Techno-Economic Impact of a Smart Battery Sorting System

Cooperative Research and Development Final Report

CRADA Number: CRD-21-17531

NREL Technical Contact: Dustin Weigl

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
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Technical Report
NREL/TP-5400-83532
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NOTICE

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Cooperative Research and Development Final Report

Report Date: July 19, 2022

In accordance with requirements set forth in the terms of the CRADA agreement, this document is the CRADA final report, including a list of subject inventions, to be forwarded to the DOE Office of Scientific and Technical Information as part of the commitment to the public to demonstrate results of federally funded research.

Parties to the Agreement: Li Industries, Inc

CRADA Number: CRD-21-17531

CRADA Title: Techno-Economic Impact of a Smart Battery Sorting System

Responsible Technical Contact at Alliance/National Renewable Energy Laboratory (NREL):

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Sponsoring DOE Program Office(s):

- Office of Energy Efficiency and Renewable Energy (EERE), Advanced Manufacturing Office (AMO)
- Office of Energy Efficiency and Renewable Energy (EERE), Vehicle Technologies Office (VTO)

Joint Work Statement Funding Table showing DOE commitment:

Estimated Costs	NREL Shared Resources a/k/a Government In-Kind
Year 1	$60,000.00
TOTALS	$60,000.00

<u>Executive Summary of CRADA Work</u>:

Create analytical framework to capture costs and benefits of the automated sorting into battery recycling including the development and deployment of various types of battery recycling technologies such as pyrometallurgical, hydrometallurgical, and direct recycling.

Li Industries, Inc. is a Virginia startup company focused on reinventing how lithium-ion batteries (LIBs) are recycled. Li Industries is focused on developing direct LIB recycling and automated battery sorting technologies in order to reduce the environmental impact of the LIB lifecycle.

This work is to be conducted in support of the American-Made Challenges Lithium-Ion Battery Recycling Prize. Li Industries and NREL will work together to understand how novel technologies, such as those being developed by Li Industries, can impact the development and economics of the battery recycling industry.

This voucher is being used to evaluate the profitability of an automated sorting system developed by Li Industries and the potential effect this increased value could have on the domestic lithium-ion battery (LIB) recycling industries in the United States. NREL has developed the Lithium-Ion Battery Resources Assessment (LIBRA) system dynamics model to project the future viability of the US LIB manufacturing and recycling industries under varying technoeconomic conditions and battery adoption scenarios over the coming decades. Additional logic was added to LIBRA to analyze the role automated sorting of recycling feedstock could play in the buildout of the industry and the impacts it has on the recovery of end-of-life (EOL) battery materials. This report summarizes the outcomes of this modeling analysis in the US context through a series of sensitivity analyses run for a range of values of a given input dimension and compared across the unsorted or automated sorting cases for LIB recycling feedstock.

For greater detail on the process and analysis, the researchers are publishing a forthcoming journal article titled *Techno-Economic Impact of a Smart Battery Sorting System for Lithium-Ion Battery Recycling and Mineral Recovery in the United States* by Weigl, et al. In the event the article is not accepted by any currently seeking publication in academic or industry journal, it may be published by NREL.

CRADA Benefit to DOE, Participant, and US Taxpayer:

- Assists laboratory in achieving programmatic scope competencies
- Uses the laboratory’s core competencies

Summary of Research Results:

This report contains Protected CRADA Information, which was produced on 07/19/2022 under CRADA No. CRD-20-17030 and is not to be further disclosed for a period of one (1) year from the date it was produced except as expressly provided for in the CRADA.

NREL Task 1 Description:

Schedule kick off meeting to confirm project specifics and work schedule

NREL Task 1 Results:

The kick off meeting was held.

NREL Task 2 Description:

Evaluate the potential impact on profitability of existing and planned battery recycling facilities of the Participant's battery sorting system. Profitability data shall be reported as change in net present value (NPV) and reduction in system capital and operating costs.

NREL Task 2 Results:

Sorting Logic in LIBRA

In LIBRA, each end-use battery application has an assumed average lifetime (which increases over time for most applications) and, when batteries reach their EOL they are retired. A fraction of the batteries that reach EOL each year are collected for distribution to recycling plants. These batteries are queued for recycling but if there isn't sufficient plant throughput in a given year to process all of the collected batteries then there is an opportunity to select which chemistries are prioritized for processing. In the unsorted case, the distribution of processed battery chemistries is a mass-weighted slice of the battery chemistries available in the collected feedstock. In the sorted case, chemistries are prioritized based on their relative cobalt content. There are also some differences in costs associated with recycling between the two cases with higher capital costs associated with the purchase and installation of battery sorting technology compared to some additional operating costs for the unsorted case representing the additional labor requirements of a more manual process. The baseline assumptions for the two feedstock distributions are given in Figure 1. Both cases are all or none- sorting applies to either all plants or no plants and all plants have the same distribution of feedstock over time for a given simulation run.

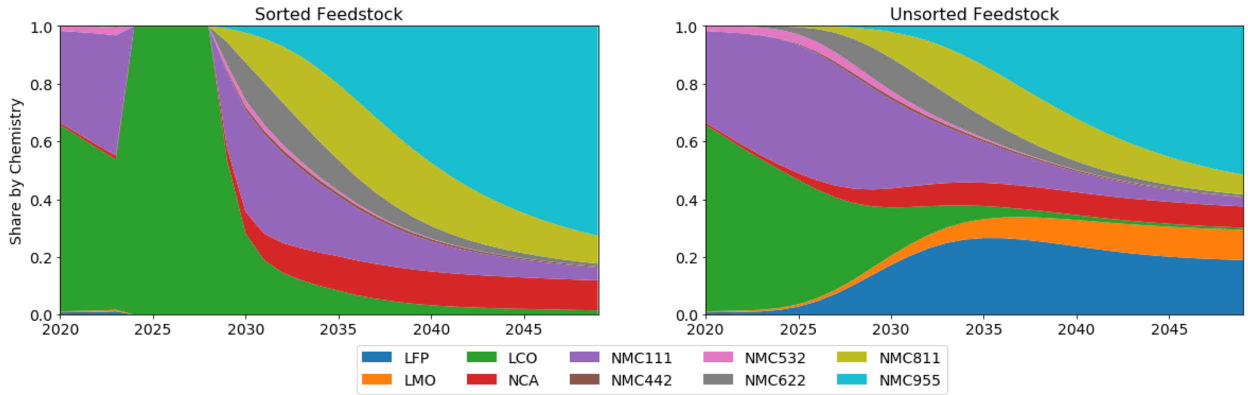

Figure 1: Battery chemistry distribution for sorted and unsorted recycling feedstock in LIBRA over time

