A simulation study of a Closed-Loop Supply Chain for EVB Remanufacturing: Operational and Environmental Analysis

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Abstract

This study develops a dynamic closed-loop supply chain model for end-of-life management of electric vehicle batteries, with a focus on remanufacturing. The model simulates different return rate scenarios and evaluates their impact on supply chain dynamics through key indicators such as the bullwhip effect, inventory amplification, and order variability. Results show that higher return rates and batteries remanufacturing can improve system stability and enable significant recovery of critical raw materials such as nickel and cobalt. These findings highlight the dual benefit of integrating the principles of circular economy into the supply chains of electric vehicle batteries, both in terms of operational and environmental performance.

Keywords: Closed-loop supply chain, Circular Economy, EVB, End-of-Life Battery Management, Critical Raw Materials Recovery

1. Introduction

In recent years, the electrification of the transport sector has become a global priority in response to the need to reduce greenhouse gas (GHG) emissions and to meet the Circular Economy (CE) objectives. Specifically, road transport is the largest contributor to transport-related emissions, accounting for 73.2% of total GHG emissions from transport in the European Union in 2022 [1]. This critical situation is expected to change as global climate challenges prompt many countries to implement policies that aim at fostering low-emission vehicle production. Here, Electric Vehicles (EVs) represent one of the most promising solutions to reduce dependence on fossil fuels and air pollution and it is predicted that will dominate the global automotive market by 2035, with an estimated 230 million vehicles on the road worldwide. This has highlighted the need for sustainable EVs lifecycle management, with a specific focus on lithium-ion batteries (LIBs), the most widely used energy storage technology due to its high energy density and long service life. The environmental impact of EVs Batteries (EVBs) production is significant, as it involves the extraction of critical raw materials such as cobalt, nickel and lithium, whose distribution is geographically concentrated. Moreover, End-of-Life (EoL) management poses a set of challenges. Current recycling rates for EVBs are inadequate because recycling technologies remain expensive, energy-intensive and inefficient, resulting in the loss of valuable materials that could otherwise be reused. Furthermore, the growing volume of battery waste threatens to overwhelm existing waste management infrastructure, highlighting the urgent need for scalable recycling solutions and comprehensive policies to manage battery disposal in a sustainable manner [2]. This has implications for the final cost of the product, as well as for production and disposal processes [3].

Recent studies have highlighted the need for a comprehensive and integrated approach to CE implementation, encompassing business models, EoL strategies, and material recovery processes to enable efficient and effective circular system [3], [4]. The right solution for a transition to a CE is to create coordinated Supply Chains (SC) that optimise each process step, from raw material management to final product distribution [5]. In addition, new SC archetypes have emerged, including the Closed loop SC (CLSC). Unlike traditional forward SCs, where raw materials are transformed into products to meet customer demand, CLSCs also incorporate reverse flows, enabling the return of products from customers back into the SC for value recovery. One of the critical aspects of SC dynamics concerns the management of ordering policies in multi-level SCs. In this context, market demand is not always transmitted linearly through the levels of the chain, but can be distorted and amplified, giving rise to the so-called Bullwhip Effect

(BWE) [6]. This phenomenon illustrates how fluctuations in demand at the downstream level can result in variations in production and orders at the upstream level of the SC. Consequently, this can lead to inefficiencies at various levels, overproduction, increased inventories, waste, and consumption of raw materials [8].

Taking all these considerations together, given the growing urgency to manage EVBs sustainably, studying CLSCs in the context of EVBs is therefore essential to develop efficient systems that support CE goals while mitigating the BWE and enhancing overall SC performance.

Therefore, this study proposes a dynamic CLSC model for EoL management of EVBs, identifying and analysing the key factors that influence the implementation of CE principles. While the adoption of EVs is growing rapidly, effective CLSC strategies in both forward and reverse flows are still limited by technological, logistic, and economic challenges. In particular, the dynamic behaviour of CLSC archetypes in the context of EVB production and recovery remains largely unexplored. To address this gap, the proposed model simulates multiple CLSC scenarios under varying return rate conditions and evaluates the dynamic performance of the system in terms of inventory amplification, bullwhip effect, and order variability. It also quantifies the environmental benefits of closed-loop strategies by estimating the avoided CO_2 emissions resulting from the recovery of critical materials such as cobalt, lithium, and nickel. In doing so, the study aims to support scalable and resilient strategies for sustainable EVB lifecycle management and to accelerate the transition toward a CE. Consequently, the following research questions are addressed: (RQ1) What is the impact of remanufacturing strategies on the dynamic behaviour of a CLSC for EoL EVBs and the recovery of critical raw materials? (RQ2) What are the environmental benefits, in terms of avoided CO_2 emissions, associated with the recovery of materials such as cobalt, lithium, and nickel through remanufacturing?

