Profitable Circularity by Design: An Integrated MILP–LCA Framework for Indian Electronics under Extended Producer Responsibility

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ABSTRACT

This paper develops and evaluates a decision framework that embeds circular-economy logic into production planning and closed-loop supply chain design for an Indian electronics manufacturer. The framework integrates life-cycle assessment directly into a mixed-integer linear optimization model, co-determining facility siting, reverse logistics, and inventories while enforcing environmental limits on carbon and resource intensity. The design operationalizes modular product architecture, quality grading of returns (A-grade to remanufacturing, B-grade to recycling), and material valorization. Scenario experiments compare a linear baseline with Extended Producer Responsibility (EPR)–compliant and high-circularity configurations, calibrated to realistic Indian take-back conditions. The article's contribution is an integrated MILP–LCA framework that endogenously computes life-cycle impacts within the supply network design, linking modular product architecture, graded return routing, and material valorization to facility siting and reverse logistics under India's EPR regime. Circular designs deliver dual dividends: up to 25% lower annual net operating costs (after valorization) and 41% less virgin material use compared to the baseline. Sensitivity analyses show that, at moderate circularity, take-back and remanufacturing yield behave as near substitutes, whereas higher ambition introduces convex trade-offs that justify discrete reverse-capacity investments. The results provide a phased, managerially actionable pathway to profitable and auditable circular operations under contemporary Indian policy.

Keywords: Circular economy, Closed-loop supply chain, Mixed-integer linear programming, Life-cycle assessment, Extended producer responsibility

1. Introduction

Manufacturing firms face intensifying pressures to decouple growth from resource use and emissions while safeguarding profitability, a challenge that has moved Circular Economy (CE) strategies from peripheral initiatives to core operations design problems [1]. Globally, electronic waste (e-waste) is growing far faster than formal recycling: 62 million tons were generated in 2022, yet only 22.3% was documented as properly collected and recycled, with valuable materials and environmental externalities left unaddressed [1]. In India, now a rapidly scaling electronics manufacturing base, policy instruments are tightening. The E-Waste (Management) Rules, 2022, which embed EPR, became operational on 1 April 2023, creating compliance obligations for take-back, channelization, and environmentally sound processing [24]. For operations managers, these trajectories imply that linear production–distribution systems must be re-architected into closed-loop designs that operationalize reuse, repair, remanufacture, and material recovery while remaining economically resilient.

Operations research on closed-loop and circular supply chains has matured, with design/optimization models now routinely addressing multi-echelon networks, facility siting, reverse flows, and multi-objective trade-offs [4–6]. Systematic reviews highlight meaningful progress but also persistent gaps: most optimization studies still treat environmental performance through limited proxies (e.g., transport or process GHGs), under-represent social objectives, and rarely integrate life-cycle–consistent environmental accounting directly within network decision models [5–6]. Recent scholarship underscores the methodological root of this gap: environmental Life Cycle Assessment (LCA) is often linked sequentially to Supply Chain Optimization (SCO), as an external module generating emissions factors that are then inserted into an optimization model, rather than integrated at the formulation level, which can create scope misalignments and data-transfer inconsistencies [7]. For CE-oriented operations, sequencing risks optimizing a network under an environmental representation that omits processes (e.g., facility construction, storage, or reverse operations) that materially influence life-cycle impacts [7].

At the product–process interface, design choices shape operational circularity outcomes. Empirical evidence from smartphones shows that modularity, ease of disassembly, and spare-parts availability co-determine repair and remanufacturing feasibility and costs, influencing optimal reverse logistics configurations and inventory policies [8–9]. These micro-level design levers interact with meso-level infrastructure realities, collection density, recycling capacity quality, and informal sector participation, which are salient in emerging economies such as India. Recent analyses of Indian e-waste circularity identify coordination frictions, incentive misalignment, and awareness gaps as primary barriers, reinforcing the need for analytically grounded, system-level decision support that is sensitive to context while yielding generalizable insights [10].

