

Article

Operationalising Circular Futures: Scenario-Based Modelling of WEEE Supply Chains

Rebecca Fussone ^{1,2} , Rachele Fussone ^{2,3} , Enrico Favazza ², Azar Mahmoud Gonbadi ⁴ , Paz Perez Gonzalez ², Jose Manuel Framinan ^{2,5}  and Salvatore Cannella ^{1,*} 

¹ DICAR—Department of Civil, Industrial Engineering and Architecture, Università degli Studi di Catania, 95123 Catania, Italy; rebecca.fussone@unict.it

² Industrial Management Research Group, Universidad de Sevilla, 41092 Seville, Spain; rachele.fussone@phd.unict.it (R.F.); efavazza@us.es (E.F.); pazperez@us.es (P.P.G.); framinan@us.es (J.M.F.)

³ Department of Physics and Astronomy “Ettore Majorana”, Università degli Studi di Catania, 95123 Catania, Italy

⁴ School of Business, Operations and Strategy, University of Greenwich, London SE10 9LS, UK; azar.mahmoumgonbadi@greenwich.ac.uk

⁵ Laboratory of Engineering for Energy and Environmental Sustainability, University of Seville, 41092 Seville, Spain

* Correspondence: cannella@unict.it

Abstract

Background: Circular economy transitions challenge conventional supply chain design and require decision-support tools that remain valid across multiple plausible futures. However, futures thinking in circular supply chain research is still used mainly as a narrative device, with limited guidance on how to translate scenario insights into model-ready assumptions. **Methods:** This paper proposes a four-step framework that converts qualitative circular-futures narratives into modelling factors and parameterised assumptions for waste electrical and electronic equipment supply chain simulation and optimisation. Four plausible circular futures, defined along economic-orientation and governance axes, are translated into operational and circularity factors and then into numerical parameters or structural modelling choices. The framework is illustrated through three applications: circular Supply Chain Resilience, electric-vehicle battery remanufacturing, and regional collection and treatment optimisation. **Results:** Circular strategies create value only when reverse flows, capacity and allocation choices are coherently aligned. Higher return rates improve resilience and material recovery but can destabilise upstream inventories when remanufacturing capacity and return shares are unbalanced. Different scenario priorities lead to distinct trade-offs across cost, emissions, resilience and circularity. **Conclusions:** This paper offers a replicable pathway for embedding plausible futures into quantitative circular supply chain models and supports more transparent decision-making under uncertainty.



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Keywords: circular economy; waste electrical and electronic equipment; futures thinking; circular supply chains; remanufacturing; reverse logistics; decision support; scenario analysis; simulation

1. Introduction

The transition towards circular economy (CE) is increasingly framed as a complex challenge involving the design and governance of supply chains (SCs), requiring systemic coordination and innovation. Circularity depends not only on technologies for repair,

reuse, remanufacturing and recycling, but also on the configuration of forward and reverse flows, the allocation of responsibilities among actors, the availability of recovery infrastructure and the policy mechanisms that shape incentives across the SC [1–3]. These issues are of particular relevance to the Waste Electrical and Electronic Equipment (WEEE) sector, where fast product obsolescence, limited critical raw materials, hazardous components and fragmented collection systems make circularity both urgent and operationally complex [4–6].

WEEE is among the fastest-growing waste streams globally. Recent estimates indicate that e-waste generation may reach 82 million tonnes by 2030 [4]. Electrical and electronic equipment contains valuable materials such as copper, aluminium, gold, lithium, nickel and cobalt, but also hazardous substances that require safe treatment. The sector therefore represents a suitable domain for the implementation of CE strategies: extending product lifetimes, recovering critical components, increasing formal collection, improving repairability and redesigning the reverse logistics can reduce pressure on virgin resources and limit the environmental impact [7,8]. At the same time, the design of WEEE SCs is subject to various sources of uncertainty. For instance, future regulations may become stricter or remain unevenly enforced; consumers may return products through formal channels or informal pathways; and recovery infrastructure may centralise around large facilities or decentralise through local loops.

In this context, futures-thinking approaches are widely adopted to explore and structure possible developments and support long-term decision-making. However, existing studies predominantly treat it as a narrative or conceptual tool, with limited attention to how scenario insights can be formally translated into modelling features. This creates a gap between exploratory analyses and quantitative decision-support tools, limiting the ability to systematically test the implications of alternative futures, assess the robustness of strategies under uncertainty and support evidence-based decision-making in complex systems. Accordingly, the methodological problem addressed in this paper is that futures-thinking outputs are often expressed as qualitative narratives, whereas SC models require operational parameters, factors and assumptions. Although structured “scenario-to-parameter-to-model” translation is already well developed in adjacent fields—including climate and energy-systems modelling, transport and policy planning, and robust SC optimisation [9–11]—these approaches are not tailored to the structural and circularity-specific requirements of WEEE SCs, an issue we develop and position the present framework against in Section 2.

Scenario narratives can effectively describe plausible future worlds by outlining coherent developments across technological, economic and regulatory dimensions, but simulation and optimisation models require these narratives to be translated into formal representations based on quantifiable inputs and decision variables, including demand patterns, lead times, return rates, capacity constraints, information-sharing structures and performance indicators. This translation is not straightforward, as it involves converting qualitative insights into consistent numerical assumptions and policy parameters that can support rigorous analysis and decision-making. As a result, a gap emerges between the richness of narrative-based scenarios and the structured data requirements of analytical models, posing a significant methodological challenge. Without an explicit translation step, scenario work risks remaining disconnected from quantitative decision support, while modelling risks exploring only narrow sensitivity ranges that do not reflect plausible futures.

This paper positions futures thinking as a methodological bridge between CE transition and SC modelling. The approach explores four plausible circular futures for WEEE SCs and converts them into parameterised modelling assumptions. This paper aims to address the following research questions:

1. How can plausible circular futures be translated into operational and circularity-related modelling factors for WEEE SCs?
2. How do alternative circular futures, once parameterised, affect resilience, operational stability and network design in WEEE SCs?

This study makes three main contributions. First, it introduces a framework that translates qualitative future narratives into model-ready assumptions for circular SC modelling. Second, it demonstrates the applicability of this framework across different modelling paradigms, including simulation and optimisation. Third, it derives both scenario-dependent and scenario-robust insights for the design and governance of WEEE SCs under uncertainty.

2. Background

The foundation of this paper lies at the intersection of futures thinking and WEEE SC modelling. This section reviews these two areas, positions the paper with respect to adjacent scenario-to-model translation approaches developed in neighbouring fields, and shows that neither futures thinking nor WEEE SC modelling, on their own, provide the translation layer that links them. In doing so, it clarifies the methodological gap addressed by the paper and motivates the three contributions stated in the Introduction.

Futures thinking and scenario analysis offer a way to engage with uncertainty. Their purpose is not to predict the most likely future but to examine multiple plausible future contexts and stress-test decisions against them [12,13]. In CE research, this is especially useful because circular transitions involve socio-technical change: regulation, market structure, consumer norms, business models, technology and infrastructure co-evolve. Scenario narratives can effectively describe plausible future worlds by outlining coherent developments across technological, economic and regulatory dimensions. For SC modelling, however, the challenge is to convert such narratives into assumptions that can be implemented in simulation or optimisation models. Recent SC research has recognised the value of scenario planning for long-term strategic decisions, SC adaptability, regulatory disruptions and transformative SC design [14–16]. Scenario-based modelling has also been used to support robust strategic capacity planning under uncertainty [17]. However, these contributions mainly use scenarios to frame strategic alternatives, assess future industry conditions or generate uncertainty cases.

The idea of translating scenario narratives into model inputs is not new in itself, and our contribution can be positioned against adjacent traditions in which this translation is comparatively mature. In climate and energy-systems research, the Shared Socio-economic Pathways explicitly pair qualitative storylines with a small set of quantified drivers—population, GDP and urbanisation—that are then fed into integrated assessment models [9,18], and subsequent work has formalised the linking of storylines with multiple operational models [19,20]. This demonstrates the feasibility of narrative-to-parameter translation, but it operates at a macro, exogenous-driver level and does not descend to the operational and structural design variables of an SC. In robust and stochastic SC optimisation, by contrast, “scenarios” denote discrete realisations of uncertain parameters—demand, returns, disruptions—characterised by probability distributions or uncertainty sets and generated or reduced to compute expected-value or robust solutions [11,21,22]. Here, scenarios are statistical constructs for hedging against parameter uncertainty rather than socio-technical narratives of alternative futures. Finally, exploratory scenario and scenario-discovery approaches in transport and policy analysis use plausible narratives to stress-test strategies [10], but the narratives typically inform a single appraisal or model and are rarely formalised into a reusable parameterisation layer. Against this backdrop, the contribution of this paper is not the general idea of narrative-to-parameter

translation but a translation layer that is, at once, specific to circular and WEEE SCs, explicit about combining numerical parameters with structural modelling choices, and transferable across both simulation and optimisation.