LIBRA tracks lithium, cobalt, and nickel through the supply chain and historically, cobalt prices have been the highest per unit mass. In 2020, cobalt was sold for $16 per pound on average on the United States spot market[1] whereas lithium carbonate and nickel sold for $3.60[2] and $6.40[3] per pound respectively. For this analysis, the chemistries with the highest concentration of cobalt are prioritized by the recycler to maximize revenue associated with the sale of recovered minerals. Prioritization of high-cobalt chemistries, LCO in particular, can be seen in the sorted feedstock mineral content distribution in Figure 2.

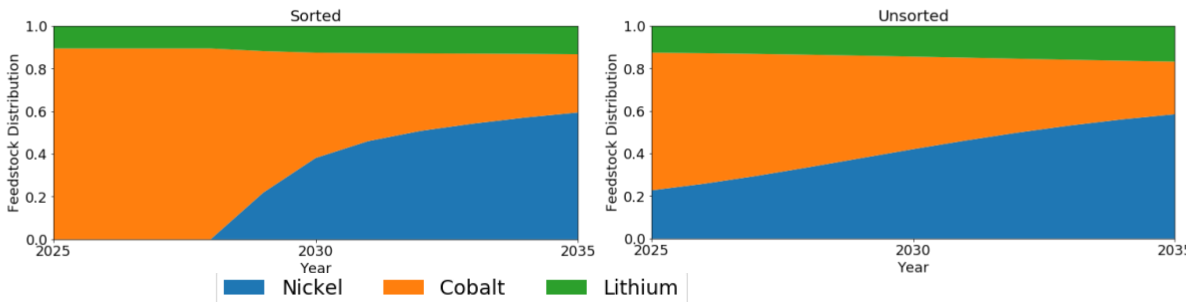

Figure 2: Mineral content distributions from 2025-2035 for the sorted and unsorted feedstock chemistry distributions shown in Figure 1

With the highest historical price per metric ton (as compared to nickel or lithium), cobalt concentration is the primary driver of potential profit for recyclers. As more recycling plants are built, lower-value chemistries are processed but the low-profit LFP and LMO chemistries are avoided almost entirely. The additional net present value of new hydrometallurgical plant construction over time for the sorting case as compared to the no sorting case is seen in Figure 3.

[1] https://pubs.usgs.gov/periodicals/mcs2021/mcs2021-cobalt.pdf
[2] https://pubs.usgs.gov/periodicals/mcs2021/mcs2021-lithium.pdf
[3] https://pubs.usgs.gov/periodicals/mcs2021/mcs2021-nickel.pdf

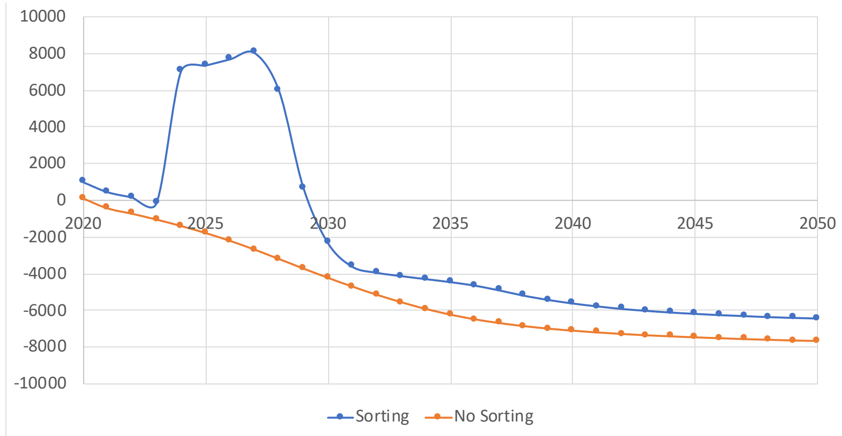

Figure 3: Net Present Value of building a hydrometallurgical recycling plant each year with or without Li Industry's sorting technology

NREL Task 3 Description:

Model the potential impact of automated sorting on the growth of the battery recycling industry, including the number of facilities that could be economically constructed, the total amount of batteries recycled, and the production of salable product materials.

NREL Task 3 Results:

Sensitivity Analysis

The following sensitivity analyses were run for their impact on the recovery of nickel, lithium, and cobalt. This analysis summary focuses on the impacts for cobalt and nickel although results for lithium were also provided to Li Industries. The results are impacted both by changes in operations at the plant level and by changes in the attractiveness of investment in new plants- leading to additional buildout of recycling capacity. The sensitivities analyzed include variations across (1) operating cost, (2) industrial learning rates, (3) process yield, and (4) the effectiveness of the battery chemistry sorting used. With sorting aimed at maximizing cobalt content in the recycling feedstock, the relative impacts on cobalt recovery show the most significant differences between the sorting and not sorting cases. However, many chemistries tradeoff between cobalt and nickel- so maximizing the processing of cobalt-heavy chemistries in turn somewhat reduces the concentration of nickel in the recycling feedstock.

The *No Sorting- Baseline* and *Auto Sorting- Baseline* cases are also shared across the different sensitivity runs. The results discussed for each of these analyses will be summarized by model results showing the share of cobalt and nickel in EOL batteries recovered through the three modeled recycling technologies from 2020-2050. These technologies include hydrometallurgical (hydro), pyrometallurgical (pyro), and direct recycling- a new technology under development that uses a relithiation treatment to refresh an EOL cathode. While the product of direct recycling is a cathode rather than mineral mass, this analysis includes the minerals contained in those cathodes in the accounting of recovered nickel and cobalt from hydro and pyro.

