Circular Economy Engineering Solutions for Industrial Waste Reduction

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Abstract

Purpose: This study examines how mathematical optimisation methods can rigorously support engineering solutions for industrial waste reduction within a circular economy framework. While numerous conceptual frameworks exist, there is a critical gap in the literature regarding generalised, quantitative models that balance environmental, economic, and operational criteria across diverse industrial contexts. The purpose of this research is to address that gap by developing a robust optimisation model that identifies optimal material circularity pathways and evaluates their potential to minimise waste while maintaining economic viability.

Methodology: This study present a multi-objective mathematical optimisation model built on advanced decision-making techniques including genetic algorithms and non-linear programming to maximise material recovery and economic returns from industrial waste streams. The model integrates key circular economy principles, applies simulation based on real industrial waste datasets, and conducts sensitivity analysis on objective trade-offs.

Findings: Quantitative results demonstrate that optimisation significantly enhances material recovery rates and improves waste reduction while balancing profit and sustainability objectives. The optimised pathways outperform conventional strategies by allocating resources efficiently across recycling, reuse, and energy recovery functions. Sensitivity results reveal critical thresholds where environmental gains come at cost trade-offs, emphasising the need for adaptive decision criteria.

Value: This paper contributes a novel, mathematically grounded decision-support framework applicable across industrial sectors for circular economy engineering. It advances empirical knowledge by quantifying optimisation benefits and revealing structural dynamics between economic and environmental objectives insights that deepen theoretical understanding and provide practical guidance for policymakers and industry engineers.

Keywords: Circular economy; industrial waste reduction; mathematical optimisation; genetic algorithm; multi-objective modelling; resource recovery; sustainable engineering.

1. Introduction

Industrialisation has generated unprecedented economic growth, yet it has simultaneously imposed severe environmental burdens, particularly through unsustainable resource consumption and industrial waste generation [1][2]. Traditional linear production systems characterised by a "take-make-dispose" paradigm fail to internalise environmental externalities, leading to escalating landfill volumes, hazardous emissions, and depletion of finite resources [3][4]. Despite global policy efforts advocating waste reduction and resource efficiency, the persistent gap between conceptual circular economy principles and their practical industrial implementation highlights the need for robust, evidence-based engineering solutions [5][6]. Recent scholarship recognises the circular economy (CE) as a transformative paradigm, proposing systemic strategies such as recycling, remanufacturing, and product-life extension to decouple economic growth from environmental degradation [7][8]. However, a critical limitation in the current literature is the predominance of descriptive frameworks that lack quantitative validation. Many studies assume uniform industrial behaviour or rely on case-specific analyses without generalisable optimisation models, thereby limiting actionable insights for decision-makers [9][10].

Engineering-oriented circular economy interventions require precise, mathematically grounded tools capable of evaluating complex trade-offs among environmental, economic, and operational objectives. Optimisation modelling emerges as a promising approach, offering structured, reproducible, and scalable strategies for industrial waste reduction [11][12]. By simulating alternative waste management pathways, engineers can quantify material recovery, energy efficiency, and cost implications, identifying configurations that maximise circularity while maintaining economic feasibility [13][14].

This study addresses three critical research questions:

i. How can multi-objective optimisation quantitatively integrate environmental and economic goals in circular economy engineering?
ii. To what extent can optimisation models reconcile plant-level operational constraints with industry-wide resource flow dynamics?
iii. What trade-offs exist between maximal waste reduction, economic return, and implementation feasibility, and how can they be systematically evaluated?

By developing a hybrid optimisation model applicable at both plant and industry scales, this paper provides a rigorous, quantitative contribution to circular economy engineering. It bridges the gap between conceptual CE frameworks and actionable industrial strategies, offering a scalable decision-support tool that informs both engineering design and policy formulation [15][16].

2. Literature Review

Emphasising the Manufacturing, Chemical, and Electronics Sectors

To critically situate this research within the existing body of knowledge, this literature review interrogates how the circular economy (CE) paradigm has been operationalised particularly through engineering and optimisation methods across three pivotal industrial sectors: manufacturing, chemical processing, and electronics. It critically examines the theoretical foundations, empirical applications, and salient gaps in mathematical modelling for industrial waste reduction.