WEEE represents a critical domain for CE implementation because electrical and electronic products have short life cycles, generate rapidly growing waste streams, and contain both hazardous substances and valuable recoverable materials. Effective WEEE management can therefore reduce environmental and health risks while supporting the recovery of metals and components that would otherwise require extraction from virgin resources [2,3,6–8]. As a result, WEEE represents not only a waste-management challenge but also an SC design and coordination problem involving manufacturers, retailers, consumers, collection facilities, waste management companies, repair and reuse operators, recyclers, producer responsibility organisations, and policymakers [3,5].

Research on WEEE SCs has developed along several complementary streams. Early work focused mainly on reverse logistics network design, collection routing and facility location, balancing transportation costs, collection points, processing centres and environmental impacts [23–25]. Other contributions examined specific recovery processes, such as mobile-phone remanufacturing, photovoltaic-module recycling, repair and refurbishment or the economic viability of different treatment pathways [7,26–29]. More recent studies have expanded the modelling scope towards stochastic and multi-objective reverse logistics, environmental impact assessment, inventory planning, pricing decisions and policy-sensitive network design [30–34]. In WEEE systems, decision problems typically involve collection design, return-flow forecasting, facility location, flow allocation, capacity planning, recycling and remanufacturing planning, pricing and coordination among multiple actors [3,5,6].

The modelling literature recognises that WEEE SCs include multiple stages: collection, sorting, disassembly, repair, refurbishment, remanufacturing, recycling, secondary-market redistribution and disposal. Recycling remains the most widely modelled recovery function, often through third-party or multi-recycler configurations, while repair, reuse and refurbishment have received increasing attention because they extend product lifetimes and preserve embedded value [2,7,35,36]. Secondary markets are also relevant because they provide an outlet for recovered products and components, while disposal remains necessary for non-recoverable fractions that must be treated safely and in compliance with environmental regulations [37–39].

Some studies focus on cost minimisation or isolated environmental indicators, while fewer models jointly explore trade-offs among cost, emissions, circularity, compliance and operational feasibility [40–43]. Moreover, closed-loop (CL) and circular SC (CSC) studies show that reverse flows can stabilise or destabilise operational performance depending on their magnitude, timing and allocation across echelons [44,45]. This makes WEEE circularity a performance question rather than a purely normative objective: the same circular principle may improve service level, emissions or material recovery in one configuration and create operational instability in another.

To address these decision problems, different methodological approaches have been used. Mathematical programming, especially mixed-integer linear and nonlinear programming, is common in strategic network design and cost–environmental optimisation [25,30,33]. Heuristic and approximate methods, including genetic algorithms, fuzzy logic and multi-criteria decision-making approaches, are often used when the network structure or objective space becomes complex [6,24]. Game-theoretic models are frequently adopted for pricing, coordination and regulatory problems, especially when manufacturers, recyclers, retailers or third-party collectors interact strategically [32,34,46]. Simulation approaches, including system dynamics, agent-based simulation and discrete-event sim-

ulation, support the analysis of inventory, returns, capacity bottlenecks and disruption behaviour, although they are still less common in WEEE operational studies than strategic optimisation models [47]. Recent work also stresses the role of digital technologies, transparency and information sharing in improving reverse-logistics efficiency and decision support [48,49].

Overall, the literature shows that futures thinking can structure uncertainty, while WEEE SC modelling can evaluate operational, economic and environmental performance under different configurations. However, limited guidance is available on how qualitative circular-futures narratives can be systematically translated into model-ready SC parameters, constraints and structural assumptions for simulation and optimisation. This creates a methodological gap between the richness of narrative-based scenarios and the structured data requirements of analytical models.

This paper addresses this gap by introducing a parameterisation layer between scenario narratives and SC models. Qualitative scenario features are translated into modelling factors and then operationalised as numerical parameters, constraints or structural assumptions to evaluate performance under different circular futures.

Taken together, the two bodies of work reviewed above remain largely disconnected, and this disconnect motivates the three contributions of the paper. The absence of a systematic translation layer motivates the first contribution, the futures-to-parameters framework itself; the paradigm-bound character of existing scenario-modelling work, which typically remains confined to a single modelling family, motivates the second contribution, the demonstration of the framework across both simulation and optimisation; and the observation that reverse flows can either stabilise or destabilise operational performance—so that circularity is a performance rather than a purely normative question—motivates the third contribution, the derivation of scenario-dependent and scenario-robust insights for the design and governance of WEEE SCs.

3. Materials and Methods

The proposed four-step framework for operationalising circular futures is summarised in Figure 1: (i) defining plausible circular futures, (ii) translating, for each scenario, their key operational and circularity features into modelling factors, (iii) parameterising the corresponding modelling assumptions, and (iv) exploring their implications through complementary simulation and optimisation case-studies.

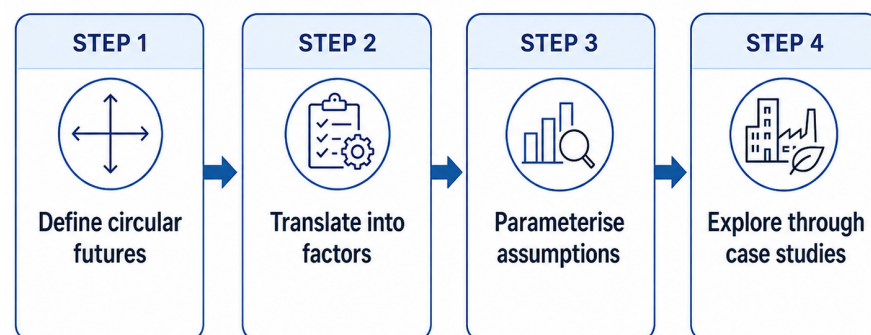


Figure 1. Four-step methodological workflow used to translate futures-thinking narratives into model-ready assumptions and scenario-based decision support.

Figure 1 presents the overall framework.

The scenario framework was developed within Exploring Plausible Circular Futures (ExPliCit), a Horizon Europe Marie Skłodowska-Curie Actions (MSCA) Staff Exchanges

project bringing together academic and non-academic partners to explore alternative CE futures and their implications for production and supply networks.

First, plausible circular futures were grounded in the project's futuring work and structured along two main axes: the economic orientation of the system, ranging from unrestricted growth to limits to throughput, and the governance structure, ranging from centralised to decentralised coordination. This construction follows the intuitive-logics ("2 × 2 matrix") tradition of scenario planning [12,50,51], in which two critical uncertainties are placed on orthogonal axes to generate four internally consistent, exploratory futures [13].

This first step built on a preceding ExPliCit work package that reviewed and classified techniques of futuring for CE research [52] and subsequently applied the resulting methodological portfolio through a project workshop and follow-up questionnaire [53]. In that process, eight candidate dichotomous dimensions were considered—including governance, technology, innovation, business models, scale of production, means of production, product ownership and growth orientation—before governance and growth orientation were selected as the two most relevant uncertainties for structuring the CE scenario space. The workshop involved academic and non-academic ExPliCit partners, and the follow-up questionnaire was completed by participants who had taken part in the workshop. The scenarios should therefore be understood as exploratory, internally coherent futures in the scenario-planning sense, rather than as probabilistic forecasts or statistically validated predictions. Their credibility rests on triangulation between the futuring literature, iterative project consultation, workshop/questionnaire feedback and subsequent WEEE-sector case-study work, where the same scenarios were projected onto circular SC mechanisms and modelling factors [54].

Crossing these two axes produces four plausible futures for WEEE SCs, as illustrated in Figure 2. The four scenarios are named according to the futures framework adopted in this study, while their position in the scenario space is defined by the combination of economic orientation and governance structure.

- Scenario 1 (S1)—Centralised circularity uptake (unrestricted growth and centralised governance): States and large corporations promote circular innovations mainly as technical solutions to support continued economic growth. CE practices focus on material efficiency, large-scale recycling, energy recovery and the substitution of primary materials with recycled inputs. However, fast product turnover, planned obsolescence and global multi-echelon SCs remain dominant. As a result, circularity may improve selected environmental indicators, such as greenhouse gas emissions, while leaving high consumption and broader ecological limits largely unchallenged.
- Scenario 2 (S2)—Planned circular loops (limits to growth and centralised governance): States, large corporations and international organisations coordinate the transition towards lower societal throughput. Decision-making is concentrated in a limited number of actors, who impose stronger controls on production, consumption and resource use. CE strategies are implemented through standardised products, product-as-a-service models, sharing systems, rationing mechanisms, taxation and centrally planned investments. SCs become more localised as global logistics become more costly, and circular districts may emerge to organise controlled material flows.
- Scenario 3 (S3)—Bottom-up circular loops (limits to growth and decentralised governance): In this scenario, citizens, communities and local autonomous organisations increasingly question the social and environmental consequences of growing consumption. Circularity is driven from the bottom up by small-scale actors and meso-level governance structures, which promote sufficiency-oriented practices, fair resource use and locally embedded circular loops. SCs become shorter and more closely linked

to local production and consumption systems. CE is understood broadly, extending beyond material and energy flows to include biogeochemical, social, care, power, and resource-governance cycles. Circular strategies prioritise refuse, reduce, rethink, repair, reuse and product-life extension over recycling. However, decentralised coordination may create operational challenges, especially in aligning production, prices, capacities, resource-sharing agreements and regional material flows.

