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1 The National Renewable Energy Laboratory
2 Evans-Peterson, LLC

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List of Acronyms and Abbreviations

BAU	business as usual
BES	battery energy storage
EV	electric vehicle
FCI	fixed capital investment
LCO	lithium cobalt oxide
LCV	light-duty commercial vehicle
LDV	light-duty vehicle
LFP	lithium iron phosphate
LIB	lithium-ion battery
LIBRA	Lithium-Ion Battery Resource Assessment
LMO	lithium-ion manganese oxide
MSP	minimum selling price
MTBF	mean time to battery failure
MWh	megawatt hour
NCA	lithium nickel cobalt aluminum oxide
NMC	lithium nickel manganese cobalt oxide battery chemistry. Following numbers indicate relative mass ratios of nickel, manganese, and cobalt (NMC111, NMC532, etc.)
NPV	net present value
PC	pre-commercial
PCT	percent
ROW	rest of the world

Executive Summary

Meeting aggressive carbon emission goals will entail widespread deployment of renewable sources of electricity. Because a significant share of these sources are variable, there is a need to develop scalable energy storage technologies. The U.S. Department of Energy is supporting efforts to increase U.S. manufacturing and recycling capabilities for lithium-ion batteries (LIBs) and to decrease costs of stationary storage batteries. Many factors influence the domestic manufacturing and cost of stationary storage batteries, including availability of critical raw materials (lithium, cobalt, and nickel), competition from various demand sectors (consumer electronics, vehicles, and battery energy storage), resource recovery (recycling), government policies, and learning in the industry, among other factors. Understanding how these factors interact and identifying synergies and bottlenecks is important for developing effective strategies for the LIB stationary energy storage system.

We developed the Lithium-Ion Battery Resource Assessment (LIBRA) model as a tool to help stakeholders better understand the following types of questions:

- What are the roles of R&D, industrial learning, and scaling of demand in lowering the barriers to the expansion of battery energy storage manufacturing?
- How do the intersections between the electric vehicle (EV) and stationary storage sectors affect the battery supply chain?
- For various stationary storage and EV penetration scenarios, what volumes of critical materials might be required and what role can resource recovery play?
- What does expected demand for both EVs and stationary storage portend for mineral resources and overall mineral scarcity?

The LIBRA model is developed using a system dynamics modeling approach to represent interactions across the segments of the battery materials supply chain. System dynamics models can capture the complex interactions and feedback between the various system components that influence supply and demand (Forrester 1987). The LIBRA model is comprised of several interacting modules that represent specific portions of the LIB supply chain. The model tracks the buildout of the domestic LIB industry over time (2020 – 2050) and in the context of competing demands for raw materials, recycling, and markets for LIBs. The LIBRA model represents major systemic feedback loops and delays across the supply chain. This report provides a complete documentation for the LIBRA model, including model assumptions, data, scenario analysis results, and sensitivity analysis of the model's input space.

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1 Introduction

In the United States the transportation and electricity sectors accounted for 54% of the total U.S. GHG emissions in 2019 (US EPA 2022). In 2021, the Biden Administration signed Executive Order 14057 which sets targets to reach net-zero carbon emissions, across the economy, by 2050 (President 2021). To meet these emission reduction targets, it is anticipated that the growth of the electric vehicle and energy storage markets will increase.

Electric vehicle (EV) sales have grown rapidly in the last decade in the United States; 3% of all new vehicle sales in 2021 were of EVs. However, significant emission reductions from vehicle electrification require significant decarbonization in the power sector. Progress in power decarbonization relies on energy storage systems that can provide reliable, on-demand energy (de Sisternes, Jenkins, and Botterud 2016; Gür 2018). Battery technologies are at the heart of such large-scale energy storage systems, and lithium-ion batteries (LIBs) are at the core of various available battery technologies.

The U.S. federal government has set ambitious goals to increase U.S. manufacturing capabilities for lithium-ion batteries (LIBs) and decrease costs to make storage more competitive in the domestic marketplace (White House 2022). However, several factors can influence the domestic manufacturing and cost of stationary storage batteries, including availability of critical raw materials (lithium, cobalt, and nickel), competition from various demand sectors (consumer electronics, vehicles, and battery energy storage), resource recovery (recycling), government policies, and learning in the industry, among other factors. The development of the LIBRA model is motivated by the following questions:

- What are the roles of R&D, industrial learning, and scaling of demand in lowering the barriers to the development of domestic battery energy storage manufacturing capacity in the United States?
- How do the intersections between the EV and stationary storage sectors affect the battery supply chain?
- For various stationary storage and EV penetration scenarios, what volumes of critical materials might be required and what role can resource recovery play?
- What does expected demand for both EVs and stationary storage portend for mineral resources and overall mineral scarcity?

In this work, we use a system dynamics modeling approach to represent interactions across the segments of the battery materials supply chain to answer these questions. System dynamics models can capture the complex interactions and feedback between the various system components that influence supply and demand. Use of system dynamics for sustainable supply-chain analysis has been reviewed in literature (Saavedra M., de O. Fontes, and M. Freires 2018; Rebs, Brandenburg, and Seuring 2019), and system dynamics has been applied to analyze renewable energy supply chains in various studies (Peterson et al. 2013; Robalino-López et al. 2014; Vimmerstedt et al. 2015; Laimon et al. 2020). Here, we use the Lithium-Ion Battery Recycling Analysis (LIBRA) model to evaluate the future of the stationary storage supply chain and to quantify the factors influencing U.S. battery production. The remaining sections in this report describe the model structure and methods used, describe the various scenarios and sensitivities used in the analysis, and summarize modeling results.

2 LIBRA Model Overview

The LIBRA model[1] is a tool for exploring scenarios related to the evolution of the supply chain for lithium-ion batteries in the United States and rest of the world (ROW). Central to the model are industry development structures that represent the buildout of manufacturing and recycling capacity for multiple LIB chemistries. Using projected new battery demand streams driven by multiple end-use categories, the model tracks the life cycle of batteries by their energy content and mass. Additionally, it tracks the movement and accumulation of key minerals (cobalt, lithium, and nickel) associated with the production, use, recycling and discarding of LIBs. The availability of these minerals is key for the expansion and stability of the domestic battery supply chain.

In this section, we provide an overview of the model. We begin by briefly discussing the system dynamics framework and the associated software tool used to develop the model. Then, we provide a high-level overview of the model architecture. We conclude with a more detailed description of the modules that comprise the model.

2.1 System Dynamics Approach

To describe the dynamics of the evolving global LIB supply chain, we draw from the system dynamics toolset and method. System dynamics modeling has a long and rich history of use in modeling the dynamics of supply and value chains (Sterman 2006). The system dynamics toolset has been used in a wide range of policy contexts to represent and simulate processes that are impacted by multiple interacting physical and social components. Essential to system dynamics models are stocks, flows, and feedback:

- **Stocks and Flows:** Accumulations, and the activities that cause them to rise and fall over time, are fundamental to the generation of dynamics. System dynamics models are built from stock and flow primitives. In LIBRA, we use stocks to account for key quantities such as supply chain inventories and manufacturing capacities. Associated flows include production and scrapping or recycling of batteries, and investment in capacity.
- **Feedback:** Dynamic social systems can contain rich webs of feedback processes. Positive (or reinforcing) feedbacks tend to be associated with growth in key quantities, while negative (or balancing) feedbacks are associated self-correcting or "goal-seeking" behavior. The LIBRA model structure captures important feedback processes within and across its modular structure.

The LIBRA model was developed by the National Renewable Energy Laboratory using the Stella software (isee systems 2010), which provides a visual language for representing stocks, flows, and feedback relationships. It uses standard numerical methods to simulate the differential equations that comprise a model.

2.2 Model Architecture

The LIBRA model aims to analyze the evolving supply chain for LIBs. Its architecture was designed to be modular and extensible (Figure 1). This design facilitates model development, testing, and analysis

[1] See "LIBRA: Lithium-Ion Battery Resource Assessment Model ," NREL, https://www.nrel.gov/transportation/libra.html

activities. Though the model is configured to evaluate the evolution of the lithium-ion battery industry from approximately 2000 to 2050, it typically is used to report prospective results from 2020 to 2050.

One set of modules, on the left of Figure 1, captures battery end uses. On the right in the figure are modules that house manufacturing and recycling industries, as well as modules that aggregate demand streams and account for mineral movements through the supply chain.

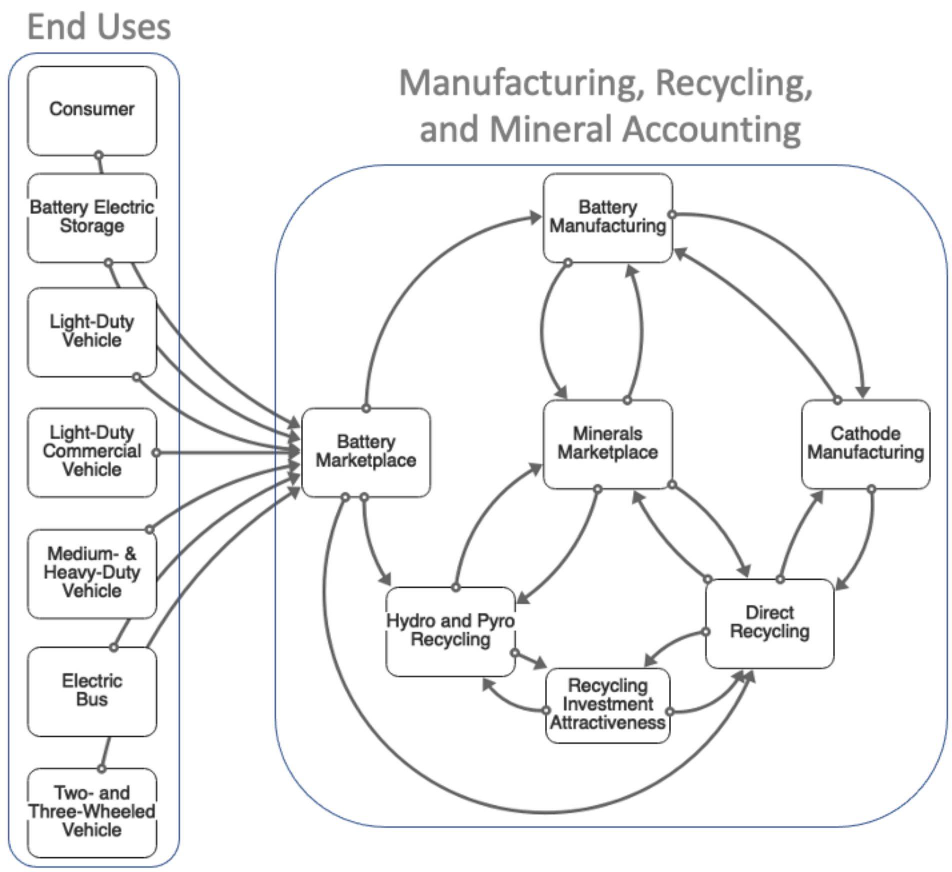

Figure 1. Modular structure of the Lithium-Ion Battery Resource Assessment (LIBRA) model

The model is divided into two regions: the United States and ROW. This geographic disaggregation enables the model to capture regional differences in techno-economic input data, as well as region-specific policy initiatives. Geographic disaggregation also enables the model to assess the relative impacts of differences in vehicle adoption rates between the United States and other countries and regions.

The model is further disaggregated to represent ten separate battery chemistries. Adoption rates for these chemistries are provided by externally derived projections within vehicle end-use modules. Projections of demand for new batteries are combined with model-generated demand for replacement batteries to estimate overall battery demand for each end-use module. These demand signals from each end-use module, along with battery retirements, are transmitted to the Battery Marketplace module where they are aggregated as battery demand, battery discards, and batteries collected for recycling. In turn, the Battery Marketplace module provides input to end-use modules that constrains battery installations whenever production is insufficient to meet demand.

An essential component of the model is its Mineral Marketplace Module. It provides stock-flow accounting structure to track cobalt, lithium, and nickel as they move through the LIB supply chain. Beginning as raw materials used in manufacturing, minerals are tracked through their life cycle as they are incorporated into different battery chemistries, embedded in end uses, and either recycled or discarded.