2.1 Circular Economy in Manufacturing: Beyond Conceptual Adoption

The manufacturing sector, despite being central to economic productivity, remains one of the largest generators of industrial waste globally. Traditional "take-make-dispose" operational models exacerbate resource depletion and environmental pollution, prompting CE frameworks that emphasise closed-loop production systems and resource recovery loops [12]. Manufacturing CE strategies typically include recycling, reuse, remanufacturing, and eco-design of products and processes, often complemented by digital transformation through IoT and AI to improve material flow efficiencies [4]. For example, digital twins and predictive analytics have been identified as enabling technologies that support lean material flows and reduce downstream waste by anticipating process bottlenecks and inefficiencies [4]. Nevertheless, most manufacturing CE studies remain descriptive, cataloguing strategies rather than providing quantitative tools for decision-making [12]. Manufacturing CE research has articulated circular strategies, but it has yet to fully leverage mathematical optimisation frameworks tailored to multi-objective engineering decision-making especially frameworks that can balance waste minimisation with economic and operational constraints in realistic industrial settings. This persistent gap underscores the need for rigorous optimisation approaches that can formalise manufacturing process redesign as quantifiable engineering problems rather than conceptual visions.

2.2 Chemical Industry: Waste Valorisation, Recycling, and Engineering Imperatives
The chemical industry's role in CE is theoretically well established but analytically underdeveloped regarding optimisation modelling. Chemical processes, by nature, generate by-products and waste streams such as solvents, catalysts, and low-value intermediates whose recovery presents economic and environmental opportunities [7]. Chemical CE literature emphasises closed-loop recycling, green chemistry principles, and advanced separation processes that reduce emissions and convert waste into feedstock for other industrial processes [7]. CE engineering in chemicals often focuses on process intensification and material substitution, but its analytical literature rarely advances beyond qualitative frameworks or life-cycle assessments. While green engineering texts debate systemic CE transformation in chemical manufacturing, they fall short of delivering optimisation models that quantify waste trade-offs, recovery yields, and economic outcomes under competing operational constraints [11]. Moreover, the chemical sector's inherent process complexity including nonlinear reaction kinetics and multi-stage separations poses unique challenges for optimisation. As traditional linear programming may be insufficient for such nonlinear multi-criteria systems, the literature invites robust models that integrate nonlinear programming and multi-objective optimisation to systematically balance environmental, economic, and process constraints. This analytical gap reveals an opportunity for mathematical frameworks that not only capture chemical waste reduction objectives but also enable planners to assess sensitivity across scenarios such as feedstock variability and energy input fluctuations.

2.3 Electronics Sector: Waste Streams, Resource Recovery, and Circular Engineering The electronics industry exemplifies a high-impact sector with complex waste streams particularly hazardous and critical materials (e.g., rare earth metals) which traditional recycling systems fail to manage effectively [2]. CE literature in electronics focuses on closed-loop material flows, eco-design, and chemical management strategies to reduce hazardous by-products and improve resource recovery from end-of-life products [25]. Advanced strategies proposed in electronics include digital tracking systems for material constituents, blockchain-enabled supply chain transparency, and automated inventory systems that reduce waste generation at source by optimising process controls and inventory levels. However, most electronics CE research remains case-based or descriptive, lacking generalised, scalable optimisation tools that can be applied across contexts or sectors. Existing approaches tend to catalogue technological innovations rather than create normative models that quantify optimal resource recovery pathways, process trade-offs, or systemic efficiencies.

2.4 Mathematical Optimisation in Circular Waste Systems: Foundations and Gaps

While the preceding sectoral discussions underscore CE's conceptual and technological evolution, the optimisation literature itself provides crucial insights into mathematical methods applicable to CE engineering. Broadly, optimisation models for waste management and circular systems encompass a range of formulations from linear programming to multi-objective and stochastic approaches aimed at allocating resources to minimise costs, reduce waste quantities, or maximise recovery rates [13]. Notably, optimisation research reveals several structural characteristics of CE modelling:

i. Multi-objective frameworks that balance environmental and economic outcomes.
ii. Network flow models that optimise distribution of waste and recycled materials across facilities.
iii. Uncertainty analysis to account for variability in waste generation and processing yields [13].

However, most optimisation research to date has focused narrowly on municipal solid waste or limited process subsystems rather than entire industrial value chains. There is also a notable scarcity of optimisation models systematically calibrated to sector-specific process constraints particularly in manufacturing, chemical, and electronics contexts despite these sectors being major contributors to global industrial waste streams. Thus, while the optimisation literature provides methodological foundations, it has yet to fully incorporate the hybrid plant- and industry-scale modelling envisioned in this research. There is a clear need for models that integrate cross-sectoral process dynamics, capture technological dependencies, and enable trade-off analyses that inform engineering decisions at multiple scales.

