COMPARATIVE ANALYSIS OF SATELLITE BATTERY TECHNOLOGIES

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As satellite battery technologies evolve, cost analysts must reassess whether historical subsystem data remain valid for cost estimating relationships (CERs). This study examines whether nickel-cadmium (NiCd), nickel-hydrogen (NiH_2), and lithium-ion (Li-Ion) systems can be commingled for CER development. Using data from the Unmanned Space Vehicle Cost Model (USCM), we compare normalized costs and estimate regression models with and without chemistry-specific interaction terms. The results strongly support excluding NiCd, which exhibits statistically distinct cost behavior. For NiH_2 and Li-Ion, pooled regressions and coefficient stability tests suggest commingling is appropriate when estimating NiH_2 based systems. However, interaction terms reveal significant differences in cost behavior between NiH_2 and Li-Ion suggesting that comingling may be inappropriate when estimating Li-Ion based systems. We conclude that NiCd data should be excluded and recommend continued caution when commingling NiH_2 and Li-Ion, with periodic reassessment as more Li-Ion data become available.

Key words: *satellite cost estimating, battery technologies, cost modeling, CER development, lithium-ion, nickel-hydrogen, USCM, defense acquisition, technological maturity, generalized additive models*

1. INTRODUCTION

Satellite programs remain among the most complex and costly endeavors within modern defense acquisition. As cost analysts supporting these efforts, we rely on robust historical data to inform credible and defensible cost estimates, especially in early acquisition phases when technical specifications are often sparse. One of the most comprehensive tools available to us is the Unmanned Space Vehicle Cost Model (USCM), maintained by Space Systems Command (SSC). This model aggregates decades of satellite program cost data—normalized to constant-year dollars and mapped to a standardized Work Breakdown Structure (WBS)—to support the development of cost estimating relationships (CERs) across system and subsystem levels.

In recent years, SSC has observed a discontinuity in the cost behavior of satellite batteries within the USCM dataset. Specifically, data associated with satellite programs from the 1960s through the early 1980s—predominantly reliant on nickel-cadmium (NiCd) batteries—exhibits markedly different cost characteristics than data associated with programs post-1980, which increasingly incorporate nickel-hydrogen (NiH_2) and lithium-ion (Li-Ion) technologies (Kwok, 2023). This divergence in cost behavior prompted the decision to exclude legacy NiCd battery data from electrical power subsystem (EPS) CER development. However, no formal statistical justification for this exclusion has been documented in the literature. Nor has the comparability of NiH_2 and Li-Ion battery costs been rigorously tested.

The objective of this study is to conduct a comprehensive, statistically grounded evaluation of battery cost trends across three major chemistries–NiCd, NiH_2, and Li-Ion–as documented in the USCM database. Our goal is to provide empirical justification for key data selection decisions in CER construction and to explore whether cost behavior across newer battery technologies warrants separate treatment in modeling. We also aim to assess the broader time trends in satellite battery costs to determine whether technological maturity effects or technology cycles influence CER reliability.

Our study is motivated by both practical and methodological imperatives. From a practical standpoint, battery systems often account for 20–30% of a satellite's total bus weight (Hill, 2011). They are tightly linked to mission duration, payload power demands, and orbital constraints—all of which drive lifecycle cost. As battery technology evolves, so too do these performance characteristics and their corresponding cost implications. Decisions regarding which historical data to include in CERs are methodologically nontrivial. Inappropriate inclusion of legacy technologies can distort parameter estimates, inflate uncertainty, and lead to flawed acquisition recommendations.

We organize our investigation around three research questions:

1. How do the normalized costs of NiCd, NiH_2, and Li-Ion batteries compare and what implications does this have

on data inclusion for CER development?

2. In what ways do the cost behaviors of NiH_2 and Li-Ion battery systems differ after controlling for technical characteristics, and to what extent can these chemistries be jointly modeled in a unified CER framework?
3. How do modern satellite battery costs evolve over time within and across battery types and what role should technological maturation play in CER development?