Against this backdrop, the present study advances sustainable operations management by proposing a decision framework that embeds CE logic into production planning and supply-chain design through a mixed-integer linear programming formulation that explicitly links reverse-logistics and facility-location choices with LCA-consistent environmental constraints and quantifies economic performance using financially interpretable indicators relevant to managerial decision making. While the empirical context is an Indian electronics manufacturer adopting modular product architecture and take-back schemes under the current EPR regime, the framework is designed to generalize across settings. To ensure environmental credibility and policy relevance, the model draws on nationally appropriate emission factors. For example, grid-emission intensities from the CO_2 Baseline Database

(Version 20), and accommodates regulatory constraints implied by the E-Waste Rules and EPR operational guidelines [3–4]. The paper explores three research questions: (RQ1) How do progressively circular configurations (repair, remanufacture, material recycling) reshape cost of goods sold and return on invested capital relative to a linear baseline? (RQ2) Under what infrastructure and design conditions do closed-loop strategies deliver joint gains in profitability and life-cycle environmental performance? (RQ3) Which reverse-flow and facility-siting patterns are robust to demand, return-rate, and emissions-factor uncertainty within India's policy environment?

Prior CLSC optimization studies typically approximate environmental performance with narrow proxies or append LCA ex post, creating boundary misalignments and data-transfer inconsistencies between the optimization and assessment layers [6], [7], [11], [20], [21]. Under-model how product-architecture choices (modularity, disassemblability, repairability) shape reverse yields, inspection grades, and routing, despite cumulative evidence that architecture strongly conditions end-of-life flows [9], [37]–[39], and give limited treatment to India-specific regulatory and inventory parameters, such as the 2022 E-Waste (Management) Rules and Central Electricity Authority grid factors, which materially affect feasibility and carbon accounting [2]–[4], [24], [25]. Accordingly, this paper develops and tests an integrated MILP–LCA decision framework that enforces life-cycle constraints within the optimization [7], [11] and operationalizes modular design and graded returns within reverse logistics [37], [39], evaluating an Indian electronics case under the 2022 E-Waste Rules with CEA v20 electricity accounting [2], [4], [25]. The profit–environment trade-off is traced using the ε-constraint paradigm [12], [26]–[28].

The study offers three contributions. First, it closes a methodological gap by integrating LCA-consistent constraints into a network optimization model so that environmental performance is computed endogenously over the full system boundary rather than appended ex post [7]. Second, it operationalizes product modularity and take-back design choices within the network model, linking design parameters to reverse yields and processing routes with empirical grounding from the electronics domain [8–9]. Third, it provides policy-salient evidence for India's CE transition by stress-testing scenarios under the 2022 E-waste rules and using Indian grid carbon intensities, yielding insights that remain transferable to other manufacturing geographies with appropriate parameterization [2–4,10]. The remainder of the paper develops the integrated framework, presents a calibrated case application to an Indian electronics firm, and reports scenario analyses that trace financial and environmental outcomes across linear-to-circular transitions.

2. Literature Review

Closed-Loop Supply Chain (CLSC) research has progressed from end-of-life waste handling toward integrated forward–reverse network design that co-optimizes economic and environmental performance. Recent reviews detail this shift and identify persistent gaps, especially the reliance on simplified environmental proxies and partial system boundaries that underrepresent life-cycle effects, thus motivating models that can treat sustainability criteria with the same rigor as cost and service objectives [5], [6].

A central response to these gaps is the structural integration of LCA with SCO. Hülagü et al. formalize SCO decisions directly in LCA matrix notation and demonstrate that the dominant "sequential" pipeline (LCA → coefficients → optimization) can misalign system boundaries and induce data-transfer inconsistencies, whereas integrated formulations internalize environmental accounting at solve time [7]. In parallel, the LCA community shows that digital technologies (IoT, big data, AI, blockchain) can furnish high-granularity primary data and traceability, thereby reducing inventory uncertainty and enabling more credible optimization-embedded LCAs. Systematic reviews map these technologies to ISO 14040/44 phases and propose combination frameworks for industrial deployment [11], [13].

