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Economic analysis of precious metal recovery from electronic waste through gas-assisted microflow extraction

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ABSTRACT

The recycling of end-of-life (EoL) electronic products is motivated by the enormous investment of resources in their creation and the environmental concerns associated with electronic waste (e-waste). Hydrometallurgical methods that utilize conventional leaching and solvent extraction are often applied to extract target materials from e-waste; however, these techniques have significant technical and economic limitations when extracting high-value, low concentration metals from complex waste streams. This study proposes and evaluates a novel process based on gas-assisted microflow extraction (GAME) that efficiently recovers precious metals from waste printed circuit boards (WPCBs). An economic analysis is conducted to verify the economic feasibility of the GAME-based process at an industrial scale. The economic outputs are further investigated to identify the most cost-effective production strategies, particularly with respect to the plant feedstock rate. It is envisioned that this study may establish a paradigm for making economically-informed decisions for sustainable technologies.

1. Introduction

The rapid technological advancement in computer and information industries drives the production of electrical and electronic products, but at the same time, also accelerates their obsolescence (Islam and Huda, 2019). As a result, the waste from end-of-life (EoL) electronics, i.e., e-waste, continues to be one of the fastest growing waste streams worldwide (Perkins et al., 2014). On the one side, e-waste inevitably imposes environmental threats as it contains hazardous and toxic materials; on the flip side, it also offers a potential secondary source of valuable/critical materials for which the primary sources (virgin materials) are subject to substantial supply risks (Dhir et al., 2021). Waste printed circuit boards (WPCBs) are identified as the major source of recoverable materials from e-waste, as they contain high-value precious metals such as gold and silver (Marra et al., 2018).

E-waste recycling (in some contexts, known as urban mining (Nakamura, 2014)) offers a solution to conserve valuable resources from used electronics, and concomitantly, to alleviate the environmental burden caused by improper EoL management (Ryter et al., 2022; Baxter et al., 2016). Currently, hydrometallurgical methods are considered the most promising approach for e-waste recycling (Gámez et al., 2019). Nevertheless, most conventional hydrometallurgical approaches cannot economically extract and recover low-concentration (but high-value) materials from complex waste stream at scale, or not even physically tenable in practice. Furthermore, there is insufficient research on the economic performance of hydrometallurgical approaches used in commercial operations (Wilson et al., 2014).

To economically recover precious metals from e-waste, one promising approach is to employ gas-assisted microflow extraction (GAME) (Yu et al., 2010). Compared to conventional solvent extraction approaches (such as bulk solvent extraction), GAME can significantly reduce material consumption thus lowering operating expenses. Remarkably, GAME can achieve high extraction efficiency when operating under high aqueous to organic ratio (A/O) that is required to extract low concentration metals from complex stream, making it perfectly suited for recovering precious metals from WPCBs.

To verify the economic feasibility of GAME in industrial practice, this study introduces a holistic GAME-based process workflow that can recover precious metals from e-waste with significantly lower chemical consumption and higher extraction efficiency. An economic analysis is conducted for the GAME-based process to ascertain the optimal

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Nomenclature

EoL	End-of-life
WPCB	Waste printed circuit board
GAME	Gas-assisted microflow extraction
BSX	Bulk solvent extraction
TEA	Techno-economic assessment
A/O	Aqueous-to-organic
KPI	Key performance indicator
AVC	Average variable cost
ATC	Average total cost
OPEX	Annual operating expenses
CAPEX	Total capital investment
NOI	Annual net operating income
NCF	Net cash flow
IRR	Internal rate of return
X	Weight of WPCBs processed per year

industrial operating strategies. The findings of this research could make an important contribution to support the sustainable e-waste management and promote the practices of material recycling.

The remainder of the paper is structured as follows. First, an overview of e-waste management and conventional solvent extraction approaches is provided in the Literature Review section. Then, the Materials and Methods section introduces the GAME-based process and proposes a two-phase methodology for economic analysis. In the Results and Discussion section, key economic results are presented and further investigated through sensitivity analysis and nonlinear regression. Finally, the paper concludes with a summary of research highlights and identifies promising areas for future research.

2. Literature review

Electronic waste (e-waste), or waste from electronic and electrical equipment (WEEE), generally refers to discarded end-of-life (EoL) electronic products and components (Mmereki et al., 2016). One characteristic that distinguishes e-waste from other waste streams is the complex mixture of materials. On the one hand, e-waste contains several hazardous elements (such as lead, mercury, and cadmium (Perkins et al., 2014)) that require special treatment and cannot be directly disposed in landfill sites. On the other hand, it also contains valuable metals such as gold, silver, palladium, and copper (Islam et al., 2020), presenting immense opportunities for value recovery. In 2019, the e-waste generated worldwide reached a record of 53.6 million metric tons, but only 17.4% was collected and recycled (Forti et al., 2020). The growing environmental concerns over the sheer volume of e-waste, along with the enormous loss of recoverable material resources, prompt the need for effective end-of-life management strategies specifically optimized for e-waste, so as to combat improper practices such as hazardous landfilling or household stockpiling (Patil and Ramakrishna, 2020).

Perhaps the most essential and iconic component of electronics is the printed circuit board (PCB), as it provides the electrical interconnections between components and is found in almost all electronics products (LaDou, 2006). While waste printed circuit boards (WPCBs) constitute only about 3 – 6 wt percentage of the total e-waste (Wang et al., 2020), they represent the most valuable part of e-waste accounting for over 40% of the total e-waste metal value (Kumar et al., 2017). In fact, the concentration of precious metals (especially gold and palladium) in PCBs can be several orders of magnitude above conventional ore deposits (Balde et al., 2017). During disposal, WPCBs are typically dismantled from common used electronics, such as mobile phones, computers, and hard disk drives (HDDs) (Cong et al., 2017), creating a pre-concentrated waste stream suitable for resource recovery.

Over the past decades, there has been an increasing interest in recycling materials from WPCBs, although large-scale economically successful recycling has yet to be achieved. It is envisaged that value recovery from WPCBs would become an integral part of an e-waste management strategy, and the lucrative economic opportunities from it could eventually foster a sustainable circular economy for electronics sector in the aggregate (Kazancoglu et al., 2022). Apart from economic factors, metal recovery from secondary feedstocks, such as WPCBs, generally entail significant reductions in embodied energy and CO_2 emissions relative to virgin materials production, which provide further environmental and societal benefit.

The metals in PCBs consists mainly of common base metals (e.g., copper, lead, aluminum, and tin), as well as other heavy metals such as cadmium and nickel (Bizzo et al., 2014). However, the primary source of recoverable value from WPCBs resides in high-value precious metals, especially gold and silver (prices ranging from \$54,514.97/kg – \$65,714.28/kg and \$592.22/kg – \$866.13/kg in 2022, respectively), even though they only make up 1% of PCB by weight (Awasthi et al., 2017). Additionally, the lower-value base metals with high-concentration (such as copper that constitutes 10–20% of PCB by weight and can be sold at a price of \$7.05/kg – \$10.73/kg in 2022) can also be co-extracted (Ghosh et al., 2015) to augment the total value available for recovery. Hydrometallurgical methods, which use chemical reagents in the aqueous phase to solubilize metals, have been the most active research area for metal recovery from WPCBs (or in a more general sense, e-waste) over the past two decades (Sivakumar et al., 2018). Compared to pyrometallurgical approaches, a hydrometallurgical route enables the selective recovery of individual metals (in this case, the precious metals), offers high controllability, and yields less hazardous emissions (Ghosh et al., 2015; Rocchetti et al., 2018).