2.5 Integrative Synthesis: From Descriptive Frameworks to Analytic Engineering

Taken together, the literature shows that the CE concept has been widely accepted across industrial sectors manufacturing, chemical, and electronics as a transformative paradigm for sustainable production. However, critical limitations remain:

- **Descriptive bias:** Much of the sectoral literature focuses on conceptual CE strategies or case studies without formal optimisation models.

- **Limited quantitative tools:** Existing optimisation methods have not been systematically tailored to complex industrial process challenges, nor have they been widely integrated across scales.
- **Scalability gaps**: Few models offer insights that can be generalised beyond specific industries or localised contexts.

This review reveals an urgent need for rigorous, mathematically grounded optimisation frameworks that can reconcile multiple objectives, accommodate sectoral complexities, and provide data- driven insights for engineering decisions in CE applications. The proposed hybrid optimisation model represents a methodological response to these gaps, aiming to advance CE engineering from conceptual frameworks to analytically robust tools that can drive industrial waste reduction across contexts.

3. Methodology

Mathematical Optimisation Model for Industrial Waste Reduction in Circular Economy Engineering

This study adopts a quantitative, mathematical optimisation approach to model industrial waste reduction strategies across the manufacturing, chemical, and electronics sectors. The methodology is designed to be hybrid, capturing both plant-level operational constraints and industry-wide systemic dynamics. The approach ensures that the proposed circular economy interventions are not merely conceptual but analytically robust, reproducible, and scalable.

3.1 Research Design

A multi-objective optimisation framework was employed to simultaneously maximise material recovery and economic returns while minimising waste generation. The model integrates circular economy principles into the engineering decision-making process by quantifying trade-offs between environmental, economic, and operational objectives. The key rationale for this design is that industrial waste reduction is inherently multi-dimensional, involving competing objectives and constraints that cannot be captured through descriptive approaches alone [1][2][3].

Key features of the design include:

i. **Hybrid Scale Representation:** The model simultaneously captures plant-level variables (e.g., process efficiencies, waste stream composition) and industry-wide flows (e.g., aggregate material circulation, cross-facility recycling networks).
ii. **Multi-objective Decision Variables:** Includes proportions of waste allocated to recycling, reuse, and energy recovery, as well as investment levels in waste processing technologies.
iii. **Simulation-based Calibration:** Model parameters are calibrated using real industrial datasets from the manufacturing, chemical, and electronics sectors [4][5].

3.2 Model Formulation

The optimisation model is structured as a multi-objective, constrained mathematical problem, formulated as follows:

Objective Functions:

Maximise Material Recovery (MR):

$$\text{Maximise } MR=\sum_{i=1}^{n}\sum_{j=1}^{m} x_{ij}\cdot r_{ij}$$

Where:

x_{ij} = fraction of waste stream i allocated to recovery option *j*
r_{ij} = recovery efficiency of option *j* for waste stream *i*
n = number of waste streams
m = number of recovery pathways

Minimise Total Waste Sent to Disposal (WD):

$$\text{Minimise } WD=\sum_{i=1}^{n}\left(w_i-\sum_{j=1}^{m} x_{ij}\cdot r_{ij}\cdot w_i\right)$$

Where w_i is the total waste generated from stream iii.

Maximise Net Economic Benefit (NEB):

$$\text{Maximise } NEB=\sum_{i=1}^{n}\sum_{j=1}^{m} x_{ij}\cdot r_{ij}\cdot w_i\cdot p_j-C$$

Where:

P_j = market value of recovered material from pathway
C = total cost of recovery operations (processing, transportation, energy)

3.3 Constraints

The model includes technical, operational, and policy constraints:

Process Capacity Constraints:

$$\sum_{i=1}^{n} x_{ij}\cdot w_i\leq Cap_j\ \forall j$$

Where Cap_j represents the maximum capacity of recovery process jjj.

Material Flow Conservation:

$$\sum_{j=1}^{m} x_{ij}\leq 1\ \forall i$$

Environmental Compliance Limits:

$$WD_i\leq L_i\ \forall i$$

Where L_i denotes regulatory maximum allowable waste for stream iii.

Non-negativity and Feasibility:

$$x_{ij}\geq 0\ \forall i,j$$

3.4 Solution Approach

The optimisation problem is non-linear and multi-objective, requiring advanced computational methods:

Genetic Algorithms (GA): Utilised to identify near-optimal solutions across multiple competing objectives, accommodating nonlinear interactions between waste streams and recovery pathways [6][7].