The critical minerals tracked in the Mineral Marketplace are primarily used to produce cathodes, the positive electrode in LIBs. Cathodes are typically produced in separate facilities from full batteries and the Cathode Manufacturing Module estimates investment in these plants by region based on a demand-pull process. Based on the forecast in demand for cathodes from the various end use modules (electric vehicles, stationary storage, and consumer electronics), the Cathode Module invests accordingly in cathode manufacturing capacity over time. The regional differences in investment are based in part on differences in minimum cathode selling price between regions. Cathode production is determined by on-line capacity and can be constrained by actual demand for cathodes as well as shortfalls in mineral availability. Specific chemistries are produced in proportion to demands for cathodes from the Battery Manufacturing Module.

Like the Cathode Manufacturing Module, the Battery Manufacturing Module analyzes investment in battery production capacity and subsequent production of batteries. Investment is based on forecasted demand for batteries which is represented as an exogenous input to the end-use demand modules. Allocation of investment between the United States and ROW is based on financial considerations as well as the relative share of demand from each region. Production capacity is allocated to production of battery chemistries in response to the size of their demand streams. Constraints imposed by the availability of cathodes can limit the downstream production of specific battery chemistries.

The Direct Recycling Module assesses the buildout of direct recycling plants, a new recycling technology that is centered on the regeneration of degraded cathode active materials (primarily focused on lithium) through a process called relithiation. Rather than separated minerals, the end-product of this process is a relithiated cathode that can then be installed in a new battery. In this module, investment is based on the profitability (expressed as a net present value metric) of this recycling option in relation to other recycling processes. In addition, investment and utilization of capacity is based on an estimate of feedstock availability withing the region. Recycled cathodes are used in the manufacture of batteries, thus reducing manufacturing demand for new cathodes and their associated mineral components.

Direct recycling of batteries operates in competition with the destructive hydrometallurgical and pyro-metallurgical methods of recycling. Hydrometallurgical (or hydro) methods involve leaching of critical elements whereas pyrometallurgical (pyro) methods involve reduction-oxidation reactions at elevated temperatures to smelt and purify the elements. Both methods facilitate recovery of minerals from the cathode and LIBRA tracks the yield of cobalt, nickel, and lithium from each battery processed through a destructive method. Investment in these pathways (both direct and destructive) is determined by the relative profitability (also expressed as a net present value metric) of each recycling pathway and the availability of recycling feedstock.

The model uses a set of techno-economic inputs to describe financial and yield parameters associated with the incremental investment in manufacturing and recycling facilities. These include estimates for facility scale, capital cost, process yield, and other parameters. The techno-economic inputs represent estimates for a fully mature nth plant industry. However, none of these industries are currently at a fully mature status. The model therefore adopts assumed values to represent initial levels of LIB industry maturity and incorporates industrial learning structures to represent the process of improving cost, yield, and scale attributes because of industry development.

2.3 End-Use Modules

LIBRA's End-Use Modules track LIBs through their life cycle in consumer, storage, and vehicle end-use settings. Using user-defined scenario inputs to generate new battery demand (denominated in megawatt-hours [MWh] for consistency across modules), each module tracks the inventories of batteries in use by battery chemistry. The modules are used to generate overall demand for new batteries and replacement batteries in the United States and ROW. Additionally, the modules generate flows of battery retirement at end of life. These retirement flows are used to determine flows of battery collection for recycling as well as battery scrappage.

In this section, we briefly describe the various end-use modules. We begin with batteries in consumer goods such as smartphones and laptop computers. Then we describe the structure of the Battery Storage Module. Finally, because Vehicle Modules are similar in structure, we outline the structure common to all Vehicle Modules. The tables in this section list the key units, inputs, and outputs for each module.

2.3.1 Consumer Module

The Consumer module provides a simple accounting structure to keep track of batteries used for consumer electronics (Figure 2). Demand for new batteries is represented as a scenario that begins with historical sales and then increases in response to annual changes in GDP for each region. This demand can be constrained if insufficient batteries are produced to support demand. As an initial modeling assumption, we assume that consumer electronic batteries use the lithium cobalt oxide (LCO) chemistry; this shifts over time such that NMC111 makes up approximately 80% of sales by 2040.

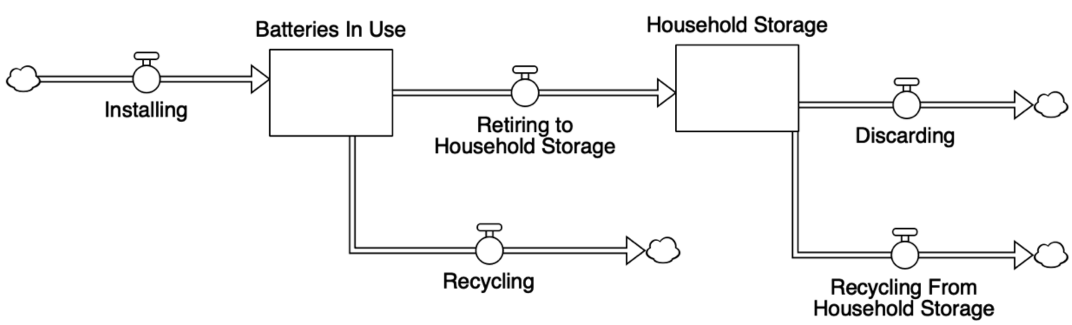

Figure 2. Life-cycle structure for a consumer electronic battery

Consumer electronics are assumed to have a lifespan of four years and are sold in higher quantities earlier in the simulation than the other demand streams. They therefore make up a large portion of the batteries reaching end of life, especially before 2030, when larger quantities of battery electric storage and EVs are starting to retire. At end of life, batteries are assumed to move into the recycling stream or into household storage. Once in household storage, batteries can be either discarded or collected for recycling. The specific rates of movement into waste or recycling streams can be set as scenario inputs.

Table 1. Consumer Module: Key Units, Inputs, and Outputs

Key Units	MWh
Key Inputs	Battery demand scenario (region, chemistry), production constraints
Key Outputs to Other Modules	Battery demand, batteries in use, battery collection for recycling, battery discards

2.3.2 Battery Electric Storage (BES) Module

The simple structure of the BES module accounts for the life cycle of stationary batteries used for storage. Demand for new batteries through 2030 is set as a scenario based on projections from the 2019 BloombergNEF Long Term Energy Storage report (Bloomberg NEF 2019). From 2030 – 2040, storage capacity is assumed to increase at the same rate.

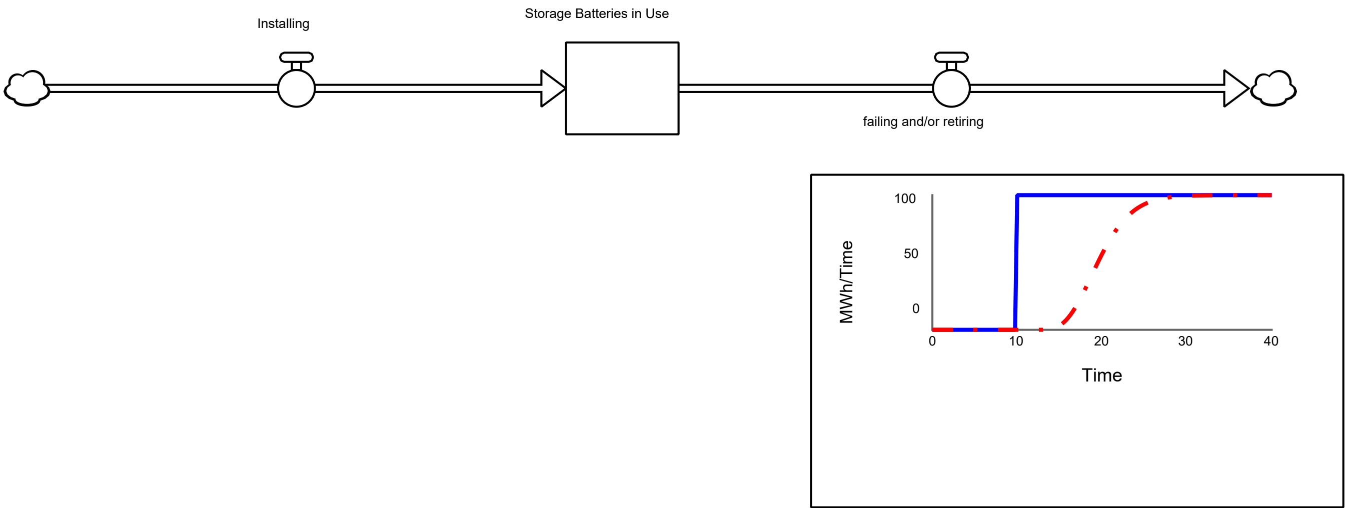

Figure 3. Stock-flow structure for the BES module, showing the delayed response of battery retirement to an increase in installation.

Internally, the model uses eight ageing vintages (known as an 8th order delay) to represent the battery retiring process (see inset in Figure 3). The average lifetime for BES batteries is assumed to be nine years in 2015 and then increases linearly to 15 years by 2040 (Kandler Smith 2017). Over time, demand for the low-cobalt NMC811 chemistry is assumed to increase (Figure 4).

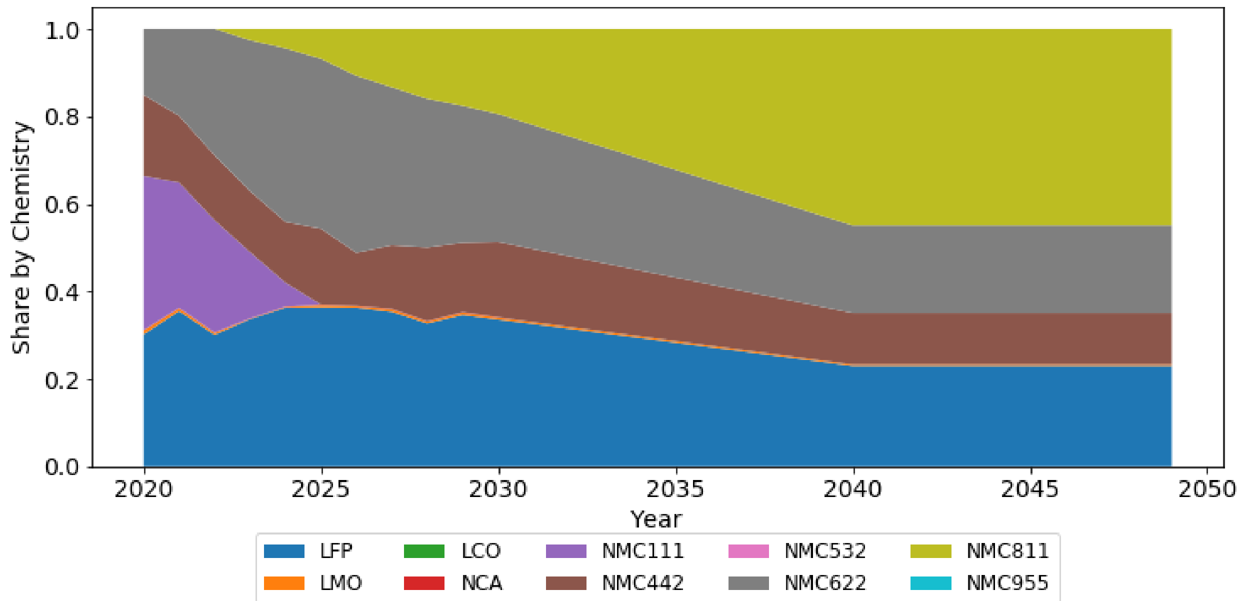

Figure 4. Distribution of new BES battery chemistry in new battery demand, 2020-2050

Table 2. BES Module: Key Units, Inputs, and Outputs

Key Units	MWh
Key Inputs	Battery demand scenario (region, chemistry), production constraints
Key Outputs to Other Modules	Battery demand, batteries in use, battery failure/retirement

2.3.3 Vehicle End-Use Modules

Each vehicle end-use module contains a parallel structure that is used to evaluate the life cycle for electric-powered vehicles and their LIBs. In this section, we begin by describing the generic structure used in each module to account for vehicles and their associated batteries. We then summarize details specific to each vehicle end-use module.

