivity analysis therefore confirms that hydrometallurgical recycling plants operate within a narrow economic margin that is highly exposed to fluctuations in lithium, nickel and cobalt markets. For industrial investors, this implies that long-term contracts, hedging strategies, or integrated value chains may play an important role in reducing exposure to commodity price volatility.

| **Scenario** | **Revenue (M€)** | **EBITDA (M€)** | **EBITDA margin** | **NPV (M€)** | **IRR** |
|---|---|---|---|---|---|
| Low Metal Price | 56.6 | -11.2 | -20% | -142 | - |
| Base Case | 80.9 | 13.1 | 16% | 42 | 21% |
| High Metal Price | 105.1 | 37.3 | 35% | 194 | 29% |

*Table 5: Impact of metal price scenarios on project profitability*

## 5.5 Key Economic Drivers

The results obtained from the different scenarios highlight the main economic variables that determine the profitability of hydrometallurgical black mass recycling plants. The analysis shows that the financial performance of the process is primarily influenced by four key drivers: feedstock price, metal market prices, plant scale and recovery efficiencies.

First, the price of black mass feedstock represents the dominant component of operating costs. As shown in the cost structure analysis, feedstock accounts for the vast majority of variable operating expenses. Since this cost scales directly with throughput, fluctuations in black mass market prices can significantly influence overall project economics.

Second, metal market prices constitute the main source of revenue uncertainty. The sensitivity analysis demonstrated that variations in lithium, nickel, cobalt and manganese prices can substantially alter project profitability. Under low metal price conditions the plant becomes economically unviable, whereas favourable market conditions can significantly improve returns. This confirms that recycling projects remain strongly exposed to global battery material markets.

Third, plant scale plays an important role through economies of scale in capital investment. Increasing plant capacity reduces specific capital costs and improves overall financial performance, even though operating costs per tonne remain relatively stable due to the dominant contribution of feedstock costs.

Process recovery rates influence the amount of valuable metals recovered from the black mass. Higher recovery efficiencies directly translate into increased product output and revenue generation, thereby improving project profitability.

These results indicate that the economic viability of lithium-ion battery recycling is determined by the interaction between technological performance and market conditions. Techno-economic models such as the one developed in this study provide a useful framework for analysing these interactions and evaluating the feasibility of recycling projects under different industrial scenarios.

# 6. Conclusions

This study developed a techno-economic model to evaluate the economic feasibility of a hydrometallurgical process for recycling lithium-ion battery black mass. The model integrates technical process parameters, cost estimation methods and financial evaluation tools in order to assess the economic performance of recycling plants under different operational and market conditions.

The results of the analysis highlight several key economic characteristics of black mass recycling systems. First, the base case scenario shows that hydrometallurgical recycling can represent an economically viable process under favourable market conditions. In the reference configuration considered in this study, the plant achieves a positive net present value and an internal rate of return above typical industrial investment thresholds, indicating the potential profitability of the process.

Second, the analysis of plant scale demonstrates the importance of economies of scale in determining project feasibility. Increasing plant capacity significantly improves financial performance by reducing specific capital costs, while operating costs per tonne remain relatively stable. As a result, medium-to-large scale facilities appear to be economically preferable for industrial deployment of black mass recycling technologies.

Third, the sensitivity analysis highlights the strong influence of metal market prices on project profitability. Since revenues are directly linked to the value of recovered lithium, nickel, cobalt and manganese products, fluctuations in commodity markets can substantially affect the economic outcome of recycling projects. Under unfavourable price scenarios the project becomes economically unviable, while higher metal prices significantly increase profitability. This result confirms that the recycling sector remains strongly exposed to global battery material markets.

Beyond the numerical results obtained for the specific case study, the techno-economic model developed in this work represents a flexible analytical framework for evaluating lithium-ion battery recycling processes. The modular structure of the model allows key parameters, such as plant scale, feedstock price, recovery efficiencies and product prices, to be easily modified. This makes it possible to explore alternative technological configurations, process improvements or evolving market conditions.

For this reason, the model can serve as a useful starting point for future research on battery recycling economics. It can be extended to analyse different recycling technologies, alternative battery chemistries, or additional cost factors as the battery recycling industry continues to evolve.

Some limitations of the present analysis should be acknowledged. The model relies on a number of simplifying assumptions regarding process performance, market prices and cost structures, which may vary in real industrial applications. Future work could therefore refine the model by incorporating more detailed process data, dynamic price scenarios, or integration with supply chain and logistics considerations. The study contributes to a better understanding of the economic drivers underlying lithium-ion battery recycling and provides a structured framework that can support both academic research and early-stage industrial evaluation of recycling projects.

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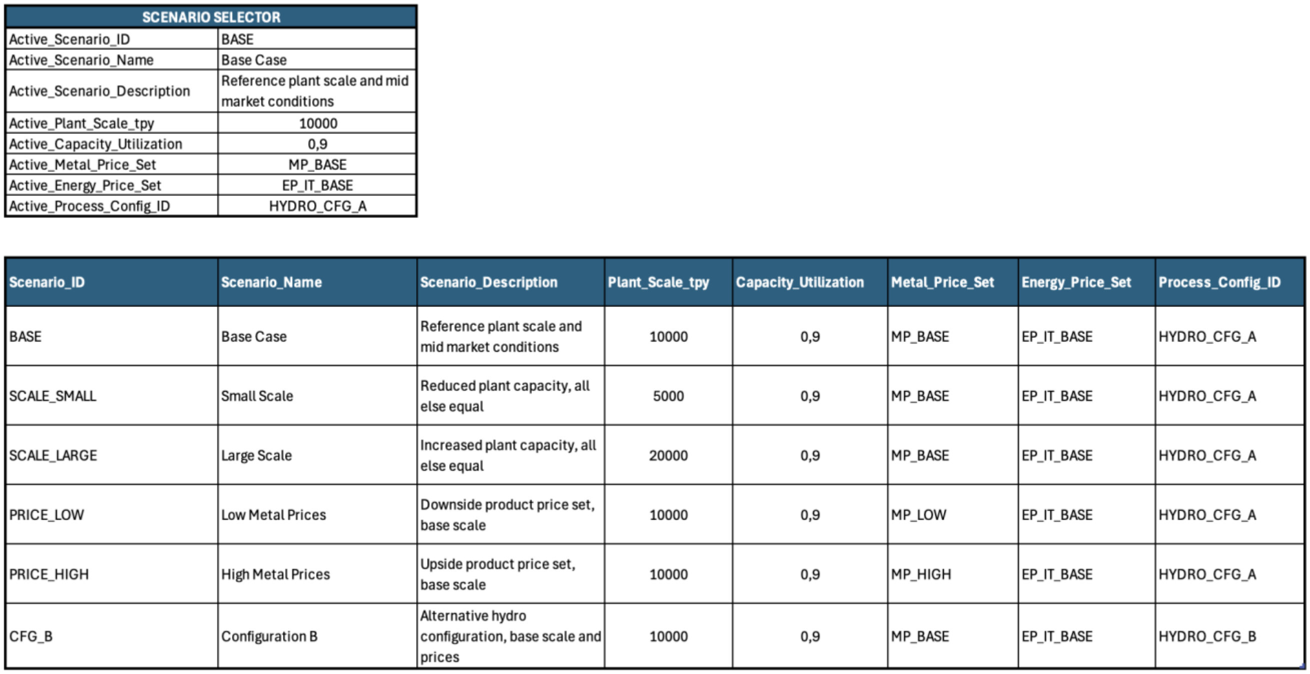
# Appendix A: Economic Model Description

## A.1 Scenario Definition

The worksheet 01_Scenarios defines the set of scenarios analysed in the techno-economic model and allows the selection of the active scenario used for the calculations. The sheet contains two main sections: a scenario database listing all predefined scenarios and a scenario selector, which activates the parameter set used by the model.



| SCENARIO SELECTOR | |
|---|---|
| Active_Scenario_ID | BASE |
| Active_Scenario_Name | Base Case |
| Active_Scenario_Description | Reference plant scale and mid market conditions |
| Active_Plant_Scale_tpy | 10000 |
| Active_Capacity_Utilization | 0,9 |
| Active_Metal_Price_Set | MP_BASE |
| Active_Energy_Price_Set | EP_IT_BASE |
| Active_Process_Config_ID | HYDRO_CFG_A |

| Scenario_ID | Scenario_Name | Scenario_Description | Plant_Scale_tpy | Capacity_Utilization | Metal_Price_Set | Energy_Price_Set | Process_Config_ID |
|---|---|---|---|---|---|---|---|
| BASE | Base Case | Reference plant scale and mid market conditions | 10000 | 0,9 | MP_BASE | EP_IT_BASE | HYDRO_CFG_A |
| SCALE_SMALL | Small Scale | Reduced plant capacity, all else equal | 5000 | 0,9 | MP_BASE | EP_IT_BASE | HYDRO_CFG_A |
| SCALE_LARGE | Large Scale | Increased plant capacity, all else equal | 20000 | 0,9 | MP_BASE | EP_IT_BASE | HYDRO_CFG_A |
| PRICE_LOW | Low Metal Prices | Downside product price set, base scale | 10000 | 0,9 | MP_LOW | EP_IT_BASE | HYDRO_CFG_A |
| PRICE_HIGH | High Metal Prices | Upside product price set, base scale | 10000 | 0,9 | MP_HIGH | EP_IT_BASE | HYDRO_CFG_A |
| CFG_B | Configuration B | Alternative hydro configuration, base scale and prices | 10000 | 0,9 | MP_BASE | EP_IT_BASE | HYDRO_CFG_B |

*Fig. 9: Worksheet 01_Scenarios*

Each scenario is defined through a combination of technical and economic parameters that determine the operating conditions of the recycling plant. These parameters include plant scale, capacity utilisation, metal price assumptions, energy price assumptions, and the selected process configuration.