2. Literature review

A literature review was conducted to develop a comprehensive understanding of the current state of EVBs and to identify the key factors that affect the integration of CE principles. Using a snowball method, the review offers a deep understanding of the challenges and strategies that enable a more circular and sustainable EVB value chain. In recent years, European policy has actively promoted the transition to a low-carbon and electrified transport system, with the goal of achieving climate neutrality by 2050, as outlined in the European Green Deal [7]. The European Union has supported the adoption of EVs through regulatory measures, financial incentives, and infrastructure investments. EVBs, and in particular LIBs, are at the core of this transition due to their energy efficiency, power density, and long lifespan. These batteries are widely used across various EVs types (BEVs, PHEVs, HEVs), industrial equipment, and stationary energy storage systems for renewable sources such as solar and wind. LIBs consist of interconnected cells structured around four essential components: the cathode, the anode, the electrolyte, and the separator [10]. The cathode stores lithium ions during charging, whereas the anode, typically composed of graphite, hosts them during discharge. The electrolyte enables ion transfer between electrodes, and the separator prevents internal short circuits while allowing ion flow. These components are enclosed in prismatic, pouch, or cylindrical cells, depending on the application needs. Among all components, the cathode plays a central role in battery performance due to the diversity of materials used in its composition. These materials significantly influence key metrics such as energy density, specific power, and overall efficiency. Lithium cobalt oxide ($LiCoO_2$) offers high energy density and is commonly used in portable electronics, although it has limited cycle life and thermal stability. Lithium iron phosphate ($LiFePO_4$) provides enhanced safety and durability at the cost of lower energy density and is increasingly adopted in EVs and stationary storage. Lithium manganese oxide ($LiMn_2O_4$) tolerates high current loads and is often mixed with nickel-based chemistries to improve performance. Lithium nickel cobalt aluminium oxide ($LiNiCoAlO_2$) offers high capacity and long cycle life and is used in high-performance EVs, while lithium nickel manganese cobalt oxide ($LiNiMnCoO_2$) stands out for its balanced trade-off between energy density, safety, and longevity [8]. Beyond the cathode chemistry, battery performance depends on the system architecture and several technical parameters. Packs consist of modules and cells arranged to meet voltage and capacity requirements. Key metrics include energy density (Wh/kg), indicating stored energy per unit weight; capacity (Ah), influenced by material structure; and indicators such as State of Charge (SoC) and State of Health (SoH), which reflect the battery's current energy level and its degradation over time, respectively.

2.1 Circular Economy in Supply Chains

As the demand for EVs increases, the production of EVBs is expected to rise accordingly, driving a greater need for critical raw materials such as cobalt, nickel, and lithium. Transitioning to a CE model is essential for sustainability, as it promotes business models that reduce environmental impact and resource waste while enhancing both material recovery and product lifespan [9]. In the EVB context, CE strategies focus on remanufacturing, reuse, repurposing for stationary applications, and recycling in collaboration with battery cell manufacturers [10], [11]. These concepts form a practical framework to extend battery lifecycles. EoL batteries undergo removal, transport, and disassembly at system, module, and cell levels, enabling reuse or recycling depending on component condition and residual value. To fully exploit the CE potential, CLSCs require suitable business models that support multiple recovery pathways, efficient collection, life-long recovery strategies, and full recovery of critical materials. Understanding and differentiating these strategies is key to implementing effective CLSC configurations. Battery reuse and remanufacturing are crucial to extending LIB lifespan. Reuse refers to the direct or partial reuse of batteries for their original function, provided a positive assessment of their condition at their EoL. Remanufacturing, typically adopted by OEMs, involves the repair or replacement of degraded components to restore performance [17] [29]. To this end, SoH is a key parameter: batteries below 70–80% SoH are usually unsuitable for EVs [13], though ageing may occur unevenly due to internal thermal gradients. In such cases, selective cell replacement can allow further reuse. When reuse or remanufacturing is not feasible, repurposing offers an alternative. Batteries with diminished SoH can serve in less demanding applications such as stationary energy storage with renewables, as well as in peak shaving, load shifting, or low-speed EVs. If a battery is no longer viable for reuse or repurposing, it enters the recycling phase, aimed at recovering valuable materials, especially lithium and cobalt, for reintegration into new production [4], [14]. Recycling generally begins with disassembly, crushing, and sieving [14], followed by metal recovery through various metallurgical techniques. Hydrometallurgy, which is based on chemical and biological treatments, allows for high-purity recovery with an energy consumption that is lower than that for pyrometallurgy, which requires high temperatures. Emerging direct recycling technologies also show promise by preserving components for reinsertion into new cells with minimal transformation. In addition, the existing literature on CLSC dynamics with multiple reverse flows is scarce [15], only few studies consider various return strategies—such as recycling, repair, and remanufacturing [16]—but still without delving into the specific characteristics of different remanufacturing processes. Here, our study fills this gap by introducing three distinct remanufacturing processes for EVB SCs.