- **Scenario 4 (S4)—Decentralised circularity uptake** (unrestricted growth and decentralised governance): In this scenario, environmental limits are recognised, although no strict constraints are imposed on throughput or economic activity. Circular practices emerge from distributed firms, local actors and decentralised organisations, supported by mild regulatory measures such as subsidies, eco-taxes and anti-monopoly policies. Economic activity becomes more dispersed, reducing the dominance of large corporations and encouraging local competition, distributed innovation and new circular business models. CE strategies aim to retain materials and energy within the economic system, improving supply security and resource efficiency. Nevertheless, weak coordination, persistent externalities and low-cost long-distance transport may sustain complex global SCs and limit the effectiveness of larger circular initiatives.

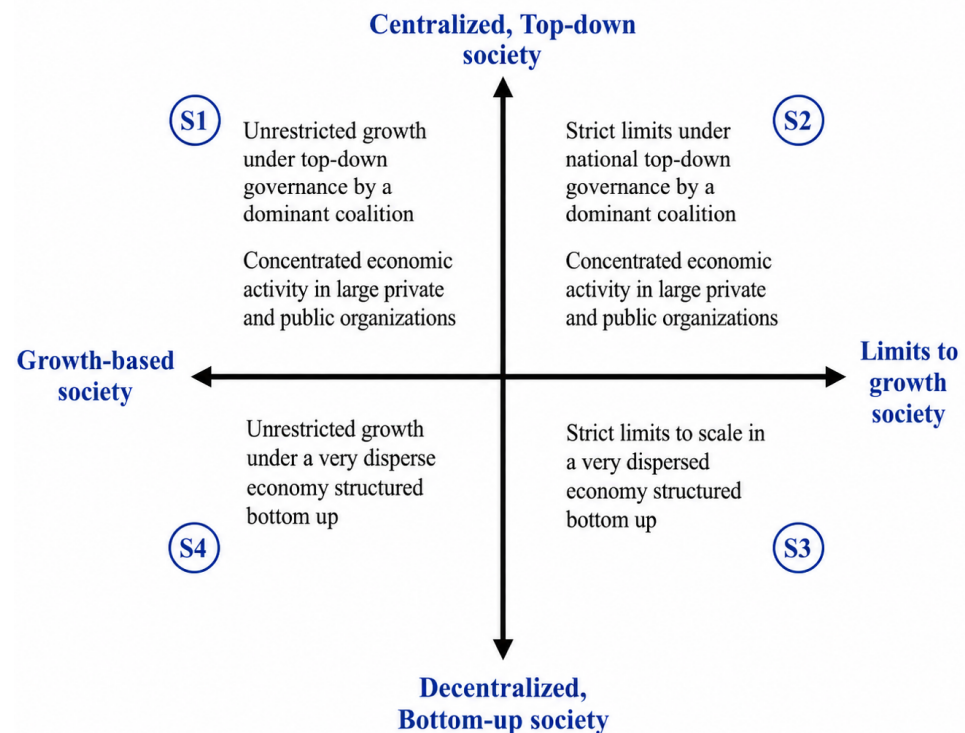


Figure 2. Scenario space for the four plausible circular futures according to economic orientation and governance locus. The horizontal axis distinguishes growth-based and limits-to-growth societies, while the vertical axis distinguishes centralised top-down and decentralised bottom-up governance.

As a second step, we translate each future circular scenario into SC modelling factors with the aim of creating a flexible CSC model. The identified modelling factors can be grouped into operational and circular features (see Table 1). Operational features characterize the linear production and processes, such as demand level and variability, manufacturing capacity constraints, number of echelons and forward lead times. Circularity features characterize the CSC archetype, i.e., the circular flows and R-imperatives such as remanufacturing share, reverse-flow lead time, reverse-flow priority rules, reverse flow

to retailers, industrial symbiosis, information sharing and consumption lead time. This step provides the conceptual link between qualitative futures-thinking narratives and the operational dimensions required by simulation and optimisation models.

These factors follow systematically from the position of each scenario on the two axes, which keeps the parameterisation internally consistent. The governance axis (centralised vs. decentralised) primarily drives the scale of the system—mean demand, the number of echelons and the extent of information sharing—so that centralised futures (S1, S2) exhibit higher mean demand and more echelons than decentralised ones (S3, S4). The growth axis (unrestricted growth vs. limits to growth) primarily drives demand variability and the intensity of reverse flows, with growth-oriented futures (S1, S4) showing higher demand variability and limits-to-growth futures (S2, S3) showing higher remanufacturing and reverse-flow intensity. Tables 2 and 3 make this axis-to-parameter mapping explicit, so that the parameterisation can be traced scenario by scenario.

Table 1. SC modelling factors used to operationalise the circular futures.

	Feature	Modelling Factor	Notation
Operational features	Supply-chain structure	Number of nodes/echelons	N
	Transportation lead time	Forward transportation lead time	LT_i
	Market demand	Mean demand	μ_D
		Demand variance	σ_D^2
	Collaboration	Information sharing	ε
	Efficiency of forward process	Coefficient of variation of lead time	CV_{L_i}
		Maximum forward production rate	$S_{\max}$
	Efficiency of reverse process	Coefficient of variation of reverse lead time	CV_{LR_i}
Circular features	Replenishment policies	Cycle policy	–
		Constraints on emissions	$E_{\max}$
	Environmental constraints	Constraints on waste/by-product generation	$W_{\max}$
	Degree of circularity	Mean return rate	α_i
		Coefficient of variation of the return rate	CV_{α}
	End-of-life dynamics	Closed-loop or open-loop configuration	–
		End-of-life cycles	R-imperative
	Industrial symbiosis	Waste rates	ω_i
	Lifecycle of the product	Consumption lead time	L_c
	Quality of end-of-life products	Mean reverse lead time	μ_{LR_i}
	Quality of treated products	Demand from the secondary market	–

Then, in the third step, the identified factors are parameterised into model-ready assumptions. This step assigns either qualitative states or numerical values to the modelling factors defined in the previous step. Some assumptions can be directly expressed as quantitative model inputs, such as demand mean and variability, treatment capacity, return rate, recovery share and lead times. Other assumptions are represented as structural modelling choices, including the activation of information sharing, the adoption of a centralised or localised network structure, the prioritisation of remanufactured products and the modelling of industrial symbiosis either as a continuous input or as a backup option.

Finally, the parameterised assumptions can be explored through modelling applications. The purpose of this step is not to reproduce the full complexity of each future but to show how futures-informed assumptions can be embedded into different decision-support models and used to assess operational, environmental and network-design implications. In this study, we developed three modelling applications, presented in the paper as case studies, in which we cover different analytical perspectives: dynamic resilience under disruption, Closed-Loop Supply Chain (CLSC) stability and material recovery, and regional

WEEE network optimisation. The three case studies are not intended as separate contributions, but as complementary instantiations of the same futures-to-parameters logic across different modelling paradigms, which strengthens the internal coherence of the framework.

Table 2. Translation of plausible futures into qualitative SC modelling assumptions.

Future	Demand	Capacity and Lead Times	Reverse Flows	Circular Policies	Network Coordination
S1: Centralised circularity uptake	High mean, high variability	No capacity limit; high forward LT; short, stable consumption LT	Low remanufacturing, low retailer returns; high reverse LT	Priority to virgin products/materials; low IS	Many echelons; info sharing on
S2: Planned CLs	High mean, low variability	Capacity constrained; low forward/reverse LT; long, variable consumption LT	High remanufacturing, high retailer returns	Priority to remanufacturing/waste; high IS	Few echelons; info sharing on
S3: Bottom-up CLs	Low mean, low variability	Capacity constrained; high forward/reverse LT; long, variable consumption LT	High remanufacturing, high retailer returns	Priority to remanufacturing/waste; medium IS	Few echelons; local info sharing
S4: Decentralised circularity uptake	Low mean, high variability	No explicit capacity limit; low forward, moderate reverse LT; short, stable consumption LT	Moderate remanufacturing, medium retailer returns	Remanufacturing for returns, virgin inputs for IS; low IS	Few echelons; limited info sharing

Note: LT = lead time; IS = industrial symbiosis.

Table 3. Operationalisation of selected modelling factors from futures analysis and industrial context.

