MODELING BATTERY MANUFACTURING COMPLEXITY

2023 ICEAA Conference

Abstract

Fossil fuels are the primary energy source used to drive our economies, but with limited supplies, the reliance on batteries has increased. Batteries are energy storage devices, and the chemical molecules react and produce voltage differences between positive and negative electrodes. These differences produce current flow in the energy forms to power products. In this study, the emphasis is researching cost and specifications to identify variables that have strong relationships with manufacturing complexity for structure.

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Modeling Battery Manufacturing Complexity

Fossil fuels are the primary form of energy used to drive our economies, but with limited supplies the reliance on batteries has increased. The chemical molecules react and produce voltage differences between positive and negative electrodes, with the anode being the positive and the cathode representing the negatively charged side (Battery Basics, 2019). These differences produce current flow in the energy forms to power products. The chemical flowing agent that enables the particles to flow between the positive and negative electrodes is called electrolytes. Many studies examine changes in the battery electrolyte to ensure safety measures are in place and to avoid flammable solvents without compromising performance (Martins et al., 2021). In addition, there has been interest and questions from many agencies pertaining to batteries. The questions were driven by the desire to gain insight into the current battery study methodology process and what elements were included (like categories of battery technology, technical parameters, range of applications, number of current data points, and range of production runs). This research project pulls data from logistics systems with manufacturer specifications and calibrates manufacturing complexity to unit prices. The data repository with over nine hundred datapoints allows users to perform modeling simulations and find variable dependencies in order to develop prediction formulas. This study includes both conventional and advanced batteries.

Battery Technologies

Common conventional chemistry makeup for batteries is comprised of Lead Acid, Nickel Cadmium (NiCd), and Nickel Metal Hydride (NiMH), which are utilized throughout the Military

land, air and sea vehicle industries and are well established. Whereas advanced batteries, including Lithium Iron Phosphate (LFP), Lithium Sulfur Dioxide (Li-SO2), and Lithium Thionyl Chloride (Li-SOCL2), are highly efficient energy sources. The designated applications for these batteries include carrying out surveillance and reconnaissance missions with robots, jammers, radios, and unmanned aerial vehicles (UAVs).

Conventional Batteries

The lead-acid battery is a well-known device used in various equipment, such as cars, construction equipment, and heavy-duty electrical backup systems. This type of battery is exceptionally heavy because of its lead-cell construction. In contrast, the nickel-cadmium battery uses a potassium hydroxide electrolyte, a cadmium and iron oxide negative electrode, and a nickel hydroxide and graphite positive electrode (Karimi et al., 2022). A NiMH battery is similar to a NiCd battery cell, but it has a hydrogen-absorbing alloy for the anode instead of cadmium. The cathode for these batteries is still nickel. NiCd and NiMH battery cells have lost their market share due to Lithium-ion Batteries' (LIBs) significant performance improvements and lower cost (Turcheniuk et al., 2021).

Advanced Batteries

Lithium-ion (Li-ion) batteries have become the leading power sources to actuate electric vehicles (EVs) and UAVs. Challenges in the application of these batteries include monitoring capacity degradation, predicting remaining life, and ensuring modification upgrades considers the current power source (Aphale et al., 2020). High power output makes Lithium-ion ideal for both the main propulsion energy source and as backup. In 2019, one company noted the achievement of performing an energy density of 260 Wh/Kg that greatly exceeded the EV

competition, lowering the overall weight and cross-section of the vehicle, which allowed longer travel range and flight time (Aphale et al., 2020). UAV cells are designed for exceptional energy density and safety. Each type of battery is produced with specific chemistry in order to fulfill commercial and consumer requirements.