3. Model Development

3.1 *Model Description*

To evaluate the potential of EVB remanufacturing, a dynamic CLSC model was developed and simulated using MATLAB R2024 [17]. The model, as depicted in Figure 1, replicates SC dynamics by integrating key processes such as battery collection, disassembly, and remanufacturing, and accounts for critical variables including demand fluctuations and EoL return rates.

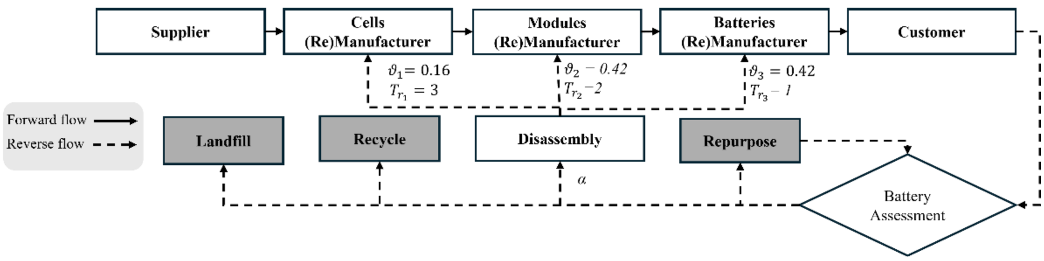

Figure 1 : Closed-loop supply chain structure.

3.2 *Hypothesis*

The simulation model relies on assumptions widely adopted in the CLSC literature [18] [16], [19]. The SC is structured as a single-product (EVB) serial SC, where each SC echelon interacts only with its immediate upstream and downstream partners. Customer demand follows a normal distribution with mean μ_D and standard deviation σ_D. Demand forecasting is based on exponential smoothing, with a smoothing constant α:

$$\hat{d}_t^i = a \cdot O_t^{i+1} + (1-a) \cdot \hat{d}_{t-1}^i \quad (1)$$

Order generation follows a periodic review Order-Up-To (OUT) policy, replenishing stock and WIP (Work in Progress) to target levels. Specifically, we use OUT and exponential smoothing as these are considered to be optimal or near-optimal policies for *iid* normal demand, therefore our study focuses on the structural causes of order/inventory amplification and not on their behavioural causes such as risk aversion or inadequate forecast. The order quantity is computed as:

$$O_t^i = max\{\hat{d}_t^i + [TNS_t^i - I_t^i] + [WIP_t^i - TWIP_t^i], 0\} \quad (2)$$

Where I_t^i represent the available inventory and WIP_t^i is the work-in-progress, *i.e.* orders not yet arrived. Moreover, $TNS_t^i = \varepsilon \cdot \hat{d}_t^i$ is the target net stock and $TWIP_t^i = T_p \cdot \hat{d}_t^i$ is the target WIP. The pipeline lead time T_p, is computed according to as follows $T_p = (1-\alpha) \cdot T_m + \alpha \cdot T_r$ [16], [18].