In a conventional hydrometallurgical process flow for e-waste recycling, the feed material is first prepared using physical-mechanical treatments (e.g., crushing, shearing, and grinding) to produce a uniformly sized product. The metals are then dissolved through leaching with different lixiviants, sometimes at elevated temperatures or in the presence of various chemical additives (Rocchetti et al., 2018). To facilitate selective and efficient recovery of precious metals from WPCBs, the leaching process must be tuned to maximize the dissolution of target elements (e.g., Au and Ag), while minimizing the contamination from copper and other base metals. Once the leaching is complete, the pregnant leaching solution (PLS) is directed to downstream separation, purification, and recovery processes, with a common approach using solvent extraction, stripping, and precipitation (Correa et al., 2018). These sequential process steps can facilitate the production of high-purity Au and Ag metals, and the details will be discussed in the Materials and Methods.

The most widely used separation and purification process in extractive metallurgy is bulk solvent extraction (BSX) (Kolar et al., 2016). Here, the aqueous leaching solution is vigorously mixed with an organic solvent, which is doped with a carefully-selected ligand that facilitates the selective recovery of valuable elements into the solvent. Industrially, BSX is applied in large continuous mixer-settler reactors with numerous countercurrent stages that are required for selective recovery. Despite its widespread utility in the minerals industry, BSX tends to be ineffective or even unviable for the selective recovery of low-concentration precious metals (e.g., Au and Ag) from the complex leaching solutions of WPCBs. This is the case because solvent extraction requires adequate mixing between the organic extractants and aqueous leaching solution (Rydberg, 2004). Due to the extremely dilute concentration of Au and Ag, BSX needs a long period of time to build up their concentration in the organic phase. This inevitably results in high consumption of chemicals and energy.

This long loading time for the organic phase to reach critical saturation values can be shortened by applying a high aqueous-to-organic phase (A/O) ratio. But for the case of BSX, a high A/O ratio would severely compromise the extraction efficiency (i.e., the percentage of target metals recovered) (El-Ashtoukhy and Fouad, 2015). An alternative to BSX is liquid-liquid two-phase microflow extraction (LLME) (Wang and Luo, 2017), which uses well-defined microchannels that provide a large specific interfacial area and a short diffusion length for the solutions. As a result, LLME can achieve a mass-transfer rate that is several orders-of-magnitude higher than BSX and thus can significantly reduce the loading time (Wang and Luo, 2017). Nevertheless, once the dimension of the microchannels is fixed, higher A/O ratio will increase the mass transfer distance and reduce the extraction efficiency (Wang et al., 2014). Consequently, although LLME methods do manage to preserve a reasonable extraction efficiency under moderately high A/O ratio, its performance could still be impaired when the A/O ratio is extremely high (Vural Gürsel et al., 2016).

To overcome this obstacle, one promising solution is to introduce a gas phase into the LLME system, i.e., establish a system based on gas-assisted microflow extraction (GAME), which has already demonstrated its potential in the recovery of metals (e.g., rare earths) from waste streams (Chen et al., 2018). The principle is to profusely generate uniformed micro gas (e.g., nitrogen) bubbles into the aqueous leaching solution, with the organic extractant molecules coated on the surface (Tan et al., 2011). Employing gas/liquid/liquid flows in the microchannels can significantly elevate the mass-transfer rate and extraction efficiency while preserving a high A/O ratio (Chen et al., 2017). Therefore, GAME is inherently geared towards recovering low-concentration target metals from a complex waste stream. The various advantages of GAME in extraction performance over conventional approaches can be highlighted through a qualitative comparison as shown in Table 1.

Even though GAME has been extensively applied in a diverse range of industries, such as foods, pharmacy, and functional material synthesis (Chen et al., 2018; Cents et al., 2001), and notably in the case of recovering rare earths from waste water (Chen et al., 2017), very limited research is available on its applications for the purification and separation of individual metals from a complex e-waste stream. In an attempt to address this need, the Virginia Tech authors have designed and optimized a prototype GAME-based process that can selectively extract high-purity precious metals from WPCBs. The complete process flow comprises physical pretreatment, an upstream leaching module, and a downstream purification module, which will be discussed in the Materials and Methods.

Although the technical viability of the proposed GAME-based process (including stability and repeatability) has been verified through rigorous experimental testing, its actual industrial implementation hinges on the economic feasibility when operated at a production scale (Moni et al., 2020). This evaluation is best defined though an economic concept of paramount importance: the economy of scale, which refers to the decrease in production cost per unit of output as the production scale increases (Antonio, 1979). In the context of circular economy and value recovery, economy of scale directly links to the volume of available waste feedstock (Kębłowski et al., 2020). In view of this, the amount of WPCBs that can be collected and processed would be a determining factor to the production efficiency of the industrial facility equipped with the new GAME-based process.

To advance the technology readiness level (TRL) of the pioneering GAME-based approach for value recovery from e-waste, quantitative analyses with reliable data are essential to create a more comprehensive appraisal of the projected economic performance and impact (Acerbi et al., 2021), thus providing valuable decision-making guidelines in scaling up the production rate to achieve an attractive economy of scale. More specifically, it is crucial to determine whether the value recovered from target metals is adequate to overcome all the costs in processing high volumes of WPCBs, including material and utility consumption, capital investment, operating labor (Gigli et al., 2019), and additional indirect and administrative expenses (Rizos et al., 2016).

This prompts the need to establish a mathematical model based upon the design of the GAME process to predict its economic feasibility at an industrial scale. In accordance with the standard procedure for project development in the chemical industry (Buchner et al., 2018), an apt strategy for this investigation is to conduct a techno-economic assessment (TEA). Through production cost-benefit modeling and financial analysis (Lauer, 2008), TEAs are extensively employed to evaluate the economic prospects of a concept, system or technology (Techno-economic assessment, 2022). TEAs not only evaluate economic feasibility by estimating key performance indicators (KPIs) (Schnuelle et al., 2020), but can also be integrated with analytical tools (such as sensitivity analysis and statistical methods) to explore technological improvement opportunities (Deng et al., 2020). In the present work, attention will largely be devoted to just the economic portion of TEA.

As the scope of inquiry may vary, there is no universal standard platform or procedure for conducting TEAs (Cortes-Peña et al., 2020). Numerous studies have been carried out to conduct TEAs on value recovery from e-waste (e.g., Diaz et al., (2020); Nguyen et al. (2017); Ghodrat et al. (2016) and Khan et al. (2016)), each featuring a unique TEA model tailored to a specific scenario. Based on a general economic model for process engineering proposed by Silla, 2003 and following the TEA guidelines provided by (US Energy Information Administration (EIA), 2015), researchers at Purdue have developed a general TEA model that can adapt to a wide range of technical domains. By applying this TEA model, the economic performance of numerous value recovery approaches has been investigated, especially in the field of e-waste management (e.g., Frost et al. (2020) and Deng et al. (2021)).