Data Methodology

In this study, the emphasis is on researching unit prices of batteries categorized by various operating environments (also known as Operating Specification): airborne military, military ships, submarines, mobile land vehicles, communication devices, and ground-to-air missiles. The Operating Specification (Op Spec) value indicates the end user's requirements based on the planned operating environment for the hardware piece (ground, air, space, sea). Battery characteristics and unit prices were pulled from a comprehensive web-based parts & logistics research tool that aggregates parts and logistics information from many national disparate government, military and commercial sources. It provides access to information on over 15 million active and historical National Item Identification Numbers (NIIN) and more than 100 million parts in the Federal Supply Catalog. Additional actions were taken to validate data from this source by pulling data sheets with battery specifications listed from manufacturers' websites and pulling technical specifications from government solicitations.

Calibration

With parametric models, it is necessary to consider the specifics and conditions of an organizations' performance measurements and current availability of materials when producing estimates, which can be accomplished with a calibration tool. Cost Object Calibration is used to compare your organization's experience or expectations to the industry standard for any cost

object. Calibration helps determine an input value or factor like manufacturing complexity for structure that will yield a calculated cost that matches an organization's target cost. Manufacturing Complexity for Structure (MCPLXS) represents a technology index for the structural portion of the assembly being described. Manufacturing Complexity is a measure of the component's technology, its producibility (material machining and assembly tolerances, machining difficulty, surface finish, etc.), and yield. Manufacturing Complexity is a significant cost and schedule driver.

During the calibration portion of this study, the weight of the batteries is entered into TruePlanning, along with the primary operating specification, date, and learning rates. Labor and material learning rates are based on power trend line to find the slope of quantity discount rate centered on contract awards data from Defense Logistics Agency (DLA). Once calculations are complete for all the batteries, each Manufacturing Complexity for Structure is calibrated to the most recent award price and the lowest pricing band. Manufacturing Complexity for Structure (MCPLXS) represents a technology index for the structural portion of the assembly being described. Manufacturing Complexity is a measure of the component's technology, its producibility (material machining and assembly tolerances, machining difficulty, surface finish, etc.), and yield. Manufacturing Complexity is a significant cost and schedule driver.

Simulations

Additional attributes were built to include capacity, battery type, rechargeable or non-rechargeable, and manufacturer to look for potential dependencies. With the help of RapidMiner, a user can load multiple simulations. In this case, we were able to see which one works best to predict manufacturing complexity for structure based on selected attributes. The

simulator tool creates predictions by analyzing the behavior of the model in the neighborhood of a single data point. There is an auto model feature that provides one with a selection of models to assist with solving problems. If there is no time constraint, the best option is to build all of them and compare their performance once they are finished. The comparison overview table displays essential results like relative error. Relative error helps one to determine the magnitude of the absolute error in terms of actual size of the measurement (measure of precision). The absolute error is the difference between forecasted and actual values.

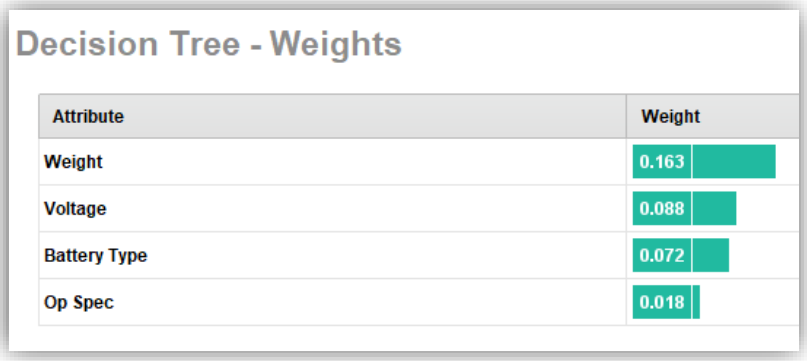

Figure 1 Simulation Model Weight Example

Through trial and error, when the data were filtered by each Operational Specification, potential dependencies were identified for Manufacturing Complexity for Structure (MCPLXS). The model provided a displayed predictions chart as a scatterplot with sufficient trend lines representing the dataset. The preferred model was the decision tree with a relative error of 1.2%. The tool displayed the weights for the attributes that show which columns have (in general) the most influence on the predictions for this specific model (Figure 1). With this model, it was discovered that the higher the voltage, the higher the predicted MCPLXS. Also,

the decrease in weight increases the predicted MCPLXS. Figure 2 shows an example of the simulation results based on changes to these attributes. With airborne military selected as the operating environment, the picture on the far left is when the voltage is set to 12 with the weight set high (above 70 lbs.). The middle image shows what happens to MCPLXS when the voltage increases. While the final image shows the result of decreasing weight.