Where multiple objectives are material, the solution strategy shapes the visibility of trade-offs to decision-makers. Recent advances in ε-constraint methods for multi-objective (integer) linear programs improve Pareto-front coverage and uniformity for managerial use, while robust variants (e.g., AUGMECON-R) address nadir-point uncertainty and computational burden in higher-dimensional fronts, practical concerns in CLSC design with cost, service, and environmental objectives [12], [13]. These methods are therefore well-suited to generate interpretable "efficient sets" under binding environmental constraints rather than exogenous penalties.

Product architecture is a first-order lever linking design to reverse-flow performance. Evidence from smartphones shows that modularity and ease of disassembly increase repair feasibility and user acceptance, with implications for remanufacturing yields, process times, and spares logistics [8], [9]. A 2025 review of disassembly systems further confirms, at system-engineering scale, that disassembly parameters (e.g., joining methods, fasteners, information flows) propagate to recovery performance across reuse, remanufacture, and recycling routes, strengthening the case for explicitly modeling design–operations coupling in CLSCs [14].

Heterogeneity and uncertainty in return quality constitute a second core lever. Empirical and analytical studies show that quality grading of returns, with grade-specific buffers and processing routes, dampens variability propagation, stabilizes throughput, and can lift profits relative to undifferentiated processing, especially at higher return volumes [15], [16]. These results motivate inventory and capacity hedges that are explicitly keyed to graded yields and route-dependent lead times in closed-loop networks.

A third lever is by-product valorization: targeted recovery of secondary materials (e.g., Au, Cu, Pd, rare metals) from electronic products. Contemporary reviews in environmental and materials chemistry document scalable routes (hydrometallurgy, DES/IL systems, and hybrid "toolbox" approaches) that improve purity and recovery factors and reduce environmental burdens relative to primary extraction, thereby strengthening the business case for circular operations when embedded in the network's objective structure [17]–[19].

Synthesizing these strands, we treat circular operations as design levers that reshape network structure, reverse-flow performance, and the feasible frontier between economic and environmental outcomes. First, because modularity and disassemblability demonstrably raise repair and remanufacturing feasibility while shortening process times [8], [9], [14], Proposition 1 states that higher modularity/disassembly-friendliness shifts the Pareto frontier outward relative to non-modular designs (weak dominance across profit and life-cycle impacts). Second, because graded returns stabilize planning and increase value capture under uncertainty [15], [16], Proposition 2 holds that implementing quality grading with grade-specific buffers improves profit-service performance at given return volumes, particularly under volatile or quality-uncertain take-back streams. Third, because modern valorization technologies simultaneously create ancillary revenues and reduce resource intensity when modeled on an LCA basis [17]–[19], Proposition 3 asserts that incorporating valorization elevates Return on Invested Capital (ROIC) while reducing cradle-to-grave impacts. Finally, because integrated LCA–SCO formulations change optimal siting, capacity, and routing relative to sequential coupling [7] and are operationally enabled by digitally enriched inventories [11], [13], Proposition 4 posits that structural integration expands the implementable set of circular strategies that are economically and environmentally efficient under real system boundaries.

This theoretical framing guides the forthcoming methods by embedding LCA-consistent mass- and impact-balance constraints into a Mixed-Integer Linear Program (MILP); operationalizing design levers (modularity, take-back scope, quality-aware buffers, reverse-facility siting, and valorization intensity) as decision variables and parameters; and using ε-constraint variants to generate managerially interpretable Pareto sets for the Indian electronics case. The narrative focus here remains conceptual to avoid duplicating methodological and contextual details that will be developed later.

3. Research Design

3.1 Case Setting and Scope

We study an anonymized Indian electronics manufacturer operating in the National Capital Region. The planning horizon is one fiscal year partitioned into four quarters; two product families (Standard, Pro) share a modular bill of materials (battery, main PCB, display, casing, camera), enabling disassembly and part recovery in reverse operations. The candidate network comprises suppliers, two alternative assembly plants (Noida and Greater Noida), three distribution centers (Delhi, Lucknow, Jaipur), and two return-processing centers (Noida and Delhi). All operational data used for modeling and scenario analysis are provided in a public workbook (Online Appendix) containing demand by DC and quarter, BOM and module masses, facility fixed costs and capacities, transport distances by arc class (supplier→plant, plant→DC, DC→return center, return center→plant), process costs (assembly, inspection, remanufacture, recycle), valorization revenues, service-level targets, and parameters that define scenario toggles (take-back rates, grading yields, and environmental caps). Scenarios reflect a Linear Baseline, EPR-Compliant circularity (conservative yields, moderate take-back), and High-Circularity (aggressive take-back, improved yields, expanded reverse buffers). The 'EPR-Compliant' settings align with the E-Waste (Management) Rules, which institutionalize producer responsibility for collection and channelization to registered recyclers, thereby necessitating credible reverse logistics in practice [2], [3].