Compared to the TEA tools in previous studies, Purdue's TEA model has several notable features. First, it starts with a preliminary cost-benefit analysis that provides simplified KPIs to quickly identify system bottlenecks before getting into more complicated long-term financial analysis (Deng et al., 2020). Second, this computational model can accommodate special cost or revenue components with a customized calculation mechanism to address particular processes (Chowdhury et al., 2021). Furthermore, unlike most other TEAs that generally rely on Microsoft Excel®, the TEA model in this study has been implemented via a graphical-based software tool (Deng et al., 2021) that streamlines the procedure of conducting TEAs. The next section will elaborate on how to apply Purdue's TEA model in the evaluation of the economic performance of precious metal recovery using the GAME-based process developed by Virginia Tech.

Table 1
Extraction performance comparison among BSX, LLME, and GAME.

Category	BSX	LLME	GAME
Mass transfer rate (Wang and Luo, 2017)	Low	High	Very high
Loading time (Kolar et al., 2016)	Long	Short	Very short
Volumetric throughputs (Kumar et al., 2012)	Low	High	Very high
Extraction efficiency under moderately high A/O (e.g., 10/1) (Vural Gürsel et al., 2016)	Low	High	High
Extraction efficiency under extremely high A/O (e.g., 100/1) (Wang et al., 2014)	Low	Low	High

3. Materials and methods

3.1. GAME-based precious metal recovery process

The GAME-based process developed by Virginia Tech primarily consists of a leaching module and a purification module. The pre-treated WPCBs will be fed into the leaching module to generate Au-Ag loaded PLS, which will go through the GAME-based purification module to extract high-purity Au and Ag metals. In addition, Cu metal will be recovered as a byproduct considering its high-concentration in WPCBs. A complete process flow diagram is illustrated in Fig. 1.

The WPCB feedstock may be sourced from a multitude of EoL

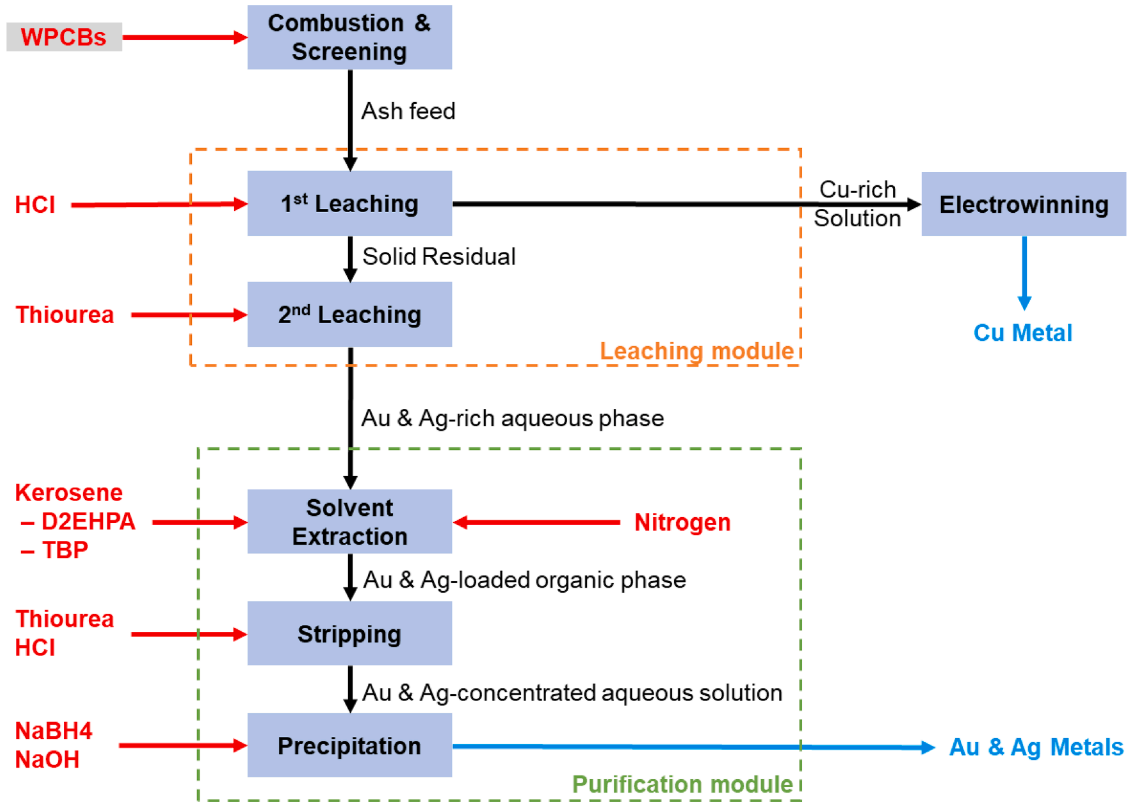

Fig. 1. GAME-based process flow for Au and Ag recovery from WPCBs.

electronic devices (e.g., mobile phones, computers, and televisions), which can be collected from e-waste recycling facilities. During the laboratory procedure, WPCB pieces (from laptop and desktop circuits) were first placed in crucibles and combusted in a muffle furnace at 800 °C. The purpose of combustion is to burn out non-metal materials (e.g., plastics) and thus separate them from metals. It is assumed that there is no loss of target output metals (i.e., Au, Ag and Cu) since their melting points are higher than the combustion temperature. The residue was then screened and collected as feed used in the subsequent leaching processes. There are two sequential leaching stages. Most of the copper, as well as other base metals, are dissolved at the first leaching stage using diluted hydrochloric acid, and the raffinate from the 1st leaching stage is sent to electrowinning for copper recovery. Almost no Au and Ag are dissolved during the 1st leaching stage; the solid residual is then fed into the second leaching stage and dissolved by thiourea (Akcil et al., 2015). After the 2nd leaching, almost all Au and Ag are leached out into the PLS and is ready for GAME-based purification, which consists of solvent extraction, stripping, and precipitation.

For the GAME-based purification module, Au-Ag loaded PLS, kerosene, and nitrogen are used as aqueous, organic, and gas phases respectively, while tributyl phosphate (TBP) and Di-(2-ethylhexyl) phosphoric acid (D2EHPA) are used as extractants (diluted in kerosene). Through solvent extraction, Au and Ag are separated from contaminants and concentrated into the loaded organic phase. Next, thiourea (dissolved in hydrochloric acid solution) was used again to strip Au and Ag from the organic phase to a highly-concentrated aqueous phase (Awadalla and Ritcey, 1991). Lastly, sodium borohydride ($NaBH_4$, dissolved in sodium hydroxide solution) was slowly added to the stripping solution to precipitate Au and Ag as particles. To obtain high-purity metals that can be sold to the market, these precipitates were then collected through filtration (Behnamfard et al., 2013) and were washed with distilled water and acetone, followed by vacuum drying (Hohnstedt et al., 1965). More detailed information regarding the GAME-based process design and relevant chemical procedures/reactions can be found in the Supporting Information (SI).