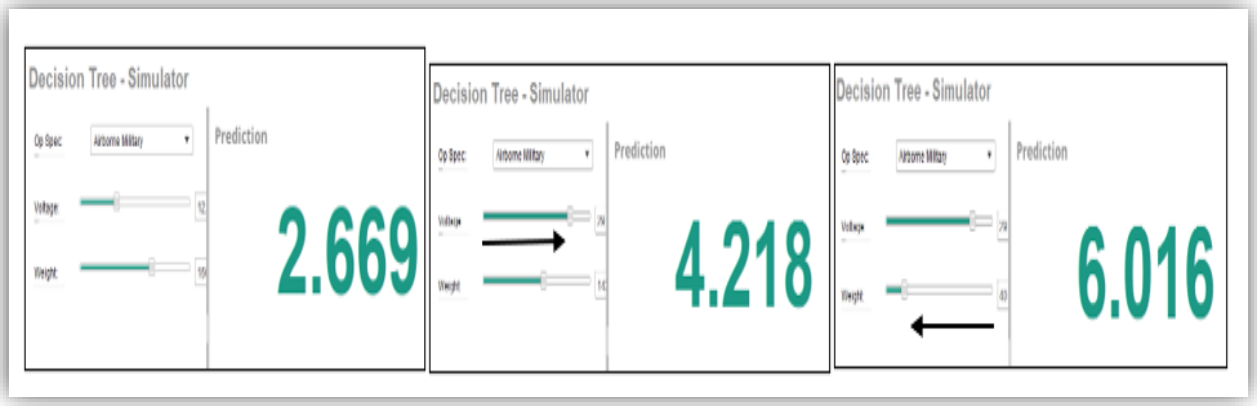

Figure 2 Simulations with Voltage and Weight

Analysis and Results

Operating Specification was the starting point for developing prediction formulas for estimating these hardware components. Op Spec drives all Hardware Component activity costs. Op Spec listed in this case study includes Mobile Land Military; Airborne Military; Mobile Land Missile; Mobile Water Military Ships; and Mobile Water Submarines. Nevertheless, it has a much more significant impact on development engineering costs than it does on manufacturing and tooling, and test costs. It measures the portability, reliability, security, testing, and documentation requirements for acceptable contract performance. For this study, the emphasis is on predicting the costs of purchasing batteries. The data under each Op Spec

includes batteries from various years of technology with multiple chemistries. The data was categorized by chemistries listed as battery types.

The Dependency Finder window in TrueFindings provides a grid of scatter plots that help users quickly find relationships and trends between columns of data and search for the presence of a correlation. One important aspect for determining whether the selected variables may be related to a dependent variable is R-Value. R-Value is the ranking of the linear correlation of the independent variables to the dependent variable. In this case the dependent variable is MCPLXS and the independent variables are weight and voltage.

Based on regression statistics on the battery datapoints, the R-value was below 0.5 under each Op Spec. One has to go a step further and look at other characteristics for filtering data. Battery type was then filtered, first with Lead Acid, Ni-Cd, Lithium Thionyl Chloride, and then Alkaline. According to the dependency finder with Lead Acid selected for Airborne Military, the R-value was 0.843 for variable voltage and 0.733 for weight (Figure 3). Whereas, with Ni-Cd selected, the R-value was 0.954 for voltage and 0.659 for the variable weight. When data is filtered by Airborne Military for Lithium Thionyl Chloride (Li-SOCL2) batteries the R Value is approximately 0.92 for both weight and voltage variables. Then, when the data is filtered by Op Spec Airborne Military with Alkaline, the R-value is 0.978 for variable weight. At times, it is good to assess multiple types of batteries to estimate and even look at multiple potential manufacturers. By adding the manufacturer as an attribute, the user can filter the data further. After running many scenarios, in the end, the best way to estimate these batteries rely heavily on the battery chemistry. Next, one can use this knowledge to develop cost estimating

relationship (CER) formulas to predict manufacturing complexities and ultimately be able to calculate unit prices.

