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NAVAL CENTER FOR COST ANALYSIS

REDUCING S-CURVE ALCHEMY:

Gold from a New SAR Database

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The work presented in this paper is preliminary and subject to change. The views and opinions expressed in this document should not be considered official Navy policy.

EXECUTIVE SUMMARY

Preamble

The alchemists of old struggled to turn base metals like tin and mercury into gold and silver. Somewhat similarly, cost analysts often struggle to generate realistic cumulative probability distribution functions, or S-curves, for acquisition costs based on an amalgam of Monte Carlo simulations and bottom-up assessments of distribution types and parameters, correlations, and risk registers. Lack of data to support underlying estimating assumptions, time constraints, and management pressure to present a point estimate further contribute to these struggles. When these obstacles are overcome, the results are sometimes exquisite and real value is added to decision making. When senior decision makers dismiss a realistic S-curve they suppose their program will be different. These decision makers argue that the realistic S-curve fails to account for advances in technology or it includes avoidable prior programmatic mistakes. But, we've seen too many S-curves at Milestone A or B that reflect a Coefficient of Variation (CV) of only about 5%.[1] A CV this low is insufficient to cover escalation uncertainty alone, not to mention all the other requirements, technical, performance, financial, and programmatic factors that can and do impart risk to the cost estimate.[2] The result, not surprisingly, is mean cost growth for DoD acquisitions of 33% at Milestone B.[3] In egregious cases, such as the Electromagnetic Aircraft Launch System (EMALS) for *Ford* Class carriers or LPD-17 *San Antonio* Class ships, cost growth can run to three digits. Every Service has examples.

> *"There are known knowns. These are things we know that we know. There are known unknowns. That is to say, there are things that we know we don't know. But there are also unknown unknowns. There are things we don't know we don't know;" – Donald Rumsfeld*

Even when S-curves are generated using best practices such as those extolled in the Joint Agency Cost/Schedule Risk Uncertainty Handbook, a major problem remains. Namely, S-curves typically address only "*known unknowns*."[4] The curves are built upon an analysis of cost risk and uncertainty – cost element by cost element, with potentially risky events tacked on for good measure. But, they fail to

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[1] A Coefficient of Variation, or CV, is a cost distribution's standard deviation divided by its mean.

[2] Inflation options, traded daily in the international market place, suggest a CV of roughly 60% for inflation forecasts 25 years out. Given escalation's percent of total then-year dollar acquisition costs, this translates into roughly 9 to 11 percentage points of CV. For details, see "Modeling the Risk and Uncertainty of Inflation Rate Projections," 2011, Society of Cost Estimating and Analysis (SCEA), Brian Flynn and Peter Braxton.

[3] This Cost Growth Factor (CGF) is computed in then-year dollars, after adjusting for changes in quantity. Raw data are from the new SAR database of the Naval Center for Cost Analysis (NCCA).

[4] "There are known knowns. These are things we know that we know. There are known unknowns. That is to say, there are things that we know we don't know. But there are also unknown unknowns. There are things we don't know we don't know;" Department of Defense news briefing of 12 February 2002; Secretary of Defense, Donald Rumsfeld.

address the *ambiguity* of the S-curve itself, or the *degree of confidence* that its proffered probabilities are correct. This confidence factor, of course, is hard to measure. The "unknown unknowns," in other words, are not explicitly captured since their probabilities are a mystery.[5]

But the situation isn't hopeless. This research, executed under the auspices of the Naval Center for Cost Analysis, led to the creation of one, authoritative database of normalized, numerical SAR data for use throughout the defense cost and acquisition communities.[6] An update of previous work, the database enables the calculation of Cost Growth Factors (CGFs) and Coefficients of Variation (CVs) based on actual or estimated end costs for hundreds of Major Defense Acquisition Programs (MDAPs).[7] The operative phrase is "end cost." The deltas between baseline cost estimates and actual costs reflect every single factor or event that could and *did* influence acquisition results. The entire range of Secretary Rumsfeld's uncertainty band is implicitly captured in the calculations, including the influence of the unknown unknowns. The CGFs and CVs, then, represent invaluable benchmarks for use in assessing the realism of S-curves generated using traditional bottom-up techniques. Given these benchmarks, the onus should be placed on the program manager to justify a low CV when their program is subject to the same DoD 5000 series acquisition rules and all of its associated requirements.