3.2 Material-Flow Analysis

We construct a mass-balanced representation of forward and reverse streams at module resolution. Material-flow analysis (MFA) is used to ensure conservation across nodes and processes and to parameterize inspection-grade yields that route returns to remanufacturing, recycling, or disposal. MFA is appropriate when the research objective is to trace stocks and flows across multiple unit processes and to support decision models with consistent system boundaries; the approach and accounting conventions follow established references in the MFA literature [22].

3.3 Life-Cycle Scope and Environmental Inventories

Environmental performance is enforced within the optimization model via binding constraints tied to LCA inventories. Consistent with ISO 14040 (principles/framework) and ISO 14044 (requirements/guidance), we specify goal and scope, define the product system and boundaries, and ensure consistency between inventory modeling and impact interpretation; where relevant, we adopt clarifications introduced in the 2020 amendments to these standards [20], [21], [22], [23]. Electricity-related emissions are computed using the Central Electricity Authority (CEA) CO_2 Baseline Database, Version 20.0 (2024), the Government of India's official reference for grid emission factors, so that scenario footprints are auditable against the national baseline [4].

3.4 Optimization Model

We formulate an MILP that co-decides facility opening for assembly plants and return centers; forward flows from suppliers→plants→DCs; reverse flows from DCs→return centers→plants; production, remanufacturing, and recycling quantities at the module level; and inventories/buffers. Decision variables include binary open/close indicators for facilities; continuous flows for each arc, period, product/module; and inventory levels. The economic objective minimizes total cost (procurement of virgin modules; assembly/reman/recycle processing; inter-facility transport; inventory holding; fixed charges), with ROIC computed from operating profit and invested capital for reporting. Environmental performance is coupled through binding constraints that cap cradle-to-grave greenhouse-gas emissions and resource intensity (e.g., virgin-material use) per scenario. In line with recent integration studies showing the pitfalls of sequential LCA-then-optimization, impacts are computed endogenously by multiplying decision-dependent activity levels by LCI coefficients within the MILP (e.g., kWh from assembly/reman/recycle and transport energy where modeled), rather than appended ex post [3].

To characterize the profit–environment trade-off, we use the ε-constraint paradigm: the economic objective is optimized subject to environmental caps ε; by varying ε across a grid, we obtain a Pareto set with good coverage/uniformity. We adopt recent enhancements to multi-objective integer programs that improve Pareto-front representation and robustness (e.g., bounding strategies and AUGMECON-type augmentation), which are well documented for managerial exploration of trade-offs [12], [13].

3.5 Scenario Parameterization

Scenarios are implemented by toggling take-back rates that determine return volumes, grade shares at inspection (A: remanufacturable; B: recyclable only; C: scrap), process yields by module and route (remanufacture vs. recycle), valorization revenues for recovered materials, and environmental caps specified as fractions of the Linear Baseline footprint. EPR-Compliant settings assume moderate take-back and conservative yields. High-Circularity increases take-back, improves yields, and expands reverse buffers to test whether circular levers can produce joint gains (financial and environmental). The caps are calibrated using the CEA v20 grid factors [25], ensuring that any "feasible" solution in the optimization is also legitimate under a nationally recognized baseline [2]–[4].

3.6 Solution Approach and Reproducibility

All experiments are solved using a modern commercial MILP solver (Gurobi 12.0); we report the solver version, optimality gap tolerance (defaulting to 1% unless otherwise noted), time limits, number of threads, and hardware configuration. Gurobi's multi-objective and parameterization facilities are utilized to automate ε-sweeps and verify status codes and feasibility/optimality certificates, as outlined in the solver's current reference manual [23]. To ensure reproducibility, the paper provides the dataset workbook, a model description with complete symbol lists, and the ε-grid specification.