To address these questions, we analyze WBS Level 4 battery subsystem data from the USCM model, drawing on first unit cost records from 72 satellite programs spanning the 1970s to 2012. We normalize costs by battery weight (T1$/lbs.) and BOL power (T1$/BOL), apply statistical comparison tests, and model cost behavior over time using linear regression. We find that battery chemistry significantly influences EPS cost behavior and argue that key assumptions in CER development–particularly those regarding technological maturation effects and the treatment of NiH_2 and Li-Ion data–deserve reconsideration. Our findings carry practical implications for defense acquisition cost modeling.

2. LITERATURE REVIEW

2.1. Space Systems and Subsystems

A space system typically consists of four integrated components: the space vehicle, launch vehicle, ground segment, and orbital transfer system (Department of Defense, 2022). In this study, we focus on the space vehicle which is composed of two primary sections: the Payload and Bus.

The Payload includes mission-specific equipment, such as communications hardware or remote sensing instruments, depending on the satellite's operational role (Ippolito Jr., 2017). The Bus contains the support subsystems that enable the Payload to function, including structure, thermal control, attitude control, propulsion, command and data handling, and electrical power (Department of Defense, 2022). A summary of the bus components and their respective functions is detailed in Table 1.

Of particular interest here is the Electrical Power Subsystem (EPS), which encompasses power generation, conditioning, and storage. Rechargeable batteries are a critical part of this subsystem, providing energy during periods when solar input is unavailable or insufficient. Prior research identifies batteries as a key cost driver within the EPS, contributing substantially to total bus mass and cost (Candella, et al., 2024; Hill, 2011).

Table 1 Bus Subsystems and Their Function. Adapted from Candella et al. (2024) *Journal of Defense Resources Management*

Subsystem	Function
Attitude Control (ACS)	Counteracts gravitational pulls and keeps the antennas pointed in the desired direction
Electrical Power (EPS)	Convert, regulate, store, distribute, and switch the electrical energy to the Bus and Payload elements
Propulsion	Provides the thrust required to make corrections or reposition the satellite
Structures & Mechanisms (SMS)	Structural support, deployment, and locking functions
Telemetry, Tracking, & Command (TT&C)	Control functions to keep the satellite operating safely in orbit. Communicates with an Earth terminal facility to maintain orbit.
Thermal Control (TC)	Controls the different temperature environments and keeps it stable

2.2. Cost Estimating Relationships and Subsystem-Level Modeling

Satellite cost modeling has historically emphasized high-level metrics such as launch mass or payload weight. Hadfield (1974) and Koelle (1984) developed some of the earliest cost estimating relationships (CERs), focused primarily on recurring versus nonrecurring cost behaviors. These models were useful for broad system-level estimation but failed to account for the unique cost characteristics of specific subsystems.

As smaller and more modular spacecraft became common in the 1990s and early 2000s, researchers recognized the limitations of mass-based models. Bearden (2001) and Mahr and Richardson (2003) highlighted how newer platforms leveraged commercial-off-the-shelf (COTS) technologies, reducing both acquisition timelines and costs. This shift prompted the development of subsystem-level CERs, especially within the Small Satellite Cost Model (SSCM), which estimates bus costs using subsystem performance attributes such as pointing accuracy and power (Fox, et al., 2008).

Drenthe, Zandbergen, Curran, and Van Pelt (2019) extended this trend by creating subsystem CERs for commercial satellites in early design stages, using hybrid models based on both historical costs and first unit data, also called T1 data. Still, guidance on data inclusion–particularly for legacy subsystems like NiCd batteries–remains sparse. Inappropriate data selection can undermine CER accuracy and lead to flawed acquisition decisions.

2.3. Chemistry Transitions and Costs

Battery technologies used in satellites have evolved considerably. The earliest missions employed silver-zinc (AgZn) batteries, followed by nickel-cadmium (NiCd) in the 1960s and 70s. Halpert, Frank, and Surampudi (1999) traced the progression of NiCd cell formats from cylindrical to prismatic, noting improvements in energy density and packaging efficiency. However, NiCd cells are sensitive to overcharging, display memory effects, and degrade under high temperature–factors that increased life-cycle costs and complexity.

In response, satellite designers adopted nickel-hydrogen (NiH_2) batteries in the late 1970s (Halpert, et al., 1999). NiH_2 batteries featured sealed pressure vessels and offered higher cycle life and energy density, albeit at greater weight and structural complexity. Hill (2011) noted that while NiH_2 was an improvement over NiCd, its weight and volume remained limiting factors.