Conclusions

Analysis

- Ad hoc observation suggests a continued underestimation of CVs in the defense cost community, especially in Program Office Estimates (POEs) for MDAPs.
    - Programs disregard the continuous push for rapid technology advancement and insertion into their program.
    - Programs underestimate the integration challenges with related weapon systems.
    - Programs underestimate the cost and schedule impacts associated with oversight and test and evaluation requirements.

- CVs tend to decrease, as expected, throughout the acquisition lifecycle as a program transitions from one milestone to another. At Milestone C in the SAR, for example, development costs are sunk and are recorded as actuals. Simply put, less dollars of funding remain at risk as a program moves to the right.

- CVs tend to decrease, as expected, after adjustments are made for changes in quantity and inflation. Sources of variation are eliminated.

[5] For an equivalent in the equities market, see the recent, seminal work of Professor Menachem Brenner, New York University's Stern School of Business, as referenced in The Wall Street Journal, 11-12 March 2017, page B2.

[6] SARs are Selected Acquisition Reports. Mandated by federal statue for each MDAP, they report information on total program acquisition cost and reasons for variation from an initial or baseline estimate.

[7] The database is a single Excel file that replaces multiple files and folders from previous work executed in 2012.

- CVs have seemingly decreased over the past decade and a half, on average.[8] But, it's unclear if *structural* cost risk has diminished, as suggested recently by USD(AT&L):[9]
    - Outliers remain, such as Joint Strike Fighter, measured from the original program baseline; the first two hulls of Littoral Combat Ship (LCS); and the Electromagnetic Aircraft Launch System (EMALS)
    - The jury is out on many current acquisition programs, such as *Columbia* Class Submarines, with actual end costs not available for another decade or two
    - SARs don't always capture full funding. For example, Remote Minehunting System was canceled for poor performance. Over $400M was spent on a reliability growth program for the system, with funding *outside* of SAR reporting
    - SARs address only MDAPs. Yet three of five critical mine counter-measure systems (ACAT IIs) to be deployed from the MH-60S Knighthawk Helicopter were canceled for poor performance or unsatisfactory system-to-platform integration
    - Comparisons of risk over time are valid only if technology is pushed to the same degree. Dr. Jamie Morin, former Director, OSD CAPE, contends that current acquisitions are not extending the state-of-art envelope as before.[10]

Database Development

- More time was spent than anticipated in cleansing historical data. Additional work is required, especially for older SARs. A new, improved taxonomy is required to assign MDAPs to Programs and Subprograms that reflect their role in a system-of-systems architecture.

- We found it *essential* to distinguish between *raw data* and analytical, or *normalized,* data in building the database. This was a major departure from previous work. The raw data comes straight out of the SARs and is *never removed* from the database and *never amended* from its initial state – as a *raw datum*. Yes, changes are allowed, and are entered in a Change Log, to support further analysis. The

[8] This conclusion holds only if two observations are excluded from the sample of Milestone B estimates for naval sea system acquisition programs: the first two hulls of Littoral Combat Ship (LCS) and the Electromagnetic Aircraft Launch System (EMALS). The first was a technically a Planning Estimate (PE) rather than a Development Estimate (DE). And the second is an estimate at the system level rather than total program level. If EMALS is included in the mix, then there's no statistically-discernable diminution in values of the CVs over time.

[9] "Performance of the Defense Acquisition System 2016 Annual Report," Under Secretary of Defense, Acquisition, Technology, and Logistics; 24 Oct 2016.

[10] Ibid.

advantage of this separation is that it gives the Department *one data set* from a reproducibility point of view.

- These tenets shaped the design of the new SAR database:
  - Complete separation of raw data from normalized data
  - Full transparency of all operations, from storage of raw data, to use of a change log, to establishment of business rules for normalization
  - Elimination of manual data entry and automation of normalization tasks, thereby minimizing subjective judgment
  - Strict adherence to the philosophy of never doing anything as a one off. Instead, we employed VBA scripts and demonstrated the success of an API in pulling data electronically and formatting it correctly. The scripts and API can run repeatedly and support reproducibility

Recommendations

Analysis

Based on the forgoing analysis, we offer these recommendations:

- Define the type of CV employed or under discussion. That is, is the CV in then-year or constant dollars? Is it adjusted for changes in quantity?

- Use a quantity-adjusted, then-year dollar CV for most acquisition programs as a default.