One of the common dynamics across these analyses is driven by the baseline assumptions for the evolution of LIB demand and technology. At the beginning of the simulation, there is more cobalt in EOL batteries than in new because of the high concentration of LCO batteries sourced from consumer electronics in the feedstock. As new battery demand increases for EVs and battery energy storage (BES), it adds greater quantities of different chemistries into the feedstock, quickly outstripping the contribution from consumer electronics. Future battery chemistries for EVs and BES also move away from the more expensive cobalt-heavy chemistries over time toward high-nickel cathodes, contributing to additional dilution of cobalt in the recycling feedstock. The dilution of cobalt over time in the system-wide aggregation of EOL batteries is particularly important when considering the impacts of sorting by chemistry as is illustrated in the following figures.

A second shared dynamic is the significant increase in mineral recovery in the auto sorting cases compared to the scenarios without sorting. This benefit is driven by a few factors. First, the higher profitability of cobalt-heavy feedstock makes investment in additional recycling capacity more attractive, leading to a more rapid increase in industrial maturity (particularly for the immature direct recycling technology). Next, that increased profitability also results in higher utilization for existing plants, which can curtail operations when the revenue from the available feedstock distribution is lower than the cost to recycle it. This is occasionally the case in the unsorted case depending on mineral prices and the concentration of low-value chemistries but is much less frequent in the automated sorting cases. Finally, the sorted feedstock distribution shown in Figure 1 contains very little LFP or LMO- two chemistries without cobalt or nickel- which maximizes the processing of EOL cathodes that *do* contain these minerals of interest.

1. Operating Cost

The following sensitivity analysis shown in Figure 4 and Figure 5 for cobalt and nickel recovery shares respectively, varied the operating cost for recycling plants to 75 and 125% of the baseline values sourced from EverBatt (Dai et al. 2019). Both variable and fixed operating costs were modified across all three recycling technologies modeled in LIBRA. While a reduction in operating cost is helpful in terms of the quantity of minerals recovered across both sorting cases, higher operating costs lead to a reduction in the long-term quantity recovered due to a reduced build out of recycling capacity. Additionally, for both cobalt and nickel the *reduction* in quantity recovered through recycling due to an *increase* in the operating cost (from baseline) is larger than the *increase* in quantity from a *reduction* in operating costs. This imbalance is due to constraints on how quickly new plants can be built in response to increases in EOL feedstock availability and is present in both the auto and no sorting cases examined. These cases also impact the time that US recycling capacity expands, with higher costs leading to delays in plant construction. We also see a delay in the start of nickel recovery in the automated sorting cases because of the heavy prioritization placed on the nickel-free LCO chemistry early in the simulation (as seen in Figure 1 and Figure 2).

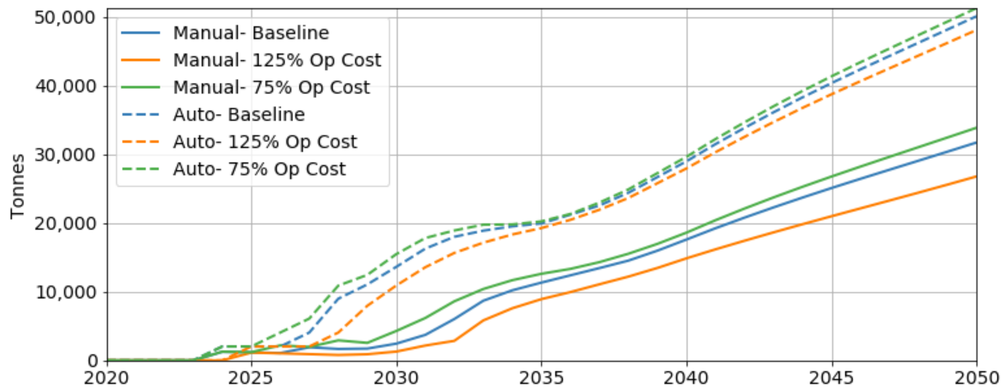

Figure 4: Tonnes of cobalt recycled across three operating cost cases with and without sorting

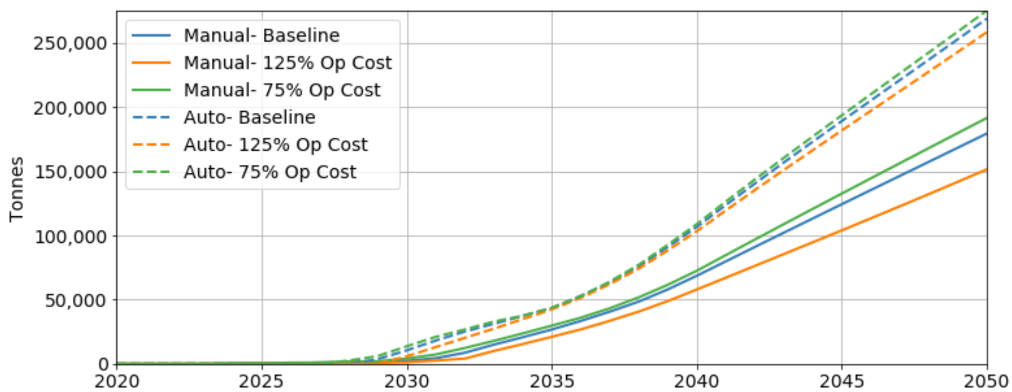

Figure 5: Tonnes of nickel recycled across three operating cost cases with and without sorting

2. Industrial Learning Rates

In LIBRA, industrial maturity ranges from 0-1 for recycling and manufacturing technologies where a value of 0 represents a brand-new technology and significant inefficiency in operations and a value of 1 represents a fully mature industry that benefits from experience gained through learning by doing. The different cases represented primarily impact direct recycling which starts at an initial commercial maturity of 0.1 whereas hydro and pyro recycling start at 0.9. As illustrated in Figure 6 and Figure 7, increasing the learning rate from the baseline value doesn't significantly impact the quantity recycled for either cobalt or nickel but slower learning can delay the construction of commercial plants. With slower learning, the recycling industry does not catch up to the quantity recycled annually achieved in the high learning cases. Variations in learning also aren't significantly different when comparing across the sets of unsorted versus sorted scenarios- the difference between the baseline and slow learning cases are roughly the same whether recyclers are using automated sorting technology.