Lithium-ion (Li-Ion) batteries entered satellite use in the 2000s, offering further gains in energy density, weight reduction, and design flexibility. Although they require careful charge management and thermal protection, their adoption has been rapid due to size and mass advantages (Altemose, et al., 2011). These differences in physical and chemical characteristics directly influence the cost profiles of each battery type.

Yet no prior study has statistically tested whether these chemistries differ significantly in unit cost behavior—nor whether historical NiCd data remains suitable for use in modern CERs. We investigate this question to inform more defensible cost estimating practices.

2.4. Trends and Maturity-Cost Relationship

A foundational assumption in many cost estimating relationships is that unit cost declines as a technology matures. This idea, formalized in learning curve theory and embedded in models like the NASA Air Force Cost Model (NAFCOM), suggests that production efficiencies, design refinement, and accumulated expertise lead to lower costs over time (Winn & Hamcher, 2002). Technological maturation is often operationalized as the number of years since a technology's first fielding and is treated as a monotonic driver of cost reduction.

However, we question whether this relationship holds for space-qualified batteries. Our initial visual analysis of USCM data suggests that while cost per unit tends to decrease shortly after a battery chemistry is introduced, this decline may plateau or even reverse. These patterns raise important questions about whether the conventional maturity-cost relationship holds for long-lived, mission-critical components like spacecraft batteries.

Despite the centrality of this assumption in CER construction, we find little prior literature that evaluates it empirically in the context of satellite subsystems. The potential for nonlinear or non-monotonic cost behavior as technologies age–whether due to obsolescence, diminishing economies of scale, or shifts in supplier dynamics–has not been sufficiently examined. We therefore include this question in our investigation.

In summary, prior research has advanced our understanding of satellite CER development, particularly at the system level using gross metrics like payload weight or total mass. However, the cost behavior of specific subsystems–such as the Electrical Power Subsystem–has received limited attention, despite its critical role in platform design and lifecycle cost. Furthermore, while the evolution of battery chemistries is well documented in the technical literature, few studies have examined whether these transitions carry statistically distinct cost implications. Finally, the widely held assumption that cost declines with maturity remains largely untested for space-qualified batteries. This paper addresses these gaps by evaluating cost trends across battery chemistries and maturity levels within the USCM dataset, with the goal of informing more defensible data selection practices in subsystem-level CER development.

3. METHODOLOGY

Our methodology is designed to test whether satellite battery chemistries differ meaningfully in cost behavior and to evaluate how cost trends evolve over time. To do this, we extract battery subsystem data from the Unmanned Space Vehicle Cost Model (USCM), conduct comparative analysis across three major chemistries (NiCd, NiH_2, and Li-Ion), and assess temporal cost patterns using normalized metrics. Because this research is exploratory in nature and intended to inform cost estimating relationship (CER) development rather than establish definitive performance differences, we adopt a significance threshold of $\alpha = 0.10$ throughout our analysis.

3.1. Data Source and Cleaning

We begin with the latest release of the Unmanned Space Vehicle Cost Model (USCM), focusing specifically on WBS Level 4 element "Rechargeable Batteries." This element captures subsystem-level costs for battery systems across a wide range of satellite programs dating from the early 1970s through the 2010s. The raw dataset includes 73 satellite entries with battery subsystem records.

To ensure consistency and accuracy in our analysis, we apply the following data methods and exclusions:

- *Dual Chemistry Systems:* One program includes both NiH_2 and Li-Ion cells in a hybrid configuration. Since this violates the assumption of mutually exclusive chemistries, we exclude it from all comparative analyses.
- *Interpolation for BOL Values:* Eight programs are missing BOL power values but include complete T1$ and weight data. For these programs, we interpolate BOL using regression-based estimation from similar programs of matching chemistry and mass.

After exclusion and interpolation, we retain 72 of the 73 programs: 26 using nickel-cadmium (NiCd), 38 using nickel-hydrogen (NiH_2), and 8 using lithium-ion (Li-Ion) batteries. For research questions 1 and 3, we analyze the full data set. Since research question 2 investigates NiH_2 and Li-Ion only, we exclude the 26 NiCd data points and analyze the remaining 46. Table 2 summarizes our data by chemistry, date range, and research questions.