Central to the vehicle end-use modules is the structure used to account for vehicles on their first or second battery (Figure 5) based on the assumed average lifetime for batteries and vehicles. Eight vintages (8^{th} order delay) are used for the first and the second battery in vehicles. Unlike storage batteries, vehicle batteries can be replaced before a given vehicle is retired, especially earlier in the simulation when the battery lifetime is low compared to the lifetime of a vehicle (assumed to be 12 years). Accordingly, each vehicle module captures both new and replacement battery demand. Finally, if vehicles are scrapped before their battery fails (e.g., because of an accident or vehicle mechanical failure), the battery is recovered from the vehicle and either discarded or recycled.

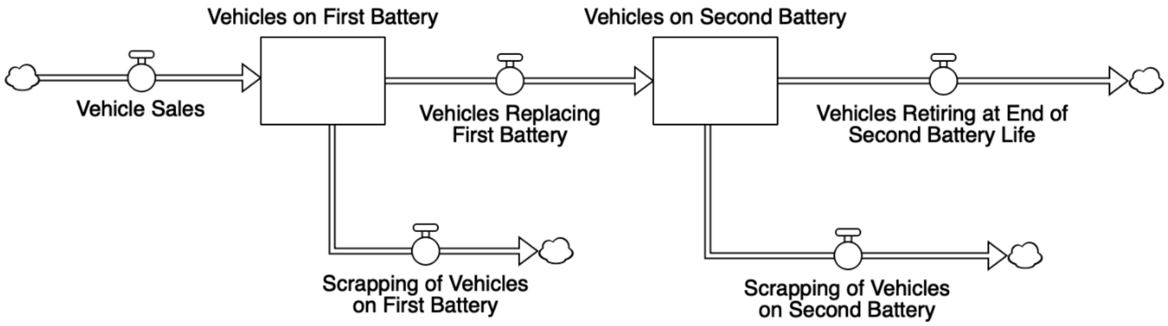

Figure 5. Model structure for co-flow of vehicles and batteries

Most of these modules incorporate both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) except for the Electric Bus and the Two- and Three-wheeled Vehicle modules which have no PHEV sales. Both the projection for vehicle sales and the distribution of chemistries used in new vehicles by vehicle type (Figure 6) are based on the 2021 Bloomberg New Energy Finance Electric Vehicle Outlook (Bloomberg NEF 2021) to 2040 and then trends are projected forward through 2050. Battery chemistries typically vary across vehicle types to optimize the performance and lifetime of the battery based on the vehicle's operational characteristics (for example, city buses tend to operate shorter duty cycles, so energy density is less of a concern, and high cost associated with use of cobalt is a concern for large commercial vehicle and thus non-cobalt chemistries dominate).

Table 3. Vehicle End-Use Modules: Key Units, Inputs, and Outputs

Key Units	MWh, Vehicles
Key Inputs	Vehicle sales scenario (region), batteries per vehicle, kWh per battery, battery chemistry scenario, production constraints, vehicle mean time to battery failure (MTBF)
Key Outputs to Other Modules	New and replacement battery demand, batteries in use, battery retirement/recovery

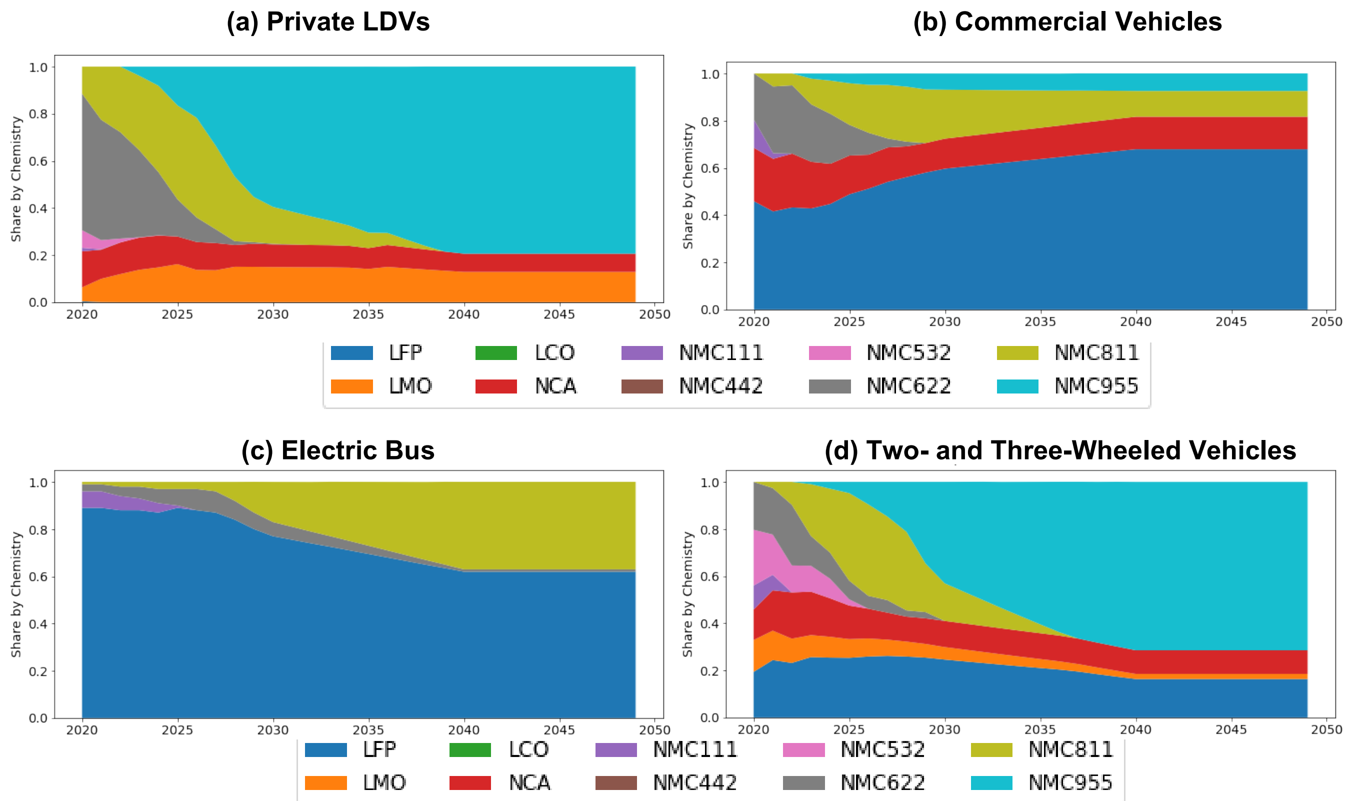

Figure 6. Distribution of new battery chemistries for each of the vehicle end-use types over time

Table 4. Vehicle Module Battery Assumptions by Vehicle Type

Vehicle Type	Battery Lifetime	Battery Energy: Linear Increase	Source
Light-duty	9 years in 2015 increasing linearly to 15 years by 2040	BEV: 48 kWh in 2020 to 90 kWh in 2040 PHEV: 10.5 kWh constant	Life: NREL Assumption Energy: NREL Assumption
Light-duty Commercial	6 years in 2015 increasing linearly to 10 years by 2040	BEV: 60 kWh in 2020 to 130 kWh in 2040 PHEV: 13 kWh in 2020 to 20 kWh in 2040	Life: NREL Assumption Energy: (International Energy Agency 2021)
Medium- and Heavy-duty Commercial	6 years in 2015 increasing linearly to 10 years by 2040	BEV: 120 kWh in 2020 to 352 kWh in 2040 PHEV: 74 kWh constant	Life: NREL Assumption Energy: (ORNL, NREL 2019)
Electric Bus	6 years in 2015 increasing linearly to 10 years by 2040	BEV: 160 kWh in 2020 to 176 kWh in 2030	Life: NREL Assumption Energy: (Bloomberg NEF 2021)
Two- and Three-Wheeled	9 years in 2015 increasing linearly to 15 years by 2040	BEV: 4.5 kWh in 2020 to 7.5 kWh in 2030	Life: NREL Assumption Energy: (Gode 2021)

2.4 Battery Manufacturing Module

The Battery Manufacturing module within LIBRA describes the development of manufacturing capacity and the subsequent production of LIBs. The model is composed of three interacting components: investment in manufacturing capacity, utilization of existing capacity to produce batteries, and financial accounting.

Investment in manufacturing capacity is represented as a demand-pull set of activities. Rather than endogenously generating investment in new facilities based on profitability metrics such as net present value, the module takes demand for new and replacement batteries as generated in end-use modules as the primary driver of investment. It should be noted that the rate of capacity expansion could be limited by factors not considered in this model.

Figure 11 provides a simplified view of the investment process. Global battery demand provides the basis for forecasted global demand, which is then compared with existing and under construction global production capacity. The resultant projected capacity shortfall or gap is then eliminated by investment in the United States and in ROW. The share of investment that is allocated to each region is determined in part by the relative cost of producing batteries in each region, and it is calibrated to reflect historical U.S. and ROW shares of investment. The calibration is used to set a weighting factor for the relative attractiveness of manufacturing capabilities in each region all else equal and this factor is used for the duration of the model simulation.

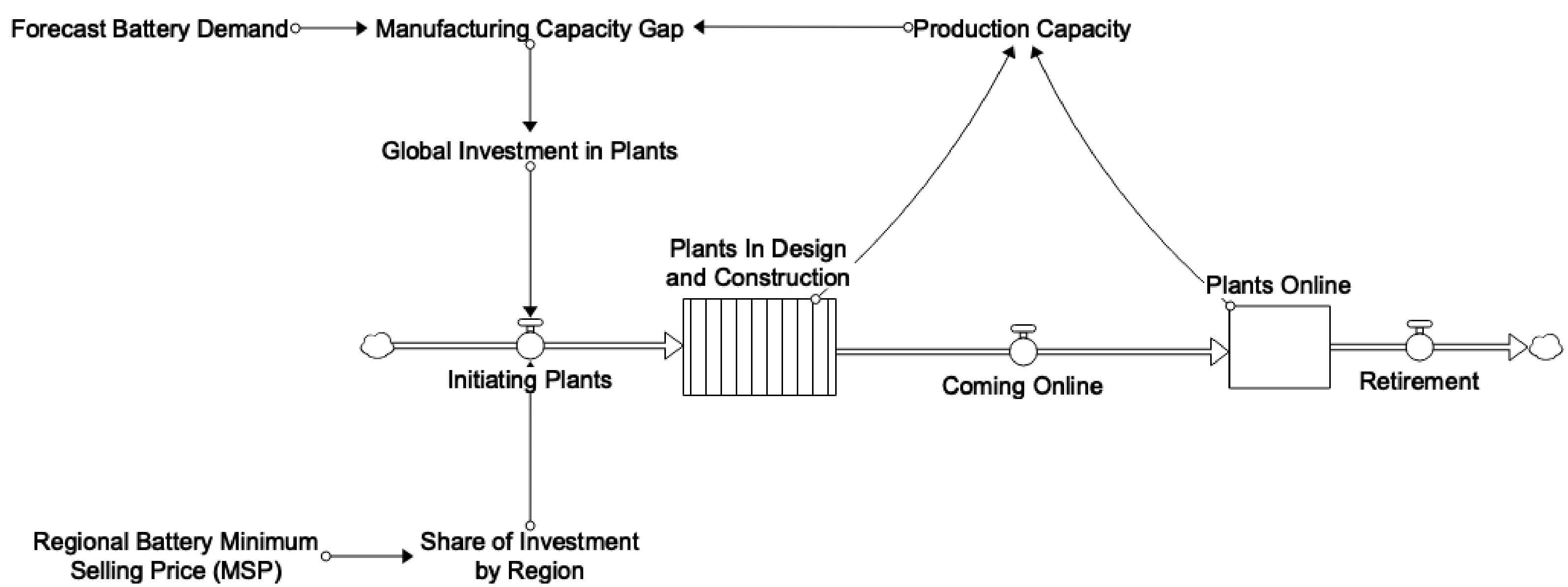

Figure 7. Simplified structure of investment in manufacturing capacity

Similar structures are used for cathode manufacturing and for battery recycling.

The model tracks facilities along with their associated production capacity. Manufacturing capacity is assumed to spend three years in design and construction. After coming online, capacity is retired at a rate determined by the scenario under consideration. In the default scenarios, retirement of facilities is assumed to be zero.