The scenario selector retrieves the parameters associated with the selected scenario ID and makes them available to the rest of the model. In the base case configuration, the selected scenario corresponds to:

$$Plant\ Scale: 10{,}000\ t/y$$

$$Capacity\ Utilization: 90\%$$

$$Metal\ Price\ Set: MP_{BASE}$$

$$Energy\ Price\ Set: EP_{IT_{BASE}}$$

$$Process\ Configuration: HYDRO_{CFG_A}$$

The annual throughput of black mass processed by the plant is calculated as:

$$Throughput = Plant\ Scale \times Capacity\ Utilization$$

where:

- $Plant\ Scale$ represents the nominal plant capacity expressed in tonnes per year (t/y)
- $Capacity\ Utilization$ represents the fraction of time the plant is effectively operating

For the base scenario, this results in:

$$Throughput\ =\ 10{,}000 \times 0.9\ =\ 9{,}000\ t/y$$

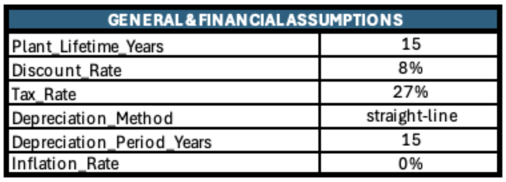
This throughput value represents the quantity of black mass processed annually by the recycling facility and serves as the main scaling parameter for the technical and economic calculations performed in the subsequent model modules.

The scenario table also defines alternative configurations used in the sensitivity analysis:

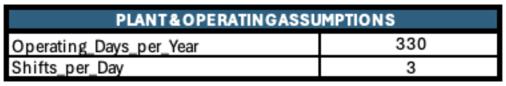
- Scale scenarios, where plant capacity varies while all other parameters remain constant
- Metal price scenarios, where the selling prices of recovered products vary to represent different commodity market conditions
- Process configuration scenarios, where alternative process setups are evaluated

## A.2 Input Parameters and Economic Assumptions

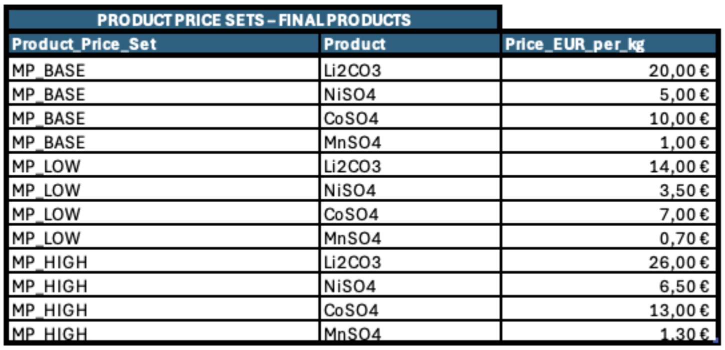
The worksheet 02_Inputs_Master contains the main technical, economic and financial parameters used throughout the techno-economic model. All scenario calculations reference this sheet, ensuring consistency and transparency in the modelling framework.



| GENERAL & FINANCIAL ASSUMPTIONS | |
|---|---|
| Plant_Lifetime_Years | 15 |
| Discount_Rate | 8% |
| Tax_Rate | 27% |
| Depreciation_Method | straight-line |
| Depreciation_Period_Years | 15 |
| Inflation_Rate | 0% |

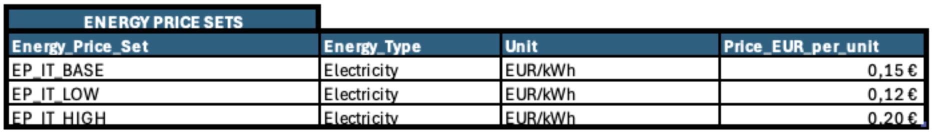


| PLANT & OPERATING ASSUMPTIONS | |
|---|---|
| Operating_Days_per_Year | 330 |
| Shifts_per_Day | 3 |



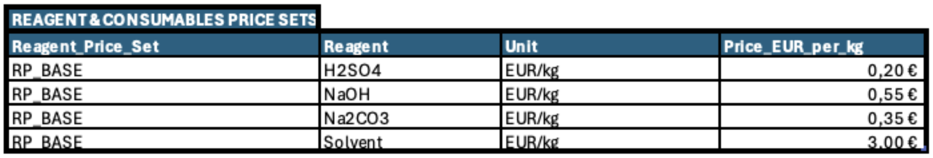
PRODUCT PRICE SETS – FINAL PRODUCTS

| Product_Price_Set | Product | Price_EUR_per_kg |
|---|---|---|
| MP_BASE | Li2CO3 | 20,00 € |
| MP_BASE | NiSO4 | 5,00 € |
| MP_BASE | CoSO4 | 10,00 € |
| MP_BASE | MnSO4 | 1,00 € |
| MP_LOW | Li2CO3 | 14,00 € |
| MP_LOW | NiSO4 | 3,50 € |
| MP_LOW | CoSO4 | 7,00 € |
| MP_LOW | MnSO4 | 0,70 € |
| MP_HIGH | Li2CO3 | 26,00 € |
| MP_HIGH | NiSO4 | 6,50 € |
| MP_HIGH | CoSO4 | 13,00 € |
| MP_HIGH | MnSO4 | 1,30 € |



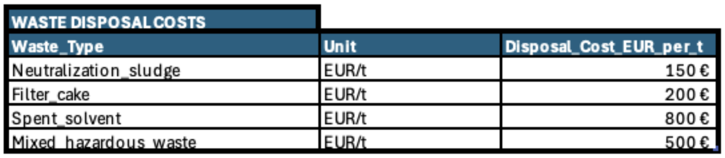
ENERGY PRICE SETS

| Energy_Price_Set | Energy_Type | Unit | Price_EUR_per_unit |
|---|---|---|---|
| EP_IT_BASE | Electricity | EUR/kWh | 0,15 € |
| EP_IT_LOW | Electricity | EUR/kWh | 0,12 € |
| EP_IT_HIGH | Electricity | EUR/kWh | 0,20 € |



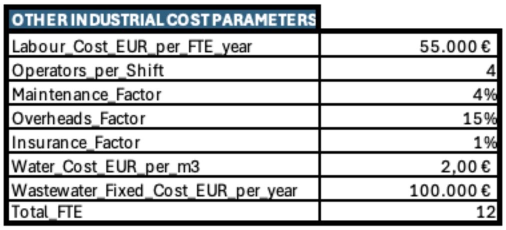
REAGENT & CONSUMABLES PRICE SETS

| Reagent_Price_Set | Reagent | Unit | Price_EUR_per_kg |
|---|---|---|---|
| RP_BASE | H2SO4 | EUR/kg | 0,20 € |
| RP_BASE | NaOH | EUR/kg | 0,55 € |
| RP_BASE | Na2CO3 | EUR/kg | 0,35 € |
| RP_BASE | Solvent | EUR/kg | 3,00 € |

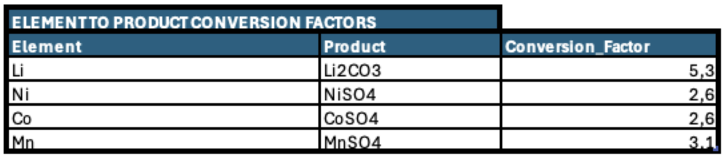


WASTE DISPOSAL COSTS

| Waste_Type | Unit | Disposal_Cost_EUR_per_t |
|---|---|---|
| Neutralization_sludge | EUR/t | 150 € |
| Filter_cake | EUR/t | 200 € |
| Spent_solvent | EUR/t | 800 € |
| Mixed_hazardous_waste | EUR/t | 500 € |



| OTHER INDUSTRIAL COST PARAMETERS | |
|---|---|
| Labour_Cost_EUR_per_FTE_year | 55.000 € |
| Operators_per_Shift | 4 |
| Maintenance_Factor | 4% |
| Overheads_Factor | 15% |
| Insurance_Factor | 1% |
| Water_Cost_EUR_per_m3 | 2,00 € |
| Wastewater_Fixed_Cost_EUR_per_year | 100.000 € |
| Total_FTE | 12 |



ELEMENT TO PRODUCT CONVERSION FACTORS

| Element | Product | Conversion_Factor |
|---|---|---|
| Li | Li2CO3 | 5,3 |
| Ni | NiSO4 | 2,6 |
| Co | CoSO4 | 2,6 |
| Mn | MnSO4 | 3,1 |

*Fig. 10: Worksheet 02_Inputs_Master*

The inputs are organised into several categories including financial assumptions, operating parameters, product prices, energy prices, reagent costs, waste disposal costs, labour parameters and element-to-product conversion factors.

## A.2.1 Financial Assumptions

The financial framework of the model is defined by a set of general economic assumptions that determine the calculation of discounted cash flows and profitability indicators.

The project lifetime is assumed to be:

$$Lifetime = 15\ years$$

The discount rate used in the Net Present Value calculation is:

$$r = 8\%$$

This rate represents the weighted average cost of capital assumed for the investment.

The corporate tax rate applied to operating profits is:

$$TaxRate = 27\%$$

Depreciation of the fixed capital investment is calculated using a straight-line method over the project lifetime:

$$Depreciation = \frac{FCI}{Lifetime}$$

where:

- $FCI = Fixed\ Capital\ Investment$
- $Lifetime = project\ duration\ in\ years$

Inflation is assumed to be zero in the model in order to perform the economic evaluation in constant real prices.

### A.2.2 Plant Operating Assumptions

The operational schedule of the recycling plant is defined through the number of operating days and shifts per day.

The plant is assumed to operate:

$$OperatingDays = 330\ days/year$$

with:

$$ShiftsPerDay\ =\ 3$$

This assumption reflects typical operating conditions of continuous chemical processing plants.

The annual plant throughput used in the model is therefore determined by the nominal plant capacity defined in the scenario sheet and the utilisation rate:

$$Throughput = Capacity_{plant} \times Utilization_{rate}$$

### A.2.3 Product Price Sets

The model includes different metal price scenarios to account for the volatility of battery material markets.

Three price sets are defined:

- MP_BASE (reference market conditions)
- MP_LOW (downside price scenario)
- MP_HIGH (upside price scenario)

Prices are expressed in euros per kilogram of final product.