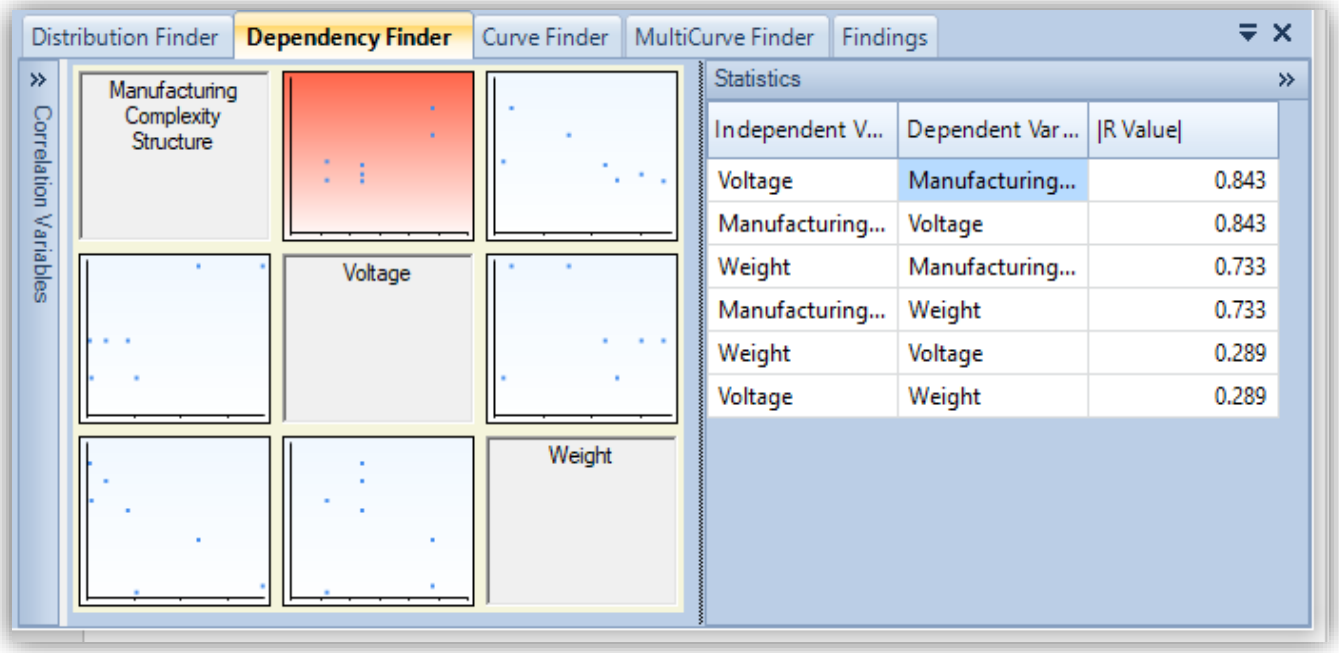

Figure 3 Dependency Finder

With the assistance of a multicurve finder tool with regression statistics, one is able to analyze scatter plots to find relationships and trends within one's data. Predictions are more complex than just the single predicted value. Predictions include a margin of error and calculate statistics to a 95 percent significance level. More precise predictions have a smaller amount of error. R-squared is relevant in these cases because it is a measure of error. The adjusted R-squared is a slightly different calculation to R-square and should be used when analyzing a multivariate model. The adjusted R-squared accounts for the number of predictors in the regression model and will only increase if the addition of the new variable improves the model more than could be expected by chance. After filtering Op Spec and numerous Battery Types,

Weight and Voltage were selected as constants using stepwise variable selection. For building prediction formulas, one example is Lead Acid batteries for Airborne Military, and Figure 4 shows the scatterplot. The multiple linear regression model for this scenario was represented by the following equation: MCPLXS = 0.126 * [Voltage] - 0.029 * [Weight] + 3.204, adjusted R-squared 0.957. An example with strong relationships to type is Alkaline batteries for Airborne Military and Figure 5 shows the scatterplot. Similarly, Lithium Thionyl Chloride (Li-SOCL2) batteries for Airborne Military data are represented in Figure 6. As one can see, in the graphs below the data points are plotted with the prediction line. In this study, filtering by Op Spec with battery type and using the independent variable values weight and voltage, one can solve for the dependent variable MCPXLS.