Within the Battery Manufacturing module, the buildout of manufacturing capacity and production of batteries aims to match the aggregated demand for batteries in each region. Manufacturing capacity is assumed to be flexible - changes in the demand for different battery chemistries impact the capacity utilization. Overall utilization of manufacturing capacity responds to global battery demand, but it can be constrained by shortfalls in cathode availability, which in turn might be constrained by mineral availability.

The Battery Manufacturing module uses a discounted cash flow structure to calculate the net present value of incremental investments in battery production facilities. This structure is then used to calculate a minimum selling price (MSP) for the production and sale of batteries by chemistry and region. The MSP is dictated by the price at which the plant breaks even between annual revenue and expenses (operating costs, loan payments, and interest). For future years, the MSP metric is used (with the aforementioned weighting factor) to allocate investment in additional manufacturing capacity between the United States and ROW. Battery feedstock costs are determined by the MSP for cathodes, calculated in the Cathode Manufacturing Module. Other techno-economic inputs associated with manufacturing operations (including items such as scale, capital costs, non-feedstock operating costs) are drawn from Bloomberg New Energy Finance's (BNEF's) BattMan 1.0.1 model (Bloomberg NEF 2021)

Table 5. Battery Manufacturing Module: Key Units, Inputs, and Outputs

Key Units	MWh, USD, megagram
Key Inputs	Demand for new and replacement batteries by chemistry and region, regional techno-economic inputs associated with new facilities, mineral density by battery chemistry, cathode supply, cathode MSP
Key Outputs to Other Modules	Battery production, cathode demand, mineral usage

2.5 Cathode Manufacturing Module

LIBRA's Cathode Manufacturing Module describes the development and operation of production capacity for lithium-ion cathodes. Key structures within the module include investment in new cathode production capacity, operation and utilization of existing capacity, and financial accounting used to determine the net present value of investments as well as the MSP of cathodes.

Like the Battery Manufacturing Module, the Cathode Manufacturing Module uses a demand-pull process to determine annual investment in new capacity. Forecasted demand for cathodes is based on the cathode requirements coming from the production of batteries. Investment in cathode production capacity responds to gaps between existing capacity and forecasted demand, after accounting for recycling of cathodes from the Direct Recycling Module. MSP of cathodes is used to determine the share of investment in each region. As with the Battery Manufacturing Module, investment shares are calibrated to reflect the historical split in U.S./ROW investment in capacity.

Overall utilization of existing cathode production capacity is based on production capacity relative to the demand for cathodes to be used in battery manufacture, and utilization is modulated over time with changes in demand and production prices. However, mineral feedstock constraints reduce utilization to below desired levels. Cathode production capacity is assumed to be flexible in its responses to changes in the mix of battery chemistries required by manufacturing, although future battery chemistries could be more distinct from today's with potential advances in battery technology leading to movement toward sodium or other non-lithium-ion chemistries.

A discounted cash flow structure is used to calculate the net present value of incremental investments in cathode production capacity. Additionally, this structure is used to determine an MSP for cathodes of different chemistries in each region. Like in the Battery Manufacturing module, the cathode MSP metric is used to allocate investment in manufacturing capacity between the U.S. and ROW. It also provides a price input to the direct recycling module and a feedstock cost input to the battery manufacturing module. Cathode MSP is determined by mineral prices and techno-economic inputs (for items such as capital cost, non-feedstock operating costs, and facility scale) that are drawn from BNEF's BattMan 1.0.1 model (Bloomberg New Energy Finance 2021).

Table 6. Cathode Manufacturing Module: Key Units, Inputs, and Outputs

Key Units	MWh, USD, Megagram
Key Inputs	Demand for cathodes by chemistry and region, regional techno-economic inputs associated with new facilities, mineral density use by battery chemistry, mineral availability supply, mineral prices, recycled cathode supply
Key Outputs to Other Modules	Cathode supply, cathode MSP, mineral usage

2.6 Recycling Modules

In contrast to the demand-pull investment process used for the Battery and Cathode Manufacturing Modules, the recycling Modules use economic forces to drive investment in recycling capacity. Two pathways—hydrometallurgical recycling and pyrometallurgical recycling—recover elemental nickel and cobalt from batteries, and these pathways are modeled in the HydroPyro module. Some hydrometallurgical recycling methods can recover lithium, and these processes will be examined in future research. A third pathway—direct recycling—renews cathodes for reuse and is represented in its own module. The Relative Investment Attractiveness Module provides a mechanism for allocating investment among the three pathways based on their relative financial attractiveness.

2.6.1 Hydro and Pyro Recycling Module

The HydroPyro Module represents the buildout of the recycling industry for the cobalt and nickel embedded in LIBs. Two recycling pathways—hydrometallurgical recycling and pyrometallurgical recycling—are represented in the module. Each process can exist within both the United States and ROW. Evolution of the recycling industry is determined by net present value of investing in incremental capacity for each pathway relative to other recycling pathways (including direct recycling). Investment can be constrained by feedstock availability.

Calculation of a net present value metric for hydro and pyro pathways is accomplished by using a discounted cash flow structure as well as techno-economic inputs (for inputs such as facility scale, capital cost, and non-feedstock operating costs) taken from the 2020 EverBatt model (Dai, Spangenberger, et al. 2009). Delivered feedstock costs can be defined as scenario inputs, as can region-specific incentives that are aimed at stimulating industry development.

Mineral price scenarios, along with the distribution of battery chemistries in the recycling stream and recycling process yield, are used to determine the potential annual revenues from recycling operations. Revenue is generated by the sale of recovered cathode minerals. A higher share of battery chemistries with higher cobalt content (such as LCO) in the recycling feedstock is more profitable due to the high price of cobalt by mass. However, forecasts for future battery chemistries indicate a movement away from high-cobalt chemistries due to its high cost, supply chain instability, and inhumane mining practices (van den Brink et al. 2020). As the chemistry distribution of end-of-life batteries moves away from high-cobalt configurations (Figure 8), the attractiveness of investment in destructive recycling pathways declines.

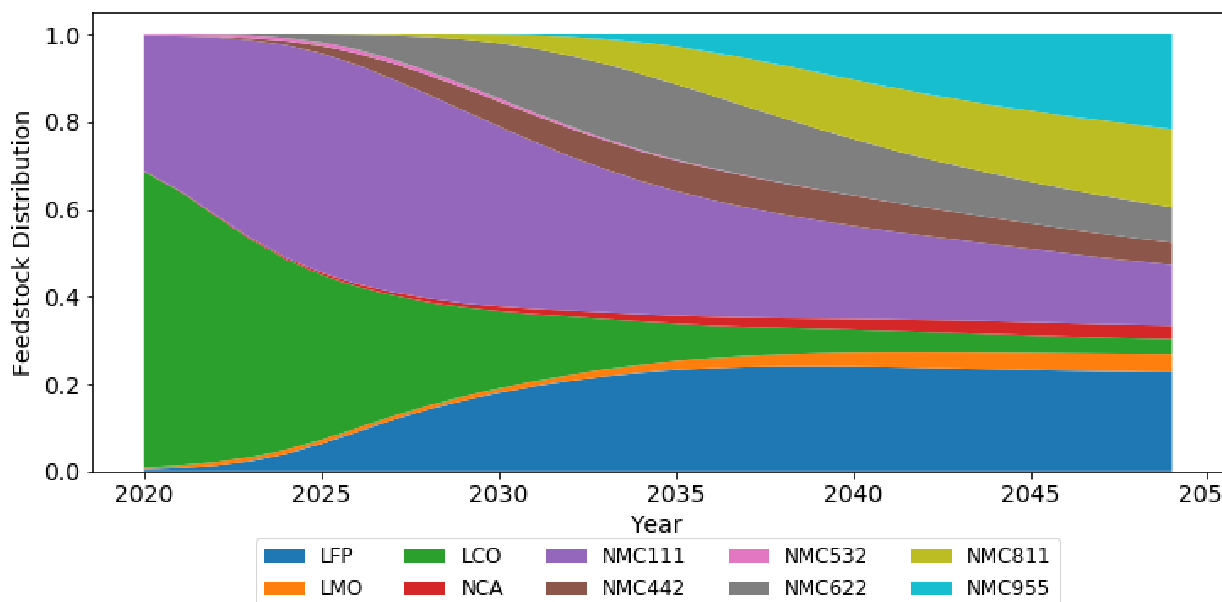

Figure 8. Distribution of chemistries for batteries reaching end-of-life and becoming available as feedstock for recycling.

Utilization of existing pyro and hydro recycling capacity is determined primarily by the cost of recycling a unit of feedstock relative to the revenue generated as a result of that recycling. As noted above, a shift over time toward chemistries with less cobalt can reduce recycling revenue streams, and as a result can lead to reduced utilization. However, the model allows for some degree of sorting in the recycling stream such that only higher-valued batteries are used.

Table 7. Hydro and Pyro Recycling Module: Key Units, Inputs, and Outputs

Key Units	USD, megagram
Key Inputs	Availability or recyclable batteries, regional techno-economic inputs associated with new facilities, mineral density use by battery chemistry, mineral prices
Key Outputs to Other Modules	Net present value metric, use of recycled batteries, recycling of cobalt and nickel

2.6.2 Direct Recycling Module

In contrast to the Pyro and Hydro recycling pathways, in which minerals are recovered through processes that destroy the battery, direct recycling involves the recovery and renewal of cathodes. Development of this recycling industry is determined by the net present value of investment in a recycling pathway in a given year, relative to the net present value for other recycling pathways. Investment can also be constrained by feedstock availability.

Like in the other recycling pathways, the net present value metric for incremental investment in direct recycling comes from a discounted cash flow structure that uses techno-economic inputs (e.g., facility scale, capital cost, and non-feedstock operating costs) from the 2020 EverBatt model (Dai, Spangenberger, et al. 2009). Delivered feedstock costs can be defined as scenario inputs, as can region-specific incentives that are aimed at stimulating industry development. An important difference in the net present value calculation is the source of revenue. While hydro and pyro revenues are determined by the sale of nickel and cobalt from recycled batteries, direct recycling revenues are set by the MSP of cathodes as determined in the Cathode Manufacturing Module. Investment in new capacity, and utilization of existing capacity, will be constrained whenever the MSP of cathodes from direct recycled batteries is higher than the MSP of newly-manufactured batteries.

Table 8. Direct Recycling Module: Key Units, Inputs, and Outputs

Key Units	USD, megagram (of cathode)
Key Inputs	Availability or recyclable batteries, regional techno-economic inputs associated with new facilities, mineral density use by battery chemistry, cathode MSP
Key Outputs to Other Modules	Net present value metric, use of recycled batteries, cathode production

2.6.3 Relative Investment Attractiveness Module

Competition between the three recycling processes is handled by logic held in the Relative Investment in Recycling Attractiveness Module. At each time step and for each region, this logic considers the plants that are online or under construction. Then, based on feedstock availability and the net present value for each of the technologies, the module determines the attractiveness of investment in each plant type. The aggregation of recycling capacity across the three processes and the different costs associated with battery feedstock sorting are also housed in this module and then passed to the Direct and Destructive Recycling Modules.

Table 9. Relative Investment Attractiveness Module: Key Units, Inputs, and Outputs

Key Units	USD, projects per year
Key Inputs	Net present value metric, attractiveness weighting factor
Key Outputs to Other Modules	Desired facilities per year, total recycling throughput

2.7 Battery Mineral Marketplace Accounting

2.7.1 Battery Marketplace Module

The Battery Marketplace Module works to connect the battery end-use modules with the manufacturing, recycling, and mineral modules. It accomplishes this purpose in three ways. First, it aggregates multiple demand, supply, and potential recycling streams from the end-use modules. Second, it converts between battery energy content and associated mineral (lithium, nickel, cobalt) mass, based on characteristics by battery chemistry given by the EverBatt model. Third, the module calculates flows of battery collection for recycling and battery discards.