3.7 Validation, Sensitivity and Robustness

We conduct sanity checks (mass balance, non-negativity, unit consistency) and reconcile activity totals with LCI inventories to prevent scope creep across the forward and reverse echelons (per ISO 14040/44 interpretation guidance). Sensitivity analyses vary return rates, inspection-grade shares, module-level yields, valorization prices, and electricity emission factors (±20%) to assess the elasticity of economic and environmental outcomes. We also test a reverse logistics disruption (a temporary capacity reduction at one return center). Robustness is evaluated by comparing solutions across ε-grid density and by using an augmented ε-constraint variant to confirm that managerial conclusions are not artifacts of front sampling [20], [21], [12], [13].

4. Results and Discussion

Under India's EPR regime and electricity accounting anchored in CEA's latest grid factors, both circular configurations in our study dominate the linear baseline on economic and environmental objectives. The policy and inventory framework is contemporary and India-specific: the E-Waste (Management) Rules shape realistic take-back structures for producers, while electricity-related impacts are computed using the CEA CO_2 Baseline Database v20 (FY 2023–24) to ensure auditable carbon accounting in the Indian context [24], [25]. Crucially, the dominance we observe is not an artifact of penalties added after the fact; it reflects how life-cycle constraints, when embedded directly into the optimization, reshape feasible network choices; an approach consistently advocated in recent SCO research using ε-constraint and related multi-objective methods [26]–[28].

Table 1 consolidates the annual results for net operating cost (after valorization) and virgin material use. Both circular scenarios achieve simultaneous material improvements on these two objectives relative to the baseline. Mechanistically, the gains arise because avoided virgin procurement from remanufacturing scales faster than the added inspection and reverse-processing outlays required to achieve policy-consistent return rates; valorization then provides a smaller but systematic revenue stream without eroding material savings. This pattern accords with recent circular closed-loop network designs that model environmental performance as a co-objective/constraint, where interior regions of “win–win” outcomes often exist before trade-offs steepen near the frontier [26]–[28], [43]–[45].

Table 1. Scenario outcomes (annual)

Scenario	Net operating cost after valorization (INR million)	Δ vs. Baseline (%)	Virgin material use (kg/year)	Δ vs. Baseline (%)
Linear Baseline	2,842.3	—	100,775	—
EPR-Compliant	2,571.6	−9.5	83,382.6	−17.3
High-Circularity	2,132.3	−25.0	59,665.8	−40.8

Source: authors’ computations

Table 2 clarifies *how* these improvements are generated operationally. The A-grade → remanufacture stream is the primary driver of procurement avoidance and thus of the dual dividends recorded in Table 1, while the B-grade → recycling stream contributes to net economics through valorization and to resource conservation via materials recovery. The observed split mirrors established results: quality grading stabilizes reverse workloads and enhances value capture in closed-loop systems subject to uncertain return quality [29], [30]. The revenue significance of recovered, precious-metal-bearing fractions, especially from printed circuit boards, has been documented in recent reviews and is now reflected in industrial deployments (e.g., Royal Mint’s e-waste gold recovery facility), strengthening the managerial case for including valorization explicitly in the objective function [31]–[34], [41], [42]. From a broader perspective, the Global E-waste Monitor 2024 underscores the scale of under-recovery worldwide, reinforcing why valorization terms represent not merely accounting detail but a meaningful lever for system performance [35], [36].