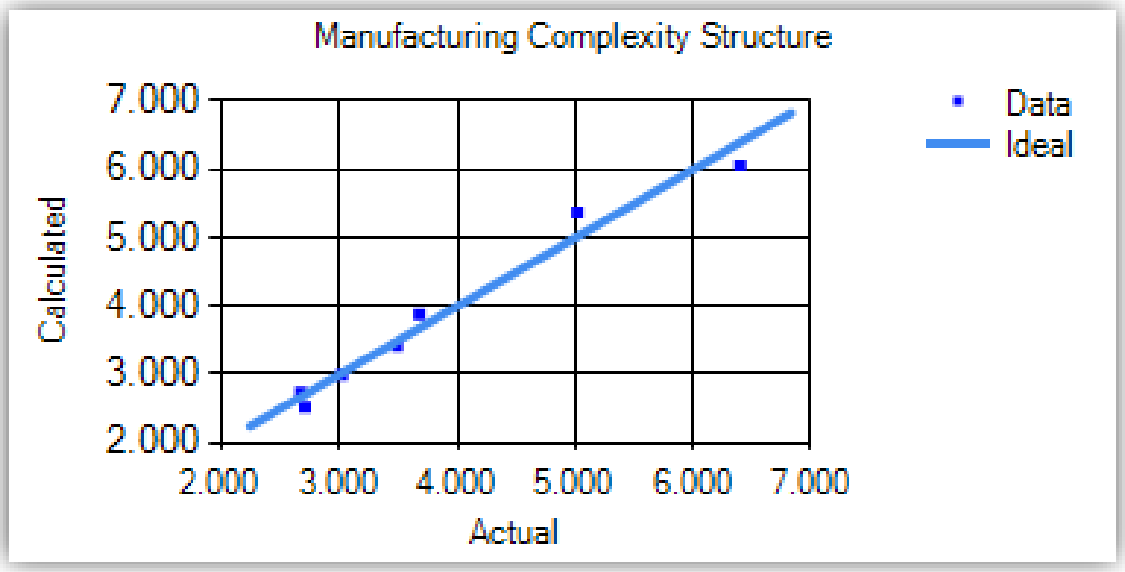

Figure 4 Scatterplot representing Lead Acid for Airborne Military

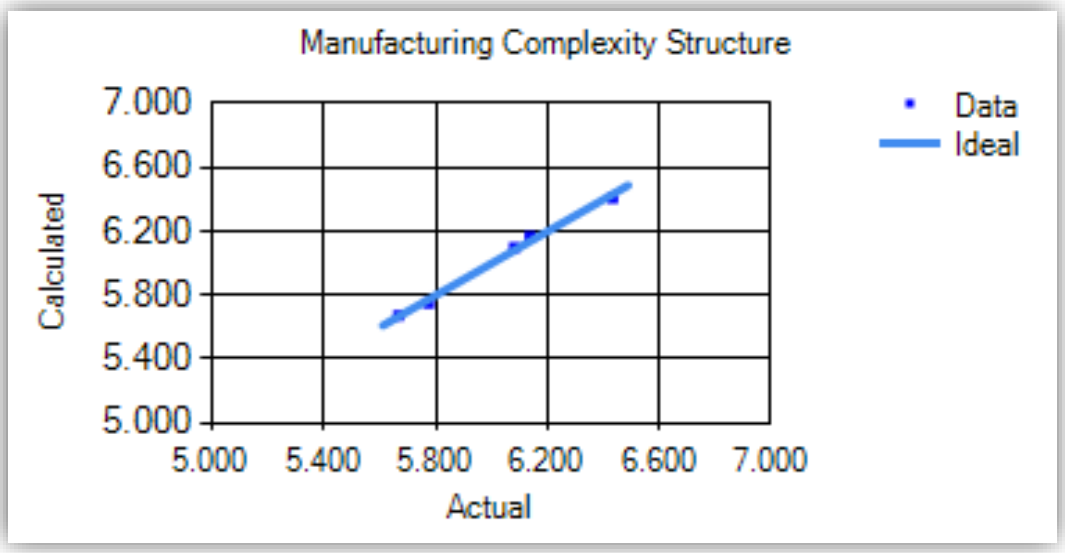

Figure 5 Scatterplot representing Alkaline for Airborne Military

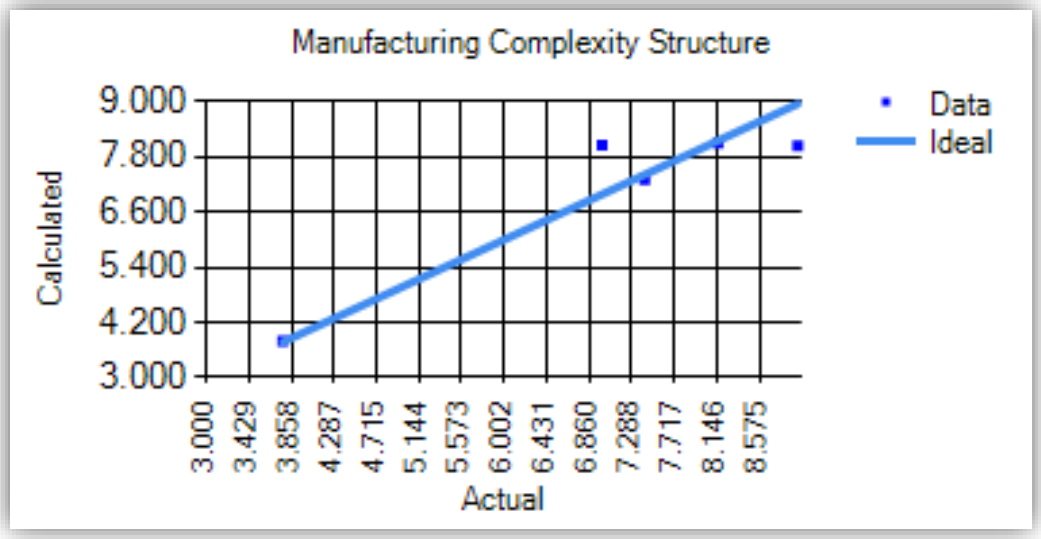

Figure 6 Scatterplot representing Li-SOCL2 for Airborne Military

Summary of Findings

The resulting battery database contains approximately nine hundred and seventy-five datapoints across one hundred and fourteen individually identifiable part numbers. The data repository serves as a useful resource for users to reach back to calibrated manufacturing

complexities with multiple attributes from numerous operating environments. The categorizes for the different types of batteries have a strong relationship to the manufacturing complexity factor and are critical to ensure the predictions are more precise with a small amount of error. On the same line of understanding how to estimate the (should) cost of batteries, one has to look at the current number of competitors and continuously relook at the availability of materials. According to an article on Statista, in 2021, China produced the largest volume of cadmium worldwide while the demand for this metal from the earth's crust increases (Garside, 2022). Li-ion batteries with cobalt lithium oxide (LCO) cathode are used for portable electronic devices and has also been reported in electric vehicles. The cathode has a high energy density with low self-discharge, but has a short lifespan, and is also very expensive due to the high content of cobalt (Martins et al., 2021). With the scarcity of metals, batteries that require materials such as nickel, cobalt, and cadmium are more costly and have dropped their ability to compete in the current market.