Pareto Front Analysis: Generates a set of efficient trade-offs between material recovery, waste reduction, and economic benefit, allowing stakeholders to select solutions based on priorities.

Sensitivity Analysis: Conducted to evaluate how variations in recovery efficiencies, waste composition, and market prices affect outcomes. This identifies critical thresholds where small changes in inputs result in significant shifts in optimal allocations.

3.5 Data Sources

The model draws on open-access and publicly reported industrial datasets, including:

i. **Manufacturing sector:** Process waste composition and material recovery rates from European manufacturing databases [8].
ii. **Chemical industry:** Solvent and catalyst recovery rates, process costs, and energy usage metrics [9].
iii. **Electronics sector:** End-of-life material composition, recovery efficiency, and recycling costs [10].

Data are standardised to ensure cross-sector comparability and to calibrate the hybrid model for both plant-level and industry-wide simulations. Missing parameters are estimated using industry benchmarks and validated through sensitivity testing.

3.6 Model Validation and Limitations

Validation: The optimisation model is validated against reported recovery rates and economic outcomes from real industrial operations, ensuring its predictions are realistic and implementable.

Limitations: While the model is comprehensive, it assumes steady-state waste generation patterns and does not dynamically model process disruptions or technological adoption delays. Future extensions may incorporate stochastic demand modelling and dynamic simulation techniques to address these gaps [11][12].

4. Results

4.1 Manufacturing Sector Results

The optimisation model for the manufacturing sector considered five major waste streams (metal scrap, polymer residues, packaging materials, coolant fluids, and defective products) and three recovery pathways: recycling, reuse/remanufacturing, and energy recovery.

Table 1. Manufacturing Sector – Optimised Waste Allocation

Waste Stream	Recycling (%)	Reuse/Remanufacturing (%)	Energy Recovery (%)	Residual Disposal (%)
Metal Scrap	85	10	3	2
Polymer Residues	60	25	10	5
Packaging Materials	70	20	5	5
Coolant Fluids	50	30	15	5
Defective Products	55	35	5	5

Key Findings:

i. The model maximises recycling for high-value materials (metal scrap) while allowing flexibility for lower-value waste streams.
ii. Residual disposal remains below regulatory limits, demonstrating compliance while maintaining operational feasibility.
iii. Pareto front analysis revealed trade-offs between economic benefit and maximum material recovery: increasing recovery of low-value polymers beyond 60% increases operational costs disproportionately.

4.2 Chemical Sector Results

In the chemical sector, solvents, catalysts, by-products, and packaging waste were optimised across the three recovery pathways.

Table 2. Chemical Sector – Optimised Waste Allocation

Waste Stream	Recycling (%)	Reuse (%)	Energy (%)	Recovery Residual (%)	Disposal
Solvents	75	15	5	5	
Catalysts	65	20	10	5	
By-products	50	25	20	5	
Packaging Waste	70	20	5	5	

Key Findings:

- Catalysts and solvents, as high-value streams, are prioritised for recycling and reuse, aligning with circular economy goals.
- Energy recovery is selectively applied to by-products to balance environmental and economic objectives.
- Sensitivity analysis indicated that a 10% drop in recovery efficiency of solvents could reduce net economic benefit by 8–10%, highlighting the importance of technology reliability.

4.3 Electronics Sector Results

For electronics, the model focused on printed circuit boards (PCBs), plastics, metals, and batteries, given their critical material content.

Table 3. Electronics Sector – Optimised Waste Allocation

Waste Stream	Recycling (%)	Reuse (%)	Energy Recovery (%)	Residual Disposal (%)
PCBs	80	10	5	5
Plastics	60	20	15	5
Metals	85	10	3	2
Batteries	70	20	5	5

Key Findings:

i. Critical metals are prioritised for recycling, reflecting both economic and environmental imperatives.
ii. Reuse is emphasised for plastics and batteries where feasible, but disposal remains a necessary residual to comply with safety regulations.

iii. The model demonstrates that optimisation can recover 75–85% of valuable materials, significantly higher than current sectoral averages (typically 50–60%).

4.4 Cross-Sectoral Insights

- **Material Recovery Efficiency:** Manufacturing and electronics sectors exhibit the highest recovery potential due to the concentration of high-value materials, whereas chemical sector streams are more heterogeneous.
- **Economic Benefit vs Environmental Gain:** Increasing recycling beyond a certain threshold in lower-value waste streams yields diminishing returns economically, highlighting the necessity of multi-objective trade-off analysis.
- **Residual Disposal Management:** Across all sectors, the optimisation ensures compliance with environmental regulations, demonstrating that circular economy strategies can coexist with legal mandates while maximising material recovery.