Table 2. Reverse-flow composition (annual)

Scenario	Remanufactured modules used (units)	Modules sent to recycling (units)	Recovered modules via recycling (units)
EPR-Compliant	418,418	350,350	202,248
High-Circularity	988,988	600,600	346,710

Source: authors’ computations

Figure 1 presents normalized indices (Baseline = 1.00) that make scenario dominance visually immediate. Figure 2 displays elasticities of net cost to +20% changes in the take-back rate and A-grade remanufacturing yield. At moderate circularity (the EPR-consistent configuration), the two levers behave as near substitutes, offering managerial freedom to trade consumer-facing inducements against engineering investments while remaining in the win–win region. As circularity deepens, elasticities increase, especially for reman yield, signaling an approach to an outer frontier where further environmental ambition requires discrete network moves (e.g., additional return-center capacity or buffer expansions). This convexity, along with the presence of supported/unsupported efficient points, is characteristic of ε-constraint frontiers in recent CLSC formulations [26]–[28].

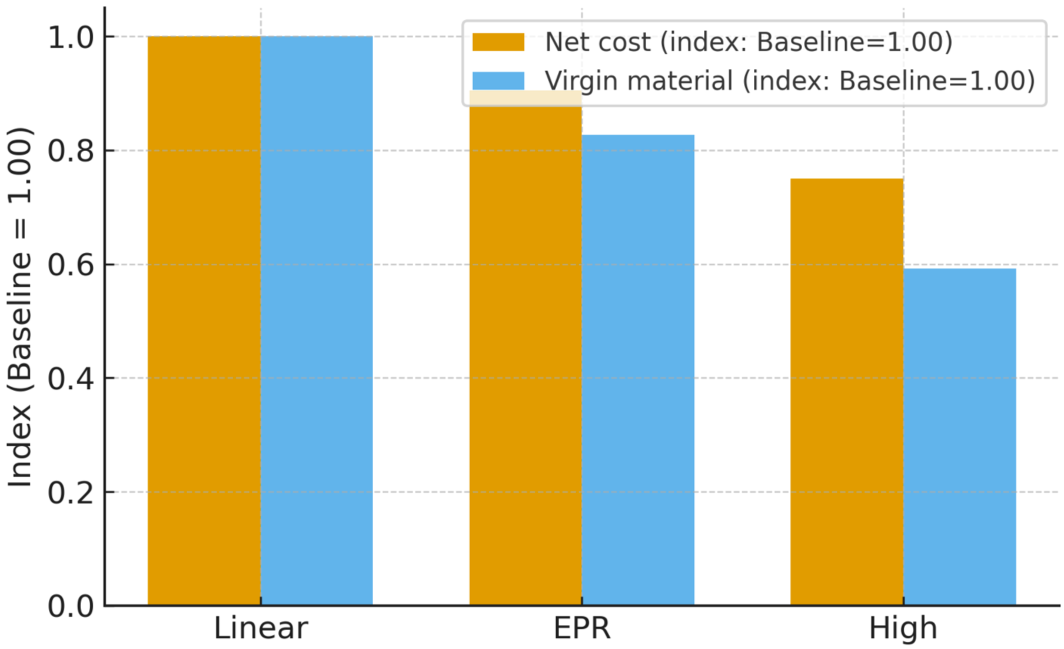

Figure 1. Normalized economics and resource use by scenario

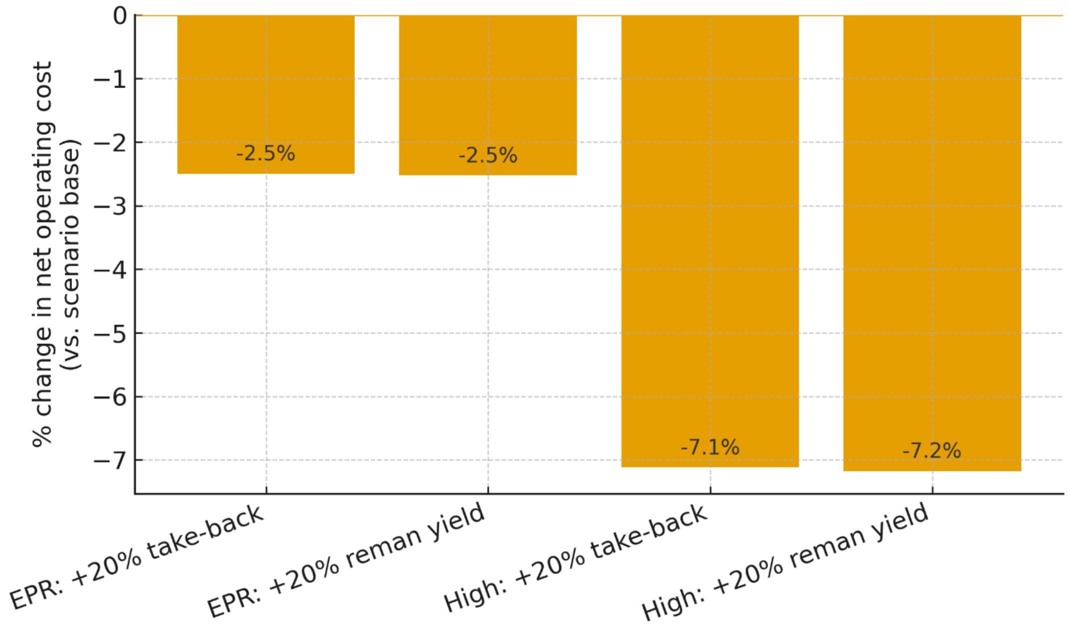

Figure 2. Net cost elasticity to circularity levers

With respect to RQ1, the evidence in Table 1 shows concurrent improvements in cost and virgin-material intensity when the model is evaluated with EPR-consistent return structures and CEA v20 factors, indicating that compliance and competitiveness can be aligned in practice [24], [25]. RQ2 is illuminated by Figure 2 and Table 2. At moderate circularity, take-back and reman-yield shocks produce similar, modest responses (substitutability). In contrast, at high circularity, the response becomes non-linear, revealing thresholds where lumpy, capacity-related decisions are justified, exactly the behavior predicted by ε-constraint multi-objective designs [26]–[28]. RQ3 points to product architecture as the dominant lever: modularity and design-for-disassembly raise module-level yields, which transmit directly into procurement avoidance and thus underwrite the dual improvements; this causal pathway aligns with recent evidence on modular smartphone architectures, disassembly effort, and repair behavior [37]–[40]. In contrast, siting and reverse capacity emerge as pivotal near the frontier, when rising reverse throughput makes additional buffers or an extra return center economical, again consistent with contemporary CLSC network studies [26]–[28], [44], [45].