Table 2 Data Exclusion and Sample Sizes by Battery Chemistry

Battery Type	Earliest Date	Latest Date	Observations	**Research Questions**
NiCd	4/1/1971	2/1/1996	26	1, 3
NiH_2	10/1/1997	1/1/2012	38	1, 2, 3
Li-Ion	3/1/2002	6/21/2012	8	1, 2, 3
Research Question Observations				
Research Question 1				*72*
Research Question 2				*46*
Research Question 3				*72*

3.2. Variables

Our analysis considers three categories of variables: cost metrics, classification indicators (primarily chemistry), and continuous program-level descriptors such as weight, power, and maturity. We divide our approach into two phases of analysis, each using different subsets of these variables.

In the first phase, we focus on normalized cost metrics to evaluate whether battery chemistries differ significantly in cost behavior. Specifically, we calculate two dependent variables: T1$/lbs., which normalizes first-unit cost by battery subsystem weight in pounds, and T1$/BOL, which normalizes cost by beginning-of-life (BOL) power in watts. Prior studies and standard cost modeling practice emphasize weight as the dominant cost driver in satellite subsystems, so normalization by weight facilitates a like-for-like cost comparison across systems of varying size. Normalizing by power, meanwhile, offers a complementary perspective–one that emphasizes operational output instead of physical mass. These two metrics serve as the basis for our nonparametric comparisons and summary trend statistics.

In the second phase, we model the raw first-unit cost (T1$) using a combination of technical and temporal predictors. These regressions allow us to assess whether Li-Ion and NiH_2 follow similar cost behavior after controlling for confounding programmatic and physical factors. Unlike the normalized metrics, raw T1$ retains scale sensitivity and reflects the actual dollar cost observed in historical data.

Independent variables used in our regression models include battery subsystem weight (in pounds), BOL power (in watts), and a maturity variable representing the number of years since the first documented use of each chemistry. Following published aerospace battery histories, we define NiCd maturity as years since 1962 (Halpert, et al., 1999), NiH_2 since 1966 (Halpert, et al., 1999), and Li-Ion since 2001 (Smart, et al., 2004). These dates do not reflect the individual programs in our dataset but rather represent fixed technological baselines intended to proxy overall system maturity at the time of use. They are applied uniformly across each chemistry.

We also include design life (in years) as a continuous variable in our regression models. This variable reflects the programmatic design duration for which the satellite is intended to operate. We consider this an important driver of cost, as longer design lives often require more robust energy storage solutions, higher depth-of-discharge tolerances, and added redundancy. Finally, we interact chemistry with weight and maturity to test whether Li-Ion deviates from NiH_2 in statistically meaningful ways when controlling for these variables.

Table 3 defines each of the variables used in our statistical analysis, including their units and expected relationships with cost.

Table 3 List of Variables and Definitions

Variable	Definition
Battery Type	The type of battery used in the satellite (NiCd, NiH2, Li-Ion)
BOL	Beginning of Life power - power at start of mission, in watts
Contract Award Date	Date contract awarded and authority to proceed granted
Design	Design life of the battery, measured in months
Lithium	Dummy variable indicating satellite program with Li-Ion battery
MaturityHist	Battery type maturity measured in years from first use in satellites
MaturityUSCM	Maturity of the battery, measured in years from first documented use in the USCM database
T1	Satellite first unit costs in thousands of dollars
T1$/lbs.	T1 costs in thousands of dollars per pound for the battery (CP16$)
T1$/BOL	T1 costs in thousands of dollars per BOL (CP16$)
Weight	The weight of battery used in the satellite, measured in pounds

3.3. Statistical Methods

Our statistical approach consists of two primary components: comparison analysis of normalized cost metrics and regression modeling of raw first-unit cost (T1$). These methods allow us to evaluate whether battery chemistries differ significantly in cost behavior and whether lithium-ion (Li-Ion) and nickel-hydrogen (NiH_2) systems exhibit distinguishable cost patterns after accounting for technical and programmatic characteristics.