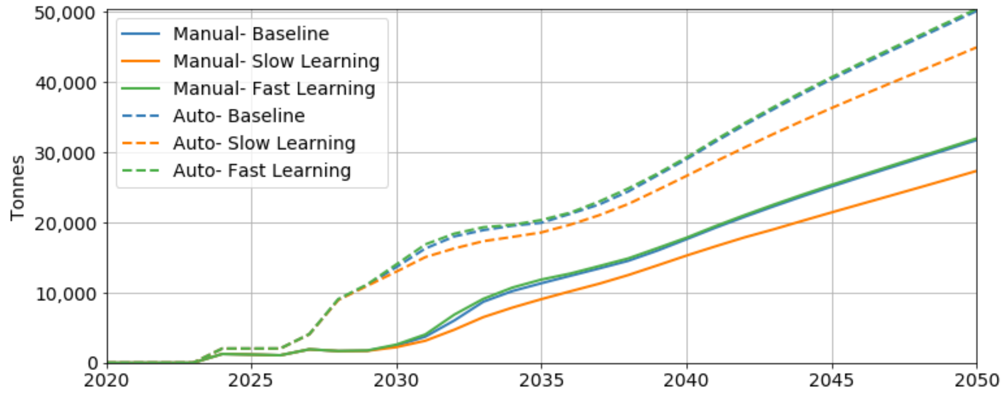

Figure 6: Tonnes of cobalt recycled across three learning rate cases with and without sorting

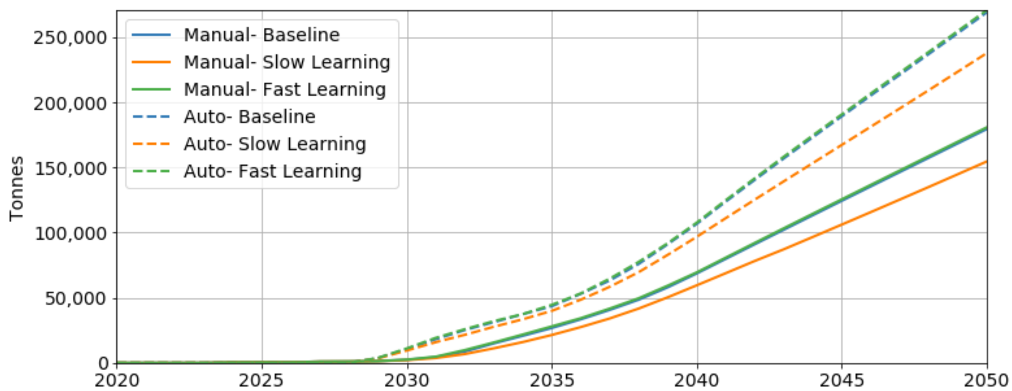

***Figure 7:* Tonnes of nickel recycled across three learning rate cases with and without sorting**

3. Process Yield

This set of scenarios vary the maximum process yield for all three recycling processes to examine the effects of 70% and 80% compared to the baseline yield. For direct recycling, the baseline cathode yield is 90% and for hydro and pyro baseline yield is assumed to be 98% for both nickel and cobalt. For cobalt recovery, reductions in process yield to 70% with automated sorting is preferable to baseline yield with manual sorting (comparing the green lines in Figure 8). Manual sorting with baseline yield results in higher quantities of cobalt and nickel recycled than automated sorting with 70% yield for nickel through ~2034 when more of the sorted feedstock distribution is comprised of nickel-heavy chemistries (Figure 9). In addition to the benefits of increased yield in terms of per unit resource recovery, the additional profitability also leads to greater buildout of recycling capacity than low yield cases for both the unsorted and sorted cases. Beyond 2035 there is a relatively stable difference in the quantity recovered across the yield scenarios (for both sorted and unsorted feedstock) for both nickel and cobalt.

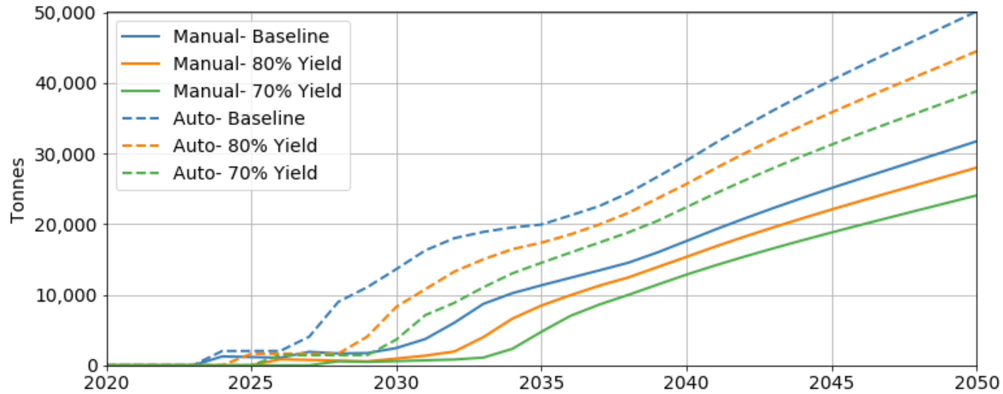

Figure 8: Tonnes of cobalt recycled across scenarios varying the process yield with and without sorting