Future	Orientation	Demand	Capacity	Reman./Returns	Policy Rule	Information Sharing	Model Scope
S1	Planned growth	Mean 100, variability 50	No constraint	Low reuse (about 2%); about 60% classified for recovery	Pull	Yes	CSC
S2	Planned limits to growth	Mean 100, variability 10	45–50 t/day (contextual)	High return (up to 55%)	Push	Yes	Forward SC + reuse/recycling
S3	Decentralised limits/bottom-up loops	Mean 50, variability 10	Capacity-constrained	High return (up to 55%)	Push	Yes	Forward SC + reuse/recycling
S4	Decentralised growth	Mean 50, variability 25	No hard constraint	Moderate returns (up to 30%)	Push (reman.); pull (IS)	No	Forward SC + reuse/recycling

Note: t/day = tonnes/day; reman. = remanufacturing; IS = industrial symbiosis. “Forward SC + reuse/recycling” denotes a forward SC augmented with reuse and recycling flows.

Case Studies Description

Across the three case studies, the same logic is retained: futures-derived assumptions are first translated into qualitative modelling factors and then into numerical parameters or structural modelling choices. Rather than testing all four scenarios in every case study, each analytical application is deliberately matched with the future configurations most relevant to the operational question under study, aligning scenario logic, model structure and decision relevance. The resilience case is therefore used as a stress test for high-circularity configurations associated mainly with planned circular loops (S2); the EVB remanufacturing case focuses on S2 and S3, where high remanufacturing and reverse-flow intensity make dynamic stability especially relevant; and the Andalusian WEEE

optimisation case is explicitly aligned with S2, where centralised governance, regional coordination and regulatory oversight are core features. It is worth clarifying what these applications are designed to demonstrate. The claim they support is the transferability of the futures-to-parameters logic across modelling paradigms—that the same translation procedure can be instantiated in simulation and in optimisation—rather than an exhaustive comparison of all four scenarios in each model. The scenario space itself is covered at the framework level, through the mapping of all four futures onto modelling factors and parameters in Tables 2 and 3, while each case then instantiates the futures most relevant to its operational question. For this reason, demonstrating one consistent method operating across three different decision problems and paradigms is sufficient to establish transferability; the corresponding limitation—that this focused coverage does not support claims about the comparative performance of every model under every possible future—is stated explicitly in Section 6.

The first case study examines resilience in a CSC, through a simulation approach, comparing a traditional forward SC, characterised by the absence of circular flows, with configurations that integrate End-of-Life (EOL) returns and industrial-symbiosis by-products [55]. This case study can be interpreted as representative of more coordinated circular scenarios, especially planned CLs (S2), where reverse flows are actively managed and aligned with forward operations. This scenario is characterised by high remanufacturing and high reverse flow, and policies prioritise both remanufacturing and waste through industrial symbiosis. The model is therefore used as a stress test of whether circular flows can act as operational buffers during sudden demand peaks in a system that is relatively centralised, characterised by low variability and highly dependent on coordinated recovery flows.

In this analysis, a discrete-event simulation model is used to introduce a disruptive event in the form of a sudden demand spike and study Supply Chain Resilience (SCR), thus allowing the analysis to focus on how different SC configurations respond under stress. The model is subject to iid normal customer demand D_t . In the baseline condition, demand has mean $\mu = 100$ and a coefficient of variation of 10%; the disruption is modelled as an abrupt increase in the mean demand from $\mu = 100$ to $\mu = 500$, while maintaining the same coefficient of variation. The simulation experiments were conducted in a MATLAB (version R2023b, The MathWorks, Inc., Natick, MA, USA) environment, following the implementation details reported in the technical case-study material [54]. The model evaluates SCR through the resilience curve derived from the temporal evolution of a performance measure, which serves as a proxy for system performance under disruption. Specifically, to provide a customer-focused approach, the service level of SC customers is used as the performance measure, using the Fill Rate (i.e., the percentage of customer demand that is immediately satisfied from available inventory). Based on this curve, a set of resilience metrics is computed, namely absorptive duration, endure duration, recovery duration, failure ratio and recovery ratio [56,57]. The distinction across the studied configurations lies in the availability and intensity of circular flows, captured by the EOL return rate α and the by-product rate ω , which are tested at moderate and high levels. These parameters reflect the extent to which circular strategies are embedded within the SC. They should not be interpreted merely as technical variables, but rather as proxies for broader structural and governance conditions, such as the degree of coordination, infrastructure development and industrial symbiosis. Overall, the case study provides a controlled setting to examine how different circular configurations, mapped to plausible future scenarios, affect resilience performance. In particular, it highlights the role of reverse flows as potential buffers against disruptions when effectively integrated into the system.

More formally, the resilience performance measure is the fill rate of node i in SC k at period t , computed as the ratio between the volume delivered to the customer and the corresponding demand:

$$FR_{t,i,k} = \frac{C_{t,i,k}}{D_{t,k}}, \quad 0 \leq FR_{t,i,k} \leq 1, \quad (1)$$

where $C_{t,i,k}$ is the quantity delivered and $D_{t,k}$ is customer demand. The resilience curve is therefore the time path $FR_{t,i,k}$ before, during and after the demand spike. Absorptive duration, endure duration and recovery duration are measured from the transition times of this curve, while failure ratio and recovery ratio quantify the share of performance lost and restored with respect to the pre-disruption fill-rate level. This formalisation makes the first case study distinct from the other applications because the output of interest is not a cost or inventory optimum but the dynamic degradation and restoration of service performance under disruption [54].

The second case study focuses on electric-vehicle battery (EVB) remanufacturing and examines how different levels of reverse-flow integration affect the dynamic behaviour of a CLSC. This case study aligns primarily with Scenario 2 (planned circular loops) and Scenario 3 (bottom-up circular loops). Both of these scenarios prioritize remanufacturing and waste management, featuring high remanufacturing percentages and high reverse flows to retailers. The model represents three remanufacturing echelons, namely battery, module and cell remanufacturing, which reflect different levels of product disassembly and recovery. This case study is particularly relevant for circular futures in which return flows, remanufacturing capacity and material recovery become central to SC design. Low return-rate settings can be interpreted as representative of weakly coordinated circularity, whereas high return-rate settings approximate futures with stronger reverse logistics and greater retention of critical materials.

The model follows a dynamic CLSC structure, simulated in MATLAB R2024, in which customer demand is generated stochastically according to a normal distribution with mean $\mu_D = 100$ and standard deviation $\sigma_D = 30$. Replenishment decisions are governed by a periodic-review order-up-to policy. Return rates α are varied across 0%, 20%, 50% and 80% to capture alternative degrees of circularity and reverse-flow availability [58]. Returned batteries are allocated across the cell, module and battery echelons through echelon-specific return shares, representing the different technological and operational capabilities required to recover value at each level. Since remanufacturing at the battery, module and cell levels involves different processing requirements and lead times, the case study allows the analysis to capture how the position of reverse flows within the SC affects operational stability.

Demand forecasting and order generation are explicitly modelled for each echelon i . The demand forecast is updated through exponential smoothing:

$$\hat{D}_t^i = aO_t^{i+1} + (1-a)\hat{D}_{t-1}^i, \quad (2)$$

where $a = 0.2$ is the smoothing parameter and O_t^{i+1} is the order received from the downstream echelon. The replenishment quantity follows a periodic-review order-up-to rule:

$$O_t^i = \max\left\{\hat{D}_t^i + \left(\text{TNS}_t^i - I_t^i\right) + \left(\text{TWIP}_t^i - \text{WIP}_t^i\right), 0\right\}, \quad (3)$$

where I_t^i and WIP_t^i denote available inventory and work in progress, while TNS_t^i and TWIP_t^i are the corresponding target net-stock and target pipeline levels. The simulation covers

8870 daily periods, including a 3030-period warm-up, and each scenario is replicated 30 times, improving reproducibility of the dynamic indicators [54].

Performance is assessed through three dynamic indicators: the order rate variance ratio, the bullwhip effect and net stock amplification. These indicators capture complementary aspects of SC behaviour, namely the variability of orders relative to market demand, the amplification of demand signals across echelons and the instability of inventory levels. In addition, the operational analysis is complemented by an environmental assessment of critical-material recovery and associated CO₂ savings, focusing on materials such as cobalt, lithium and nickel [59,60]. Overall, this application provides a controlled setting to examine how alternative return-rate and reverse-flow allocation assumptions influence CLSC dynamics. In particular, it focuses on the role of return allocation, remanufacturing lead times and echelon-specific dynamics in shaping operational stability and environmental recovery potential.

The three dynamic KPIs are computed as

$$BWE_i = \frac{\text{Var}(O_i)}{\text{Var}(O_{i-1})}, \quad OrVrR_i = \frac{\text{Var}(O_i)/\mu_{O_i}}{\text{Var}(D)/\mu_D}, \quad NSAmP_i = \frac{\text{Var}(I_i)}{\text{Var}(D)}. \quad (4)$$

Thus, the second case study differs analytically from the resilience case because it evaluates endogenous operational amplification across echelons rather than disruption recovery at a single performance curve.