The findings support all four propositions advanced in the study. Proposition 1 is borne out by the co-movement of remanufacturing volumes (Table 2) with reductions in net cost and virgin-material use (Table 1), in line with recent modeling and empirical work on modularity, repairability, and remanufacturing viability [37]–[40]. Proposition 2 is reflected in the consistent A-grade/B-grade routing and its economic/resource consequences, matching the literature on quality-differentiated returns [29], [30]. Proposition 3 is visible in the contribution of recycled fractions to net economics without undermining material savings, in step with the 2023–2024 reviews and current industrial practice in precious-metal recovery [31]–[34], [41], [42]. Finally, Proposition 4 is supported by the outward shift of the feasible set when LCA-consistent constraints are incorporated into the optimization, precisely the behavior advocated by recent integration studies and observed here in scenario outcomes, elasticities, and the composition of flows [26]–[28].

For Indian electronics manufacturers, the results suggest that economically attractive circularity is attainable at moderate take-back and reman-yield levels when modular design and grade-aware routing are implemented. The same modeling foundation supports auditable carbon disclosure once process-level LCI coefficients are specified, provided CEA v20 factors [25] are used. Our experiments hold forward transport flows constant and abstract from informal-sector leakage and secondary-market price volatility. A full MILP with stochastic returns and prices would sharpen the efficient frontier and enable policy counterfactuals (e.g., deposit-refund calibration, recycler accreditation stringency). These extensions align with the current research trajectory in sustainable CLSC network design, which couples environmental constraints with robustness, reliability, and resilience considerations [43]–[45].