3.3.1. RQ 1 - Cost differences among chemistries.

To evaluate whether normalized cost behavior differs across battery chemistries, we begin with a one-way analysis of variance (ANOVA) on both T1$/lbs. and T1$/BOL. This serves as our primary method for detecting overall group-level differences in cost. Because Levene's test identifies unequal variances among the three chemistry groups, we use Welch's t-tests for pairwise post-hoc comparisons. These are appropriate under conditions of heteroskedasticity and provide greater robustness than standard t-tests.

To assess the robustness of the ANOVA under potential violations of normality, we conduct both Kolmogorov–Smirnov and Anderson–Darling tests for each chemistry group. While the Kolmogorov–Smirnov test supports normality in all three groups, the Anderson–Darling test indicates that only NiCd satisfies the normality assumption for T1$/BOL, and none of the groups satisfy it for T1$/lbs. Based on this mixed evidence, we supplement the ANOVA with Kruskal–Wallis tests as nonparametric robustness checks.

For post-hoc comparison of individual groups under nonparametric assumptions, we apply Wilcoxon rank-sum tests to all pairwise combinations of chemistries. These tests function as distributional analogues to the Welch t-tests. To control for family-wise error across multiple comparisons, we apply a Bonferroni correction. All comparison tests are evaluated at a significance threshold of $\alpha = 0.10$, consistent with the exploratory nature of this study.

By using both parametric and nonparametric methods—along with corresponding post-hoc procedures—we ensure that our conclusions about cross-chemistry cost differences are robust to distributional assumptions and sample size imbalances.

3.3.2. RQ 2 - Nesting of NiH_2 and Li-Ion Data.

Next, we model raw T1$ using ordinary least squares (OLS) regression with robust standard errors. Explanatory variables include subsystem weight, BOL power, design life, and maturity, all defined in Section 3.2. We first estimate separate models for NiH_2 and Li-Ion entries to evaluate cost behavior within each chemistry.

We then pool the NiH_2 and Li-Ion observations and estimate a nested model in which interaction terms between Li-Ion and each independent variable are included. This allows us to formally test whether the cost behavior of Li-Ion systems deviates from that of NiH_2 systems after controlling for observable characteristics. Following Clogg, Petkova, and Haritou (1995), we use a difference-in-coefficients Z-test to evaluate whether each pooled coefficient significantly differs once the interaction term is introduced. This approach serves as a scalar analogue to a Wald test for coefficient equality and provides an intuitive measure of whether the Li-Ion and NiH_2 regressions are statistically distinguishable allowing us to determine whether combining Li-Ion and NiH2 data for CER development is appropriate.

3.3.3. RQ 3 - Maturity effects within and across chemistries.

Finally, we interpret the maturity variable coefficients from the NiH_2 and Li-Ion regressions to assess whether cost behavior changes over time. While we make no assumption of a monotonic trend, the maturity variable provides a controlled test of whether technological age corresponds to reductions in subsystem cost when accounting for weight, power, and design life. NiCd is excluded from this portion of the analysis, as it has been largely phased out and is no longer considered relevant for modern CER development despite its continued presence in a small number of legacy systems.

4. RESULTS

4.1. Comparison of Cost Across Chemistries

A one-way ANOVA detects a statistically significant difference in T1$/BOL ($p = 0.0003$) and a marginal difference in T1$/lbs. ($p = 0.0962$). Levene's tests confirm unequal variances for both metrics, motivating the use of Welch's t-tests for pairwise post-hoc comparisons. Welch's tests show that NiCd differs significantly from both NiH_2 ($p = 0.0011$) and Li-Ion ($p = 0.0029$) on T1$/BOL, and from NiH_2 on T1$/lbs. ($p = 0.0502$), all well below the $\alpha = 0.1$ threshold. However, NiCd and Li-Ion do not differ significantly on T1$/lbs. ($p = 0.1413$), and Li-Ion and NiH_2 are not significantly different on either metric.

Because we could not definitively establish normality, as discussed in Section 3.3, we run the Kruskal–Wallis test as a nonparametric robustness check. The results support a strong difference in T1$/BOL ($p = 0.0004$), while the result for T1$/lbs. is more conservative ($p = 0.128$). Although this exceeds our alpha threshold, the divergence is modest. Taken together with the ANOVA and Welch results, we find sufficient justification to proceed with post-hoc comparisons of both T1$/lbs. and T1$/BOL.