- Define CV benchmarks as ranges at each milestone. As a corollary, establish a "trigger point" or floor for CV estimates, for each milestone, below which a call-for-explanation will be required.

Database Development

To support the CADE vision of a fully integrated information system of cost and technical data, we recommend adoption of these tenets for future SAR database development:

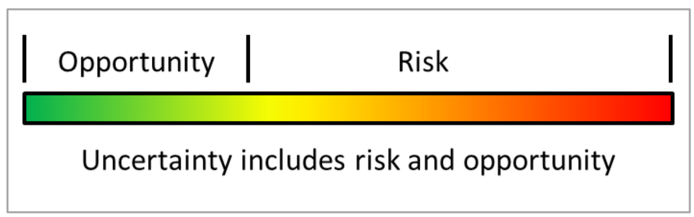
- The architecture must isolate raw data
- The architecture must normalize raw data separately to preserve the integrity of raw data
- The architecture must maintain an audit trail of all changes or modifications to raw or normalized data
- Calculation threads must be separated from raw and normalized data
- All normalization and calculation steps must be shown and documented separately and transparently.

INTRODUCTION

Background

The Department requires MDAP and pre-MDAP life-cycle cost estimates throughout the many stages of the requirements process and into formal acquisition at Milestone A and beyond. The estimates are needed for affordability assessments, evaluations of alternatives prior to Milestone A, capability portfolio analysis, programming, budgeting, and acquisition decision making. DoD Instruction 5000.73, *Cost Analysis Guidance and Procedures*, defines the products, reviews, and timelines needed to generate these life-cycle cost estimates for ACAT IC and ID programs.[11] More specifically, the instruction covers requirements for Program Office Estimates (POEs), Independent Cost Assessments (ICAs) and Component Cost Positions (CCPs) by the Service Cost Centers, and Independent Cost Estimates (ICEs) executed by the OSD CAPE.

A common thread runs through all of these estimates, of whichever purpose and pedigree, – namely, the presence of uncertainty. At this point it's worthwhile to define some terms. The Defense Acquisition University defines risk, opportunity, and uncertainty as follows. Risk includes all of the things that could adversely impact a program and add costs while opportunities are areas where savings could be realized. The entire range of risks and opportunities is cost uncertainty. These definitions are not universal. Within and outside the DoD the terms risk and uncertainty are often used interchangeably.



Estimates, to compound difficulties, are sometimes required when little about a program's total definition is known. At the Capability Based Assessment (CBA) in JCIDS, for example, the Joint Staff requires an evaluation of the affordability of potential materiel solutions to a capability gap, thus necessitating ROM estimates of investment and sustainment costs.[12] Downrange at Milestone A, a preferred solution has just emerged from an Analysis of Alternatives. But years of system engineering and development, weapon system production, and decades of operating and support costs lie ahead and need to be estimated. Further, even at Milestones B and C, estimates are sometimes based on data samples of limited size that are challenging and costly to obtain. Strong efforts are sometimes required to squeeze usable information from an inconsistent set of data. When historical observations are fit to statistical regressions the results typically come with large standard errors.

[11] DoD Instruction 5000.02, "Operation of the Defense Acquisition System," defines the requirement for Independent Cost Estimates in the Department, as prescribed by federal statute.

[12] Joint Capability Integration and Development Systems (JCIDS). See CJCSI 3170.01I for additional details.

For these reasons, a life-cycle cost estimate, when expressed as a single number, is merely one outcome or observation in a probability distribution of potential costs. A cost estimate is stochastic rather than deterministic, with uncertainty and risk determining the shape and variance of the distribution.

As noted previously, "Risk" and "uncertainty" are often used interchangeably, but they are not the same and are often defined differently within different professional communities. The Noble laureate Frank Knight distinguishes the two terms in a definition that's quoted today in financial publications and economic textbooks:

> *"Uncertainty must be taken in a sense radically distinct from the familiar notion of Risk, from which it has never been properly separated.... The essential fact is that 'risk' means in some cases a quantity susceptible of measurement, while at other times it is something distinctly not of this character; and there are far-reaching and crucial differences in the bearings of the phenomena depending on which of the two is really present and operating.... It will appear that a measurable uncertainty, or 'risk' proper, as we shall use the term, is so far different from an unmeasurable one that it is not in effect an uncertainty at all."*[13]