The relationship between scenarios is defined as:

$$Price_{LOW} = Price_{BASE} \times 0.7$$

$$Price_{HIGH} = Price_{BASE} \times 1.3$$

These price sets are applied to the following products:

- lithium carbonate $Li_2CO_3$
- nickel sulphate $NiSO_4$
- cobalt sulphate $CoSO_4$
- manganese sulphate $MnSO_4$

Total revenue is therefore calculated as:

$$Revenue = \sum_i (Product_i \times Price_i)$$

where $Price_i$ is selected according to the active metal price scenario.

### A.2.4 Energy Price Assumptions

Electricity costs are defined through alternative energy price sets:

- EP_IT_BASE
- EP_IT_LOW
- EP_IT_HIGH

The base electricity price assumed in the model is:

$$ElectricityPrice = 0.15\ €/kWh$$

Energy costs in the operating cost model are calculated as:

$$EnergyCost = EnergyConsumption \times ElectricityPrice$$

where $EnergyConsumption$ is determined by the process intensity defined in the process basis sheet.

### A.2.5 Reagent and Consumables Prices

The model includes several reagents required in the hydrometallurgical process.

These include:

- sulphuric acid $H_2SO_4$
- sodium hydroxide $NaOH$
- sodium carbonate $Na_2CO_3$
- organic solvent

The total reagent cost is calculated as:

$$ReagentCost = \sum_{j} (Consumption_j \times Price_j)$$

where:

- $Consumption_j = \ reagent\ consumption\ per\ tonne\ of\ feedstock$
- $Price_j = \ reagent\ unit\ price$

### A.2.6 Waste Disposal Costs

Waste streams generated during the recycling process include:

- neutralisation sludge
- filter cake
- spent solvent
- mixed hazardous waste

The cost of waste disposal is calculated as:

$$WasteCost = \sum_{k} (Waste_k \times DisposalPrice_k)$$

where:

- $Waste_k = quantity\ of\ waste\ stream\ k\ generated\ by\ the\ process$
- $DisposalPrice_k = disposal\ cost\ per\ tonne$

### A.2.7 Labour and Industrial Cost Parameters

Labour costs are calculated based on the number of operators and their annual salary.

Total labour cost is determined as:

$$LabourCost = FTE \times Salary_{FTE}$$

where:

- $FTE \ = \ number\ of\ full\ time\ employees$
- $Salary_{FTE} = annual\ labour\ cost\ per\ employee$

Maintenance costs are estimated as a fraction of the fixed capital investment:

$$MaintenanceCost = MaintenanceFactor \times FCI$$

Overheads and insurance are also calculated using proportional factors:

$$Overheads = OverheadFactor \times LabourCost$$

$$Insurance = InsuranceFactor \times FCI$$

### A.2.8 Element-to-Product Conversion Factors

Recovered metals are converted into battery-grade salts according to stoichiometric conversion factors.

The conversion from elemental metal mass to final product mass is defined as:

$$Product_i = Metal_i \times ConversionFactor_i$$

For example:

$$Li_2CO_3 = Li_{recovered} \times 5.3$$

where the factor represents the molecular mass ratio between the final product and the contained metal.

Similar conversion relationships are applied for:

- nickel sulphate
- cobalt sulphate
- manganese sulphate

These conversion factors allow the model to translate recovered metal quantities into marketable chemical products.

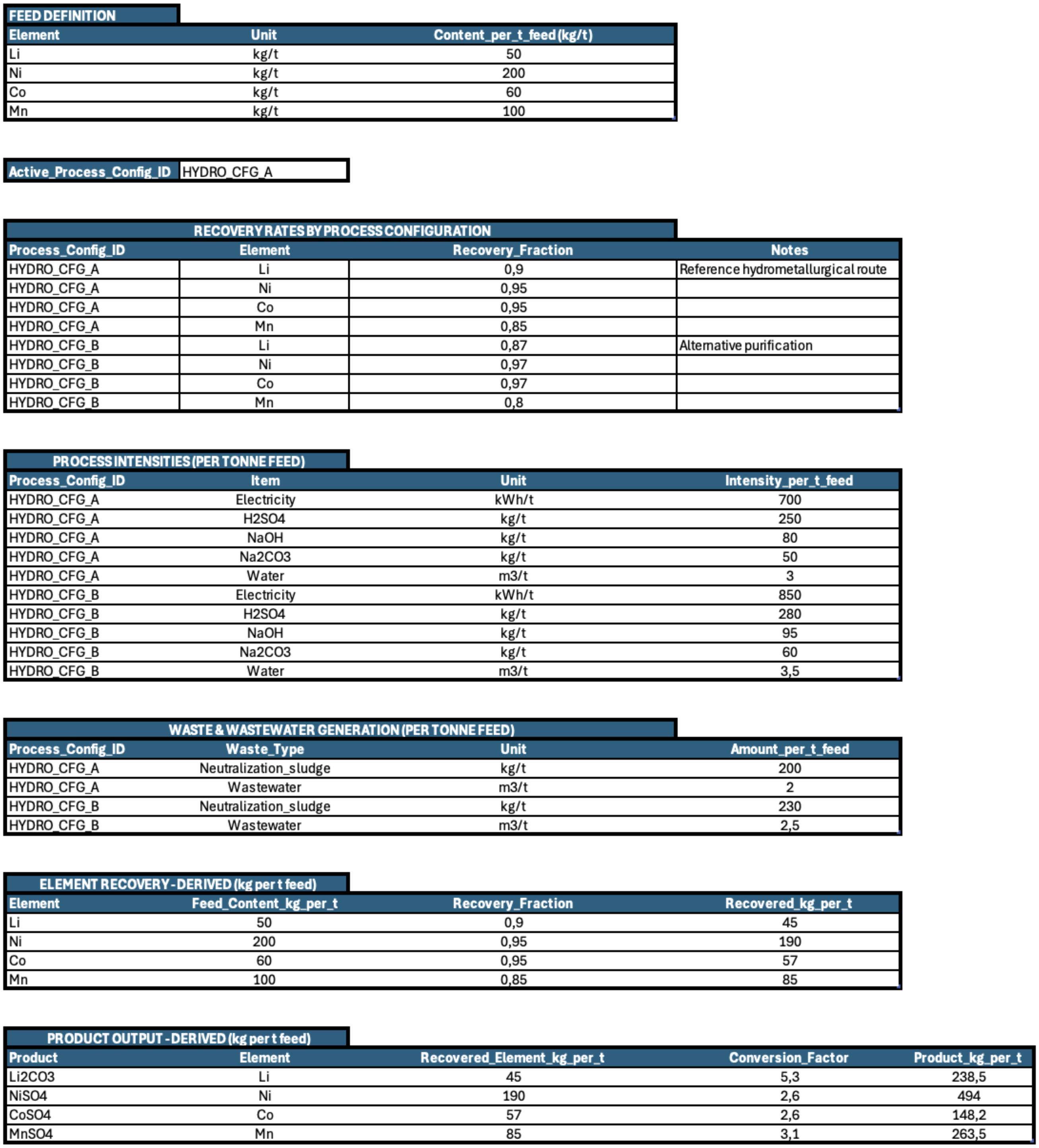
## A.3 Process Basis and Production Model

The worksheet 03_Process_Basis defines the technical parameters of the hydrometallurgical recycling process and calculates the physical production outputs derived from the processing of lithium-ion battery black mass. This sheet represents the core mass balance module of the techno-economic model.

The calculations include:

- feed composition
- metal recovery rates
- process consumption intensities
- waste generation
- product output generation

These parameters allow the model to estimate the quantities of recoverable metals and final chemical products generated per tonne of feedstock.



**FEED DEFINITION**

| Element | Unit | Content_per_t_feed (kg/t) |
|---|---|---|
| Li | kg/t | 50 |
| Ni | kg/t | 200 |
| Co | kg/t | 60 |
| Mn | kg/t | 100 |

| | |
|---|---|
| **Active_Process_Config_ID** | HYDRO_CFG_A |

**RECOVERY RATES BY PROCESS CONFIGURATION**

| Process_Config_ID | Element | Recovery_Fraction | Notes |
|---|---|---|---|
| HYDRO_CFG_A | Li | 0,9 | Reference hydrometallurgical route |
| HYDRO_CFG_A | Ni | 0,95 | |
| HYDRO_CFG_A | Co | 0,95 | |
| HYDRO_CFG_A | Mn | 0,85 | |
| HYDRO_CFG_B | Li | 0,87 | Alternative purification |
| HYDRO_CFG_B | Ni | 0,97 | |
| HYDRO_CFG_B | Co | 0,97 | |
| HYDRO_CFG_B | Mn | 0,8 | |

**PROCESS INTENSITIES (PER TONNE FEED)**

| Process_Config_ID | Item | Unit | Intensity_per_t_feed |
|---|---|---|---|
| HYDRO_CFG_A | Electricity | kWh/t | 700 |
| HYDRO_CFG_A | H2SO4 | kg/t | 250 |
| HYDRO_CFG_A | NaOH | kg/t | 80 |
| HYDRO_CFG_A | Na2CO3 | kg/t | 50 |
| HYDRO_CFG_A | Water | m3/t | 3 |
| HYDRO_CFG_B | Electricity | kWh/t | 850 |
| HYDRO_CFG_B | H2SO4 | kg/t | 280 |
| HYDRO_CFG_B | NaOH | kg/t | 95 |
| HYDRO_CFG_B | Na2CO3 | kg/t | 60 |
| HYDRO_CFG_B | Water | m3/t | 3,5 |

**WASTE & WASTEWATER GENERATION (PER TONNE FEED)**

| Process_Config_ID | Waste_Type | Unit | Amount_per_t_feed |
|---|---|---|---|
| HYDRO_CFG_A | Neutralization_sludge | kg/t | 200 |
| HYDRO_CFG_A | Wastewater | m3/t | 2 |
| HYDRO_CFG_B | Neutralization_sludge | kg/t | 230 |
| HYDRO_CFG_B | Wastewater | m3/t | 2,5 |

**ELEMENT RECOVERY - DERIVED (kg per t feed)**

| Element | Feed_Content_kg_per_t | Recovery_Fraction | Recovered_kg_per_t |
|---|---|---|---|
| Li | 50 | 0,9 | 45 |
| Ni | 200 | 0,95 | 190 |
| Co | 60 | 0,95 | 57 |
| Mn | 100 | 0,85 | 85 |

**PRODUCT OUTPUT - DERIVED (kg per t feed)**

| Product | Element | Recovered_Element_kg_per_t | Conversion_Factor | Product_kg_per_t |
|---|---|---|---|---|
| Li2CO3 | Li | 45 | 5,3 | 238,5 |
| NiSO4 | Ni | 190 | 2,6 | 494 |
| CoSO4 | Co | 57 | 2,6 | 148,2 |
| MnSO4 | Mn | 85 | 3,1 | 263,5 |

*Fig. 11: Worksheet 03_Process_Basis*

## A.3.1 Feedstock Composition

The composition of the incoming black mass is defined in terms of elemental metal content per tonne of feedstock.