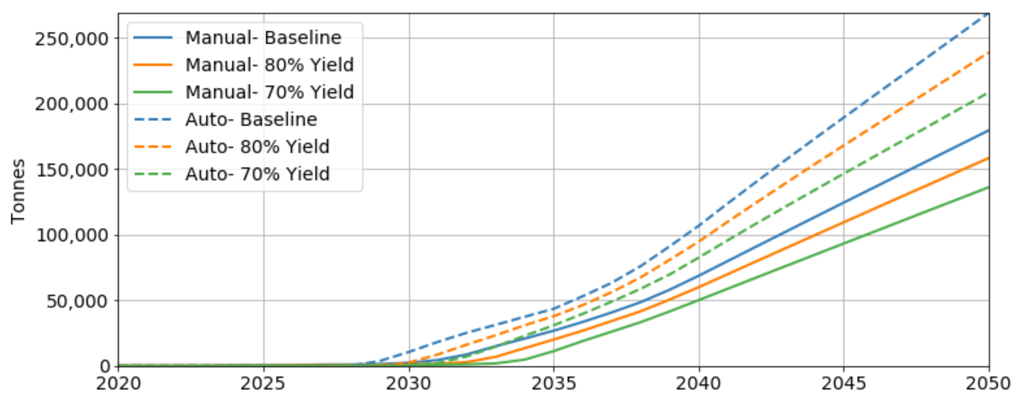

Figure 9: Tonnes of nickel recycled across scenarios varying the process yield with and without sorting

4. Sorting Efficiency

The *Auto Sorting* case used in the previous analyses in this report assume *high sorting efficiency*. In that case, if a battery that is identified as a high priority chemistry is available for recycling, it will be recycled before any battery chemistries with lower priority. The medium and low efficiency cases examined in this sensitivity analysis evaluate conditions where *some* low priority batteries will be recycled before high priority chemistries. The differences among the four sorting efficiency cases are given in Figure 10. Note that as the sorting efficiency increases, the distribution of LFP and LMO shrink while the concentration of LCO is maximized.

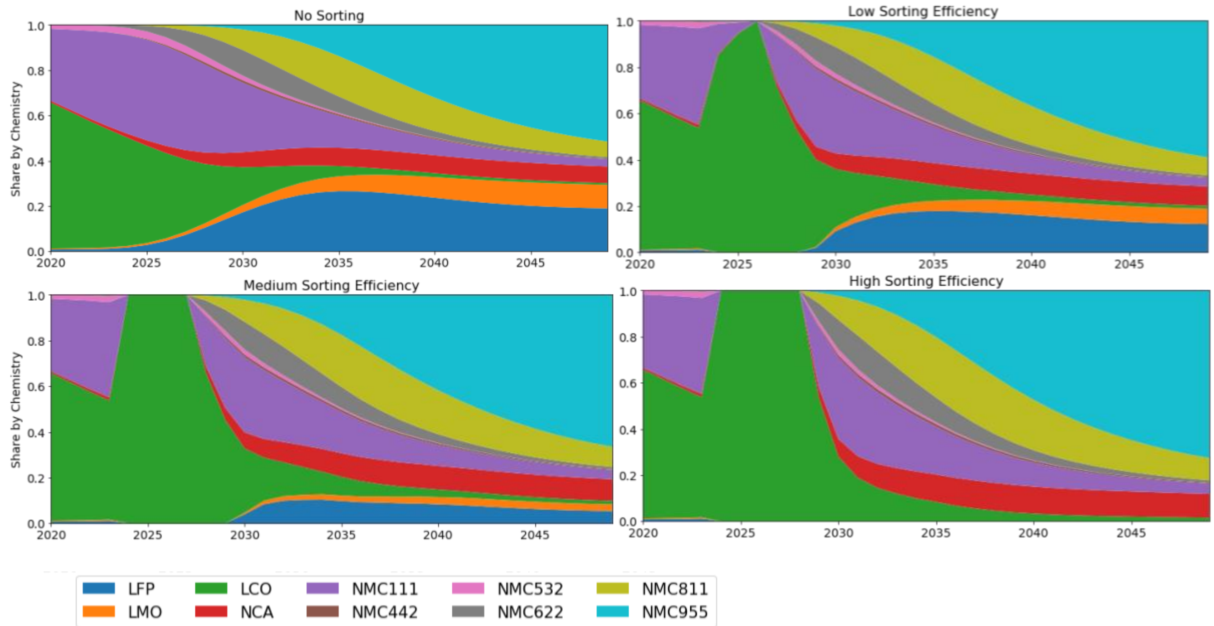

Figure 10: Battery feedstock chemistry distributions varying sorting efficiency. The High Sorting Efficiency case is the same as the baseline Auto Sorting examined in the other sensitivity analyses

Sorting is particularly impactful for the amount of cobalt recycled before 2035 when LCO batteries still comprise a significant share of EOL batteries. Looking across the high, medium, and low efficiency cases shown in Figure 11, it is evident that even incremental control over the composition of the feedstock distribution can be important for increasing how much is recovered. In contrast, the recovery of nickel is inversely impacted by sorting efficiency from 2025-2030 because the low-cobalt chemistries generally have higher concentrations of nickel (Figure 12). However, the increased profitability offered by high efficiency sorting leads to greater buildout of recycling capacity in the long run and that case results in the highest long-term recovery beyond 2030 even though the amount of nickel recovered from 2020-2027 is negligible.

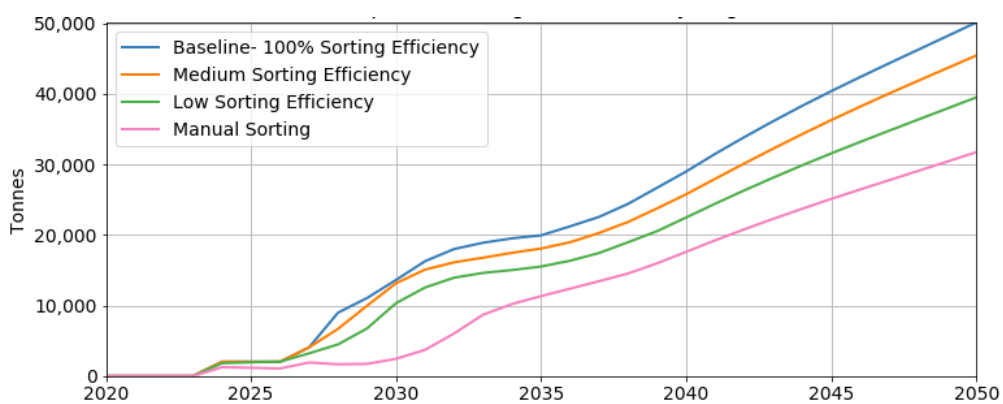

Figure 11: Tonnes of cobalt recycled across four scenarios varying the assumed efficiency of the automated sorting process