3.2. Economic analysis methodology

The primary objective of this study is to conduct an economic analysis for the operation of a WPCB processing facility (referred to as "GAME facility") that deploys the process design as depicted in Fig. 1 and described above. The proposed economic analysis methodology consists of two phases: a process economic assessment (Phase I) and an improvement opportunity analysis (Phase II). While a TEA model/software will be used to perform these tasks, as noted previously, our emphasis is largely limited to the economic aspects of the GAME-based process.

Phase I aims to evaluate economic feasibility of the process under study at an industrial level using a set of predetermined assumptions. It starts with collecting and synthesizing the pertinent process information that serves as inputs for the existing TEA model (to be discussed in Section 3.3), including lab-scale or experimental data of the GAME-based process (summarized in Section 3.4), and results from prior studies (e.g., cost estimation models for electrowinning (Kordosky and Dorlac, 1986)). Next, a software tool (see Section 3.5) is used to calculate/estimate the industrial-scale mass balance and generate economic results for a baseline scenario (to be discussed in Section 4.1.1). Furthermore, to compare the economic performance of the GAME-based process with conventional approaches, a comparative analysis will be conducted (results are discussed in Section 4.1.2).

Phase II aims to expand upon the economic results generated from Phase I to identify improvement opportunities in process design and operating settings, and the variables of interest may vary from case to case. As explained in the Literature Review, the economic feasibility of the GAME facility depends on the production scale. In view of this, in this study a sensitivity analysis will be conducted to investigate the impact of the annual feedstock rate on relevant economic performance metrics. Based on the theoretical data generated through a sensitivity analysis (i.e., the economic results under different production scales), statistical learning tools will be applied to provide more insights into how to leverage the economies of scale. The detailed results and discussion of Phase II will be presented in Section 4.2.

The GAME-based process in this work serves as a case study to demonstrate the complete workflow of using the two-phase methodology to provide economically-informed insights for decision making in technology development. However, the application of the two-phase methodology is not limited to the GAME-based process and WPCB recycling. The underlying cost-benefit modeling (in Phase I) can be tailored to any specific process flows; the scope of the sensitivity analysis (in Phase II) can be narrowed down to any subset of internal factors (e.g., process design variables) and external factors (e.g., logistics costs). For the preceding reasons, the two-phase economic analysis methodology proposed in this study is adoptable to the economic assessment and analysis of a diverse range of technologies.

3.3. TEA model

The Purdue's TEA model consists of two parts: a preliminary cost-benefit analysis and a comprehensive financial analysis. The preliminary cost-benefit analysis aims to model the total production cost (C) and revenue (R) on an annual basis. For the case of the GAME facility, let the annual production amounts (in mt) of Au, Ag, and Cu be denoted as Q_1, Q_2, Q_3, and their market prices per mt be denoted as P_1, P_2, P_3. Accordingly, the structure of the preliminary cost-revenue model is outlined in Fig. 2.

The exact mathematical model that underpins Fig. 2 is explained in the SI. To summarize the salient points, the annual production cost (C) consists of four components that are interlinked. The direct cost is considered as a variable cost since it directly depends on the mass balance flow during the operation, whereas the other three components collectively constitute the fixed costs that are necessary to establish the facility. In summary, the calculation of the annual net profit (P) can be expressed in Eq. (1).

$$P = R - C = \sum_{i=3}^{3} R_i - C = \sum_{i=3}^{3} P_i Q_i - (C_D + C_c + C_I + C_G). \tag{1}$$

Based upon the results from the preliminary cost-benefit analysis, the comprehensive financial analysis is conducted by considering economic factors such as interest rate, depreciation, and inflation (see SI for details). The main goal is to generate a net cash flow (NCF) plot that illustrates inflow and outflow of funds of each year throughout the facility's lifespan. Based on the NCF, certain KPIs that factor in the time value of money will be calculated, such as net present value (NPV) and internal rate of return (IRR), which will be explained in the Results and Discussion.

3.4. Data collection

The primary mass balance of the GAME-based process consists of the material consumption in leaching and purification modules and the amount of target metals (Au, Ag, Cu) produced. The lab-scale data for processing 2.66 kg of WPCBs are calculated based on experimental data curated by Virginia Tech and relevant reaction stoichiometry (provided in SI). Other materials consumed, such as the anode used in electrowinning, as well as nonreactive substances (deionized water and nitrogen), are estimated through empirical models from literature (Kordosky and Dorlac, 1986; Free, 2014) and are excluded from the primary mass balance. The purchasing prices of input materials (industrial grade) and the selling prices of output metals (commercial grade) were procured from multiple credible online databases (e.g., Argus, LME, Trading Economics, MineralPrices.com) or merchant invoices, and the relevant sources are provided in the SI. Table 2 provides a summary of the lab-scale data and price assumptions.

Table 2
Primary mass balance (lab-scale) and price assumptions.

Major inputs for processing 2.66 kg WPCBs		
Material Name	Lab-scale net consumption	Industrial grade price (unit cost)
HCl (converted to 0.75 mol/L)	24.39L	$14.35/m^3$
Thiourea	109.16 g	$6600/mt
D2EHPA	1.46 g	$2200/mt
NaOH	33.74 g	$330/mt
NaBH4	61.22 g	$30,000/mt
TBP	1.2 g	$1870/mt
Kerosene	3.62 L (can be reused)	$1000/m^3$
Outputs from processing 2.66 kg WPCBs		
Product name	Lab-scale yield	Commercial grade price (unit revenue)*
Au metal	1.015 g	P_1 = $56,916.73/kg
Ag metal	4.071 g	P_2 = $718.93/kg
Cu metal	814.94 g	P_3 = $9.46/kg

* The prices of Au, Ag, Cu are based on the data in December 2021, and each of them falls into the corresponding price range in 2022 as discussed in the Literature Review.

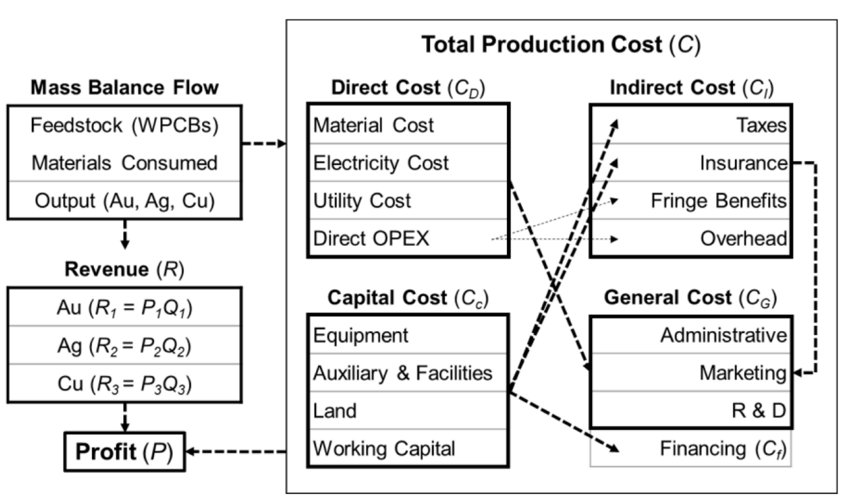

Fig. 2. Production cost-revenue model.