A return rate α, defines the percentage of products sold that were returned from the customer to the SC and then go through the remanufacturing. It captures the efficiency of remanufacturing processes and directly affects the volume of units available for remanufacturing, indeed (1- α) units are sent to recycling or disposal. The time the product is retained by the customer, known as consumption lead time, is stochastic and follows a normal distribution $N(\mu_{T_c}, \sigma_{T_c}^2)$. Returns follow a push policy: Once received, they are inspected and, according to their quality, sent for remanufacturing. Here, high-quality returns are directly processed at the batteries manufacturer (retailer) level, enabling faster reintegration into the SC. In contrast, lower-quality returns are sent to the modules or cell manufacturers after the disassembly process, where more extensive remanufacturing activities are necessary, thus a higher lead time is assumed. Thus, remanufacturing lead times vary based on product quality [15] and these delays are captured by the parameter T_r, defined per echelon. As a consequence of the push policy, *i.e.,* the most adopted in CLSC studies [20] each echelon, directly updates its inventory when receiving the return flow. Returns are distributed across echelons according to return shares ϑ_i. Specifically, each echelon receives a portion $\vartheta_i \cdot \alpha$ of total returns, *i.e.,* $\sum_{i=1}^{3} \vartheta_i = 1$. The return share reflects the capability to remanufacture batteries as batteries, or disassembling and manufacturing modules or cells, thus, this distribution reflects not only the allocation of returned batteries but also influences the stability and predictability of product return flows within the SC.

Finally, manufacturing lead times are deterministic, no negative orders are allowed, supplier capacity is assumed to be unconstrained, backlog, and partial shipments are allowed [23].

3.3 *Model Design*

This section describes the operational sequence of events of the CLSC model. At each period t, the customer demand is generated stochastically from a normal distribution. The simulation proceeds sequentially through the echelons, where the following operations are performed. (1) It receives ordered products and updates the inventory and WIP. (2) It receives downstream demand and satisfies it fully or partially based on available inventory and updates the inventory accordingly. (3) It computes the demand forecast and the new desired OUT level. (4) It issues new orders according to the OUT level.

4. Experiments

4.1 *Design of experiments*

A Design of Experiments (DoE) approach was adopted to evaluate the CLSC model under varying return rate scenarios. The input parameters were based on industry data, literature and informed assumptions where necessary. Multiple scenarios were designed to test the model under varying operating conditions, such as different return rates and EVB models. The simulation assumes a stable market based on 2022 German sales data for 100 Tesla Model Y (Model S) and modelled as a normal distribution (μ_D= 100, σ_D = 30). The return rate parameter (α) was tested at 0%, 20%, 50%, and 80% [24], the other simulation factors are summarised in Table 1. In particular, the consumption lead time was set by considering the actual average value of approximately 8 years [24], [25]. Each scenario ran for 8,870 daily periods, including a 3,030-period warm-up, and was replicated 30 times.

An environmental assessment was also performed to estimate material recovery and CO_2 savings from recycling. Saved emissions (SE) have been computed per each material by using this formula: $SE_m(t) = CR_m(t)\ x\ GWP_m$[21]; where $SE_m(t)$ is the cumulative CO_2 saved (saved emissions) in terms of avoided extraction of material *m* at time *t;* $CR_m(t)$ [kg] is the cumulative recovered weight of material *m* at time *t;* and GWP_m $[kg\ CO_{2eq}/kg]$ is the global warming potential of material *m.*

Since aggregate sales of Model Y in Germany in 2022 are comparable to those of Model S in the United States in the same year, this model was also selected for inclusion in the environmental impact comparison for batteries with different chemistries. This allowed a meaningful comparison under similar market conditions. Table 2 reports the composition of the material and the emission factors.

Table 1: Simulation Parameters.

Parameters		**Value**	**Source**
D	Daily Customer Demand	$N(100, 30^2)$	[18], [22]
T_c	Consumption lead time	$N(2500, 500^2)$	[23], [24]
T_{r_i}	Remanufacturing lead time for echelon *i*	[3;2;1]	[25]
T_m	Manufacturing lead time	3	[25]
ε	Safety stock factor	1	[18]
a	Smoothing factor	0.2	[18]
α	Return rate	[0; 0.20 ;0.50; 0.80]	[23], [24]
ϑ_i	Return share	[0.16;0.42;0.42]	[26]

Table 2: Material Content and Emission Factors of Tesla Model S and Model Y Battery Packs [27].