Table 10. Battery Marketplace Module: Key Units, Inputs, and Outputs

Key Units	MWh
Key Inputs	End-use battery demand
Key Outputs to Other Modules	Battery demand, battery supply, mineral collection for recycling, battery discard

2.7.2 Minerals Marketplace

The Minerals Marketplace Module provides an accounting structure to track minerals (lithium, cobalt, nickel) associated with LIBs, as batteries move from pre-cradle to grave (Figure 9). The stock-flow structure pulls virgin minerals from the reserve of newly mined material to a regional inventory. Inventory then moves to cathode and battery manufacturing to meet the needs of the various demand streams (EVs, BES, and consumer electronics). At end of life, minerals are either collected to be recycled or landfilled, and they exit the system. Minerals in batteries processed by destructive recycling plants are returned to regional inventories less process losses and are assumed to be the same quality as newly mined minerals. Minerals in directly recycled cathodes reenter the model structure with newly-manufactured cathodes available for battery manufacturing and are assumed to compete directly with those cathodes.

Mineral prices are exogenous, with historical prices based on the U.S. Geological Survey and future prices increasing by 2% annually (U.S. Geological Survey (USGS) 2021). We assume this simple static annual growth in future prices to reflect a continuous increase in demand for these critical battery materials.

Table 11. Minerals Marketplace: Key Units and Inputs

Key Units	Megagrams
Key Inputs	Cathode production, battery production, battery installation in end uses, battery collection at end-of-life, battery recycling, battery discard

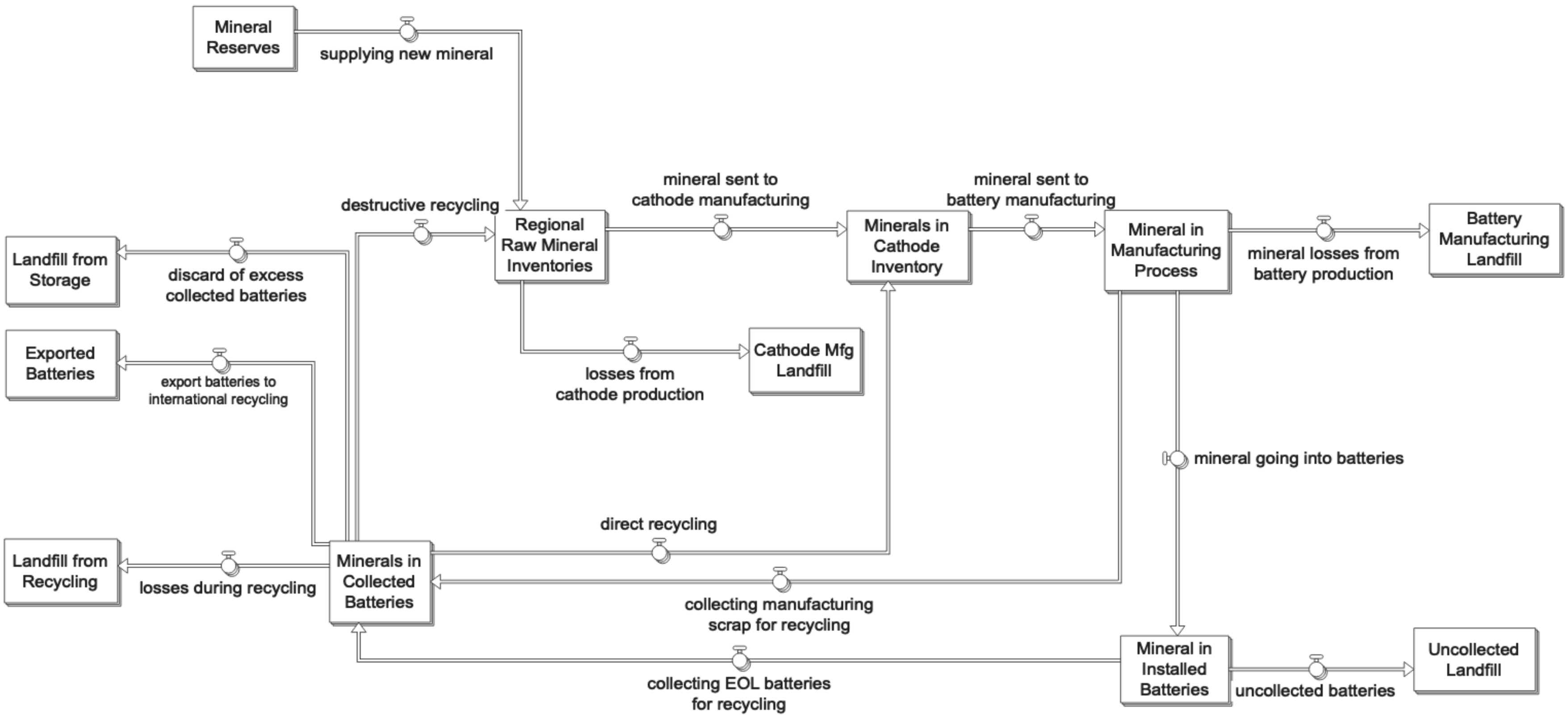

Figure 9. Tracking minerals through battery life cycle

Stocks represent different quantities of minerals embedded in batteries at different stages of their life cycle. Flows move minerals through the life cycle and are connected to flows in other modules.

3 Scenario Development

For the purposes of tractability, we use vignettes to develop our scenarios for further analysis. Vignettes are thematic groups of model parameters with specific values which, when combined, can be used to define a scenario. The vignette approach allows us to easily vary across sets of model parameters for evaluation of modeled scenarios. For the scenarios assessed in this report, we first developed a set of ten vignettes to categorize relevant input parameters for use in scenario analysis. Each vignette was established by conceptually grouping impacts, actions, or characteristics of the LIB supply chain. We also made these groupings based on areas of interest with potential for impacting the development of the BES manufacturing industry and related components of the supply chain. The vignettes span both battery manufacturing and recycling, and they include parametric levers that range from the simulation of government policies (e.g., incentives and subsidies) or financial specifications (e.g., tax/interest rates and loan terms) to the operating characteristics of the plants themselves. A description of each vignette and a summary of the parameters included in each can be found in Table 12.

Table 12. Designed Vignettes with Sample Subset of Variations

ID	Vignette Name	Description	Sample Variations
1	Business as Usual	Default values for model	N/A
2	Battery Adoption	Related to the demand for batteries across battery types, including storage, EVs, and consumer electronics	• Low/High EV Adoption • Low/High BES Sales
3	Manufacturing	Parameters defining the construction and operation of battery and cathode manufacturing facilities	• Low/High Op Costs • Low/High Fixed capital investment [FCI] • Large Plant Throughput • Low/High Yield
4	Manufacturing Learning	Parameters defining the progression of industrial learning for cathode and manufacturing plants	• High Cathode Maturity • High Manufacturing Maturity • Low/High Cathode Progress Ratio
5	Battery Tech	Parameters relating to the expected useful lifetime for batteries	• Short/Long Average EV Battery Lifetime
6	Minerals	Parameters relating to mineral economics and handling	• Low/High Material Costs • Low/High Cathode Material Price • Close Mineral Price Coupling • Long-term Battery Storage
7	Finance	Parameters relating to the cost to invest and operate cathode/battery manufacturing plants or recycling plants	• Low/High Debt Interest Rate • 5% Tax Rate • Low/High Rate of Return • Short/Long Loan Term • High Capital Investment
8	Government Policy	Parameters driving policy intervention	• Manufacturing Loan Guarantee • Manufacturing Feedstock Subsidy • Manufacturing FCI Subsidy

ID	Vignette Name	Description	Sample Variations
9	Recycling	Parameters defining the construction and operation of recycling facilities	• Low/High Operating Cost • Low/High FCI • Large Plant Throughput • Low Yield
10	Recycling Learning	Parameters defining the progression of industrial learning for recycling plants	• Low Commercial Maturity • Low/High Progress Ratio

The LIBRA model is built on a business-as-usual (BAU) case with parameter values derived primarily from Argonne National Laboratory's EverBatt model (Dai, Spangenberger, et al. 2009). Variations on the BAU case are created by varying subsets of the parameter groups to simulate specific development paths for the industry. Most of the values for the defined variations are percentage shares of the BAU value that range from 50% to 150% depending on the parameter. The share selected for each parameter is based on judgement by the LIBRA developers.

We defined three to nine variations for each vignette. These variations are labeled with a numerical ID that, when combined with the vignette ID can be used as a unique identifier for storage in and retrieval from our Postgres database instance. This database was not used to generate the initial results included in this report, but it will be a useful framework for additional scenario analysis.

3.1 Scenarios

We compiled 50 variations across 10 vignettes to illustrate the wide range of cases where LIBRA could be applied in evaluating potential futures for the U.S. LIB supply chain. Table 12 summarizes the vignettes and provides a sample of the variations included under each. These variations can be used to estimate the conditions under which the BES manufacturing industry can grow in the United States versus conditions that stifle development. Variations can also be used to target other steps in the supply chain, such as the mineral supply, cathode production, or battery end of life, including hydrometallurgical, pyrometallurgical, and direct recycling.

We then developed seven scenarios (Table 13) that are composed of different variations from each vignette from Table 12. The first column in Table 13 lists the scenario names, each of which is defined by the combination of variations selected across the vignettes listed in the first row. The EverBatt-driven Baseline scenario uses the BAU variations for all vignettes, and each of the other scenarios is paired with the two scenarios straddling the BAU values across a subset of the vignettes. For example, Carbon Economy and Green Economy represent cases that are driven by less or more adoption of "green" technology, respectively, than the Baseline scenario.

Table 13 Definitions of Analyzed Scenarios

Scenario	Battery Adoption	Manufacturing	Manufacturing Learning	Battery Technology	Minerals	Finance	Government Policy	Recycling	Recycling Learning
Baseline	BAU	BAU	BAU	BAU	BAU	BAU	BAU	BAU	BAU
Carbon Economy	Low EV adoption	Low yield	BAU	BAU	High cathode price	High debt interest rates	BAU	High FCI	BAU
Green Economy	High EV adoption	High yield	BAU	Long EV battery life	Low cathode price	Low debt interest rates	Cathode/ Manufacturing loan guarantees	BAU	BAU
Slow Development	BAU	Low yield	BAU	Long EV battery life	High material cost	High debt interest rates	BAU	BAU	BAU
Fast Development	BAU	High yield	BAU	Short EV battery life	Low material cost	Low debt interest rates	Cathode/ Manufacturing FCI subsidy	BAU	BAU
Slow Learning	BAU	BAU	High progress ratio cathode and manufacturing	BAU	BAU	Short loan term	BAU	BAU	High progress ratio
Fast Learning	BAU	BAU	Low progress ratio cathode and manufacturing	BAU	BAU	Long loan term	Cathode/ Manufacturing feedstock subsidy	BAU	Low progress ratio

These seven scenarios were run in LIBRA, with a primary focus on the maturity of the domestic U.S. battery manufacturing industry, to see how they impacted the different portions of the supply chain represented in the model. Figure 10 shows the industrial maturity of the domestic industry across the seven scenarios. The Slow and Fast Learning scenarios are differentiated primarily by changes in the learning rate for the industry, whereas maturity under the other scenarios is driven by differences in battery manufacturing techno-economics and demand.

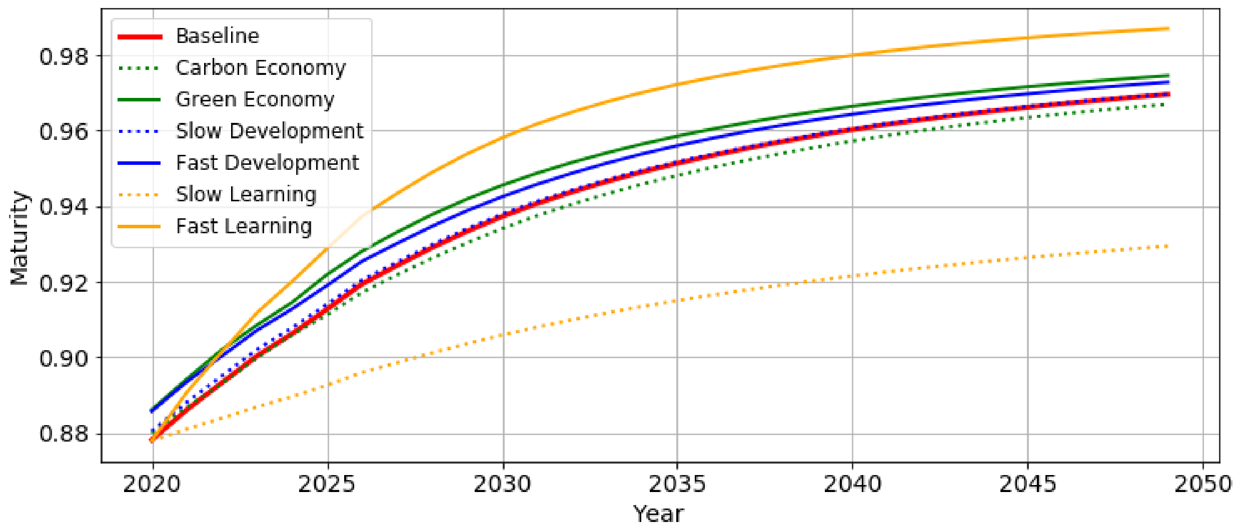

Figure 10. Industrial maturity of U.S. battery manufacturing

The outliers in U.S. manufacturing output are the Carbon and Green Economy scenarios, with low and high energy technology adoption respectively. The other scenarios differ based on the attractiveness for investment in battery manufacturing capabilities in the United States. For example, the High Yield variation from the Manufacturing vignette used in the Fast Development scenario enables higher manufacturing output for similar levels of investment in U.S. manufacturing plants.