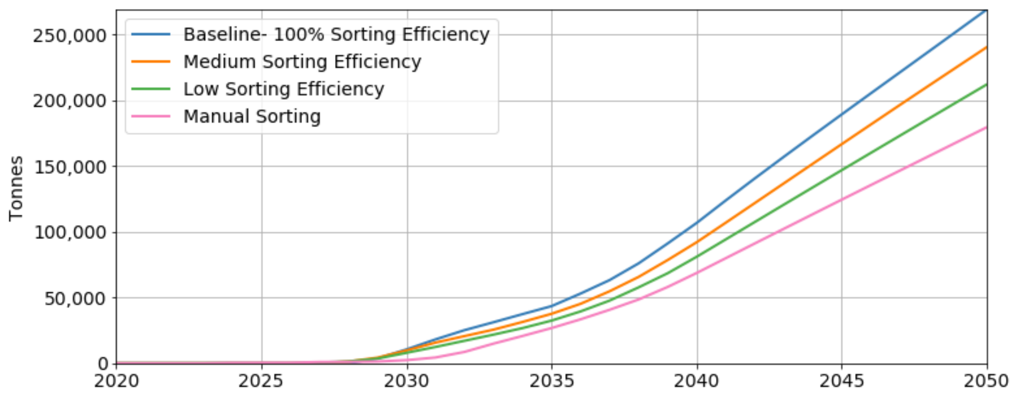

Figure 12: Tonnes of nickel recycled across four scenarios varying the assumed efficiency of the automated sorting process

NREL Task 4 Description:

Determine the impact of sorting on the types of batteries that are recycled and the reduction in the number of batteries sent to landfills.

NREL Task 4 Results:

We output the share of end-of-life batteries that were recovered annually from the same four scenarios summarized for Task 3. These results are similar to those above, but are scaled relative to the quantity of EOL batteries each year. Batteries that are not recycled in a given year can be stored for one year before they are landfilled. In reality, this storage time could potentially be longer if there is an economic incentive for recyclers to keep that feedstock for when they have increased recycling throughput relative to the available feedstock. The recovery rate results for nickel and cobalt across these four scenarios are presented without additional analysis because the quantity of batteries reaching end-of-life is not impacted by the enabling of battery sorting or by the inputs that are varied in each scenario.

1. Operating Cost

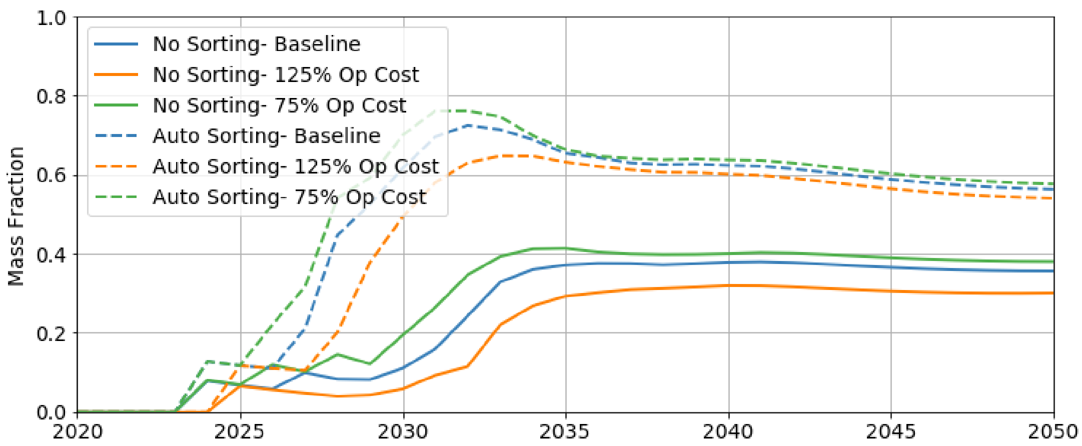

Figure 13: Share of cobalt contained in EOL batteries recovered through recycling across three operating cost cases

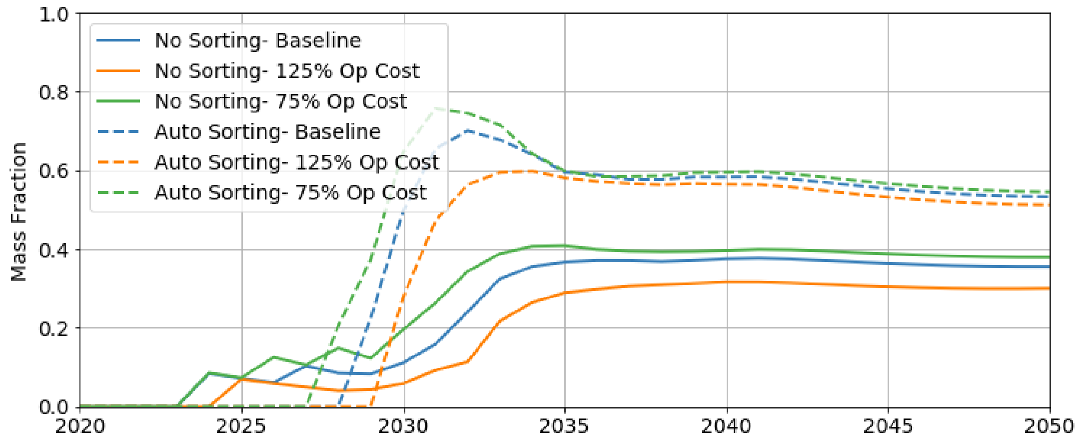

Figure 14: Share of nickel contained in EOL batteries recovered through recycling across three operating cost cases