Material	**Model S [kg] LFP**	**Model Y [kg] NMC 811**	**CO2e [kg CO2/kg]**
Co sulfate	3.33	5.96	14
Li carbonate	10.00	5.96	12
Ni sulfate	71.67	46.50	20

4.2 Key Performance Indicators

In the context of a CLSC, Key Performance Indicators (KPIs) are essential for evaluating the system's efficiency and identifying sources of instability. This study focuses on three main indicators widely adopted in the literature: *Order Rate Variance Ratio* (*OrVrR*), *Bullwhip Effect* (*BWE*), and *Net Stock Amplification* (*NSAmp*). These KPIs provide complementary insights into the propagation of demand variability and its impact on inventory and ordering behavior across the SC. Table 3 summarises the three KPIs used in this study to assess the dynamics of the CLSC model.

Table 3: Key Performance Indicators CLSC dynamics.

Name	**Formula**	**Purpose**	**Interpretation**
Bullwhip Effect	$BWE_i = \frac{V[O_i]}{V[O_{i-1}]}$	Measures amplification of order variability through the SC.	Higher values indicate distortion of the demand signal and inefficiencies in all echelons [8].
Order Rate Variance Ratio	$OrVrR_i = \frac{V[O_i]/\mu_{O_i}}{V[D]/\mu_D}$	Evaluates the order variability at echelon i relative to market demand [19].	Highlights signal distortion normalised by order and demand means.
Net Stock Amplification	$NSAmp_i = \frac{V[I_i]}{V[D]}$	Measures inventory variability in response to demand.	Higher values reflect unstable stock levels, higher holding costs, and reduced responsiveness.

5. Results and Findings

The results and findings obtained in this study have been reported in this section. Specifically, order variability has been analysed through *OrVrR* and *BWE*, while inventory variability has been assessed using *NSAmp*. Figure 3 illustrates *OrVrR* for the three remanufacturing echelons under different return rate scenarios (α). As expected, *OrVrR* is higher for the upstream echelons, particularly the cell manufacturer, which shows greater sensitivity to demand variability. In particular, the cell echelon exhibits a moderate increase in *OrVrR* as α increases from 0 to 0.5, followed by a slight decrease at α = 0.8. In contrast, both the module and battery echelons display relatively stable *OrVrR* values across all scenarios, suggesting that the integration of reverse flows does not significantly exacerbate order variability in these echelons, indicating that remanufacturing practices at these levels can be implemented without amplifying dynamic instability within the CLSC.

Table 4: Summary table comparing performance across return rate scenarios.

α		Cells	Modules	Batteries		Cells	Modules	Batteries		Cells	Modules	Batteries
0.2	***BWE***	1.92	3.22	3.09	***OrVrR***	24.38	12.10	3.39	***NSAmp***	4.85	5.06	1.44
0.5		1.77	2.46	2.91		25.99	12.52	3.70		6.38	5.41	1.37
0.8		1.21	1.41	2.73		25.08	12.10	4.14		12.36	5.48	1.35

Figure 2 shows a general decrease in *BWE* as the return rate (α) increases, suggesting that the reverse flow could play a stabilising role in the CLSC. The reduction is most pronounced at the module echelon, which benefits from both a high return share (ϑ_2 = 42%) and its intermediate position in the SC. The cell echelon, despite its upstream position, experiences a smaller effect due to lower return allocation (ϑ_1 = 16%) and longer remanufacturing delays. Conversely, the battery echelon, although receiving the same share of returns as the modules (ϑ_3 = 42%), shows a more modest reduction in *BWE*, likely due to its proximity to final demand where order amplification is intrinsically lower. The observed differences between *OrVrR* and *BWE* trends across echelons is due to the fact that *OrVrR* normalises both variances by their respective means. While *BWE* is the most widely used indicator for in the CLSC field, its weighted version, i.e. *OrVrR*, should be also taken into account in order not to miss the information related to the average order variation. Indeed, it results that in the upstream echelons, the average demand is reduced because of the presence of the reverse flows. In fact, for any echelon *i,* the average issued order/demand μ_i is affected by returns according to: $\mu_i = \mu_{i-1} - \alpha \cdot \vartheta_i \cdot \mu_d$. As a consequence, the variance-to-mean ratio becomes inflated at upstream echelons, like cell manufacturers, even if the actual variance does not increase significantly. Specifically, up to α = 0.5, the effect of reducing mean demand dominates over stabilisation of order variance, leading to an increase in *OrVrR* in the cell echelon. Beyond α = 0.5, however, the stabilizing effect of higher return flows becomes stronger, resulting in a slight decrease in the *OrVrR*.