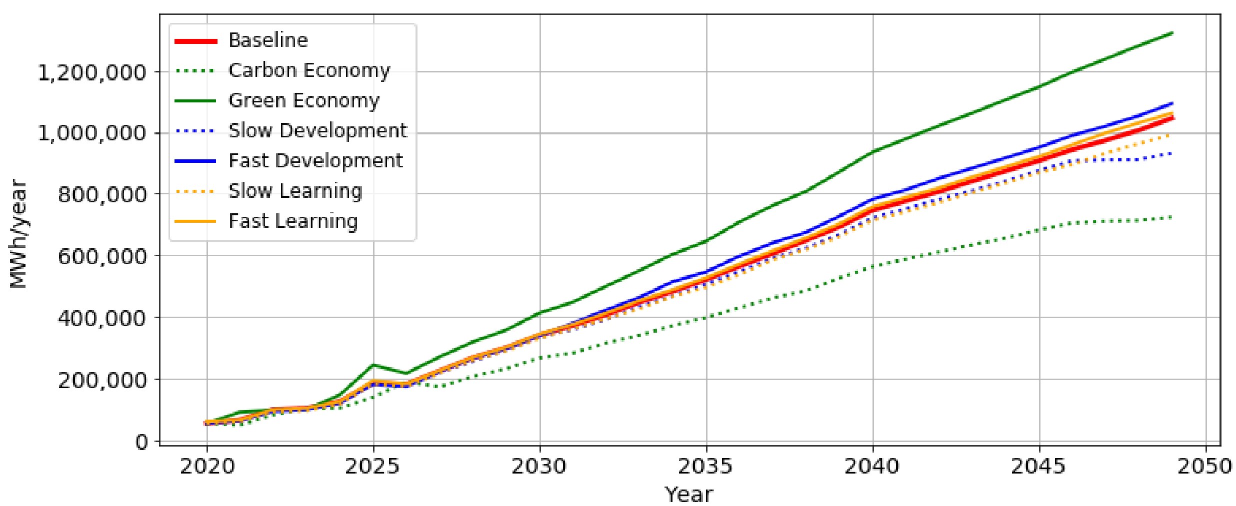

Figure 11. U.S. battery manufacturing output

3.2 Sensitivity Analysis

We also ran a sensitivity analysis on the LIBRA model to determine the prioritization of input factors in terms of how variation in their value might (or might not) be correlated to variations in selected model outputs. We chose the Morris method, which randomizes factor values between a given minimum and maximum to determine parametric elementary effects on a selected output (the changes in an output that can be linked directly to changes in a single input) (Morris 1991, Ruano, Seco and Ferrer 2012). While this method is useful for determining relative amounts of influence of a large set of factors qualitatively, further study is required to determine absolute amounts of influence and the exact nature of any nonlinearities in parameter co-variance.

We selected battery manufacturing output in the year 2040 as our output factor of interest for this study. After running the elementary effects study, we identified 20 influential factors by selecting the 90th percentile of the L^2 norm of μ^* and σ, where μ^* is an indicator of overall influence and σ is an indicator of nonlinearity and interactions with other factors. A nonzero L^2 norm indicates an influential factor and higher values indicate greater influence. While a higher σ values indicate nonlinear interactions, those interactions are not investigated in this work.

The factor names shown in Table 14 are structured as <Module Name>.<Parameter Name> [Array Value], where the modules include those shown in the top-level model structure from Figure 1. Three factors stand out as most influential:

- LDV.V Sales Multiplier (and other vehicle sales multipliers)
- Cathode.Retirement Fraction (for the United States and ROW)
- LDV.MTBF V 1 (average time to failure for an LDV battery).

Each vehicle sales multiplier for the various vehicle types—LDVs, light-duty commercial vehicles, medium- and heavy-duty vehicles, and two- and three wheeled vehicles—is impactful for the total battery manufacturing output of the United States, as they are significant drivers of annual demand. E-buses are included in LIBRA, but they are not sold in significant quantities in the United States, based on sales projection used from Bloomberg NEF (2021). Variations in the Cathode.Retirement Fraction in the United States and ROW can lead to significant impacts on the long-term battery manufacturing output of the United States, as the availability of cathodes is critical for the viability of the overall supply chain.

Finally, LDV.MTBF V 1, the mean time to battery failure (MTBF) for LDVs, controls the average lifetime for light-duty vehicle batteries: 8 years for the BAU case. LIBRA assumes a vehicle battery can be replaced at most one time with an average assumed vehicle lifetime of 12 years. This parameter can be a powerful driver of battery demand from EVs and therefore influences the total U.S. battery manufacturing output in 2040. Another parameter of note, Minerals Market.mineral price growth rate, is an assumed annual monotonic growth in the future prices of lithium, nickel, and cobalt used in LIB manufacturing to reflect their rapidly increasing demand. Though these prices have been historically volatile, a monotonic increase more easily isolates the trending effects of variations in other input parameters. The top influential factors listed in Table 14 are generally expected results from this analysis in terms of their potential to influence the U.S. battery manufacturing output by 2040.

Table 14. Ordered Influential Factors for Total 2040 U.S. Manufacturing Output

Rank	Factor	Normalized L^2 Norm	μ^*	σ	Description
1	LDV.V Sales Multiplier	1.00000	118,545	12,821	Multiplier used to modify the projection for annual sales of light-duty EVs
2	Cathode.Retirement Fraction [ROW]	0.88212	99,074	24,211	Fraction of cathode plants that are retired annually in ROW
3	Cathode.Retirement Fraction [US]	0.52286	57,875	21,757	Fraction of cathode plants that are retired annually in the United States
4	LCV.V Sales Multiplier	0.25235	35,425	5,468	Multiplier used to modify the projection for annual sales of light-duty commercial EVs
5	MHDV.V Sales Multiplier	0.16171	24,058	4,972	Multiplier used to modify the projection for annual sales of medium- and heavy-duty commercial EVs
6	LDV.MTBF V 1	0.11280	19,106	5,918	Mean time for the failure of light-duty vehicle batteries (first battery for vehicle)
7	Manufacturing. Initial MSP Metric [NMC811]	0.03998	8,154	8,640	Initial MSP for NMC811 batteries
8	Manufacturing.Retirement Fraction [US]	0.01870	5,449	5,847	Fraction of battery manufacturing plants that are retired annually in the United States
9	Manufacturing. Initial MSP Metric [LFP]	0.01045	5,011	5,642	Initial MSP for lithium iron phosphate (LFP) batteries
10	Manufacturing.FCI Scale Factor	0.00914	3,672	4,770	FCI exponent scaling factor used to assess impact of economies of scale on FCI
11	Minerals Market.Mineral Price Growth Rate	0.00850	4,634	5,213	Annual assumed growth rate in lithium, cobalt, and nickel prices
12	Manufacturing. Initial MSP Metric [NMC532]	0.00740	3,797	4,750	Initial MSP for NMC532 batteries
13	Manufacturing. Initial MSP Metric [NMC622]	0.00721	5,285	6,306	Initial MSP for NMC622 batteries
14	Manufacturing. Initial MSP Metric [LMO]	0.00701	3,853	4,766	Initial MSP for lithium-ion manganese oxide (LMO) batteries
15	Manufacturing. Initial MSP Metric [NMC955]	0.00502	6,481	7,569	Initial MSP for NMC955 batteries
16	LDV.Order of the Delay	0.00472	4,126	5,055	Average LDV lifetime

Rank	Factor	Normalized L^2 Norm	μ^*	σ	Description
17	Manufacturing. Initial MSP Metric [NCA]	0.00382	3,498	4,501	Initial MSP for lithium nickel-cobalt-aluminum oxide (NCA) batteries
18	Manufacturing.Mature Industry Rate of Return as PCT[US]	0.00165	3,506	4,642	Assumed required rate of return for the battery manufacturing industry
19	Two3Wheel.V Sales Multiplier	0.00014	3,005	3,965	Multiplier used to modify the projection for annual sales of two- and three-wheeled electric vehicles
20	Manufacturing.Initial MSP Metric [LCO]	0.00000	3,463	4,495	Initial MSP for lithium cobalt (LCO) batteries

4 Summary

The LIBRA model has been developed to provide insight into the LIB industry and its potential buildout in response to market factors and technological advancements. LIBRA is designed to be modular and extensible; therefore, it can be readily updated to include additional regions, technologies, and markets. We present seven scenarios that were developed in coordination with DOE and represent a range of plausible conditions. Our results from the scenario analysis show that under the Green Economy Scenario there is the potential for around a 25% increase in domestic LIB manufacturing capacity as compared to the Baseline Scenario. From the sensitivity results, the model factors that are most influential on the manufacturing capacity are the sales forecasts for EVs, rate of cathode retirement, and the average time for LIB failure. The results presented in this report serve to illustrate the utility of the LIBRA model as a tool to aid in decision support and to evaluate plausible future scenarios of varying market conditions.

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Appendix A. Summary of Sensitivity Analysis Factors

Table A-1. Elementary Effects Factor Ranges

Factor	Minimum	Maximum
Cathode.Pct of Time Online[US]	0.85	0.95
Cathode.Background Subs[FCI]	0	1
Cathode.Background Subs[Feedstock]	0	1
Cathode.Background Subs[Loan]	0	1
Cathode.Background Subs[Price]	0	1
Cathode.Debt Interest Rate as Pct[US]	8	12
Cathode.Expected Fixed Op Cost[ROW]	90	360
Cathode.Expected Fixed Op Cost[US]	180.5	722.0
Cathode.Expected Tax Rate[US]	0	0.2
Cathode.FCI Scale Factor	0.5	2.0
Cathode.initial MSP metric[LCO]	7,500	30,000
Cathode.initial MSP metric[LFP]	250	1,000
Cathode.initial MSP metric[LMO]	250	1,000
Cathode.initial MSP metric[NCA]	5,000	20,000
Cathode.initial MSP metric[NMC111]	5,000	20,000
Cathode.initial MSP metric[NMC442]	5,000	20,000
Cathode.initial MSP metric[NMC532]	5,000	20,000
Cathode.initial MSP metric[NMC622]	5,000	20,000
Cathode.initial MSP metric[NMC811]	5,000	20,000
Cathode.initial MSP metric[NMC955]	5,000	20,000
Cathode.Mature Industry FCI[ROW]	2,941.5	11,766.0
Cathode.Mature Industry FCI[US]	3,268.5	13,074.0
Cathode.Mature Industry Rate of Return as PCT[US]	10	20
Cathode.Policy Start[FCI]	2022	2030
Cathode.Policy Start[Feedstock]	2022	2030
Cathode.Policy Start[Loan]	2022	2030
Cathode.Policy Start[Price]	2022	2030
Cathode.term of loan[US]	8	12
Consumer.recycle rate from drawer[US]	0.0	0.1
DirectRecycle.Pct of Time Online[US]	0.85	0.95
DirectRecycle.Avg transport miles[US, Road]	400	500
DirectRecycle.Avg transport miles[US, TrainRail]	400	500