Let $C_i$be the concentration of element i in the black mass feedstock expressed in kg of element per tonne of feed.

For each element, the mass entering the process per tonne of feedstock is therefore:

$$Metal_{i,feed} = C_i$$

### A.3.2 Metal Recovery

The hydrometallurgical process recovers a fraction of the metals contained in the feedstock.

For each element $i$, the recovery fraction is defined as $R_i$.

The mass of recovered metal is calculated as:

$$Metal_{i,recovered} = Metal_{i,feed} \times R_i$$

where:

- $Metal_{i,feed} = metal\ content\ in\ feedstock$
- $R_i = recovery\ fraction\ of\ the\ process$

For the alternative configuration HYDRO_CFG_B, slightly different recoveries are assumed to reflect a modified purification route.

### A.3.3 Recovered Metal per Tonne of Feed

Using the feed composition and recovery fractions, the quantity of recovered metals per tonne of processed black mass is calculated as:

$$RecoveredMetal_i = C_i \times R_i$$

### A.3.4 Element-to-Product Conversion

Recovered elemental metals are converted into marketable battery precursor chemicals.

The conversion is performed using stoichiometric conversion factors:

$$Product_i = RecoveredMetal_i \times CF_i$$

where:

- $CF_i = conversion\ factor\ from\ metal\ mass\ to\ product\ mass.$

These factors reflect the molecular weight ratios between the recovered metal and the final chemical compound.

For example:

$$Li_2CO_3 = Li_{recovered} \times 5.3$$

### A.3.5 Product Output per Tonne of Feed

The resulting product output per tonne of black mass processed is therefore:

$$Product_{kg/t} = RecoveredMetal_{kg/t} \times CF_i$$

The total product output per tonne of feedstock is therefore:

$$TotalProduct = \sum Product_i$$

### A.3.6 Process Consumption Intensities

The sheet also defines the process consumption intensities per tonne of feedstock processed. These parameters represent the main variable inputs required by the hydrometallurgical process.

For each input $j$, the total consumption is calculated as:

$$Consumption_j = Intensity_j \times Throughput$$

where:

- $Intensity_j = consumption\ per\ tonne\ of\ feedstock$
- $Throughput = annual\ plant\ throughput$

These consumption values are later used in the operating cost module to estimate variable operating expenses.

### A.3.7 Waste and Wastewater Generation

The process generates several waste streams which must be treated or disposed of.

Waste generation is defined per tonne of processed feedstock.

For each waste stream $k$:

$$Waste_k = WasteIntensity_k \times Throughput$$

Waste streams considered include:

- neutralisation sludge
- wastewater

These quantities are used in the cost model to estimate waste treatment and disposal costs.

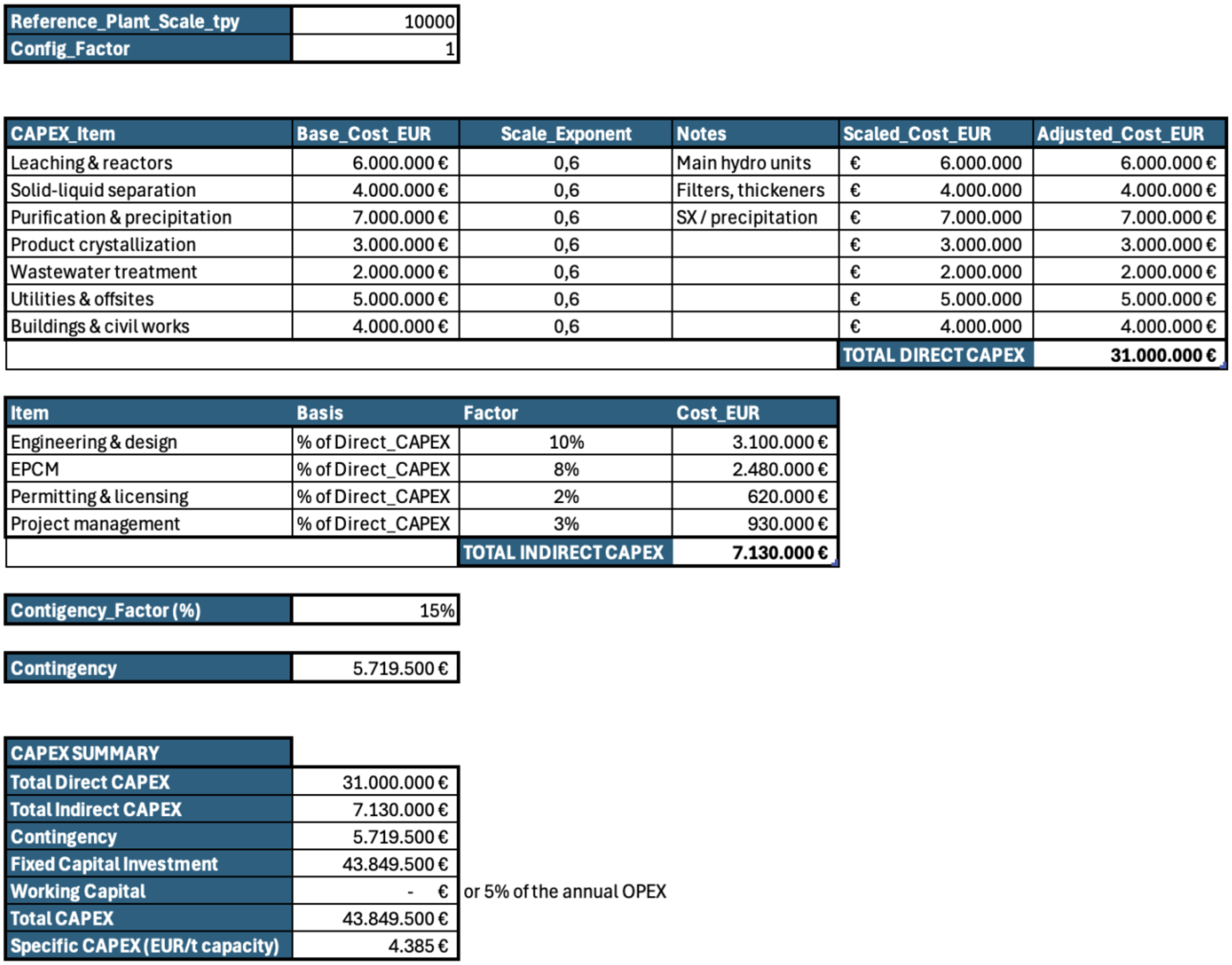
## A.4 Capital Expenditure Model

The worksheet 10_CAPEX estimates the capital investment required to construct the hydrometallurgical recycling plant. The calculation follows a typical techno-economic estimation approach used in early-stage process evaluations, where equipment costs are scaled from reference values and additional indirect costs are estimated using cost factors.

The capital investment model includes three main components:

- Direct capital costs
- Indirect capital costs
- Contingency allowance

These components together determine the Fixed Capital Investment (FCI) of the project.



| | |
|---|---|
| Reference_Plant_Scale_tpy | 10000 |
| Config_Factor | 1 |

| CAPEX_Item | Base_Cost_EUR | Scale_Exponent | Notes | Scaled_Cost_EUR | Adjusted_Cost_EUR |
|---|---|---|---|---|---|
| Leaching & reactors | 6.000.000 € | 0,6 | Main hydro units | € 6.000.000 | 6.000.000 € |
| Solid-liquid separation | 4.000.000 € | 0,6 | Filters, thickeners | € 4.000.000 | 4.000.000 € |
| Purification & precipitation | 7.000.000 € | 0,6 | SX / precipitation | € 7.000.000 | 7.000.000 € |
| Product crystallization | 3.000.000 € | 0,6 | | € 3.000.000 | 3.000.000 € |
| Wastewater treatment | 2.000.000 € | 0,6 | | € 2.000.000 | 2.000.000 € |
| Utilities & offsites | 5.000.000 € | 0,6 | | € 5.000.000 | 5.000.000 € |
| Buildings & civil works | 4.000.000 € | 0,6 | | € 4.000.000 | 4.000.000 € |
| | | | | TOTAL DIRECT CAPEX | **31.000.000 €** |

| Item | Basis | Factor | Cost_EUR |
|---|---|---|---|
| Engineering & design | % of Direct_CAPEX | 10% | 3.100.000 € |
| EPCM | % of Direct_CAPEX | 8% | 2.480.000 € |
| Permitting & licensing | % of Direct_CAPEX | 2% | 620.000 € |
| Project management | % of Direct_CAPEX | 3% | 930.000 € |
| | | TOTAL INDIRECT CAPEX | **7.130.000 €** |

| | |
|---|---|
| Contigency_Factor (%) | 15% |

| | |
|---|---|
| Contingency | 5.719.500 € |

| CAPEX SUMMARY | | |
|---|---|---|
| Total Direct CAPEX | 31.000.000 € | |
| Total Indirect CAPEX | 7.130.000 € | |
| Contingency | 5.719.500 € | |
| Fixed Capital Investment | 43.849.500 € | |
| Working Capital | - € | or 5% of the annual OPEX |
| Total CAPEX | 43.849.500 € | |
| Specific CAPEX (EUR/t capacity) | 4.385 € | |

*Fig. 12: Worksheet 10_CAPEX*

## A.4.1 Equipment Cost Scaling

The cost of each major process unit is estimated starting from a reference cost defined for a reference plant capacity.