These results indicate that, although the remanufacturing process introduces some distortion in demand signals, particularly for those with moderate return shares (*e.g.,* ϑ_1 = 16% for cells), it generally contributes to stabilising the overall SC by dampening demand amplification.

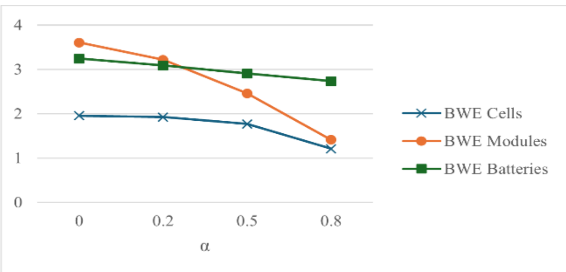

Figure 2 : *BWE trend.*

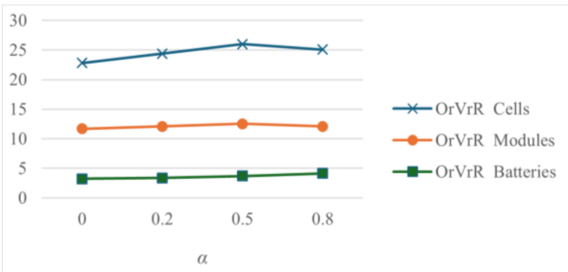

Figure 3 : *OrVrR* trends.

Figure 2 shows the trends for the *NSAmp*, revealing different dynamics across echelons. The cell echelon shows a sharp increase in *NSAmp* as the return rate rises, likely due to its upstream position and relatively low share of returns

(ϑ_1 = 16%), which limits the buffering effect of reverse flows and inventory fluctuations. In contrast, the module echelon, receiving a larger share of returns (ϑ_2 = 42%), shows only a slight increase in *NSAmp*, suggesting a better balance between inflows and demand. Finally, the battery echelon, being closest to the customer and also receiving the 42% of returns, displays consistently low *NSAmp* values that slightly decrease, indicating that the inventory is stable also for increased reverse volume.

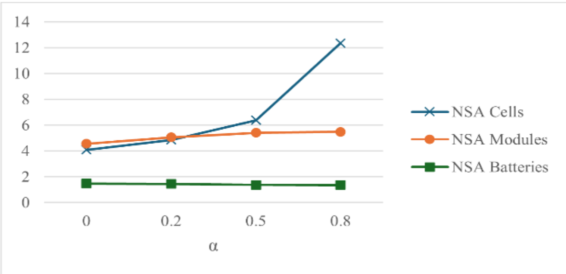

Figure 2 : *NSAmp* trends.

Now we move to the analysis of critical material, focussing on the cumulative recovery of cobalt, lithium and nickel, and estimated the CO_2 savings across the same return rate scenarios using literature-based emission factors. Table and Table   in Appendix , report the annual recovery potential of cobalt, lithium, and nickel from EoL Tesla Model Y (NMC 811) and Model S (LFP) batteries in Germany, across different return rate scenarios (α = 0.2, 0.5, 0.8). For both models, the amount of recovered material increases over time as batteries sold in earlier years reach EoL. As expected, higher return rates lead to significantly greater recovery quantities. Model Y shows a higher recovery of nickel due to its NMC chemistry, while Model S exhibits a higher lithium-to-cobalt ratio, consistent with LFP-based compositions. In particular, from 2029 onwards, the annual recovery of nickel from Model Y under α = 0.8 exceeds 1 million kg/year, highlighting the substantial potential for secondary raw material supply through remanufacturing strategies.

Figure 3 illustrates the cumulative CO_2 savings from the recovery of cobalt, lithium, and nickel for the Tesla Model Y under three return rate scenarios (α = 0.2, 0.5, 0.8). For Model Y, which adopts an NMC chemistry with a high nickel content, CO_2 savings from nickel recovery dominate the total environmental benefit. Cobalt recovery also plays a significant role, especially at high return rates. For Model S, nickel recovery clearly dominates total CO_2 savings due to the significantly higher nickel content in the battery composition (71.7 kg per battery vs. 3.3 kg Co and 10 kg Li). However, cobalt and lithium still contribute considerably, especially at higher return rates, demonstrating the cumulative environmental benefit of recovering multiple critical materials over time.