2. *Industrial Learning Rates*

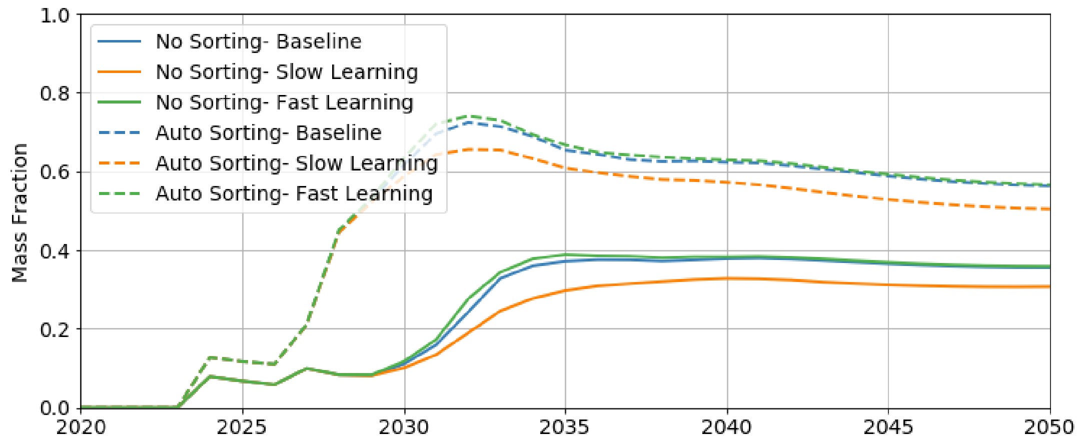

Figure 15: Share of cobalt contained in EOL batteries recovered through recycling across three scenarios varying the industrial learning rate

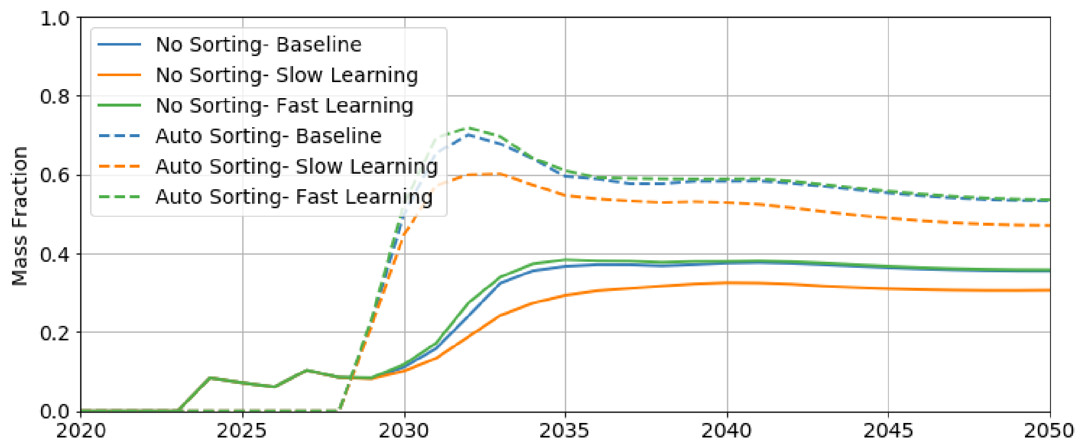

Figure 16: Share of nickel contained in EOL batteries recovered through recycling across three scenarios varying the industrial learning rate

3. *Process Yield*

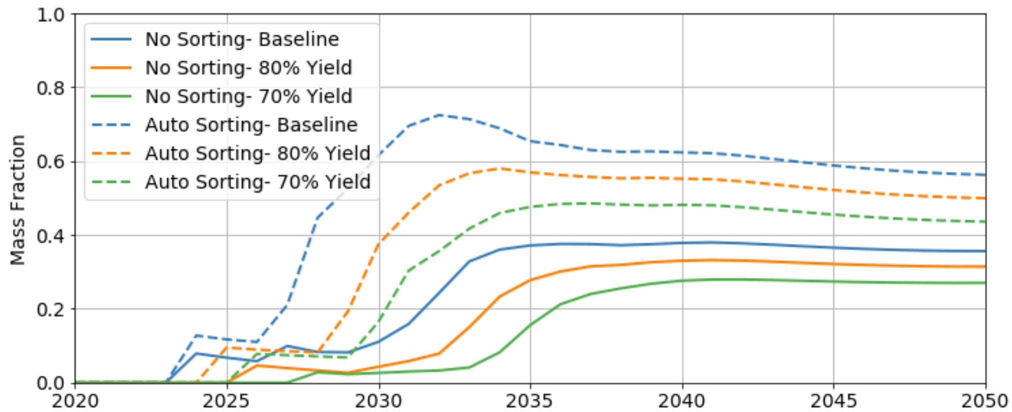

Figure 17: Share of cobalt contained in EOL batteries recovered through recycling across three scenarios varying the process yield

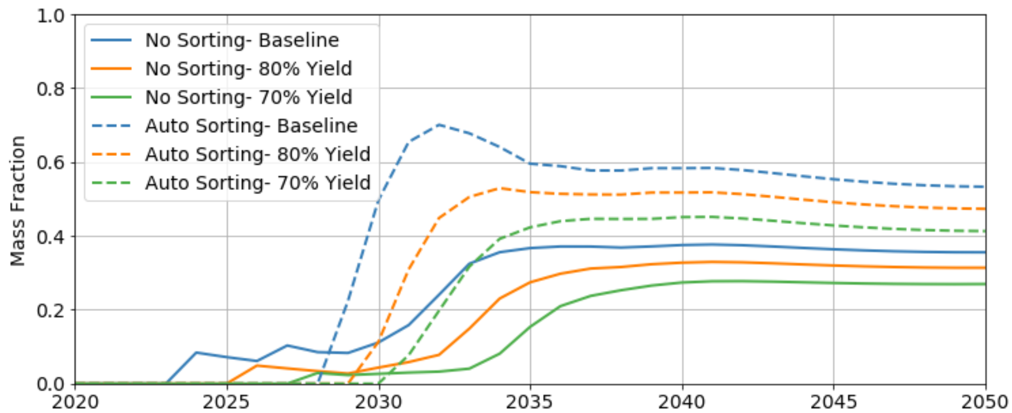

Figure 18: Share of nickel contained in EOL batteries recovered through recycling across three scenarios varying the process yield