3.5. TEA software

In this work, the economic analysis is conducted with the aid of the LSM TEA Full® software tool (Deng et al., 2021), which was developed based on the TEA model discussed in Section 3.3. This Python-based software features a user-friendly graphical interface that can effectively collect process information thus streamlining the procedures for conducting TEAs. Accordingly, the process flow diagram of the GAME-based process (illustrated in Fig. 1) is recreated by connecting customizable block objects on a canvas. The screenshots of the software interface when analyzing the GAME-based process, as well as a brief overview of the software are included in the SI.

The essential data to initiate the economic assessment/analysis – including lab-scale material and energy consumption and equipment configurations – are imported into the software by setting up either the global variables that influence the whole system or the parameters of each individual process blocks. Based on the data input through the frontend interface, the software converts the lab-scale mass balance (discussed in Section 3.4) into an industrial-scale mass flow at the backend, generates economic metrics (e.g., cost and revenue breakdowns, KPIs), and then presents the results in Microsoft Excel® spreadsheets. In addition, the software can run multiple scenarios during a single session, which enables the comparison of the economic performance under different operating strategies.

4. Results and discussion

4.1. Process economic assessment

4.1.1. Baseline scenario

The GAME facility is assumed to have a 20-year lifespan and operate 260 days per year. According to a report on Indiana's e-waste recycling, the average mass of e-waste processed by a typical recycling facility is around 500 mt/year (Indiana Department of Environmental Management, 2020). Alternatively, a previous study on HDD dismantling (Cong et al., 2017) as well as private communications between the authors and several data destruction companies indicate that an approximate proportion of WPCBs in e-waste is 5%. Therefore, a relatively conservative estimate for the annual amount of WPCBs processed at a single facility would be 25 mt/year. For a baseline scenario with a feedstock rate of 25 mt/year, a TEA was performed using the software discussed in Section 3.4, and the detailed assumptions and outputs are included in the SI.

First, as a quick overview of the preliminary cost-benefit analysis on an annual basis, the breakdowns of annual production cost (C) and revenue (R) are shown in Fig. 3. The pie chart on the left shows that the direct cost (variable cost) is expected to constitute more than half of the annual production cost, indicating that a change in production target will tend to greatly influence the overall plant expenditures. It should be noted that the CAPEX in Fig. 3 is an annualized value that is calculated by dividing the estimated total CAPEX (to be discussed) by the plant life ($T = 20$ years). As the annualized CAPEX accounts for less than 5% of the annual production cost, it can be concluded that the required initial capital investment is not a significant cost driver for the process.

In Fig. 3, according to the bar chart of revenue breakdown, it is evident that the gold metal is the predominant source of revenue, even though its concentration in WPCB is extremely low. In contrast, even though the copper makes up around 30 wt% of the WPCBs according to the experimental data, its contribution to the total revenue is a full order-of-magnitude less than that of gold. Nevertheless, comparing the numbers in both charts in Fig. 3, the extra income from the copper as a byproduct still covers a substantial proportion of the production costs, showing its vital role in enhancing the economic competitiveness of the GAME facility. As a high-level summary of the economic performance under the baseline scenario, the results of certain KPIs (along with their definitions) are presented in Table 3, which indicate an overall promising economic performance of the GAME-based process when processing 25 mt WPCBs per year.

4.1.2. Comparative analysis

Although uncertainties inevitably exist in the economic results as numerous assumptions and estimations were made, the TEA model still offers an platform to compare the process under study with established/competing technologies under consistent assumptions (Diaz and Lister,

Table 3
Selected KPIs for economic performance under the baseline scenario.

KPI	Value	Definition and Explanation
OPEX	$361,061/year	Annual operating expenses, $C - Cc - Cf$
CAPEX	$345,130	Total capital investment, $C_C T$
Average variable cost (AVC)	$27.0/kg	Variable cost per unit of output, $C_D / \sum_{i=3}^{3} Q_i$
Average total cost (ATC)	$49.2/kg	Total cost per unit of output, $(OPEX * T + CAPEX) / \sum_{i=3}^{3} Q_i T$
Unit revenue	$83.4/kg	Revenue per unit of output, $R / \sum_{i=3}^{3} Q_i$
Annual profit (P)	$235,886/year	The annual net profit before tax, $P = R - C$
Break-even point (BEP)	11.4 mt/year	Minimum WPCBs need to be processed to cover the fixed cost
Net present value (NPV)	$1,654,094	The present value of net cash flows (NCF) over the plant life
Payback period	2 years	The time it takes to recover the cost of the initial investment
Internal rate of return (IRR)	88.8%	The discount rate at which the benefit is equivalent to the cost

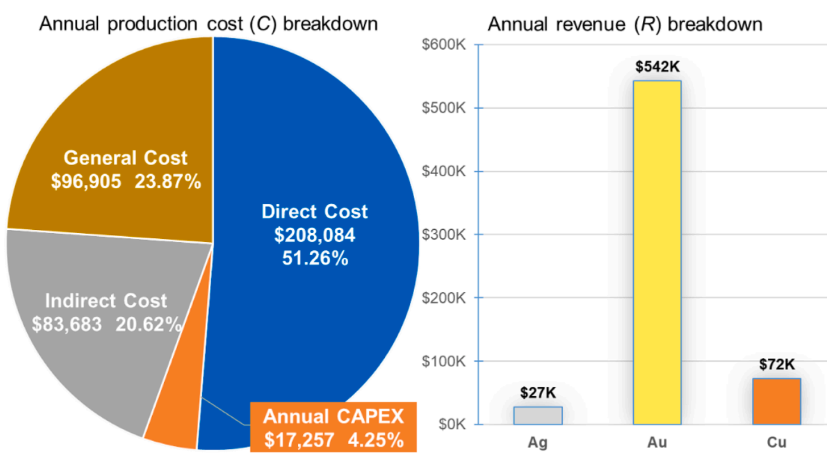

Fig. 3. Breakdowns of annual production cost (C) and annual revenue (R).

2018). To demonstrate the economic advantage of GAME compared to conventional BSX approaches, it is crucial to conduct a comparative analysis through the lens of the same TEA model. Accordingly, two comparative scenarios were designed where BSX replaces GAME in the solvent extraction step. The economic results of these two BSX-based scenarios are then compared to the GAME-based baseline scenario.

The first scenario (BSX1) keeps the same level of A/O ratio as in the baseline (10/1), which does not change the usage of materials during purification but results in a much lower extraction efficiency (i.e., the percentage of Au and Ag recovered) that is estimated to be 20% (El-Ashtoukhy and Fouad, 2015; Vural Gürsel et al., 2016). The second scenario (BSX2) applies a much lower A/O ratio (1/2), which directly results in significantly higher consumption of materials during purification, but under such a low A/O ratio, the BSX can be assumed to achieve the same extraction efficiency as GAME. The mass balances in the two comparative scenarios were based on experimental data from Virginia Tech, and all other assumptions (e.g., annual feedstock rate X and plant life T) stay the same. After inputting relevant data into the software, the economic results for the two BSX scenarios are generated. The economic performance of the three scenarios can be compared through Table 4, and more detailed explanation may be found in SI.