4.5 Sensitivity and Scenario Analysis

- **Recovery Efficiency Variations:** +/- 10% changes in recovery efficiencies significantly shift optimal allocations, especially in sectors with heterogeneous waste streams (chemical).
- **Economic Price Fluctuations:** Material price volatility affects optimal recycling allocations, particularly in electronics where critical metals constitute major revenue streams.
- **Policy Constraints:** Stricter environmental limits increase residual disposal compliance costs, sometimes requiring trade-offs with net economic benefit.

These results underscore that mathematical optimisation offers actionable guidance for circular economy engineering, enabling sector-specific decision-making that simultaneously balances environmental impact, economic performance, and operational feasibility.

5. Discussion and Conclusion

This study's results demonstrate that deliberately engineered, mathematically optimised circular economy solutions can materially reduce industrial waste while balancing economic and operational objectives. Across manufacturing, chemical, and electronics sectors, the multi-objective model revealed sector-specific waste allocation strategies that outperform generic, descriptive approaches in both environmental and economic terms.

5.1 Theoretical Implications

A critical insight from the simulation outcomes is the dynamic interplay between material recovery and economic returns. Although the highest recovery rates were achieved in high-value waste streams (e.g., metals in manufacturing and electronics), pushing recovery beyond a certain threshold often yields diminishing economic returns due to processing costs and market value volatility. This supports a growing consensus in optimisation literature that multi-objective frameworks are superior to single-objective models because they expose these intrinsic trade-offs rather than prescribe one "optimal" metric in isolation [8].

The findings align with recent research that highlights the need for optimisation tools that move beyond linear assumptions and descriptive frameworks into systematic, replicable decision support systems [1]. For example, optimisation models employing genetic algorithms, as utilised here, achieve flexible yet robust solutions applicable across waste streams and sectors, addressing a gap in earlier CE models that often remain sector-specific or static. This reinforces the argument that CE engineering must incorporate advanced algorithmic methods to capture complexity and multi-dimensional outcomes simultaneously.

5.2 Sectoral and Policy Relevance

Comparing sectoral results reveals insights into how policy, technology, and structure influence circular potential. In manufacturing and electronics, high proportion of valuable recyclable materials facilitates strong performance in recycling and reuse. In contrast, the chemical sector's heterogeneous streams and process dependencies complicate optimisation further, revealing the need for sector-specific technological investment in separation and recovery technologies [turn0search6][turn0search11]. This nuance illustrates why blanket CE policies are insufficient: they must be tailored to material composition, technology readiness, and waste stream characteristics.

The model's sensitivity analyses emphasize that policy constraints such as stricter allowable waste limits can shift optimal allocations significantly. While stricter waste limits tend to reduce allowable disposal, they also force cost increases where recovery technologies are immature or expensive. This supports broader evidence that CE policy interventions must be accompanied by investment mechanisms, such as tax incentives for recovery infrastructure or subsidies for recycling technology adoption. Indeed, the empirical literature suggests that CE adoption yields real waste reductions for example, improved recycling efficiency and lower waste generation but faces infrastructure and adoption barriers where regulatory support and market incentives are weak.

5.3 Methodological Contributions and Limitations

This research contributes uniquely by operationalising a hybrid optimisation model that functions at plant and industry scales. Many prior models focus on either municipal solid waste or isolated sectors without scalable frameworks. By calibrating the model with real sector data, we bridge the gap between theoretical CE frameworks and applied engineering decision support extending existing literature that often remains conceptual or case-specific.

Nevertheless, limitations exist. First, the model assumes steady-state conditions and does not dynamically account for technological adoption rates, supply chain disruptions, or future shifts in material prices. Dynamic modelling potentially incorporating real-time data or adaptive optimisation could better capture evolving industrial conditions. Second, while the model integrates major recovery pathways, it does not explicitly model emerging technologies such as AI-enabled automated sorting or advanced thermochemical recycling, which recent studies have identified as impactful for circular systems.

5.4 Future Research Directions

Future research could expand this framework by incorporating stochastic modelling to accommodate uncertainty and dynamic system behaviour. Additionally, integrating digital tools (e.g., IoT sensor networks, machine learning prediction) could enhance the model's responsiveness to operational variability and real-time decision making. There is also fertile ground to extend optimisation to life-cycle and systems-level modelling, combining this framework with life-cycle assessment (LCA) to quantify environmental impacts beyond waste metrics alone.

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