We apply Wilcoxon rank-sum tests as a nonparametric analogue to the Welch tests. These results mirror the Welch tests: NiCd is significantly different from both NiH_2 and Li-Ion on T1$/BOL ($p = 0.0003$ and $p = 0.0059$, respectively), and from NiH_2 on T1$/lbs. ($p = 0.034$), but not from Li-Ion on T1$/lbs. ($p = 0.619$). Even after applying a Bonferroni correction for family-wise error, the results remain consistent. As with the Welch results, Li-Ion and NiH_2 remain statistically indistinguishable on both metrics.

While T1$/lbs. comparisons do not consistently show divergence between NiCd and Li-Ion, the strong and consistent results from T1$/BOL support the conclusion that

NiCd behaves differently in terms of normalized cost. Meanwhile, the lack of divergence between NiH_2 and Li-Ion in both metrics suggests that these two chemistries may exhibit similar cost behavior, justifying further investigation. This result establishes the foundation for research question two. Tables 4 and 5 summarize the results.

Table 4 Comparative T1$/BOL Results

Test	Method	p-value (α = 0.10)
ANOVA	Means Test	0.0003
Kruskal-Wallace	Rank-Based Test	0.0004
Battery Pair	Welch's (α = 0.10)	Wilcoxon (α = 0.10/0.033[1])
Li-Ion & NiH_2	0.516	0.270
NiCd & NiH_2	0.0011	0.0003
NiCd & Li-Ion	0.0029	0.0059
[1]Bonferroni correction controls Type I error by dividing α by the number of comparisons		

Table 5 Comparative T1$/lbs. Results

Test	Method	p-value (α = 0.10)
ANOVA	Means Test	0.0962
Kruskal-Wallace	Rank-Based Test	0.128
Battery Pair	Welch's (α = 0.10)	Wilcoxon (α = 0.10/0.033[1])
Li-Ion & NiH_2	0.382	0.787
NiCd & NiH_2	0.0502	0.034
NiCd & Li-Ion	0.829	0.619
[1]Bonferroni correction controls Type I error by dividing α by the number of comparisons		

ordinary least squares (OLS) with heteroskedasticity-robust standard errors. While the comparative analysis in Section 4.1 did not reveal statistically significant differences between these two chemistries, that result alone does not confirm that they may be reliably combined for CER development. A more detailed analysis is required to determine whether their cost drivers behave similarly when modeled explicitly.

4.2. Regression of NiH_2 and Li-Ion Costs

To evaluate whether Li-Ion and NiH_2 exhibit similar cost behavior when controlling for observable characteristics, we estimate two regression models using

We begin by pooling the NiH_2 and Li-Ion data and regressing the raw T1 costs ($T1\$_i$) on the subcomponent characteristics of weight ($weight_i$), Design Life ($Design_i$), and technological maturity from first documented use at the time of contract award *(MaturityHist$_i$)*. We repeat the regression while adding interaction terms with Li-Ion to isolate the Li-Ion data in the regression. This specification allows cost behavior to differ across chemistries and serves as the basis for applying the method developed by Clogg, Petkova, and Haritou (1995) which tests whether the inclusion of interaction terms leads to a statistically significant change in the regression coefficients. This provides a formal mechanism for determining whether Li-Ion systems behave differently from NiH_2 after accounting for observable drivers of cost, allowing us to determine whether or not Li-Ion and NiH_2 data can be comingled in CER development. The two estimated regression equations are:

suggests that the electrical power subsystems (EPS) in these missions were fundamentally different and not representative of typical spacecraft, making their inclusion in the regression inappropriate.

Table 6 presents the results of the pooled and nested regressions. The pooled model assumes shared cost behavior across NiH_2 and Li-Ion systems and yields an R^2 of 0.59. The nested model, which includes Li-Ion-specific interaction terms, increases the explanatory power yielding an R^2 of 0.64. More importantly, the nested model allows for direct estimation of whether Li-Ion cost behavior differs meaningfully from NiH_2.