The third case study concerns regional WEEE collection and treatment in Andalusia, Spain, focusing on the FAEL–RECILEC configuration. It aligns primarily with planned CLs (S2), where circularity is supported by stronger regulatory oversight, regional coordination, regional self-sufficiency and the planned organisation of recovery flows. A multi-objective mixed-integer linear programming (MILP) model is used to optimise a circular CLSC network under Extended Producer Responsibility (EPR) and Right-to-Repair (R2R) constraints. The model jointly considers total system cost, transport and operational CO₂ emissions, and circularity, defined as the share of collected WEEE directed towards repair, reuse or recycling rather than disposal. In this case, the modelling focus is on how coordinated implementation of EPR and R2R can operationalise the planned circular loops vision by balancing economic, environmental and circularity objectives within a regional WEEE system.

The network includes forward flows from manufacturers to retailers and customers and reverse flows from customers, retailers and municipal clean points to warehouses, waste managers, repair and reuse facilities, recycling plants and disposal sites. The main decisions concern facility activation, transport-link selection and flow allocation across the network. Capacity, service-radius, flow-conservation and policy-compliance constraints are included to represent regional accessibility, operational feasibility and regulatory requirements.

A weighted-sum approach is adopted to explore different combinations of economic, environmental and circularity priorities. Four optimisation scenarios are considered: a cost-led baseline, an emissions-led configuration, a circularity-led configuration and an integrated policy-driven configuration. Overall, this application provides a controlled setting to examine how policy constraints, infrastructure assumptions and optimisation priorities shape regional WEEE network design and the trade-offs among cost, emissions and circularity.

The Andalusian case is formalised as a deterministic MILP with continuous forward flows x_{ij}^f , reverse flows x_{ij}^r , processed quantities u_i , binary facility-opening variables y_i and binary link-activation variables z_{ij} . Its three objective functions are

$$Z_1 = \sum_{(i,j) \in N} t_{ij} (x_{ij}^f + x_{ij}^r) + \sum_{i \in N} f_i y_i + \sum_{i \in N} v_i u_i + \alpha \sum_{i \in N, j \in N_d} x_{ij}^r - \sum_{(i,j) \in N} r_{ij} (x_{ij}^f + x_{ij}^r), \quad (5)$$

$$Z_2 = \sum_{(i,j) \in N} e_{ij} (x_{ij}^f + x_{ij}^r) + \sum_{i \in N} \phi_i u_i, \quad (6)$$

$$Z_3 = 1 - \frac{\sum_{i \in N, j \in N_d} x_{ij}^r}{\lambda}, \quad (7)$$

where Z_1 minimises total cost net of revenues, Z_2 minimises transport and process emissions, and Z_3 maximises circularity by reducing the share of collected WEEE sent to disposal. In the weighted formulation, the model minimises $Z = w_1 Z_1 + w_2 Z_2 - w_3 Z_3$, with $w_1, w_2, w_3 \in [0, 1]$.

The main constraints ensure demand satisfaction and WEEE return generation; forward and reverse flow conservation; facility activation and capacity feasibility; link activation; maximum service radius; EPR compliance; R2R compliance; and variable domains. Representative policy constraints are

$$\frac{\sum_{i \in N_{wm}, j \in N_{ru} \cup N_{rc}} x_{ij}^r}{\lambda} \geq \gamma, \quad RP \geq \delta, \quad (8)$$

with $\gamma \geq 0.85$ for EPR recovery and $\delta \geq 0.80$ for the R2R reparability threshold. The optimisation was implemented in Python (version 3.10, Python Software Foundation, Wilmington, DE, USA), using the Pyomo modelling language (version 6.6) within a Jupyter Notebook (version 6.5) environment. The regional scale is based on data from the FAEL–RECILEC Andalusian WEEE system, with transport distances parameterised in the 10–120 km range within the Andalusian network and policy parameters reported in [54]. This third case study is therefore structurally different from the two simulation cases: it optimises network configuration and policy-constrained flow allocation rather than dynamic recovery or order-amplification behaviour.

4. Results

A primary result of this study concerns the parameterisation process itself, namely the systematic translation of futures-thinking outputs into model-ready assumptions. Tables 2 and 3 synthesise this translation by linking qualitative scenario features with quantitative and rule-based modelling choices. This demonstrates the feasibility of operationalising scenario-based insights into a structured set of inputs that can be directly employed within simulation models. The results indicate that this translation does not require a uniform level of numerical precision across all parameters. Instead, assumptions can be operationalised at different levels of quantification, depending on their characteristics. In particular, several factors can be consistently represented through quantitative inputs, including demand mean and variability, treatment capacity, return rates and recovery shares. These variables can be readily incorporated into the modelling framework as numerical parameters. At the same time, the evidence highlights that other factors are operationalised through categorical or rule-based representations. This heterogeneity allows the model to incorporate both well-characterised numerical inputs and less structured qualitative assumptions within a unified framework. In particular, Table 2 identifies the qualitative dimensions, such as demand patterns, capacity constraints, reverse flows, circular policies and network coordination, that differentiate the scenarios, while Table 3

formalises their quantitative and rule-based operationalisation (e.g., demand levels and variability, return rates, capacity limits and policy rules such as push or pull mechanisms). These elements jointly define distinct SC network configurations, ranging from highly centralised to decentralised circular setups. Overall, the results demonstrate that heterogeneous futures-thinking outputs can be systematically organised into a coherent set of model-ready features and factors, thereby providing an explicit and traceable linkage between scenario development and model-based analysis. More broadly, these findings reinforce the role of modelling as a tool to support the understanding and decision-making of complex SCs and processes. In this respect, the identified features and factors are not tied to a specific modelling paradigm but can be readily employed across different modelling approaches, including simulation as well as mathematical optimisation models, thus enhancing the transferability and applicability of the proposed framework.

The values reported in Tables 2 and 3 should therefore be read as traceable operational assumptions rather than hypothetical parameter choices. Their rationale is based on a triangulation between industrial evidence, European policy targets, established modelling benchmarks and the internal business-model logic of each scenario. Capacity-related parameters are anchored in technical information collected through the project case studies and partner evidence reported in [54]. For instance, the 45–50 tonnes/day value used as a contextual capacity for FR1 treatment reflects the operational processing capacity observed for large appliances, while the regional scale of the Andalusian optimisation model is informed by the WEEE collection and treatment volumes managed through the FAEL–RECILEC system. Similarly, recovery and disposal assumptions are calibrated against industrial evidence on waste-stream classification, including recoverable and non-recoverable fractions observed in partner operations.

Circularity-related parameters are linked to policy targets and real WEEE collection evidence. In the MILP case, the EPR recovery requirement is represented as a binding minimum recovery threshold of $\gamma \geq 85\%$, consistent with the recovery logic of Directive 2012/19/EU as operationalised in the case-study material. The R2R condition is represented through a repairability threshold of $\delta \geq 80\%$, reflecting European policy initiatives aimed at extending product lifetimes and increasing repairability. Return-rate assumptions are also informed by the FAEL–RECILEC collection context, including the observed growth of WEEE collection in Andalusia from approximately 1500 to more than 2200 tonnes per year over the analysed period. These values are not used as universal constants but as scenario-consistent inputs for translating different circularity ambitions into model-ready parameters [54].

The demand parameters follow the same traceability logic. Baseline demand settings, such as the mean value of 100 units and the coefficient-of-variation assumptions used in the simulation cases, are consistent with established CLSC simulation practice and EVB remanufacturing studies, while the consumption lead-time assumption reflects evidence on EVB use and replacement cycles [58,61]. High variability in S1 and S4 represents growth-oriented and more open-market configurations, where product replacement, short life cycles, continuous product introduction and less coordinated demand signals can generate stronger fluctuations. By contrast, lower variability in S2 and S3 reflects circular futures in which Product-as-a-Service, sharing-based models, producer responsibility and longer product-use cycles stabilise flows and reduce replacement-driven demand peaks. This rationale explains why the same modelling factor, such as demand variability or return rate, receives different values across scenarios: each value is selected to remain coherent with the underlying scenario narrative, industrial evidence, modelling literature and policy context. This traceability is particularly important because the three analytical cases use different mathematical structures—resilience simulation, dynamic CLSC simulation

and MILP network optimisation—and therefore require different formula designs and parameter interpretations.