As is evident from Table 4, both comparative scenarios (BSX1 and BSX2) are estimated to have negative annual profit and NPV, indicating they tend to be economically infeasible in industrial practice. For BSX1, the low extraction efficiency of Au and Ag leads to a significantly lower income from selling the products (reflected in lower unit and annual revenues), which is far from enough to cover the production cost. BSX2, on the other hand, is able to yield the same amount of precious metals as in the baseline, but at a substantially higher cost (reflected in higher AVC, ATC, and C compared to the baseline). Through the comparative analysis, it has been numerically justified that GAME indeed has a great economic advantage over conventional BSX approaches in extracting low-concentration precious metals from complex e-waste stream, since a high A/O ratio proves to be a necessary condition for both technical viability and economic feasibility.

4.2. Improvement opportunity analysis

As discussed in the Literature Review, economies of scale play a decisive role in determining to the economic feasibility of the proposed GAME-based process. Although economies of scale are typically measured by the amount of output produced, for the cases of circular economy or waste management, it is more applicable to monitor the amount of waste feedstock processed, which is (in most cases) linearly correlated to the production volume.

In Table 3, it is noticeable that for the baseline scenario the unit revenue is significantly higher than the unit cost (or ATC). This result shows that the substantial economic potential can be leveraged by increasing the target amount of WPCBs processed per year (denoted as X, with the baseline scenario value being $X_0 = 25$ mt). Higher X can lead to significantly lower unit cost (either AVC or ATC), even though increasing the scale of production may require extra workforce and capital investment. Nevertheless, exceedingly high X could also result in a “diseconomy of scale.” For instance, in order to achieve a high processing volume, the facility may need to transport e-waste from distant sources, which could result in exceedingly high logistical costs. In summary, it is vital to select the optimal X to exploit the full economic potential of the GAME-based process.

Table 4
Economic performance comparison between GAME and BSX cases.

Configurations and selected KPIs	Baseline	BSX1	BSX2
Solvent extraction mechanism	GAME	BSX	BSX
A/O ratio	10/1	10/1	1/2
Extraction efficiency	100%	20%	100%
WPCB processed (X)	$X_0 = 25$ mt/year	$X_0 = 25$ mt/year	$X_0 = 25$ mt/year
Average variable cost (AVC)	$27.0/kg	$27.2/kg	$50.41/kg
Average total cost (ATC)	$49.2/kg	$49.4/kg	$82.7/kg
Unit revenue	$83.4/kg	$24.3/kg	$83.4/kg
Annual total production cost (C)	$405,928/year	$405,928/year	$694,306/year
Annual revenue (R)	$641,814/year	$186,212/year	$641,814/year
Annual profit (P)	$235,886/year	-$219,716/year	-$52,496/year
Net present value (NPV)	$1,654,094	-$2,217,428	-$409,570

4.2.1. Sensitivity analysis

This section will examine the impacts of X (ranging from 15 to 700 mt) on some critical KPIs generated from TEA, with the results illustrated in Figs. 4, 5, and Table 5. First, regarding the average cost in Fig. 4 (a), it is noticeable that both AVC and ATC (defined in Table 3) display a periodic sawtooth pattern. This behavior is because in the proposed TEA model, some cost-driven intermediate variables (e.g., number of operators or pieces of equipment) are formulated as step functions of X and will increase to the next incremental level once X reaches a set threshold. Despite the wide fluctuation when X is low, both graphs overall demonstrate a rapidly decreasing trend, indicating the significant cost advantages gained from scaling up the amount of WPCB feedstock. As X continues to increase, AVC hits its lowest value at $23.4/kg when X reaches 105 mt (X_1), whereas ATC hits its lowest value at $42.9/kg when X reaches 165 mt (X_2). Further increasing X beyond these optimal levels will not lead to further reduction in average costs; in fact, the average cost slightly trends upward in both plots as X becomes larger, owing to increasingly larger logistical and managerial costs.

To get a better quantitative understanding of the economies of scale, it would also be beneficial to investigate the CAPEX (defined in Table 3) and annual net operating income (NOI, calculated as R – OPEX) under different X values. The ratio between NOI and CAPEX is commonly known as the cash-on-cash return (CoC) in financial analysis, which is used to evaluate how efficiently the operation of the facility can cover the initial investment. It can be observed from Fig. 4(b) that the CoC is below 1 under the baseline scenario, since CAPEX is slightly above NOI. However, as X increases, NOI begins to surpass CAPEX. This means that enough revenue is generated in one year, in principle, to cover the entire capital investment. From this perspective, moving from the baseline scenario (X_0) to say, a processing rate of X_1 or X_2 produces a CoC greater than one (the benefit outweighs the extra cost). The long-term economic performance of the GAME facility under different feedstock amounts can be demonstrated by comparing NCF and IRR as shown in Fig. 5.

The NCF at the three levels of X (X_0, X_1, X_2) are graphically presented by the height of bars in corresponding color. As is evident from Fig. 5, the economic improvement from increasing the production scale is significant, and one may conclude that the annual feedstock rate should be set at 165 mt to achieve minimal production cost per unit product. Nevertheless, it should also be noted that there is little improvement in IRR from X_1 to X_2. In fact, the IRR curve tends to flatten out as X becomes increasingly larger. As IRR can be interpreted as the annual rate of growth that an investment is expected to generate, it is the dominant benchmark in comparing different operating scenarios (Patrick and French, 2016). In view of this, if the investment budget is somewhat limited, processing 105 mt WPCBs per year is the most advisable. An overall comparison of the economic performance between the three scenarios is given in Table 5.

4.2.2. Implementing regression splines

As explained above, the AVC/ATC plots show as a jagged zigzag pattern since some TEA elements are modeled as step functions of X. However, this simplified modeling approach may not be sufficiently flexible to characterize real industrial practice, where managers are