4. *Sorting Efficiency*

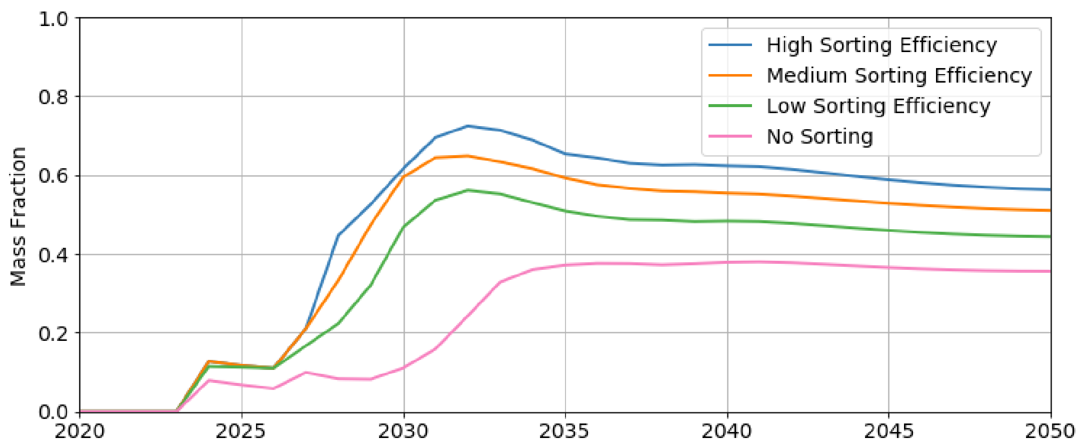

Figure 19: Share of cobalt contained in EOL batteries recovered through recycling across four scenarios varying the assumed efficiency of the automated sorting process

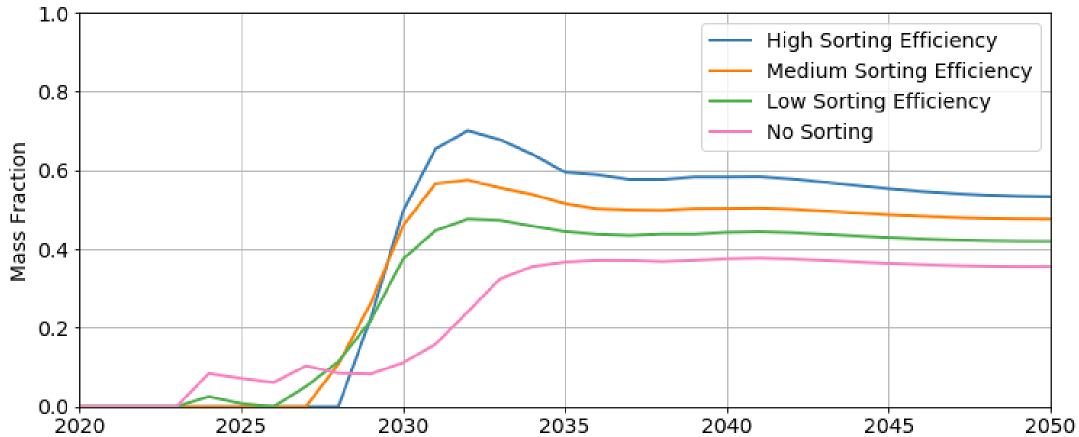

Figure 20: Share of nickel contained in EOL batteries recovered through recycling across four scenarios varying the assumed efficiency of the automated sorting process

Key Takeaways

Across all the sensitivity analyses examined, the benefits of automated sorting technology for battery recycling are clear in terms of their influence on the rate of mineral recovery from EOL batteries. This impact is driven by a few factors linked to the minimizing of low-value LFP and LMO and maximizing of LCO and other valuable cobalt-heavy chemistries in the distribution of feedstock processed by recyclers.

- In a throughput-constrained recycling network, any LMO or LFP batteries recycled could result in the landfilling or export of another battery containing nickel and/or cobalt, effectively reducing the domestic mineral recovery rate.

- Cobalt has the highest price per unit mass, making its recovery a valuable component for profit-seeking recyclers. Those profits drive more investment in recycling plants, expanding the annual recycling capacity of the system, and reducing the share of batteries that aren't recycled in the United States.

- Plants are particularly incentivized to take advantage of a high concentration of EOL consumer electronics LCO batteries early on using automated sorting. As the number of plants, the scale of available feedstock, and variation in battery chemistries increase over time, the competition for LCO and other highly profitable chemistries reduces the average profitability of recycling plants system wide.

- Variations in input parameters have similar marginal impacts on mineral recovery rates from the baseline outcome when comparing cases with no sorting or automated sorting. However, the benefits of battery sorting for recovery rates can outweigh some adverse variations in plant characteristics (such as operating costs or process yield).

- The effectiveness of battery sorting is constrained by the evolution of the battery market. If future end-use applications move rapidly toward cobalt-free chemistries, then the marginal benefit of automated sorting will be curtailed significantly.

Taking these outcomes into consideration, the benefits of battery sorting are significant to both the profit of US recyclers and the country as a whole for maximizing the recovery of critical battery materials.

NREL Task 5 Description:

CRADA Final Report – Preparation and submission in accordance with Article X

NREL Task 5 Results:

The CRADA report was prepared and submitted in accordance with Article X. This Final Report serves to meet that requirement.

Partner Task 1 Description:

The Participant will collect, analyze, and provide estimated cost data to NREL including capital investment requirements, operating costs, and scaling factors to estimate the value of sorting at different locations and for different quantities of batteries.

Partner Task 1 Results:

This data was provided by the partner.

Partner Task 2 Description:

The Participant will specify the battery chemistries sorted into the product bins and the ranges of battery chemistries that could be achieved with varying sorting specifications.

Partner Task 2 Results:

This data was provided by the partner.

Subject Inventions Listing:

None

ROI #:

None