This result is further highlighted by the case study analysis, in which the parameterisation logic is applied across diverse contexts through different modelling approaches and targets diverse performance indicators, while maintaining consistency in the underlying feature–factor structure. In the CSC resilience case study, parameterisation is used to analyze and compare alternative SC configurations, enabling a direct assessment of how different circularity patterns affect system performance under disruption. Specifically, in this case study, the comparative analysis demonstrates that the circular configurations generally outperform the forward benchmark when a sudden shock in demand occurs. When EOL returns and by-product flows are introduced, the SC exhibits a clear improvement in both absorptive and recovery dynamics for the retailer and the manufacturer. It means that the reliance on circular flows to meet high or volatile demand (such S2) becomes crucial, leveraging the enhanced resilience of the CSC model. The results highlight a general pattern: increasing the availability of circular flows enhances the system’s absorptive and restorative capacities, reducing the duration and severity of disruption impacts. Thus, the introduction of EOL returns and by-products shortens the endure duration by increasing the recovery, i.e., the SC performance levels remain at a suppressed state for a shorter duration and begin to recover at an earlier stage. For instance, as shown in Table 4, when moderate values of the circular rates are considered (e.g., $(\omega, \alpha) = (0.4, 0.4)$), the endurance duration decreases while the recovery duration increases. Similarly, with higher circular rates (e.g., $(0.4, 0.7)$), the endurance duration further declines to 10, and recovery is achieved earlier; moreover, an improvement in the absorptive duration is also observed. This behavior is consistent with more structured circular configurations, such as those described in planned CL futures, where high remanufacturing rates and coordinated reverse flows provide additional sources of supply. At the same time, the benefits are not uniform across the SC. The positive impact of circularity depends on how returns and by-products are distributed across SC nodes. Both the retailer and the manufacturer can benefit from increased circular flows, but resilience gains materialize only when these flows are accessible at the appropriate echelon.

Table 4. Selected resilience metrics from the CSC case study (case study 1).

Node	(ω, α)	ad	ed	rd	fr at t_e	rr at $t_s + 1$
Retailer	(0, 0)	0	14	3	0.00	0.16
Retailer	(0, 0.4)	1	12	3	0.20	0.42
Retailer	(0, 0.7)	1	9	5	0.20	0.10
Retailer	(0.4, 0)	0	13	4	0.00	0.85
Retailer	(0.7, 0)	0	12	4	0.00	0.95
Retailer	(0.4, 0.4)	0	12	5	0.00	0.79
Retailer	(0.4, 0.7)	1	10	4	0.30	1.00
Retailer	(0.7, 0.4)	0	11	4	0.00	1.00
Retailer	(0.7, 0.7)	1	12	2	0.50	1.00
Manufacturer	(0, 0)	0	14	2	0.00	0.47
Manufacturer	(0, 0.4)	0	14	2	1.00	0.08
Manufacturer	(0, 0.7)	0	14	2	1.00	0.54
Manufacturer	(0.4, 0)	0	13	2	0.00	1.00
Manufacturer	(0.7, 0)	2	11	2	1.00	1.00
Manufacturer	(0.4, 0.4)	0	13	4	0.00	0.86

Note: ad = absorptive duration; ed = endure duration; rd = recovery duration; fr = failure ratio; rr = recovery ratio. Durations are expressed in simulation time units and ratios are expressed as percentages.

In the EVB remanufacturing case, the proposed futures-informed methodology is applied by translating different circular futures into alternative return-rate and reverse-

flow assumptions. Low return-rate settings represent futures in which circularity remains marginal or weakly coordinated, whereas high return-rate settings approximate futures with stronger reverse logistics, higher remanufacturing intensity and greater material retention. The model therefore acts as a dynamic test of how circular assumptions affect both operational stability and environmental performance.

Operationally, increasing return rates generally reduces the bullwhip effect, as shown in Figure 3a. The bullwhip effect describes the amplification of demand or order fluctuations as they move upstream along the SC: even small variations in final demand can generate larger oscillations in orders, production and inventory at upstream echelons. In this case, the reduction is especially visible at the module echelon, where the intermediate SC position and a high return share allow reverse flows to buffer demand fluctuations. The order rate variance ratio complements this interpretation by assessing how strongly the orders issued by each echelon fluctuate relative to final market demand, as reported in Figure 3b. In qualitative terms, it shows whether an echelon is translating market demand into stable replenishment behaviour or into more volatile ordering patterns.

Battery and module echelons show relatively stable order-rate variance under increasing return rates, suggesting that remanufacturing at these levels can be introduced without strongly amplifying operational instability. The cell echelon is more sensitive because it is upstream and receives a lower share of returns. In this case, higher return rates can inflate the order rate variance ratio even when absolute order variance does not increase substantially because average upstream demand is reduced by the availability of reverse flows.

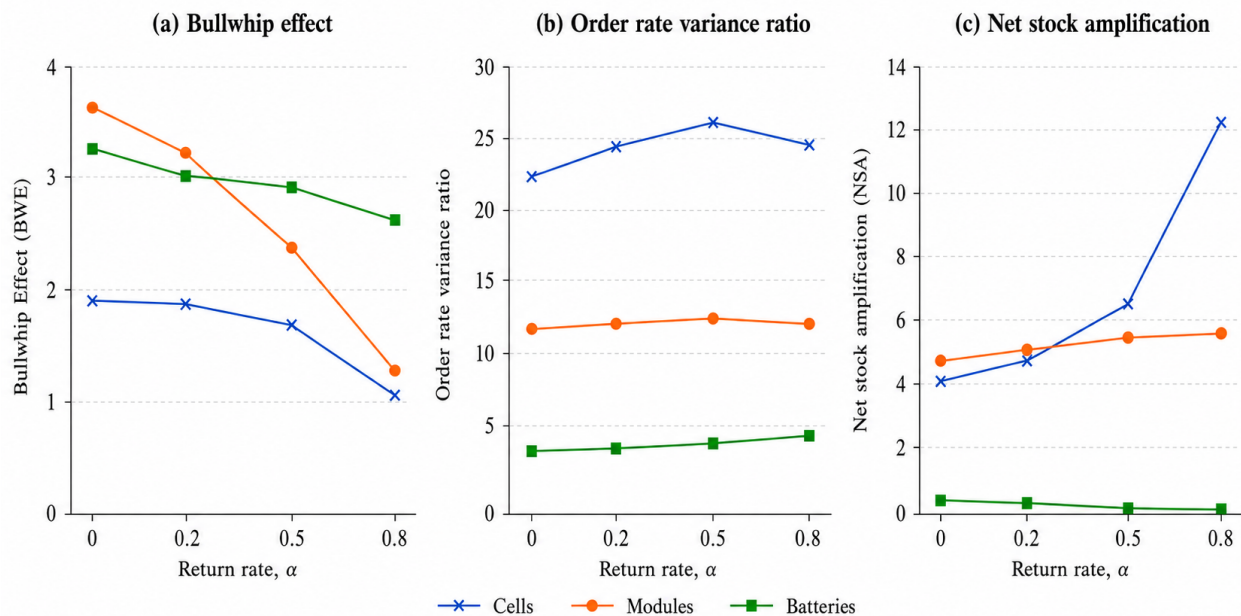
The inventory-side indicator, net stock amplification, captures how strongly inventory positions fluctuate across the SC, as shown in Figure 3c. Qualitatively, higher net stock amplification signals greater oscillation between excess stock and shortage risk. Results show that this risk is more pronounced at the cell echelon, where lower return allocation and longer remanufacturing delays limit the stabilising effect of circular flows. The environmental assessment points in the opposite direction: higher return rates increase the recovery of cobalt, lithium and nickel and generate larger CO₂ savings. From 2029 onward, annual nickel recovery from the Model Y case under an 80% return rate exceeds 1 million kg/year. The case therefore shows that high remanufacturing is desirable for material recovery, but its operational value depends on how returns are allocated across echelons and whether upstream capacity and lead times are planned consistently with the circular future being modelled.

The regional WEEE collection and treatment case study operationalises scenario-specific assumptions through the definition of alternative optimisation priorities and policy constraints, which directly shape the model's objective functions, capacity settings and admissible flows across the SC network. These modelling choices mirror the translation of qualitative factors into quantitative and rule-based inputs, allowing four optimisation scenarios (cost-, emissions-, circularity- and policy-led) to be interpreted as distinct system configurations.

The cost-led baseline favours a centralised and economically efficient network: it opens one warehouse, uses one repair centre and one reuse centre, and leaves 14% of WEEE to disposal. This configuration minimises fixed and operational costs but limits the exploitation of higher-value circular pathways. The emissions-led scenario shifts towards a more decentralised network by opening two warehouses and using two reuse centres. This reduces transport intensity, lowers disposal to 9%, and cuts emissions by 26% relative to the baseline, although total cost increases by 12%.

The circularity-led scenario produces the strongest recovery-oriented configuration. It opens two warehouses, uses two repair centres and three reuse centres, reduces disposal

to 4% and reaches 94% circularity. However, this improvement comes with higher system complexity: total cost increases by 18% and emissions rise by 9% relative to the baseline, mainly due to additional handling and routing towards specialised recovery facilities. The integrated policy-driven scenario provides a more balanced outcome. By combining landfill-tax incentives with enhanced repair and reuse capacity, it opens two warehouses, uses two repair centres and two reuse centres, reaches 91% circularity, reduces emissions by 18% and limits the cost increase to 10%.



Note. α is the return rate of end-of-life (EoL) batteries, defined as the proportion of EoL batteries collected and returned to the supply chain.

Figure 3. Dynamic operational indicators for the EVB remanufacturing case under different return rates α : (a) bullwhip effect; (b) order rate variance ratio; and (c) net stock amplification.