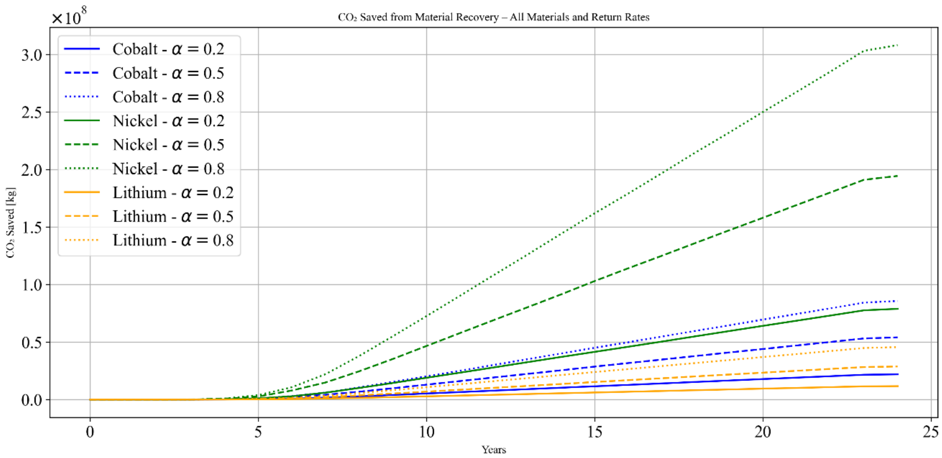

Figure 3 : Cumulative CO_2 savings from raw materials recovery for Tesla Model Y in Germany (2022–2045).

6. Conclusions

This study develops and analyses a dynamic CLSC model for the EoL management of EVBs, focusing on remanufacturing, *i.e.,* distinguish batteries, modules and cells remanufacturing, and its impact on operational dynamics and environmental benefits. This simulation-based approach provides valuable insights into the feasibility and effectiveness of CLSCs in the EVB sector, supporting the broader adoption of CE practices in battery management. The results suggests that higher return rates can enhance system overall performance by reducing order variability and demand amplification. Particularly, the batteries remanufacturing echelon achieves the best overall trade-off among the selected dynamic performance indicator, whereas performance improvements are less evident, or even counterbalanced, in cells manufacturing, where lower return shares and longer remanufacturing lead times may introduce inventory instability. Additionally, substantial quantities of critical materials, particularly nickel and cobalt, can be recovered over time, resulting in significant CO_2 savings. These findings support the adoption of CE strategies and demonstrate the importance of incorporating remanufacturing into SC design to enable circularity in the EVB sector. Furthermore, while the environmental benefits of higher return rates and increased recycling are well recognized, the simulation results underline how these practices also lead to improvements in dynamic performance, linking environmental and operational benefits. This dual impact reinforces the value of CE strategies not only for sustainability but also for enhancing SC stability and dynamics.

From a managerial standpoint, the model highlights where CE investments and incentive policies could be most effective within the EVB SCs. Since the remanufacturing of batteries demonstrates the best overall performance in terms of operational and environmental indicators, efforts should focus on leveraging the quality of EoL products to maximize the benefits associated with circularity. By ensuring high standards in the disassembly and selection of used batteries, firms can enhance the efficiency of remanufacturing processes. Furthermore, it must be considered that reducing dependence on virgin critical raw materials also leads to a decrease in transportation costs and emissions associated with their supply. In the traditional linear production of EVs, materials are extracted in supplier countries, which are generally geographically distant from the manufacturing countries, *i.e.* this geographical gap constitutes one of the major issues in EV production. Therefore, by implementing CLSC, it is possible to significantly reduce not only the extraction-related costs and emissions, but also those associated with the transportation of raw materials. In this context, CLSC implementation enables a more balanced approach where operational performance (such as variability in orders and inventory management), environmental performance (by reducing emissions), and economic performance (by lowering costs) can be mutually improved, achieving an effective trade-off among all these dimensions. Moreover, in line with the definition of sustainability, the social dimension should also be considered to have a wider picture. For instance, from the final consumer's perspective, the choice to purchase an EV contributes at an individual level to sustainable development by opting for a solution that reduces the emissions associated with urban transportation.