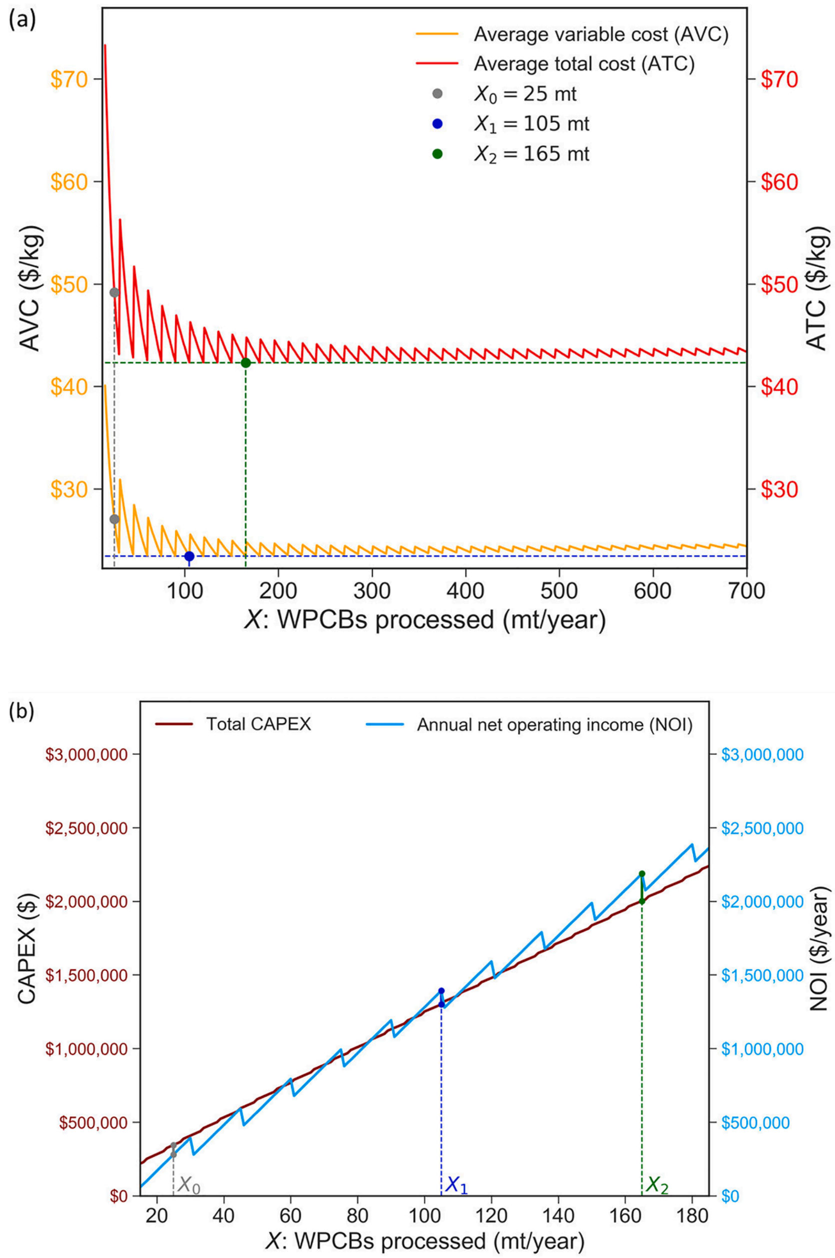

Fig. 4. (a) average costs (b) CAPEX & NOI vs. annual feedstock amount (X).

unlikely to make dramatic changes to workforce or capital outlays only to meet a marginal increase in a processing target. Practically, what is more expressive than the AVC/ATC data themselves are the underlying trends and patterns, which can be extrapolated through statistical learning.

To gain statistical insights into the AVC/ATC data as shown in Fig. 4, it might be tempting to fit one single high-degree polynomial over the entire range of X. However, doing so tends to impose a global structure on the whole dataset, which is particularly undesirable considering that the variability and trend of average costs are evolving as X increases. One solution to remedy this problem is to extend the standard polynomial regression to piecewise polynomial regression, which divides a dataset into different regions (bins) and fits low degree polynomial functions on each of these subsets (James et al., 2013). The collection of returned polynomials in all subsets is called a regression spline. Compared to single polynomial curves, regression splines are more flexible and well suited to capture the sectional structure and evolving pattern of the data.

In a regression spline, the points where the division occurs are called "knots," which intuitively present the internal boundaries within the dataset where the trend and pattern are expected to alter. For AVC or ATC data, there are two boundaries (knots) of interest. The first one is the point where the decreasing rates start to slow down, as the benefit from increasing production scale starts to saturate when X reaches a certain level. The second boundary is positioned near where an upward trend starts to appear, as the diseconomy of scale becomes discernible.

An algorithm has been developed to search for the optimal locations to place the two knots. The principle of this approach is to minimize the root mean square error (RMSE) of the regression splines, and the related pseudocode is summarized in the SI. As a result, $X_{low} = 30$ and $X_{high} = 147$ are chosen as the optimal knots to segregate both AVC and ATC data into three subsets, each representing a unique data pattern. The fitted cubic splines with the optimal selection of knots are illustrated in Fig. 6, which are superimposed on the original data (presented by small dots).

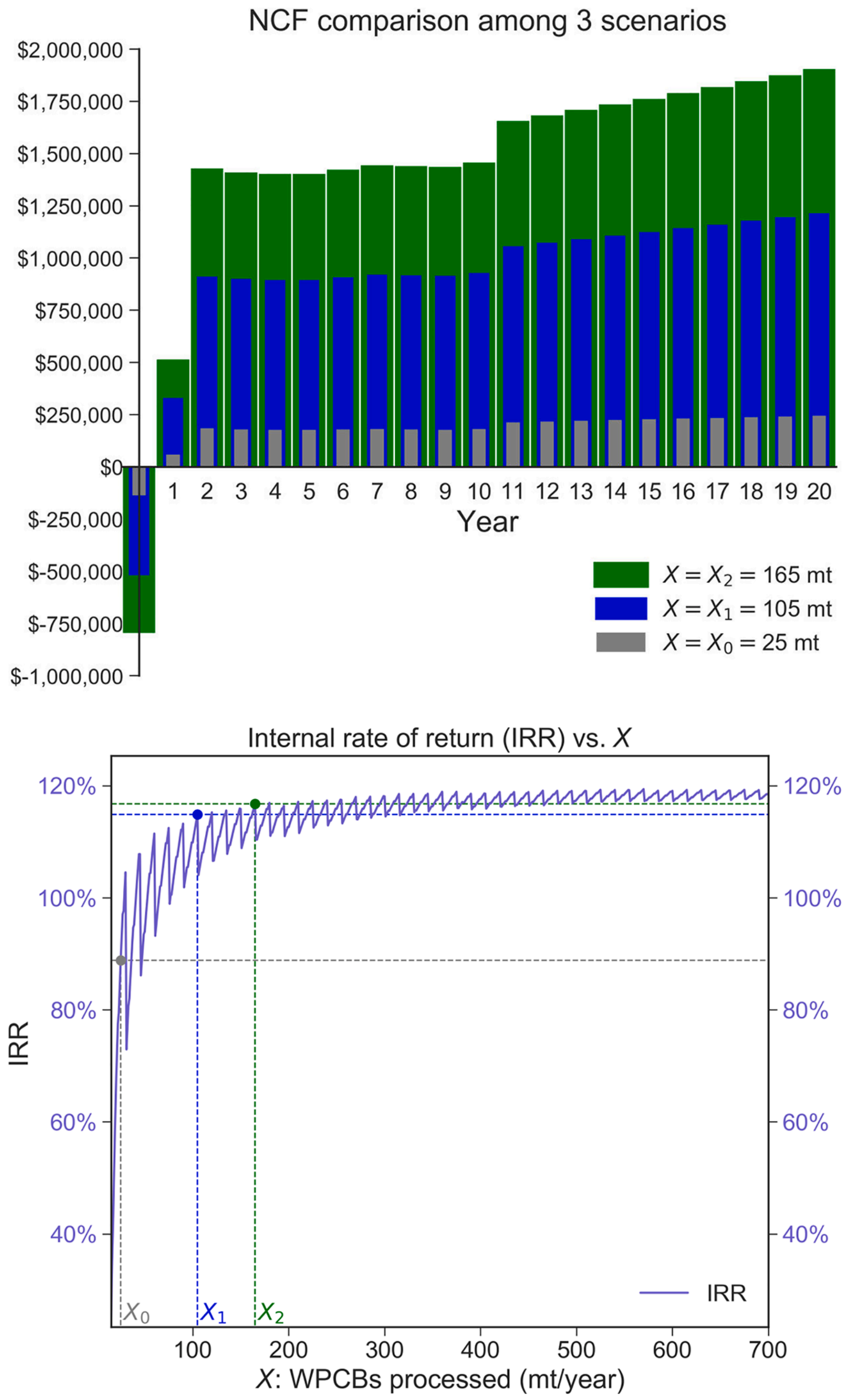

Fig. 5. Long-term economic performance comparison.