The scaled cost of equipment i is calculated using the widely used capacity scaling equation:

$$Cost_i = Cost_{ref,i} \left( \frac{Capacity}{Capacity_{ref}} \right)^n$$

where:

- $Cost_{ref,i} = reference\ cost\ of\ equipment\ i$
- $Capacity = plant\ capacity\ for\ the\ analysed\ scenario$
- $Capacity_{ref} = reference\ plant\ capacity$

- $n = scaling\ exponent$

The reference capacity used in the model is:

$$Capacity_{ref} = 10{,}000\ t/y$$

For chemical process equipment, a typical scaling exponent of:

$$n = 0.6$$

is applied, reflecting the economies of scale observed in industrial equipment costs.

### A.4.2 Direct Capital Costs

Direct capital costs correspond to the installed cost of the main process units and supporting infrastructure.

The total direct capital cost is therefore calculated as:

$$DirectCAPEX = \sum_i Cost_i$$

### A.4.3 Indirect Capital Costs

In addition to equipment costs, several indirect cost components are included to account for engineering, project management and permitting activities.

These costs are estimated as percentages of the direct capital investment.

For each indirect component $j$:

$$IndirectCost_j = Factor_j \times DirectCAPEX$$

The total indirect capital cost is therefore:

$$IndirectCAPEX = \sum_j IndirectCost_j$$

### A.4.4 Contingency Allowance

A contingency allowance is included to account for uncertainties typical of early-stage cost estimation.

The contingency cost is calculated as:

$$Contingency = ContingencyFactor \times (DirectCAPEX + IndirectCAPEX)$$

where:

$$ContingencyFactor = 15\%$$

### A.4.5 Fixed Capital Investment

The Fixed Capital Investment (FCI) represents the total capital required to construct the plant.

$$FCI = DirectCAPEX + IndirectCAPEX + Contingency$$

### A.4.6 Working Capital

Working capital represents the funds required to support plant operations during the initial operating period.

In the model, working capital is estimated as a fraction of annual operating costs:

$$WorkingCapital \ = \ 0.05 \times OPEX_{annual}$$

where:

- $OPEX_{annual} = total\ annual\ operating\ expenditure$

### A.4.7 Total Capital Investment

The total capital investment of the project is therefore:

$$CAPEX_{total} = FCI + WorkingCapital$$

### A.4.8 Specific Capital Cost

The model also calculates the specific capital intensity of the recycling plant.

$$CAPEX_{specific} = \frac{CAPEX_{total}}{PlantCapacity}$$

expressed in euros per tonne of installed processing capacity.

## A.5 Operating Cost Model

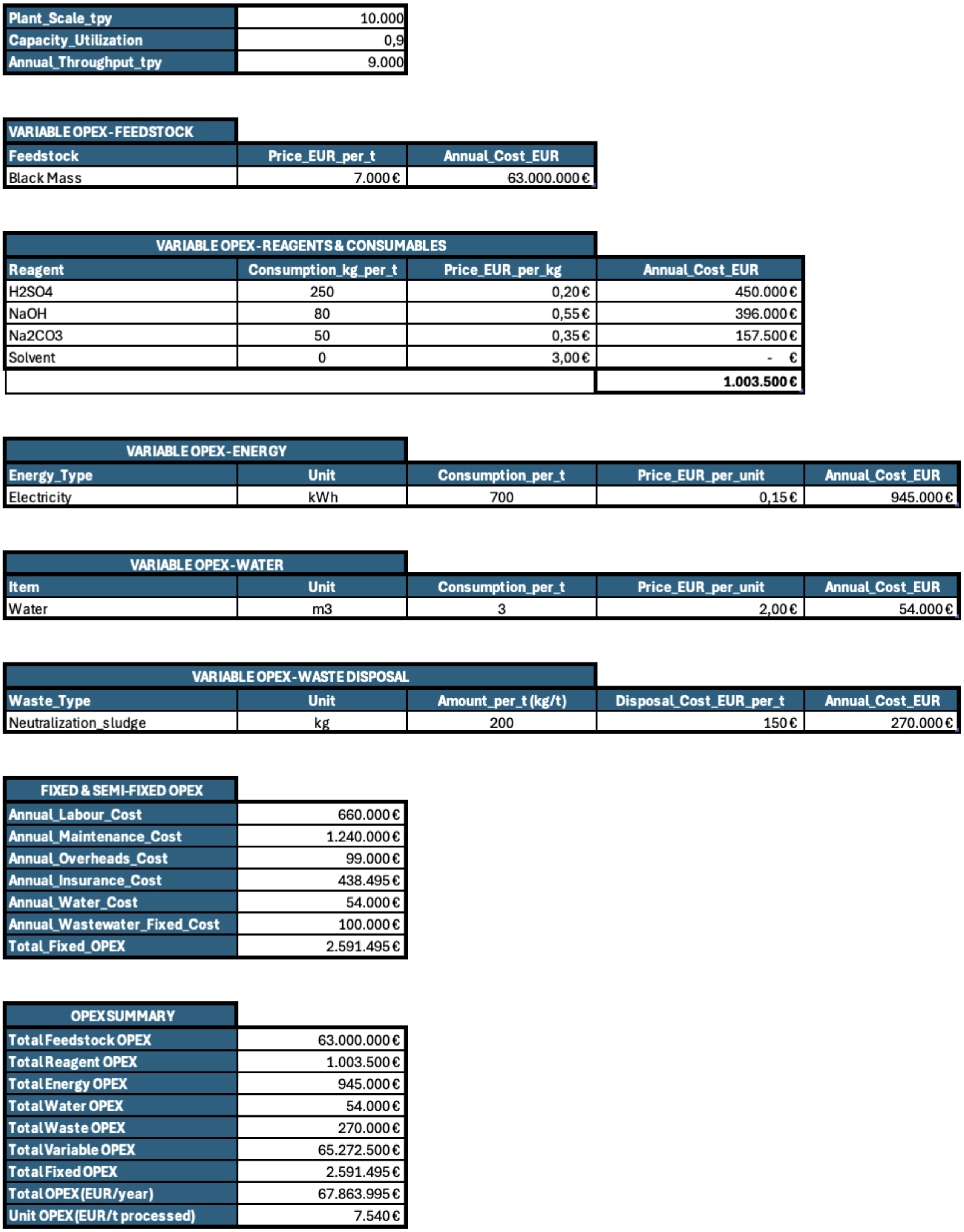
The worksheet 11_OPEX estimates the annual operating costs of the hydrometallurgical recycling plant. The model distinguishes between variable operating costs, which scale with plant throughput, and fixed or semi-fixed operating costs, which are largely independent of production volume.

The total operating expenditure is therefore calculated as:

$$OPEX_{total} = OPEX_{variable} + OPEX_{fixed}$$

where:

- $OPEX_{variable} = variable\ operating\ costs$
- $OPEX_{fixed} = fixed\ and\ semifixed\ operating\ costs$



| | |
|---|---|
| **Plant_Scale_tpy** | 10.000 |
| **Capacity_Utilization** | 0,9 |
| **Annual_Throughput_tpy** | 9.000 |

| **VARIABLE OPEX-FEEDSTOCK** | | |
|---|---|---|
| **Feedstock** | **Price_EUR_per_t** | **Annual_Cost_EUR** |
| Black Mass | 7.000 € | 63.000.000 € |

| **VARIABLE OPEX-REAGENTS & CONSUMABLES** | | | |
|---|---|---|---|
| **Reagent** | **Consumption_kg_per_t** | **Price_EUR_per_kg** | **Annual_Cost_EUR** |
| H2SO4 | 250 | 0,20 € | 450.000 € |
| NaOH | 80 | 0,55 € | 396.000 € |
| Na2CO3 | 50 | 0,35 € | 157.500 € |
| Solvent | 0 | 3,00 € | - € |
| | | | **1.003.500 €** |

| **VARIABLE OPEX-ENERGY** | | | | |
|---|---|---|---|---|
| **Energy_Type** | **Unit** | **Consumption_per_t** | **Price_EUR_per_unit** | **Annual_Cost_EUR** |
| Electricity | kWh | 700 | 0,15 € | 945.000 € |

| **VARIABLE OPEX-WATER** | | | | |
|---|---|---|---|---|
| **Item** | **Unit** | **Consumption_per_t** | **Price_EUR_per_unit** | **Annual_Cost_EUR** |
| Water | m3 | 3 | 2,00 € | 54.000 € |

| **VARIABLE OPEX-WASTE DISPOSAL** | | | | |
|---|---|---|---|---|
| **Waste_Type** | **Unit** | **Amount_per_t (kg/t)** | **Disposal_Cost_EUR_per_t** | **Annual_Cost_EUR** |
| Neutralization_sludge | kg | 200 | 150 € | 270.000 € |

| **FIXED & SEMI-FIXED OPEX** | |
|---|---|
| **Annual_Labour_Cost** | 660.000 € |
| **Annual_Maintenance_Cost** | 1.240.000 € |
| **Annual_Overheads_Cost** | 99.000 € |
| **Annual_Insurance_Cost** | 438.495 € |
| **Annual_Water_Cost** | 54.000 € |
| **Annual_Wastewater_Fixed_Cost** | 100.000 € |
| **Total_Fixed_OPEX** | 2.591.495 € |

| **OPEX SUMMARY** | |
|---|---|
| **Total Feedstock OPEX** | 63.000.000 € |
| **Total Reagent OPEX** | 1.003.500 € |
| **Total Energy OPEX** | 945.000 € |
| **Total Water OPEX** | 54.000 € |
| **Total Waste OPEX** | 270.000 € |
| **Total Variable OPEX** | 65.272.500 € |
| **Total Fixed OPEX** | 2.591.495 € |
| **Total OPEX (EUR/year)** | 67.863.995 € |
| **Unit OPEX (EUR/t processed)** | 7.540 € |

*Fig. 13: Worksheet 10_OPEX*

### A.5.1 Plant Throughput

Operating costs are calculated based on the annual plant throughput defined by the selected scenario.

$$Throughput = PlantScale \times CapacityUtilization$$

This throughput value is used to scale all variable operating costs.