A study presented at the Conference on Intelligent Computation in Manufacturing Engineering dives into the process chain in battery cell manufacturing and how inconsistencies between the energy required for each step were found to be related to different battery cell types (Grimm et al., 2021). This study's findings on the differences between cell manufacturing energy levels lead to the importance of understanding the operational side of manufacturing for each specific battery type. An analyst should consider additional factors such as the vendors' facility capacity, complexity handling minerals, and even identify potential opportunities (e.g. automation). There have been discussions on how electrode coating, drying, cell formation, and aging contribute to 48% of the entire manufacturing cost, as seen in Figure

5, which can be costly if the battery type requires wet coating (Liu et al., 2021). Also, the demand for battery travel time and capacity is getting larger, so the price value of this storage is very high (Karimi et al., 2022). Hence, the method of battery efficiently charging and discharging, which ultimately affects the life of the battery, is a vital aspect for consumers and commercial industries.

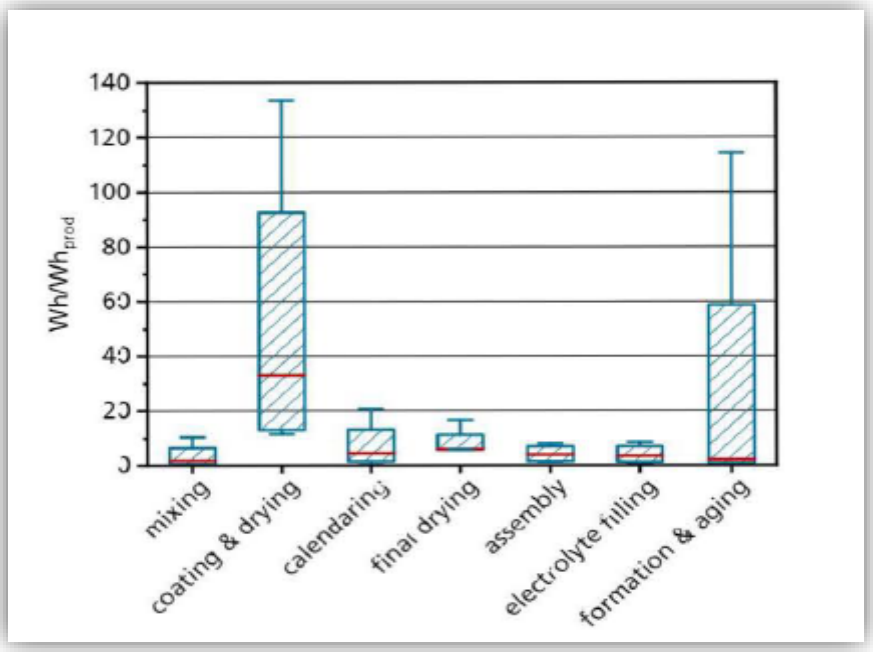

Figure 7 Boxplot diagram for energy demand of process steps

Limitations and Future Research

With the lack of insight into manufacturers' contractor rates built in the unit prices on the contracts, assumptions were made to utilize set values for overhead, general and administrative, and fee or profit. This known limitation can alter data results and findings; nevertheless, the behavior of variables was consistent across the board. In addition, it would be beneficial to gain insight into touch labor and automation built into the manufacturing process.

Going forward, the hope is to expand the analysis to increase the scope of data collection, including the ability to fill gaps for battery characteristics and build confidence across datasets for each operating environment. Databases used for building cost estimating relationships (CERs) must be both timely and accurate, containing the latest existing data reflecting technologies similar to that of the system of interest. The success of validity for CERs will depend on accumulating more data from other sources.

Bio

Sara McNeal is currently a Solutions Consultant with Unison. She has spent the last 12 years performing quantitative, qualitative, and business analyses for U.S. Air Force, Space Force, NASA, United Nations, and Army. While on active duty, she was an Aviation Electrician on F/A-18's in the Navy. In the Army, she was Satellite Communications Specialist and Mission Leader on Personnel Security Detachment team for senior leadership escorts and recovery missions. She deployed in support of Operation Enduring and Iraqi Freedom.

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