Factor	Minimum	Maximum
DirectRecycle.Background Subs[FCI]	0	1
DirectRecycle.Background Subs[Feedstock]	0	1
DirectRecycle.Background Subs[Loan]	0	1
DirectRecycle.Background Subs[Price]	0	1
DirectRecycle.Debt Interest Rate as Pct[US]	8	12
DirectRecycle.degree of price coupling by mineral[Co]	0.05	0.3
DirectRecycle.degree of price coupling by mineral[Li]	0.05	0.3
DirectRecycle.degree of price coupling by mineral[Ni]	0.05	0.3
DirectRecycle.Expected Fixed Op Cost	480	680
DirectRecycle.Expected Tax Rate[US]	0.0	0.2
DirectRecycle.Expected transport costs per mile[US, Road]	1	3
DirectRecycle.Expected transport costs per mile[US, TrainRail]	0.05	0.15
DirectRecycle.FCI scale factor	0.1	0.5
DirectRecycle.Initial Indices of Commercial Maturity[US]	0.7	0.9
DirectRecycle.Initial Indices of PC Maturity[US]	0.7	0.9
DirectRecycle.Initial Indices of Pilot Maturity[US]	0.7	0.9
DirectRecycle.Mature Industry Equity Fraction[US]	0.25	0.5
DirectRecycle.Mature Industry FCI[US]	26,143,257.9	104,573,032.0
DirectRecycle.Mature Industry Rate of Return as PCT[US]	10	20
DirectRecycle.Mature Thruput Capacity	9,400	13,400
DirectRecycle.Max facility starts[US]	50	200
DirectRecycle.NPV metric Other	10,000	20,000
DirectRecycle.PC Progress Ratios[US]	0.6	0.9
DirectRecycle.Pilot Progress Ratios[US]	0.7	0.8
DirectRecycle.Policy Start[FCI]	2022	2030
DirectRecycle.Policy Start[Feedstock]	2022	2030
DirectRecycle.Policy Start[Loan]	2022	2030
DirectRecycle.Policy Start[Price]	2022	2030
DirectRecycle.Progress Ratios Commercial[US]	0.6	0.9
DirectRecycle.Retirement Fraction[US]	0.0	0.1
DirectRecycle.Road Share of Transport	0.1	0.3
DirectRecycle.term of loan[US]	8	12
DirectRecycle.time to engage price coupling[Co]	2010	2020
DirectRecycle.time to engage price coupling[Li]	2010	2020

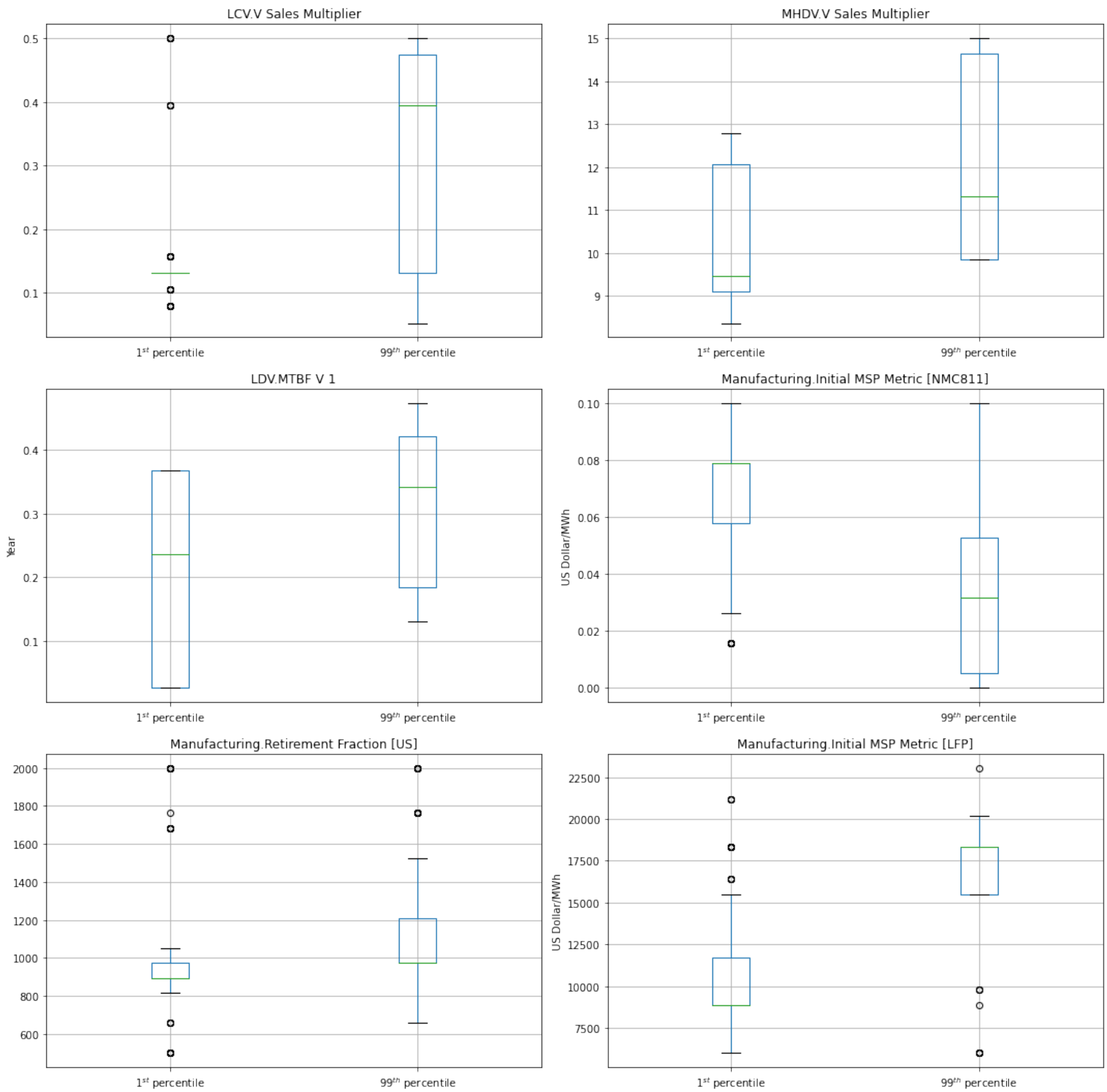
Factor	Minimum	Maximum
DirectRecycle.time to engage price coupling[Ni]	2010	2020
DirectRecycle.Working Capital pct as fraction	0.05	0.15
EBus.V Sales multiplier	0.0	0.5
HydroPyro.Pct of Time Online[US, hydro]	0.85	0.95
HydroPyro.Pct of Time Online[US, pyro]	0.85	0.95
HydroPyro.Avg transport miles[US, Road]	400	500
HydroPyro.Avg transport miles[US, TrainRail]	400	500
HydroPyro.Background Subs[FCI]	0	1
HydroPyro.Background Subs[Feedstock]	0	1
HydroPyro.Background Subs[Loan]	0	1
HydroPyro.Background Subs[Price]	0	1
HydroPyro.Base feedstock cost by chemistry[LCO]	0	100
HydroPyro.Base feedstock cost by chemistry[LFP]	0	100
HydroPyro.Base feedstock cost by chemistry[LMO]	100	300
HydroPyro.Base feedstock cost by chemistry[NCA]	0	100
HydroPyro.Base feedstock cost by chemistry[NMC111]	1,900	2,100
HydroPyro.Base feedstock cost by chemistry[NMC442]	0	100
HydroPyro.Base feedstock cost by chemistry[NMC532]	0	100
HydroPyro.Base feedstock cost by chemistry[NMC622]	-2,100	-1,900
HydroPyro.Base feedstock cost by chemistry[NMC811]	-1,100	-900
HydroPyro.Base feedstock cost by chemistry[NMC955]	0	100
HydroPyro.Debt Interest Rate as Pct[US, hydro]	8	12
HydroPyro.Debt Interest Rate as Pct[US, pyro]	8	12
HydroPyro.degree of price coupling by mineral[Co]	0.05	0.3
HydroPyro.degree of price coupling by mineral[Li]	0.05	0.3
HydroPyro.degree of price coupling by mineral[Ni]	0.05	0.3
HydroPyro.Expected Fixed Op Cost[hydro]	400	600
HydroPyro.Expected Fixed Op Cost[pyro]	750	1,050
HydroPyro.Expected Tax Rate[US]	0.0	0.2
HydroPyro.Expected transport costs per mile[US, Road]	1	3
HydroPyro.Expected transport costs per mile[US, TrainRail]	0.05	0.15
HydroPyro.FCI scale factor[hydro]	0.1	0.5
HydroPyro.FCI scale factor[pyro]	0.1	0.5
HydroPyro.fraction of Commercial cost growth anticipated	0.8	1.2

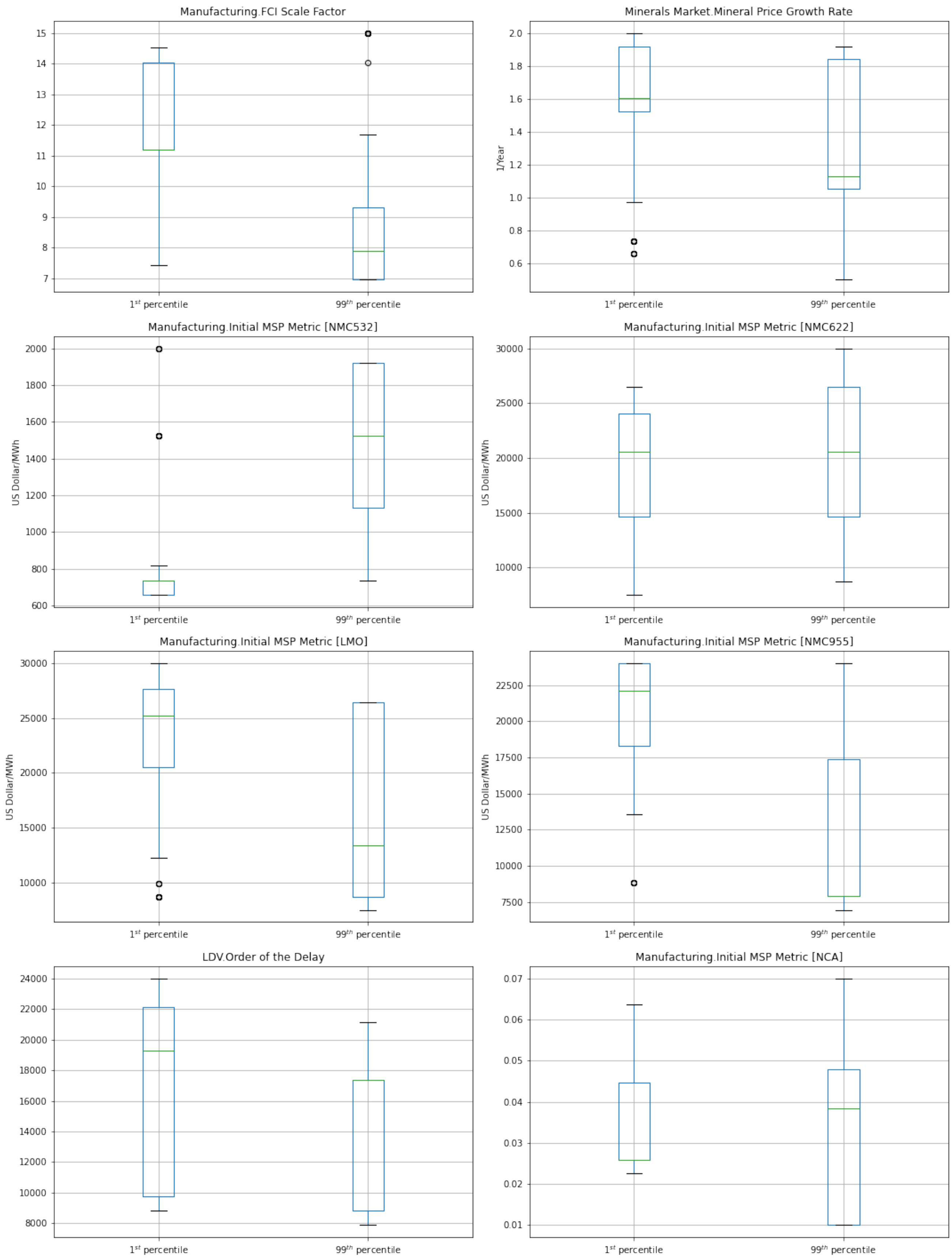
Factor	Minimum	Maximum
HydroPyro.Initial Indices of Commercial Maturity[US, hydro]	0.7	0.9
HydroPyro.Initial Indices of Commercial Maturity[US, pyro]	0.7	0.9
HydroPyro.Initial Indices of PC Maturity[US, hydro]	0.7	0.9
HydroPyro.Initial Indices of PC Maturity[US, pyro]	0.7	0.9
HydroPyro.Initial Indices of Pilot Maturity[US, hydro]	0.7	0.9
HydroPyro.Initial Indices of Pilot Maturity[US, pyro]	0.7	0.9
HydroPyro.Mature Industry Equity Fraction[US]	0.25	0.5
HydroPyro.Mature Industry FCI[US,hydro]	22,463,349.8	89,853,399.2
HydroPyro.Mature Industry FCI[US,pyro]	40,783,268.7	163,133,075
HydroPyro.Mature Industry Rate of Return as PCT[US]	10	20
HydroPyro.Mature Thruput Capacity[hydro]	9,400	13,400
HydroPyro.Mature Thruput Capacity[pyro]	9,400	13,400
HydroPyro.Max facility starts[US]	50	200
HydroPyro.NPV metric Other	10,000	20,000
HydroPyro.PC Progress Ratios[US, hydro]	0.6	0.9
HydroPyro.PC Progress Ratios[US, pyro]	0.6	0.9
HydroPyro.Pilot Progress Ratios[US, hydro]	0.7	0.8
HydroPyro.Pilot Progress Ratios[US, pyro]	0.7	0.8
HydroPyro.Policy Start[FCI]	2022	2030
HydroPyro.Policy Start[Feedstock]	2022	2030
HydroPyro.Policy Start[Loan]	2022	2030
HydroPyro.Policy Start[Price]	2022	2030
HydroPyro.Policy Targeted Pathways[hydro]	0	1
HydroPyro.Policy Targeted Pathways[pyro]	0	1
HydroPyro.Progress Ratios Commercial[US, hydro]	0.6	0.9
HydroPyro.Progress Ratios Commercial[US, pyro]	0.6	0.9
HydroPyro.Retirement Fraction[US, hydro]	0.0	0.1
HydroPyro.Retirement Fraction[US, pyro]	0.0	0.1
HydroPyro.Road Share of Transport	0.1	0.3
HydroPyro.term of loan[US, hydro]	8	12
HydroPyro.term of loan[US, pyro]	8	12
HydroPyro.time to engage price coupling[Co]	2010	2020
HydroPyro.time to engage price coupling[Li]	2010	2020
HydroPyro.time to engage price coupling[Ni]	2010	2020