### A.5.2 Feedstock Cost

The purchase of black mass feedstock represents the dominant operating cost in the recycling process.

Annual feedstock cost is calculated as:

$$FeedstockCost \ = \ Throughput \times Price_{BM}$$

where:

- $Price_{BM} = black\ mass\ purchase\ price$

### A.5.3 Reagent Consumption

Reagents are consumed in the hydrometallurgical process according to the process intensities defined in the Process Basis sheet.

The annual reagent consumption is calculated as:

$$ReagentConsumption_j = Throughput \times Consumption_j$$

where:

- $Consumption_j = reagent\ consumption\ per\ tonne\ of\ feedstock$

The annual reagent cost is therefore:

$$ReagentCost_j = ReagentConsumption_j \times Price_j$$

The total reagent cost is obtained by summing the cost of each reagent:

$$TotalReagentCost = \sum_j ReagentCost_j$$

### A.5.4 Energy Consumption

Electricity consumption is calculated based on the process energy intensity.

$$EnergyConsumption = Throughput \times EnergyIntensity$$

where:

- $EnergyIntensity = electricity\ consumption\ per\ tonne\ of\ feedstock$

The annual electricity cost is therefore:

$$EnergyCost = EnergyConsumption \times ElectricityPrice$$

### A.5.5 Water Consumption

Water consumption is also estimated based on a specific consumption intensity per tonne of processed feedstock.

$$WaterConsumption = Throughput \times WaterIntensity$$

The annual water cost is calculated as:

$$WaterCost = WaterConsumption \times WaterPrice$$

### A.5.6 Waste Disposal

The hydrometallurgical process generates several waste streams that must be treated or disposed of.

For each waste stream $k$, the total quantity generated is calculated as:

$$Waste_k = Throughput \times WasteIntensity_k$$

The associated disposal cost is then:

$$WasteCost_k = Waste_k \times DisposalPrice_k$$

The total waste disposal cost is obtained by summing the cost of all waste streams.

### A.5.7 Fixed and Semi-Fixed Operating Costs

Fixed and semi-fixed operating costs include labour, maintenance, overheads and insurance.

The total labour cost is calculated as:

$$LabourCost = FTE \times Salary_{FTE}$$

Maintenance costs are estimated as a fraction of the fixed capital investment:

$$MaintenanceCost = MaintenanceFactor \times FCI$$

Overheads are estimated as a percentage of labour cost:

$$Overheads = OverheadFactor \times LabourCost$$

Insurance costs are calculated as:

$$InsuranceCost = InsuranceFactor \times FCI$$

Additional fixed costs such as wastewater treatment are also included.

### A.5.8 Total Operating Cost

The total operating cost is calculated as the sum of variable and fixed operating costs:

$$OPEX_{total} = OPEX_{variable} + OPEX_{fixed}$$

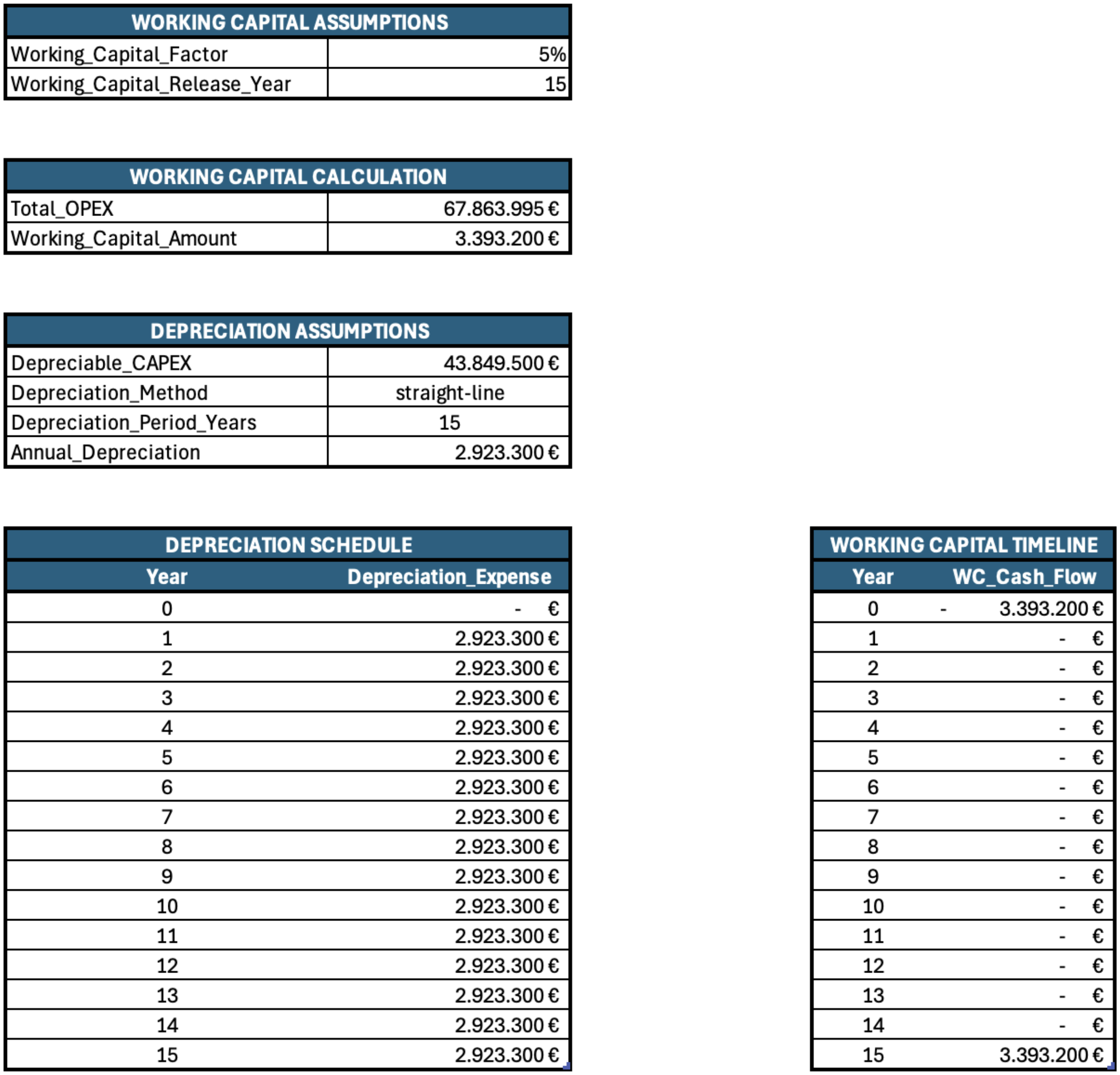
### A.5.9 Unit Operating Cost

The cost of processing one tonne of black mass is defined as:

$$UnitOPEX = \frac{OPEX_{total}}{Throughput}$$

## A.6 Working Capital and Depreciation Model

The worksheet 12_WorkingCapitalDepreciation defines the financial assumptions related to working capital requirements and capital depreciation over the project lifetime. These elements are required for the calculation of annual cash flows and financial indicators such as NPV and IRR.



| WORKING CAPITAL ASSUMPTIONS | |
|---|---|
| Working_Capital_Factor | 5% |
| Working_Capital_Release_Year | 15 |

| WORKING CAPITAL CALCULATION | |
|---|---|
| Total_OPEX | 67.863.995 € |
| Working_Capital_Amount | 3.393.200 € |

| DEPRECIATION ASSUMPTIONS | |
|---|---|
| Depreciable_CAPEX | 43.849.500 € |
| Depreciation_Method | straight-line |
| Depreciation_Period_Years | 15 |
| Annual_Depreciation | 2.923.300 € |

| DEPRECIATION SCHEDULE | |
|---|---|
| Year | Depreciation_Expense |
| 0 | - € |
| 1 | 2.923.300 € |
| 2 | 2.923.300 € |
| 3 | 2.923.300 € |
| 4 | 2.923.300 € |
| 5 | 2.923.300 € |
| 6 | 2.923.300 € |
| 7 | 2.923.300 € |
| 8 | 2.923.300 € |
| 9 | 2.923.300 € |
| 10 | 2.923.300 € |
| 11 | 2.923.300 € |
| 12 | 2.923.300 € |
| 13 | 2.923.300 € |
| 14 | 2.923.300 € |
| 15 | 2.923.300 € |

| WORKING CAPITAL TIMELINE | |
|---|---|
| Year | WC_Cash_Flow |
| 0 | - 3.393.200 € |
| 1 | - € |
| 2 | - € |
| 3 | - € |
| 4 | - € |
| 5 | - € |
| 6 | - € |
| 7 | - € |
| 8 | - € |
| 9 | - € |
| 10 | - € |
| 11 | - € |
| 12 | - € |
| 13 | - € |
| 14 | - € |
| 15 | 3.393.200 € |

*Fig. 14: Worksheet 12_WorkingCapital_Depreciation*

### A.6.1 Working Capital Assumptions

Working capital represents the funds required to finance the day-to-day operations of the plant, including inventories, accounts receivable, and short-term operating expenses.

In the model, working capital is estimated as a fraction of the annual operating expenditure.

$$WorkingCapital = WorkingCapitalFactor \times OPEX_{annual}$$

where:

- $WorkingCapitalFactor = 5\%$
- $OPEX_{annual} = total\ annual\ operating\ cost$

### A.6.2 Working Capital Timeline

Working capital is assumed to be invested at the start of the project and released at the end of the plant lifetime.