Taking all these considerations together, this study makes a significant contribution to the field of EVB SCs dynamics. Given that the EVB market is projected to experience substantial growth, yet remains in its early stages with the EoL cycles of most currently deployed batteries still ongoing, it results essentials to explore potential future scenarios and to promote further research aimed at supporting the sustainable development of this sector. In this regard, future research could explore the integration of additional recovery strategies such as recycling and repurposing, as well as techno-economic aspects related to the establishment and operation of recycling facilities, including the associated costs, energy consumption, and the availability of skilled labor. Finally, it would be valuable to simulate the impact of external shocks, such as the introduction of tariffs on primary materials, on the dynamic and sustainable performance, as well as on resilience of CLSCs.

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Appendix

Table 5: Recovered Materials [kg] (Co, Li, Ni) from EoL Tesla Model Y batteries under Varying Return Rates.

	a = 0.2			*a* = 0.5			*a* = 0.8		
	Co	**Li**	**Ni**	**Co**	**Li**	**Ni**	**Co**	**Li**	**Ni**
2022	0	0	0	0	0	0	0	0	0
2023	0	0	0	0	0	0	0	0	0
2024	0	0	0	0	0	0	0	0	0
2025	101.3	101.3	790.5	935.9	935.9	7300.2	0.0	0.0	0.0
2026	2169.9	2169.9	16925.2	6593.1	6593.1	51426.6	8828.6	8828.6	68863.2
2027	7910.6	7910.6	61702.6	18778.0	18778.0	146468.0	29400.9	29400.9	229327.1
2028	17871.8	17871.8	139400.4	51719.8	51719.8	403414.8	67702.0	67702.0	528075.4
2029	31242.9	31242.9	243694.9	68530.6	68530.6	534538.6	112310.0	112310.0	876018.3
2030	40256.4	40256.4	313999.6	96077.5	96077.5	749404.9	155731.8	155731.8	1214708.2
2031	42521.6	42521.6	331668.7	105681.1	105681.1	824312.8	169108.9	169108.9	1319049.3
2032	44810.8	44810.8	349523.9	111254.9	111254.9	867788.2	172655.8	172655.8	1346715.5
2033	43922.5	43922.5	342595.7	111290.7	111290.7	868067.2	175016.5	175016.5	1365128.6
2034	44643.8	44643.8	348221.9	110718.4	110718.4	863603.4	176792.9	176792.9	1378984.9
2035	45031.3	45031.3	351244.3	109615.6	109615.6	855001.3	174831.7	174831.7	1363687.2

Table 6: Recovered Materials [kg] (Co, Li, Ni) from EoL Tesla Model S batteries under Varying Return Rates.

	a = 0.2			*a* = 0.5			*a* = 0.8		
	Co	**Li**	**Ni**	**Co**	**Li**	**Ni**	**Co**	**Li**	**Ni**
2022	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2023	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2024	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2025	56.7	170.0	1218.3	523.3	1570.0	11251.7	0.0	0.0	0.0
2026	1213.3	3640.0	26086.7	3686.7	11060.0	79263.3	4936.7	14810.0	106138.3
2027	4423.3	13270.0	95101.7	10500.0	31500.0	225750.0	16440.0	49320.0	353460.0
2028	9993.3	29107.6	209420.2	28920.0	86760.0	621780.0	37856.7	113570.0	813918.3
2029	17470.0	31242.9	243694.9	38320.0	114960.0	823880.0	62800.0	188400.0	1350200.0
2030	22510.0	40256.4	313999.6	53723.3	161170.0	1155051.7	87080.0	261240.0	1872220.0
2031	23776.7	42521.6	331668.7	59093.3	177280.0	1270506.7	94560.0	283680.0	2033040.0
2032	25056.7	44810.8	349523.9	62210.0	186630.0	1337515.0	96543.3	289630.0	2075681.7
2033	24560.0	43922.5	342595.7	62230.0	186690.0	1337945.0	97863.3	293590.0	2104061.7
2034	24963.3	44643.8	348221.9	61910.0	185730.0	1331065.0	98856.7	296570.0	2125418.3
2035	25180.0	45031.3	351244.3	61293.3	183880.0	1317806.7	97760.0	293280.0	2101840.0

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