Factor	Minimum	Maximum
HydroPyro.Working Capital pct as fraction	0.05	0.15
HydroPyro.Years in D and C[US, hydro]	2	4
HydroPyro.Years in D and C[US, pyro]	2	4
DirectRecycle.Years in D and C[US]	2	4
LCV.V Sales multiplier	0.0	0.5
LDV.MTBF V 1	8	15
LDV.MTBF V 2	8	15
LDV.Order of the Delay	6	15
LDV.time to recycle batteries	0.3	0.7
LDV.V Sales multiplier	0.0	0.5
Manufacturing.Pct of Time Online[US]	0.85	0.95
Manufacturing.Background Subs[FCI]	0	1
Manufacturing.Background Subs[Feedstock]	0	1
Manufacturing.Background Subs[Loan]	0	1
Manufacturing.Background Subs[Price]	0	1
Manufacturing.Debt Interest Rate as Pct[US]	8	12
Manufacturing.Expected Fixed Op Cost[US]	0.02623	0.10492
Manufacturing.Expected Tax Rate[US]	0.0	0.2
Manufacturing.FCI Scale Factor	0.5	2.0
Manufacturing.initial MSP metric[LCO]	7,500	30,000
Manufacturing.initial MSP metric[LFP]	500	2,000
Manufacturing.initial MSP metric[LMO]	500	2,000
Manufacturing.initial MSP metric[NCA]	7,500	30,000
Manufacturing.initial MSP metric[NMC111]	7,500	30,000
Manufacturing.initial MSP metric[NMC442]	7,500	30,000
Manufacturing.initial MSP metric[NMC532]	7,500	30,000
Manufacturing.initial MSP metric[NMC622]	6,000	24,000
Manufacturing.initial MSP metric[NMC811]	6,000	24,000
Manufacturing.initial MSP metric[NMC955]	6,000	24,000
Manufacturing.Mature Industry FCI[US]	468.838743	1875.354970
Manufacturing.Mature Industry Rate of Return as PCT[US]	10	20
Manufacturing.Policy Start[FCI]	2022	2030
Manufacturing.Policy Start[Feedstock]	2022	2030
Manufacturing.Policy Start[Loan]	2022	2030

Factor	Minimum	Maximum
Manufacturing.Policy Start[Price]	2022	2030
Manufacturing.term of loan[US]	8	12
MHDV.V Sales multiplier	0.0	0.5
Minerals Market.desired mineral inventory coverage	0.2	0.8
Minerals Market.effect of mineral price elasticity on demand[Co]	-0.3	0.3
Minerals Market.effect of mineral price elasticity on demand[Li]	-0.3	0.3
Minerals Market.effect of mineral price elasticity on demand[Ni]	-0.3	0.3
Minerals Market.effect of mineral price elasticity on supply[Co]	-0.3	0.3
Minerals Market.effect of mineral price elasticity on supply[Li]	-0.3	0.3
Minerals Market.effect of mineral price elasticity on supply[Ni]	-0.3	0.3
Minerals Market.global mineral Index price $ per lb[Co]	15	25
Minerals Market.global mineral Index price $ per lb[Li]	2	4
Minerals Market.global mineral Index price $ per lb[Ni]	1.5	2.5
Minerals Market.mineral inventory adjustment time[Co]	0.1	0.3
Minerals Market.mineral inventory adjustment time[Li]	0.1	0.3
Minerals Market.mineral inventory adjustment time[Ni]	0.1	0.3
Minerals Market.mineral price growth rate	0.01	0.07
Minerals Market.recyclables coverage	1.5	2.5
Two3Wheel.V Sales multiplier	0.0	0.5
Cathode.Retirement Fraction[US]	0.0	0.1
Cathode.Retirement Fraction[ROW]	0.0	0.1
Manufacturing.Retirement Fraction[US]	0.0	0.1
Minerals Market.time to remove overage[LFP]	1	100
Minerals Market.time to remove overage[LMO]	1	100
Minerals Market.time to remove overage[LCO]	1	100
Minerals Market.time to remove overage[NCA]	1	100
Minerals Market.time to remove overage[NMC111]	1	100
Minerals Market.time to remove overage[NMC442]	1	100
Minerals Market.time to remove overage[NMC532]	1	100
Minerals Market.time to remove overage[NMC622]	1	100
Minerals Market.time to remove overage[NMC811]	1	100
Minerals Market.time to remove overage[NMC955]	1	100

Appendix B. Local Sensitivity Analysis Results




Manufacturing.FCI Scale Factor
1st percentile
99th percentile
Minerals Market.Mineral Price Growth Rate
1/Year
1st percentile
99th percentile
Manufacturing.Initial MSP Metric [NMC532]
US Dollar/MWh
1st percentile
99th percentile
Manufacturing.Initial MSP Metric [NMC622]
US Dollar/MWh
1st percentile
99th percentile
Manufacturing.Initial MSP Metric [LMO]
US Dollar/MWh
1st percentile
99th percentile
Manufacturing.Initial MSP Metric [NMC955]
US Dollar/MWh
1st percentile
99th percentile
LDV.Order of the Delay
1st percentile
99th percentile
Manufacturing.Initial MSP Metric [NCA]
1st percentile
99th percentile

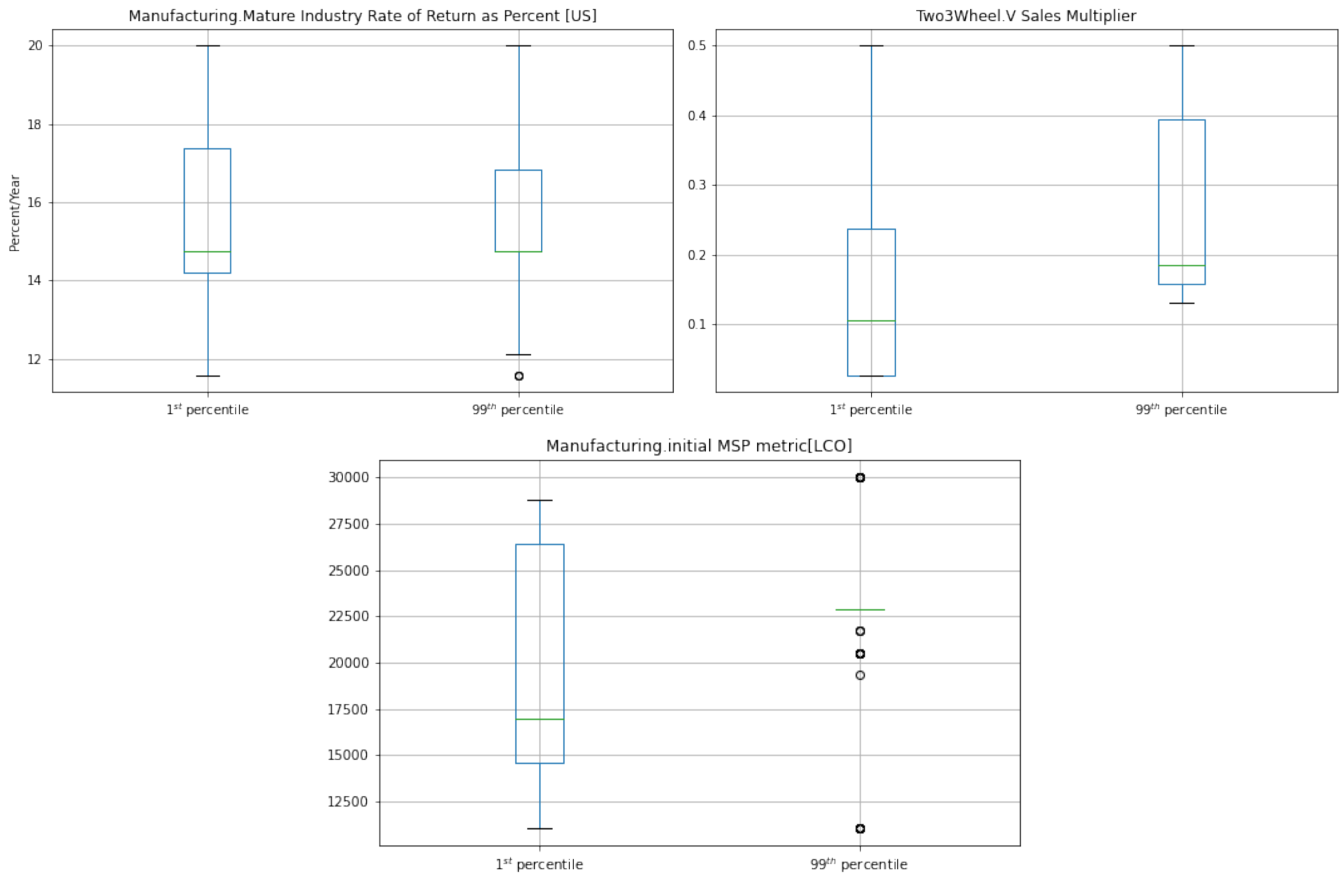


Figure B-1. Boxplots of the three most influential factors as determined by the elementary effects sensitivity study showing factor settings that resulted in 2040 U.S. manufacturing output values in the 1st and 99th percentiles

The median is marked by the green line in the center or at the edge of the box. The edges of the boxes mark the first and third quartiles. The whiskers mark 1.5 * quartile 1 or quartile 3; individual points beyond the whiskers mark outliers. Factors with overlap between the 1st percentile and 99th percentile likely have interactions or nonlinear effects on manufacturing output.