Overall, the regional WEEE case shows that cost, emissions and circularity priorities lead to materially different network designs. Cost minimisation favours centralisation, emissions reduction favours spatial decentralisation and circularity maximisation requires additional repair and reuse capacity. The policy-driven configuration suggests that balanced policy packages can improve circularity and emissions performance without the stronger cost and operational penalties observed in single-objective strategies. Thus, the second research question is addressed by showing that plausible futures and policy priorities not only shape performance outcomes but also the underlying infrastructure, routing and recovery configuration of the WEEE network. The resulting network configurations and performance indicators are summarised in Table 5.

Table 5. Regional WEEE network configuration and performance by optimisation scenario (case study 3).

Scenario	Warehouses	Repair Centres	Reuse Centres	Disposal Share	Cost Index	Emissions Index	Circularity
Cost-led baseline	1	1	1	14%	1.00	1.00	86%
Emissions-led	2	1	2	9%	1.12	0.74	88%
Circularity-led	2	2	3	4%	1.18	1.09	94%
Integrated policy-driven	2	2	2	6%	1.10	0.82	91%

Note: Cost and emissions are normalised to the cost-led baseline.

The corresponding material-flow and environmental–economic outcomes are reported in Table 6.

Table 6. Material flow and environmental-economic outcomes in the regional WEEE case (case study 3).

Scenario	Repair (t)	Reuse (t)	Recycling (t)	Disposal (t)	Total Cost (EUR Million)	Emissions (t CO ₂ /Year)
Cost-led baseline	8500	4000	73,500	14,000	52.3	12,400
Emissions-led	9200	5100	76,700	9000	58.6	9200
Circularity-led	12,000	8500	75,500	4000	61.8	13,500
Integrated policy-driven	10,800	6300	76,900	6000	57.4	10,300

Three general findings emerge. First, circularity improves system performance only when reverse-flow capacity, timing and allocation are designed together. Higher return rates are not automatically beneficial: they improve resilience and material recovery but can increase inventory amplification upstream if remanufacturing capacity and return shares are unbalanced. Second, recovery infrastructure is a recurring bottleneck. In the regional WEEE case, increasing repair and reuse capacity is the main driver of circularity improvements; in the battery case, upstream cell remanufacturing becomes the critical stability point; and in the CSC case study, access to returns and by-products determines resilience gains. Third, policy packages outperform single levers. Landfill taxation, EPR/R2R thresholds, service-radius constraints, information sharing, and capacity investment should be aligned because each lever affects a different performance dimension.

5. Discussion

This study demonstrates that futures thinking can extend beyond a purely narrative exercise within CE research when systematically translated into modelling factors and assumptions. In this perspective, futures become a structured means to explore how CSC may behave under different socio-technical scenarios/configurations. This shift is particularly relevant in the context of WEEE SCs, where strategic and infrastructural decisions, e.g., development of warehouses, treatment facilities, digital traceability systems, repair capacity and remanufacturing partnerships, are inherently long term and exhibit limited adaptability once implemented. Integrating futures-based assumptions into modelling frameworks enables a more nuanced evaluation of SC performance under uncertainty. Specifically, it supports the assessment of whether a given circular strategy remains robust across alternative future conditions or whether its effectiveness is contingent upon specific assumptions, thereby revealing potential structural fragilities. In this respect, the findings highlight that demand, capacity constraints, return rates, lead times, priority rules, information sharing and network structure provide a practical and operational vocabulary for bridging futures thinking and modelling. While some assumptions can be directly quantified based on industrial evidence—such as recovery rates, treatment capacities and return share—others are more appropriately represented as structural modelling choices, including push versus pull policies, the presence of industrial symbiosis or the number of echelons in the network. The proposed approach therefore relies on a balanced operationalisation, enabling both numerical and structural representations to coexist within a coherent modelling architecture.

The validity and practical relevance of the proposed framework are strengthened by its implementation in three complementary case studies. These applications show how the futures-to-parameterisation pathway can be operationalised across different modelling contexts: CSC resilience under demand disruption, EVB remanufacturing dynamics and regional WEEE collection and treatment optimisation. The three cases represent different

decision problems and modelling paradigms within WEEE circularity. The first case isolates resilience mechanisms by focusing on return flows α and industrial-symbiosis flows ω as buffers against demand shocks. The second case focuses on dynamic stability and critical-material recovery, where return rates, remanufacturing lead times and echelon-specific allocation are the most relevant factors. The third case addresses strategic network design, where facility location, routing, capacity and policy-compliance constraints determine whether EPR and R2R objectives can be implemented regionally. In this sense, the case studies provide analytical grounding for the framework, demonstrating that futures-informed assumptions can be translated into diverse model structures, performance indicators and decision-support problems while preserving consistency between scenario narratives and modelling choices.

Beyond demonstrating applicability, the case studies generate substantive insights into how circular strategies behave under different futures-informed assumptions. As summarised in Table 7, some findings are closely linked to specific futures, while others have broader validity across the explored scenarios. The aim is to demonstrate analytical transferability: the same framework can guide factor selection, parameter calibration and model design across simulation and optimisation settings. This distinction is relevant because it shows that the framework can support both context-specific analysis and the identification of more robust managerial and policy implications.

The CSC resilience case study and the EVB remanufacturing case study are especially informative for futures characterised by stronger circular-loop integration, such as planned CL futures and bottom-up circular loops. In these contexts, high reverse flows, remanufacturing intensity and coordinated recovery infrastructure become central to SC design. The results indicate that circular flows can improve resilience, reduce demand amplification and increase critical-material recovery. However, these benefits depend on the coherent planning of capacity, lead times, return allocation and echelon-specific remanufacturing capabilities. Therefore, the value of circularity is not determined by the return rate alone but by the extent to which reverse flows are operationally integrated into the SC.

The regional WEEE collection and treatment case complements this perspective by showing how different policy and infrastructure priorities lead to distinct network configurations. Cost minimisation favours a more centralised and economically efficient network, emissions reduction favours spatial decentralisation, and circularity maximisation requires additional repair and reuse capacity. The integrated policy-driven configuration provides a more balanced outcome, suggesting that combined policy packages can improve circularity and emissions performance without the stronger cost and operational penalties observed in single-objective strategies. These results reinforce the usefulness of the framework for assessing how future-oriented assumptions affect not only performance outcomes but also the underlying infrastructure, routing, and recovery configuration of the WEEE network.

Table 7 provides a cross-case synthesis of these findings. The table shows how each case study operationalises a specific subset of the futures assumptions, identifies the most sensitive SC nodes and supports a distinct class of decisions. Taken together, the cases illustrate why circular strategies should be evaluated as coherent configurations of flows, capacity, lead times and policy mechanisms rather than as isolated interventions.

Across the three case studies, a set of common insights becomes apparent. First, circular strategies improve performance only when reverse flows, capacities and allocation choices are coherently designed together, rather than treated as separate adjustments. Second, recovery infrastructure and coordination mechanisms are central conditions for circularity to generate operational and environmental value. Third, integrated policy packages are more effective than isolated levers in improving circular WEEE system performance because they jointly influence flows, capacities and behavioural incentives.

Table 7. Cross-case synthesis of future alignment, operational mechanisms and decision-support implications.

Case Study	Most Relevant Futures	Factors and Indicators	Sensitive Nodes	Decision-Support Implication
CSC resilience	Planned circular loops; bottom-up circular loops	End-of-life return rate α and industrial-symbiosis by-product rate ω under a demand spike. Resilience is assessed through absorptive, endure and recovery durations, failure ratio and recovery ratio.	The retailer benefits from product returns, while the manufacturer benefits from by-products used as alternative inputs.	Circular flows can strengthen absorptive and restorative capacity. Returns and industrial-symbiosis processes should be designed jointly and made available to the nodes that need them during disruptions.
EVb remanufacturing	Planned circular loops; bottom-up circular loops	Return rates α of 0%, 20%, 50% and 80% are allocated across battery, module and cell echelons. Indicators include bull-whip effect, order rate variance ratio, net stock amplification, material recovery and CO ₂ savings.	The cell manufacturer is the most sensitive node because it is upstream and receives a lower return share. The module echelon shows the strongest stabilising effect.	High returns improve critical-material recovery and can reduce demand amplification. Return-share allocation, reverse lead times and upstream capacity must be planned together to avoid inventory instability.
Regional WEEE collection and treatment	Planned circular loops	A multi-objective network model evaluates EPR and R2R thresholds, landfill taxation, recovery capacity and service-radius constraints. Outcomes include cost, emissions, circularity and disposal rates.	Repair and reuse centres are critical under circularity-led configurations. Waste managers and logistics providers are affected by network decentralisation.	Integrated policy packages provide the most balanced results. Fiscal disincentives for disposal should be aligned with recovery-capacity investment and spatial planning.