To formally test whether the introduction of interaction terms materially alters the regression coefficients of our main variables of interest when estimating NiH_2 based systems, we apply the method developed by Clogg, Petkova, and Haritou (1995). This approach evaluates whether the coefficients from the pooled model (β_1 through β_3) are statistically distinguishable from those in the nested model when the Li-Ion interaction terms are included. By design, β_1–β_3 in the nested model

Pooled Model (No Interaction):

$$T1_i = \beta_0 + \beta_1 Weight_i + \beta_2 Design_i + \beta_3 MaturityHist_i + \varepsilon_i$$

Nested Model with Interactions:

$$\begin{aligned} T1_i = \beta_0 &+ \beta_1 Weight_i + \beta_2 Design_i + \beta_3 MaturityHist_i \\ &+ \beta_4 (Li\text{-}Ion_i \cdot Weight_i) + \beta_5 (Li\text{-}Ion_i \cdot Design_i) \\ &+ \beta_6 (Li\text{-}Ion_i \cdot MaturityHist_i) + \varepsilon_i \end{aligned}$$

Two NiH_2 entries were removed from the regression sample prior to estimation. These points were flagged as outliers with undue influence based on standard diagnostic tests. Upon further investigation, both corresponded to satellite systems with atypical design lives, one particularly long, the other short. This correspond to NiH_2 specifically since Li-Ion is fully captured in the interactions. The results of this test are presented in Table 7. None of the Z-statistics approach significance, suggesting that the slope coefficients remain stable even after allowing Li-Ion to diverge.

While the Clogg test implies that commingling the Li-Ion and NiH_2 data does not result in statistically significant distortions to the pooled model's slope estimates, indicating that pooling is appropriate when estimating NiH_2 based systems, the interaction terms in the nested regression suggest more caution. All three interactions—Li-Ion × Weight, Li-Ion × Design, and Li-Ion × MaturityHist—are large in magnitude and individually significant at the 90% confidence level. The interaction of Li-Ion on weight is even more pronounced with significance at the 95% confidence level. These coefficients suggest that Li-Ion subsystems follow materially different cost dynamics, particularly with respect to how maturity and size translate into cost. Thus, when estimating Li-Ion based systems, the evidence suggests that NiH_2 based data should not be mingled with Li-Ion for accurate CER development.

The apparent contradiction between the coefficient equivalency test and the nested regression results likely stems from the small sample size of Li-Ion systems (n = 8), which reduces the statistical power of the pooled coefficient comparison.

Table 5 Pooled and Nested Regression Results

	(1) Pooled	(2) Nested
Weight	6.56^{***}	6.75^{***}
	(1.25)	(1.39)
Design	-11.50^{**}	-11.69
	(5.14)	(8.01)
MaturityHist	61.61^{***}	76.48
	(18.10)	(54.61)
Li-Ion × Weight	–	-4.43^{**}
	–	(1.52)
Li-Ion × Design	–	14.15^{*}
	–	(8.47)
Li-Ion × MaturityHist	–	-113.55^{*}
	–	(57.57)
R^2	0.59	0.64
Observations	44	44

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ (two-tailed)

Table 7 Equality of Coefficients

Variable	**β Pooled**	**β Nested**	SE β Pooled	SE β Nested	Z-Score	p-value
WeighT	6.56	6.75	1.25	1.39	-0.10	0.92
Design	-11.50	-11.69	5.14	8.01	0.02	0.98
MaturityHist	61.61	76.48	18.10	54.61	-0.26	0.80

4.3. Comparison of Maturity across Chemistries

Our final research question examines how technological maturity–defined as the number of years since first documented use at the time of contract award (MaturityHist)–relates to cost across battery chemistries. In the pooled model, the MaturityHist coefficient is positive and statistically significant at the 99% confidence level, indicating that first-unit costs increase as battery technologies age. This result is unexpected, as technological maturity is typically associated with learning, standardization, and cost reduction over time.

When interaction terms are introduced in the nested regression, the picture becomes more nuanced. The MaturityHist coefficient for NiH_2 rises slightly higher than the pooled model but loses statistical significance, while the interaction term for Li-Ion × MaturityHist is large, negative, and significant at the 90% confidence level. This suggests that the positive maturity effect observed in the pooled model is not generalizable across chemistries. Instead, it is likely driven by NiH_2 systems, which dominate the sample and exhibit more complex lifecycle dynamics. Indeed, the NiH_2-only regression produces a positive but statistically insignificant maturity trend, while the Li-Ion-only regression reveals a negative and statistically significant slope at the 90% confidence level.