5. Conclusions

This paper focused on designing and evaluating an integrated MILP–LCA framework for circular operations in Indian electronics under EPR, asking when circular configurations jointly improve profitability and life-cycle performance, and which levers (take-back, remanufacturing yield, facility siting/buffers) matter at different ambition levels. This study advances a decision framework that embeds circular-economy logic within production planning and supply-chain network design, integrating life-cycle constraints directly into the optimization. In contrast to ex-post penalization, the model enforces environmental limits within the feasible set, enabling the identification of interior configurations that improve both profitability and resource performance. Calibrated to India's regulatory and energy context, the E-Waste (Management) Rules, and the CEA’s CO_2 Baseline Database v20 for FY 2023–24, the framework yields policy-relevant insights rather than hypothetical patterns [24], [25]. In combination with contemporary multi-objective methods for closed-loop design (including ε-constraint formulations), the approach demonstrates how environmental and economic gradients can be aligned over a broad region before trade-offs steepen near the frontier [26]–[28].

Empirically, the evidence shows that circular configurations dominated the linear baseline in terms of annual net operating cost (after valorization) and virgin material use in the focal electronics case. Three mechanisms underlie this result. First, modular product architecture yields A-grade remanufacturing, which directly translates into avoided virgin procurement and, in turn, dual benefits in cost and material intensity. Second, quality grading of returns stabilizes reverse workloads while routing B-grade items to recycling, creating separated streams for functional and material substitution. Third, valorization of precious-metal–bearing fractions contributes a systematic revenue that co-finances reverse operations without eroding material savings, an effect that is consistent with current industrial deployments of e-waste metal recovery and the global evidence base on the economic value at stake in under-recovered flows [35], [41], [42]. Together, these mechanisms explain why improvements are material rather than marginal when life-cycle constraints are integrated into network decisions [26]–[28].

For managers operating under India's EPR regime, the results imply a pragmatic sequencing strategy. At moderate circularity, take-back programs and engineering investments that enhance A-grade remanufacturing yields behave as near substitutes, providing room to trade off consumer-facing inducements (e.g., deposit refunds, collection partnerships) against design-for-remanufacture and repair tooling while remaining in the "win–win" region. As circularity deepens, elasticities rise, and the system moves toward the outer frontier; at that point, lumpy decisions, additional return-center capacity, larger reverse buffers, or location adjustments, become economically defensible. Because electricity-related impacts are computed using CEA v20, the same modeling layer supports auditable carbon reporting once process-level life-cycle inventory coefficients are specified, facilitating consistent disclosure under India’s evolving sustainability and EPR guidelines [25].

Policy-wise, the findings provide a quantitative rationale for aligned interventions. Producer take-back targets and credible recycler accreditation (as embedded in the current rules) underpin the interior region where economic and environmental gradients co-move [24]. Complementary measures that support modular product architecture (e.g., repairability standards, access to parts and manuals) and that stabilize secondary-material markets (e.g., standards for recycled content, price-risk instruments) can enlarge that region. Given the scale of value loss documented in recent assessments of e-waste flows, prioritizing high-value fractions (notably PCB-borne precious metals) is consistent with both fiscal prudence and environmental materiality [35], [41], [42].

The study has limitations that delineate a research agenda. Forward logistics were held fixed, and the analysis abstracted from informal-sector leakage and secondary-market price volatility. A multi-period MILP with stochastic returns and prices would sharpen the efficient frontier, support policy counterfactuals for deposit-refund calibration and accreditation stringency, and capture interactions across product generations. Methodologically, robust or distributionally robust extensions could hedge against parameter uncertainty; decomposition-based matheuristics could help scale the integrated lifecycle-constrained formulation to larger networks; and multi-impact LCA (water, toxicity, critical-material depletion) could replace single-metric carbon constraints without sacrificing tractability [26]–[28], [43]–[45]. Finally, field calibration with firm-level operational data in India would test the external validity of the elasticities and thresholds observed in this study.

Building on these results, the next steps would be to examine a stochastic, multi-period extension to capture uncertainty in returns, quality, and secondary-market prices, decomposition-based or matheuristic solvers to scale the integrated formulation to larger networks, multi-impact LCA constraints (e.g., water, toxicity, critical-material depletion) beyond carbon while preserving tractability, and field calibration with firm-level Indian data to validate elasticities, test policy counterfactuals (deposit-refund strength, recycler accreditation), and support auditable disclosures.

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Conflicts of Interest

The authors confirm that there are no conflicts of interest.

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