The main implications of the findings are primarily managerial and are closely connected to the futures-informed nature of the proposed framework. Managers can use the framework to evaluate circular strategies under multiple plausible futures, rather than optimising decisions for a single expected trajectory. This is particularly important for investments in reverse logistics, repair capacity, remanufacturing infrastructure, digital traceability and local recovery networks, whose value depends on future demand patterns, regulation, consumer behaviour, technology availability and governance structures. In this sense, futures thinking supports managerial decision-making by revealing which circular strategies remain robust across alternative scenarios and which strategies are conditional on specific future assumptions.

The analysis also suggests that managers should not treat return-rate maximisation as an isolated target. Instead, its effectiveness is conditional on the SC's ability to inspect, allocate and process returns at the echelon where value recovery is maximised and operational instability is minimised. Moreover, infrastructural capacity has a critical role in enabling the operational feasibility of circular strategies. Producer responsibility organisations and waste managers should prioritise infrastructure bottlenecks, especially repair and reuse capacity, as circularity targets may remain unattainable in practice if not supported by adequate physical and organisational capabilities. This underscores the importance of aligning strategic objectives with operational constraints.

From a policy perspective, this study points to the need for coordinated interventions that combine regulatory measures with capacity development and spatial planning. For instance, fiscal disincentives for disposal, such as landfill taxes, may effectively reduce

disposal rates, but in the absence of sufficient recovery capacity, they risk primarily shifting costs rather than improving circular outcomes. Similarly, service-radius constraints may reduce emissions, but without balanced facility placement they may increase fixed costs. R2R and EPR thresholds can stimulate recovery, but without traceability and information sharing they may be difficult to implement. Overall, these findings reinforce the importance of adopting a systemic perspective, in which performance targets, infrastructural capacity and policy instruments are jointly configured to ensure both the effectiveness and feasibility of CE strategies.

A further implication concerns the dual role of circular flows within SCs. On the one hand, they can act as buffers during disruptions, enhancing SCR; on the other hand, they may introduce additional variability due to the inherent uncertainty in return timings, quantities and quality. Consequently, CSCs should be evaluated through a multidimensional set of performance indicators. Metrics such as service level, recovery time, material recovery, emissions, cost, stock amplification and compliance capture distinct system properties and cannot be meaningfully collapsed into a single circularity score without losing decision-relevant information.

From a methodological perspective, these findings suggest that futures thinking should be embedded early in the SC modelling process. Rather than developing a model first and subsequently applying generic sensitivity analyses, futures-based scenarios can be used to define internally consistent and decision-relevant combinations of parameters. This approach helps prevent unrealistic configurations of assumptions, such as combining high local self-sufficiency with globally hyper-specialised lead times, or imposing strong repair mandates in the absence of adequate recovery capacity. Evidence from the case study applications further highlights how futures thinking can guide not only the selection of parameter values but also the structuring of modelling choices and evaluation criteria.

At the same time, anchoring modelling decisions in scenario narratives enhances the transparency and interpretability of assumptions, thereby facilitating communication with industrial and policy stakeholders. By making underlying hypotheses more explicit and contextually grounded, futures-informed modelling supports more robust, credible and actionable decision-making in complex CSC systems. This occurs because modelling inputs are no longer presented as isolated technical assumptions but as assumptions that can be traced back to explicit future contexts. Stakeholders can therefore understand why a model assumes, for example, high reverse-flow availability, decentralised recovery, stronger information sharing or constrained treatment capacity. This traceability makes assumptions easier to discuss, validate and revise, strengthening the credibility and practical usefulness of the modelling process.

6. Conclusions

This paper proposed a futures-to-parameters framework that translates qualitative circular futures narratives into model-ready assumptions for WEEE SC simulation and optimisation. The specific analytical conclusion is that circularity improves SC performance only when reverse flows, recovery capacity and allocation rules are designed as a coherent system. Circular strategies are therefore not universally beneficial by default; their value depends on where returns enter the SC, how quickly they can be processed, and whether the infrastructure and policy setting are consistent with the future being modelled.

The resilience case shows that CSC configurations with end-of-life returns and industrial-symbiosis by-products generally outperform the forward benchmark during demand shocks. Circular flows improve absorptive and restorative capacities, reducing the time spent at degraded performance levels and enabling earlier recovery for the retailer and manufacturer.

This supports the conclusion that circular flows can act as operational buffers, especially in planned circular-loop futures where reverse flows are actively coordinated.

The EVB remanufacturing case shows a second, more conditional conclusion. Higher return rates increase material recovery and CO₂ savings, and they generally reduce the bullwhip effect, particularly at the module echelon where reverse flows buffer demand variability. However, the benefits are not uniform across the chain. The cell echelon remains more vulnerable to inventory instability and net stock amplification because it is upstream, receives a lower return share and faces longer remanufacturing delays. High circularity therefore requires echelon-specific planning of return allocation, remanufacturing lead times, and capacity, rather than simply maximising the aggregate return rate.

The regional WEEE optimisation case identifies explicit trade-offs among cost, emissions and circularity. Cost-led optimisation favours centralised networks and higher disposal. Emissions-led optimisation favours spatial decentralisation and shorter transport distances. Circularity-led optimisation requires more repair and reuse capacity but increases handling complexity and cost. The integrated policy-driven configuration provides the most balanced result: by combining landfill tax incentives with repair/reuse capacity expansion, it reaches 91% circularity, reduces emissions by 18% relative to the cost-led baseline, and limits the cost increase to 10%. This supports the conclusion that integrated policy packages outperform isolated single-objective levers.

Methodologically, the case studies show that the proposed framework can link scenario narratives to quantitative model design without forcing all assumptions into a single modelling structure. The framework helps avoid unrealistic combinations of assumptions, such as high local circularity with globally extended lead times or strict repair mandates without recovery capacity. Its main contribution is therefore a transparent and replicable pathway for moving from plausible futures to model-ready assumptions, while preserving internal consistency between future narratives, parameter values, constraints and performance indicators.

From a managerial and policy perspective, the findings emphasise the need to jointly consider circularity objectives, infrastructural constraints, and system variability. CSCs introduce not only additional value recovery opportunities, but also new sources of uncertainty. Consequently, performance should be assessed through multi-dimensional metrics capturing service levels, recovery dynamics, costs, emissions, and resilience.

Methodologically, embedding futures thinking early in the modelling process enables the construction of more coherent and decision-relevant scenarios, overcoming the limitations of generic sensitivity analyses. This approach also enhances transparency and improves communication with industrial and policy stakeholders by making modelling assumptions more explicit and contextually grounded.

Despite these contributions, some limitations remain. First, the parameterisation is necessarily semi-hypothetical. Although the models are anchored in operational profiles, material flows, and industrial evidence from the eleven partner organisations analysed in the ExPliCit case study work, including FAEL, RECILEC and FG Recycling, these data are projected into future contexts that do not yet exist. The resulting parameters should therefore be interpreted as informed estimates for exploring structural robustness and decision sensitivity, rather than as exact forecasts of future WEEE SC behaviour. Second, the selection of the two scenario axes—economic orientation and governance structure—involved a degree of judgement by the research team. This introduces some subjectivity, mitigated through the preceding participatory futuring process, including a workshop with 14 academic and industrial participants and a follow-up questionnaire completed by nine participants, which supported the internal coherence of the selected dimensions [53]. Third, this study does not perform a full cross-scenario test of every analytical model across

all four futures. The analysis focuses on the technically most relevant and transformative circular configurations for the WEEE sector, especially planned circular loops, rather than combinations with weaker policy or industrial relevance. This focused coverage allows the paper to derive more specific decision-support insights for circular transition planning, but it limits claims about the comparative performance of every model under every possible future. Fourth, the models rely on simplified behavioural assumptions—in particular, fixed return shares and rule-based ordering rather than adaptive consumer or firm behaviour—and they do not propagate parameter uncertainty through the analysis: scenario parameters are treated as point values rather than distributions, so the results characterise structural sensitivity rather than probabilistic risk.

Future research can extend the approach in several directions. New futures could be developed around geopolitical material scarcity, informal-sector integration, digital product passports, AI-enabled sorting or consumer sufficiency norms. The models could be expanded to include uncertainty, learning effects, investment timing and category-specific WEEE flows. The methodology could also be tested by extending the framework to additional sectors, for example, in textiles, packaging, construction materials, medical devices or automotive components, where circularity likewise depends on the interaction between future regulation, infrastructure, product design and SC coordination.

Further work could also explore hybrid approaches combining simulation and optimisation to support robust decision-making in highly uncertain and evolving CE contexts.

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Abbreviations

The following abbreviations are used in this manuscript:

CE	Circular Economy
SC	Supply Chain
SCR	Supply Chain Resilience
CL	Closed-Loop
CSC	Circular Supply Chain
CLSC	Closed-Loop Supply Chain
WEEE	Waste Electrical and Electronic Equipment
EOL	End-of-Life
EPR	Extended Producer Responsibility
EVB	Electric Vehicle Battery
MILP	Mixed-Integer Linear Programming
R2R	Right-to-Repair

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