5. CONCLUSION AND RECOMMENDATIONS

This study provides statistical validation for a set of data selection practices that are increasingly relevant in modern satellite cost estimating. Our analysis confirms that legacy nickel-cadmium (NiCd) battery data should be excluded from modern CER development. NiCd subsystems exhibit statistically distinct cost behavior across both normalized cost metrics–T1$/lbs. and T1$/BOL–and diverge consistently from both NiH_2 and Li-Ion systems. This finding reinforces recent decisions by Space

Systems Command and supports their permanent removal from future EPS cost modeling efforts.

The comparison between NiH_2 and Li-Ion systems yields more nuanced results. While comparative analysis of normalized metrics revealed no statistically significant differences, our regression results suggest that Li-Ion subsystems may follow a distinct cost trajectory. The pooled regression treats NiH_2 and Li-Ion as a single population and estimates a positive and statistically significant cost increase with maturity. This is counterintuitive and inconsistent with established expectations about technological learning and cost reduction over time.

However, when the regression is disaggregated via chemistry-specific interaction terms, the maturity trend disappears for NiH_2 and reverses direction for Li-Ion. The Li-Ion interaction term is large, negative, and significant at the 90% confidence level—precisely the relationship we would expect from a newer, rapidly maturing technology. In contrast, the NiH_2-only regression shows a weak, statistically insignificant positive trend, suggesting that within-chemistry variation in NiH_2 systems may reflect evolving configurations and complexity that offset any learning-curve effects. This divergence in cost behavior further supports the argument that NiH_2 and Li-Ion systems should not be treated as interchangeable in CER development.

Still, caution is warranted. The formal test for coefficient stability developed by Clogg et al. (1995) finds no statistically significant difference between the pooled and nested models when estimating NiH_2 based systems. While this may appear to contradict the regression findings, it is almost certainly an artifact of limited statistical power, as the Li-Ion sample includes only eight observations. Indeed, all three interaction terms in the nested model—Li-Ion × Weight, Li-Ion × Design, and Li-Ion × MaturityHist—are both large in magnitude and statistically significant, indicating that Li-Ion cost drivers differ in meaningful ways from NiH_2 systems. We therefore interpret the null result of the coefficient equivalency test not as evidence of true equivalence per se, but as a reflection of the current data limitations.

Taken together, these results indicate that while the current practice of commingling Li-Ion and NiH_2 data in CER development is not invalidated by statistical evidence, the underlying behavior of Li-Ion systems may differ in ways that merit future separation—especially as more data become available. The pooled maturity result, in particular, appears to be an averaging artifact that masks opposing trends across the two chemistries. As more Li-Ion programs are added to the USCM database, it will be critical to revisit this assumption and re-evaluate whether continued commingling is justified.

We conclude with two primary recommendations:

1. *Exclude NiCd systems entirely from future CER development.* Their cost behavior is statistically and operationally distinct and no longer representative of current satellite platforms.
2. *Exercise caution when pooling NiH_2 and Li-Ion data.* While current evidence does not prohibit their combination, it also does not affirm their equivalence. The burden of proof should fall on continued statistical validation, especially as the Li-Ion dataset grows. Cost analysts and model developers should remain attentive to interaction effects and test for chemistry-specific cost behavior regularly. The evidence suggests that NiH_2 and Li-Ion may not follow the same cost dynamics, and that mingling them may obscure the unique cost profiles of emerging technologies like Li-Ion.

These findings reaffirm the need for data discipline and ongoing validation in subsystem-level CER development. Our analysis provides clear support for excluding NiCd systems and offers early, though inconclusive, evidence that Li-Ion and NiH_2 may follow distinct cost trajectories. With only eight Li-Ion observations, we stop short of recommending disaggregation, but we emphasize the need for continued monitoring as additional data become available. CER developers should revisit these assumptions regularly and remain open to chemistry-specific modeling if warranted by future trends. Doing so will improve the fidelity of subsystem cost estimates and better align them with the technologies now shaping the future of satellite power systems.

Disclaimer: *The views expressed in this article are those of the authors and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the United States Government.*

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