As observed from Fig. 6, the regression splines successfully capture the sectional patterns of data, which are consistent with the analyses in 4.2.1. The range between the left knot to the right knot (30 mt/year –147 mt/year) can be interpreted as an "efficient processing interval." An annual processing amount below 30 mt should be avoided as the production scale may not be sufficient to capitalize on the investment for the basic infrastructure of the facility. Moreover, if existing feedstock target falls inside the efficient processing interval, the facility could raise the processing amount up to around 147 mt to enhance the production efficiency. Although large-scale production is generally feasible, it also requires enormous investment and could potentially involve high risks. Therefore, if the budget is limited, from a conservative standpoint, targeting a processing amount of more than 147 mt per year is not recommended.

4.3. Industrial and managerial implications

In Section 4.2.1, it was noted that the minimum average variable cost is achieved for a WPCB processing rate of $X_1 = 105$ mt/year. This rate falls within the "efficient processing interval" obtained from Section 4.2.2. Nevertheless, when the processing target increases to $X_2 = 165$ mt/year (to minimize the average total cost rather than the average variable cost), the actual change in the ATC/AVC and IRR from X_1 is fairly small. The very modest cost advantages gained by moving from X_1 to X_2 (which represent nearly 50% increase in processing rate) are likely outweighed by the additional pressures and uncertainties in marketing,

Table 5
Comparison of selected KPIs among the baseline and improved scenarios.

KPI	Baseline	Minimal AVC	Minimal ATC
WPCB processed (X)	X_0 = 25 mt/year	X_1 = 105 mt/year	X_2 = 165 mt/year
OPEX	$361,061/year	$1,303,539/year	$2,048,712/year
CAPEX	$345,130	$1299,023	$2002,031
Average variable cost (AVC)	$27.0/kg	$23.4/kg	$23.5/kg
Average total cost (ATC)	$49.2/kg	$42.4/kg	$42.3/kg
Unit revenue	$83.4/kg	$83.4/kg	$83.4/kg
Annual profit (P)	$235,886/year	$1,223,205/year	$1,926,994/year
Break-even point (BEP)	11.4 mt/year	38.7 mt/year	60.5 mt/year
Net present value (NPV)	$1,654,094	$8,523,206	$13,419,558
Payback period	2 years	2 years	2 years
Internal rate of return (IRR)	88.8%	114.9%	116.8%

financing, and employee supervision. With this in mind, the authors would recommend a processing target of 105 mt/year.

Besides, the planning of the actual industrial deployment of the GAME facility could be confounded by other factors, which necessitates further investigations into relevant KPIs or even specific cost components (outlined in Fig. 2). Such factors can be involved in facility construction, supply chain stability (e.g., the amount of WPCBs collected may be insufficient to meet the processing target), logistic difficulties, and regulations. For example, in order to establish the facility, aside from lowering production cost per unit product, it is also crucial to select a processing rate (i.e., a value of X) with a CAPEX (illustrated in Fig. 4) that is less than the budget for capital investment. However, if the operation of the facility has proved to be lucrative, it is generally advised to further expand the production target to achieve higher annual net income (as shown in the NCF in Fig. 5) by making further investment in hardware and expanding labor force. In any case, it is always imperative to periodically monitor the economic KPIs and to continuously fine-tune production target and operation settings.

5. Conclusions

This study has evaluated the economic performance of an innovative GAME-based process for recovering precious metals from e-waste. To conduct economic analysis, a TEA model was implemented with the aid of a software tool. With the goal of achieving economies of scale, sensitivity analysis and statistical learning were applied to search for cost-effective industrial production scales. The results indicated a promising economic prospect of the GAME-based process, which may incentivize investments and facilitate its industrial deployment. The most significant intellectual contribution of this work is a two-phase analytical paradigm that integrates conventional cost-benefit models with other advanced analytical approaches. The proposed two-phase economic analysis methodology, accompanied by the software tool, can be further adopted in analyzing the economic feasibilities for a broader range of nascent technologies, especially in the fields of sustainable management and resource conservation. In future efforts, the GAME-based process can be adapted to the recycling of other high-value extractable materials (such as cobalt, vanadium, and rare earths) from complex waste streams. To support decision making, the two-phase economic analysis methodology can be employed to identify system bottlenecks and explore improvement strategies.

CRediT authorship contribution statement

Sidi Deng: Conceptualization, Methodology, Data curation, Software, Formal analysis, Writing – original draft. **Zhongqing Xiao:** Investigation, Resources, Methodology, Validation, Resources, Writing – review & editing. **Wencai Zhang:** Investigation, Resources, Validation, Writing – review & editing, Supervision. **Aaron Noble:** Investigation, Methodology, Validation, Writing – review & editing. **Subodh Das:** Resources, Project administration, Funding acquisition. **Yuehwern Yih:** Validation, Writing – review & editing. **John W. Sutherland:** Writing – review & editing, Project administration, Funding acquisition, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

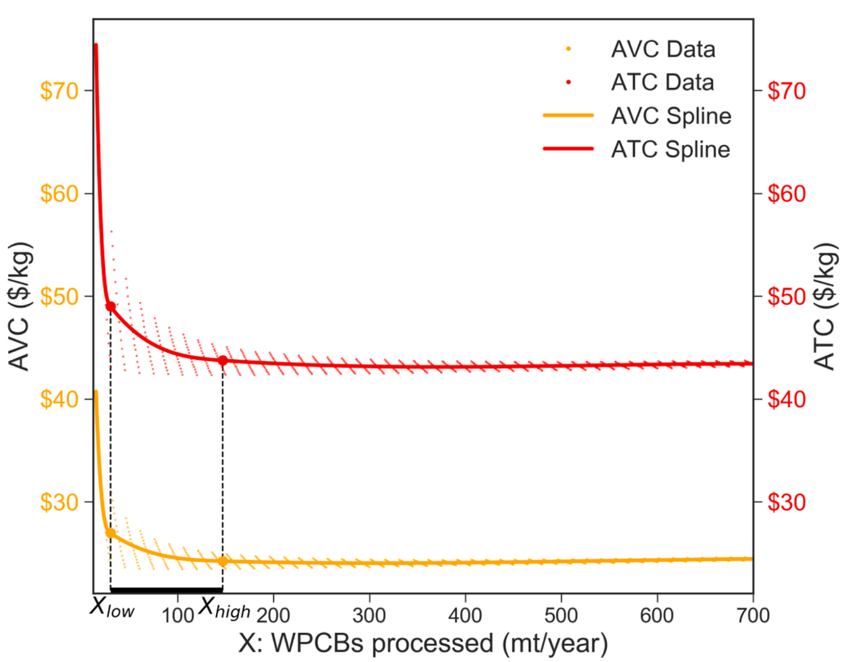

Fig. 6. The optimal cubic splines for average costs.

the work reported in this paper.

Data Availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2022.106810.

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