The cash flow profile is therefore:

- Year 0: working capital investment
- Years 1–14: no additional working capital changes
- Year 15: full working capital release

This can be expressed as:

$$WC_{t=0} = -WorkingCapital$$

$$WC_{t=T} = WorkingCapital$$

where $T$ is the plant lifetime.

This assumption reflects a typical modelling approach used in techno-economic analyses of industrial facilities.

### A.6.3 Depreciation Method

Capital depreciation is included in the financial model in order to account for the reduction in asset value over time and to correctly estimate taxable income.

The model applies straight-line depreciation over the economic lifetime of the plant.

$$Depreciation = \frac{DepreciableCAPEX}{DepreciationPeriod}$$

where:

- $DepreciableCAPEX \; = \; fixed\ capital\ investment$
- $DepreciationPeriod \; = \; plant\ lifetime$

## A.6.4 Depreciation Schedule

The depreciation schedule distributes the depreciation expense uniformly across the operating lifetime of the plant.

$$Depreciation_t = AnnualDepreciation$$

$$for: t \; = \; 1, 2, 3, \ldots, 15$$

No depreciation is applied in year 0, as the plant is assumed to become operational from year 1.

## A.6.5 Role in the Financial Model

Depreciation does not represent a cash outflow but reduces the taxable income of the project. The taxable profit is therefore calculated as:

$$TaxableIncome = \; EBIT - Depreciation$$

Taxes are then calculated as:

$$Taxes = TaxRate \times TaxableIncome$$

Finally, depreciation is added back when calculating operating cash flow.

$$CashFlow = NetIncome + Depreciation$$

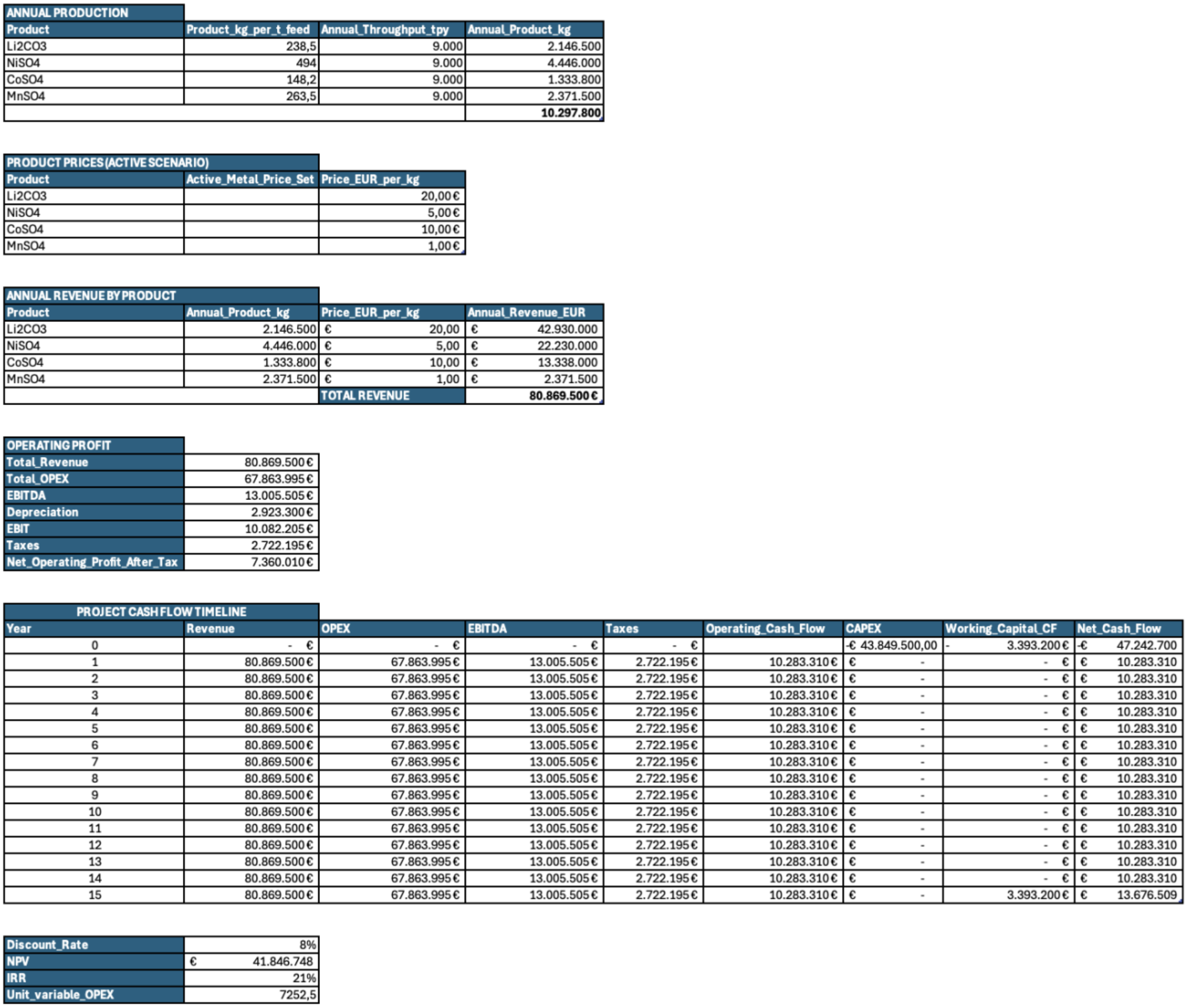
This treatment ensures that the model correctly accounts for the fiscal effect of capital depreciation in the project financial evaluation.

## A.7 Revenue, Cash Flow and Financial Performance Model

The worksheet 20_CashFlows converts the technical and cost outputs of the previous model modules into annual financial results and project cash flows. This sheet integrates production volumes, product prices, operating costs, depreciation and working capital movements in order to generate the full project cash flow timeline used for the investment appraisal.

The worksheet is organised into five main blocks:

- annual production
- revenue calculation
- operating profit calculation
- project cash flow timeline
- financial indicators



**ANNUAL PRODUCTION**

| Product | Product_kg_per_t_feed | Annual_Throughput_tpy | Annual_Product_kg |
|---|---|---|---|
| Li2CO3 | 238,5 | 9.000 | 2.146.500 |
| NiSO4 | 494 | 9.000 | 4.446.000 |
| CoSO4 | 148,2 | 9.000 | 1.333.800 |
| MnSO4 | 263,5 | 9.000 | 2.371.500 |
| | | | **10.297.800** |

**PRODUCT PRICES (ACTIVE SCENARIO)**

| Product | Active_Metal_Price_Set | Price_EUR_per_kg |
|---|---|---|
| Li2CO3 | | 20,00 € |
| NiSO4 | | 5,00 € |
| CoSO4 | | 10,00 € |
| MnSO4 | | 1,00 € |

**ANNUAL REVENUE BY PRODUCT**

| Product | Annual_Product_kg | Price_EUR_per_kg | Annual_Revenue_EUR |
|---|---|---|---|
| Li2CO3 | 2.146.500 | € 20,00 | € 42.930.000 |
| NiSO4 | 4.446.000 | € 5,00 | € 22.230.000 |
| CoSO4 | 1.333.800 | € 10,00 | € 13.338.000 |
| MnSO4 | 2.371.500 | € 1,00 | € 2.371.500 |
| | | **TOTAL REVENUE** | **80.869.500 €** |

**OPERATING PROFIT**

| | |
|---|---|
| **Total_Revenue** | 80.869.500 € |
| **Total_OPEX** | 67.863.995 € |
| **EBITDA** | 13.005.505 € |
| **Depreciation** | 2.923.300 € |
| **EBIT** | 10.082.205 € |
| **Taxes** | 2.722.195 € |
| **Net_Operating_Profit_After_Tax** | 7.360.010 € |

**PROJECT CASH FLOW TIMELINE**

| Year | Revenue | OPEX | EBITDA | Taxes | Operating_Cash_Flow | CAPEX | Working_Capital_CF | Net_Cash_Flow |
|---|---|---|---|---|---|---|---|---|
| 0 | - € | - € | - € | - € | | -€ 43.849.500,00 | - 3.393.200 € | -€ 47.242.700 |
| 1 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 2 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 3 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 4 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 5 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 6 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 7 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 8 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 9 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 10 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 11 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 12 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 13 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 14 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | - € | € 10.283.310 |
| 15 | 80.869.500 € | 67.863.995 € | 13.005.505 € | 2.722.195 € | 10.283.310 € | € - | 3.393.200 € | € 13.676.509 |

| | |
|---|---|
| **Discount_Rate** | 8% |
| **NPV** | € 41.846.748 |
| **IRR** | 21% |
| **Unit_variable_OPEX** | 7252,5 |

*Fig. 15: Worksheet 20_CashFlows*

### A.7.1 Annual Production

The first block reports the annual production of final products derived from the Process Basis sheet.

For each product $i$, annual production is calculated as:

$$AnnualProduction_i = ProductYield_i \times Throughput$$

where:

- $ProductYield_i = output\ of\ product\ i\ per\ tonne\ of\ black\ mass\ feed\ (kg/t)$
- $Throughput = annual\ throughput\ of\ black\ mass\ (t/y)$

The total annual product output is therefore:

$$AnnualProduction_{total} = \sum_i AnnualProduction_i$$

### A.7.2 Product Prices

The annual revenue calculation uses the active product price set selected in the Scenario sheet.

For each product $i$, the model retrieves the corresponding $Price_i$ from the active scenario price set.

These prices are expressed in $€/kg$ and are used directly in the revenue calculation.

### A.7.3 Revenue Calculation

Annual revenue from each product is calculated as:

$$Revenue_i = \ AnnualProduction_i \times Price_i$$

Total annual revenue is obtained by summing the revenues of all recovered products:

$$Revenue_{total} = \sum_i Revenue_i$$

Unit revenue per tonne of black mass processed is:

$$UnitRevenue = \frac{Revenue_{total}}{Throughput}$$

### A.7.4 Operating Profit Calculation

The worksheet then combines revenues with annual operating costs and depreciation to determine the project's operating profitability.

Earnings before interest, taxes, depreciation and amortisation are calculated as:

$$EBITDA = Revenue_{total} - OPEX_{total}$$

Operating profit after depreciation is calculated as:

$$EBIT = EBITDA - Depreciation$$

Corporate taxes are applied to EBIT:

$$Taxes = EBIT \times TaxRate$$

Net operating profit after tax is therefore:

$$NOPAT = EBIT - Taxes$$

### A.7.5 Operating Cash Flow

Depreciation is a non-cash expense and is therefore added back to NOPAT to calculate operating cash flow:

$$OperatingCashFlow = NOPAT + Depreciation$$

Equivalently:

$$OperatingCashFlow = EBITDA - Taxes$$

This value is assumed to remain constant over the operating lifetime in the absence of inflation or dynamic price assumptions.

### A.7.6 Project Cash Flow Timeline

The project cash flow timeline extends over the full project lifetime and includes capital expenditure, operating cash flows, and working capital movements.

At the initial investment stage, the model includes:

- total capital investment

- working capital investment

Thus, the initial net cash flow is:

$$NetCashFlow_0 = -\ CAPEX_{total} - WorkingCapital$$

For each operating year $t = 1, 2, \ldots, 15$, the annual net cash flow is:

$$NetCashFlow_t = OperatingCashFlow_t$$

provided no additional capital expenditures are assumed.

In the final year, the model assumes full release of working capital:

$$NetCashFlow_T = OperatingCashFlow_T + WorkingCapital$$

### A.7.7 Net Present Value

The Net Present Value is calculated by discounting all project cash flows over the plant lifetime:

$$NPV = \sum_{t=0}^{T} \frac{NetCashFlow_t}{(1+r)^t}$$

where:

- $r\ =\ discount\ rate$
- $T\ =\ project\ lifetime$

### A.7.8 Internal Rate of Return

The Internal Rate of Return (IRR) is defined as the discount rate that sets the Net Present Value equal to zero:

$$\sum_{t=0}^{T} \frac{NetCashFlow_t}{(1+IRR)^t} = 0$$

### A.7.9 Unit Variable Operating Cost

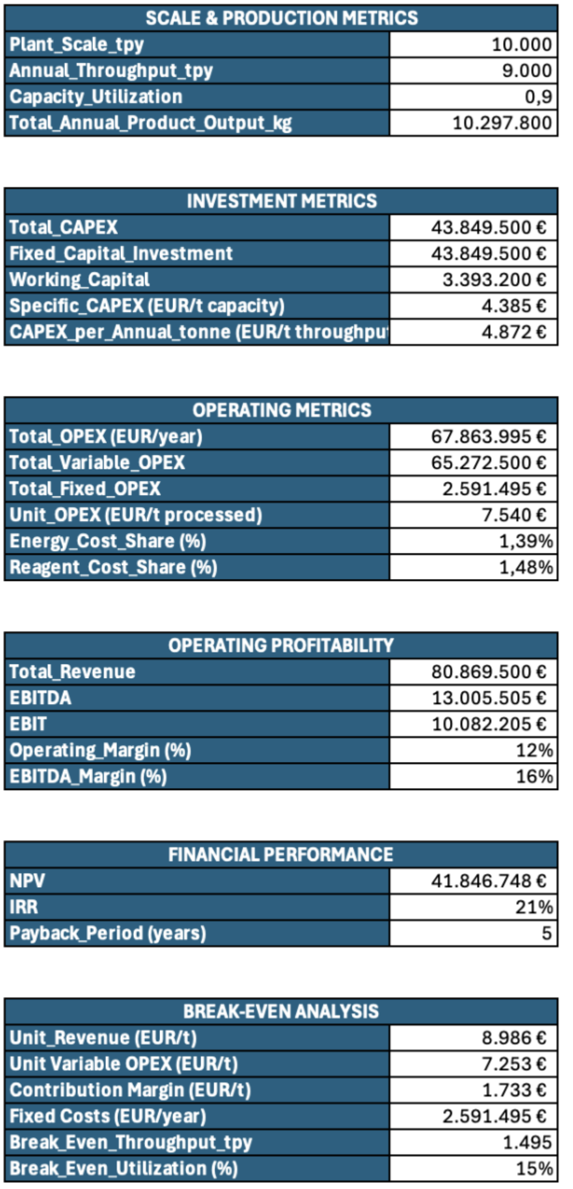
The model also calculates unit variable OPEX, defined as:

$$UnitVariableOPEX = \frac{OPEX_{variable}}{Throughput}$$

This value is later used in the break-even analysis.

## A.8 Key Performance Indicators

The worksheet 21_KPIs summarises the main technical, economic and financial indicators generated by the techno-economic model. The purpose of this sheet is to provide a compact overview of the key results derived from the previous model modules, including plant scale, capital investment, operating costs, profitability and financial performance.



| SCALE & PRODUCTION METRICS | |
|---|---|
| Plant_Scale_tpy | 10.000 |
| Annual_Throughput_tpy | 9.000 |
| Capacity_Utilization | 0,9 |
| Total_Annual_Product_Output_kg | 10.297.800 |

| INVESTMENT METRICS | |
|---|---|
| Total_CAPEX | 43.849.500 € |
| Fixed_Capital_Investment | 43.849.500 € |
| Working_Capital | 3.393.200 € |
| Specific_CAPEX (EUR/t capacity) | 4.385 € |
| CAPEX_per_Annual_tonne (EUR/t throughpu | 4.872 € |

| OPERATING METRICS | |
|---|---|
| Total_OPEX (EUR/year) | 67.863.995 € |
| Total_Variable_OPEX | 65.272.500 € |
| Total_Fixed_OPEX | 2.591.495 € |
| Unit_OPEX (EUR/t processed) | 7.540 € |
| Energy_Cost_Share (%) | 1,39% |
| Reagent_Cost_Share (%) | 1,48% |

| OPERATING PROFITABILITY | |
|---|---|
| Total_Revenue | 80.869.500 € |
| EBITDA | 13.005.505 € |
| EBIT | 10.082.205 € |
| Operating_Margin (%) | 12% |
| EBITDA_Margin (%) | 16% |

| FINANCIAL PERFORMANCE | |
|---|---|
| NPV | 41.846.748 € |
| IRR | 21% |
| Payback_Period (years) | 5 |

| BREAK-EVEN ANALYSIS | |
|---|---|
| Unit_Revenue (EUR/t) | 8.986 € |
| Unit Variable OPEX (EUR/t) | 7.253 € |
| Contribution Margin (EUR/t) | 1.733 € |
| Fixed Costs (EUR/year) | 2.591.495 € |
| Break_Even_Throughput_tpy | 1.495 |
| Break_Even_Utilization (%) | 15% |

*Fig. 16: Worksheet 21_KPIs*

### A.8.1 Scale and Production Metrics

The first section reports the main production indicators of the recycling plant.

Plant capacity is defined as the nominal quantity of black mass that can be processed annually:

Actual annual throughput depends on the assumed capacity utilisation rate:

$$AnnualThroughput = PlantScale \times CapacityUtilization$$

The total annual production of battery-grade salts is obtained from the process mass balance and represents the combined output of lithium carbonate, nickel sulphate, cobalt sulphate and manganese sulphate.

### A.8.2 Investment Metrics

The investment indicators summarise the capital requirements of the project.

The total capital expenditure (CAPEX) includes fixed capital investment and working capital:

$$CAPEX_{total} = FCI + WorkingCapital$$

Specific capital intensity indicators are also calculated in order to normalise the investment cost relative to plant size.

The specific CAPEX per unit of installed capacity is defined as:

$$SpecificCAPEX = \frac{CAPEX_{total}}{PlantScale}$$

while the CAPEX per tonne of annual throughput is calculated as:

$$CAPEX_{throughput} = \frac{CAPEX_{total}}{AnnualThroughput}$$

These metrics allow comparison with capital intensity values reported in the literature for similar recycling facilities.

### A.8.3 Operating Metrics

This section summarises the main operating cost indicators derived from the OPEX model.

Total operating expenditure includes both variable and fixed costs:

$$OPEX_{total} = OPEX_{variable} + OPEX_{fixed}$$

Unit operating cost is calculated by normalising annual OPEX by plant throughput:

$$UnitOPEX = \frac{OPEX_{total}}{AnnualThroughput}$$

The sheet also reports the relative contribution of energy and reagent costs to total operating expenses, highlighting the structure of the cost base of the recycling process.

## A.8.4 Operating Profitability

Operating profitability is evaluated using standard financial indicators.

Earnings before interest, taxes, depreciation and amortisation are calculated as:

$$EBITDA = Revenue - OPEX$$

Operating profit after depreciation is given by:

$$EBIT = EBITDA - Depreciation$$

Profitability is further expressed through margin indicators:

$$EBITDA\ Margin = \frac{EBITDA}{Revenue}$$

$$Operating\ Margin = \frac{EBIT}{Revenue}$$

These indicators provide a measure of the operational efficiency of the recycling process.

## A.8.5 Financial Performance

The financial performance of the project is assessed using two standard investment indicators.

The Net Present Value (NPV) is calculated by discounting all project cash flows over the plant lifetime:

The Internal Rate of Return (IRR) is defined as the discount rate that sets the NPV equal to zero.

The model also reports the payback period, defined as the number of years required for cumulative project cash flows to become positive, indicating the recovery of the initial investment.

### A.8.6 Break-Even Analysis

The final section evaluates the minimum production level required for the plant to cover its fixed operating costs.

The break-even throughput is calculated using the contribution margin:

$$Contribution\ Margin = UnitRevenue - UnitVariableOPEX$$

The break-even production level is therefore:

$$BreakEvenThroughput = \frac{FixedCosts}{ContributionMargin}$$

The break-even utilisation rate is obtained by normalising this value by the installed plant capacity:

$$BreakEvenUtilization = \frac{BreakEvenThroughput}{PlantScale}$$

This indicator provides a measure of the operational resilience of the project to fluctuations in plant utilisation.