For Knight, uncertainty is akin to Secretary Rumsfeld's *unknown unknowns*; it is a risk that is immeasurable. "Risk" for Knight, however, is similar in nature to the definition proffered in DoD's risk management guide, as illustrated in Figure 1. Risk is an amalgam of probability and consequence:

> *"Risks are future events or conditions that may have a negative effect on achieving program objectives for cost, schedule, and performance. Risks are defined by (1) the probability (greater than 0, less than 1) of an undesired event or condition and (2) the consequences, impact, or severity of the undesired event, were it to occur."*[14]

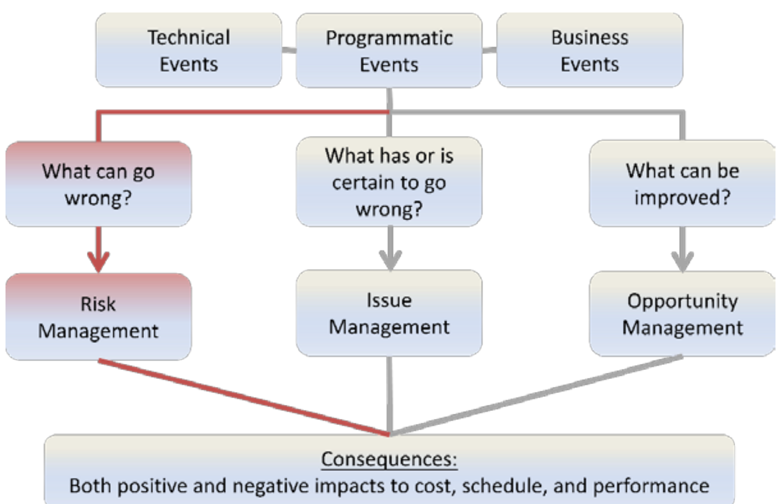


Figure 1

[13] "Risk, Uncertainty, and Profit," University of Chicago, Knight, Frank; 1921.

[14] Department of Defense *Risk, Issue, and Opportunity Management Guide for Defense Acquisition Programs*, page 9, June 2015

In defense cost analysis, uncertainty differs from Knight's view, and includes observations falling above and below a mean point estimate. That is, uncertainty represents the noise associated with the use of factors, percentages, CERs, and other parametric techniques that are used in producing a life-cycle cost estimate.

In any event, need is established along with a clear understanding of the challenge – developing "a calculus of probability" for cost estimates decades ahead.[15]

Techniques and Applications

Best practices in cost risk analysis are defined comprehensively and cogently in the Joint Agency Cost Schedule Risk and Uncertainty Handbook (JA CSRUH).[16]

> *"The Handbook serves as a reference for Navy, Marine Corps, Army, Air Force and NASA cost analysts for incorporating risk and uncertainty within cost estimates. The Handbook incorporates consideration of schedule uncertainty, risk registers, historical uncertainty in input parameters, improved risk expert elicitation, and other recent areas on innovations. Concepts are developed using one consistent example."*

As the Handbook suggests, the S-curve, or cumulative probability distribution of cost, is the gold standard for the representation of uncertainty. These curves are used by industry and government throughout the international defense cost community, and are often briefed at the highest levels in DoD and major corporations.

A recent application by the Naval Center for Cost Analysis, as depicted in Figure 2, demonstrates the power and utility of the S-curve in illuminating acquisition issues of interest to the Chief of Naval Operations, the DON's Acquisition Executive, USD(AT&L), and the Congress in:

- Comparing POE and ICA acquisition cost estimates
- Comparing cost estimates to a Congressionally-mandated cost cap
- Estimating the probability that cost cap will be exceeded
- Estimating a shortfall in funding relative to a President's Budget.

Note the use of a 5% CV in the Program Office Estimate (POE). This disturbingly low value is the catalyst for the current research, or the development of benchmark values based on historical acquisition results. Of dubious validity, the 5% value falls beneath historical norms at Milestone B by a wide margin, even after adjusting for changes in quantity. Yes, the acquisition program in question might possible be far less risky than average because of unique circumstances. But to such a degree? The benchmarks serve as a gauge for establishing norms and for placing a burden of proof on the proponent of a substantial deviation from the average.

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[15] General Theory of Employment, Interest, and Money, Keynes, John Maynard, 1936.

[16] Downloadable from https://www.NCCA.Navy.mil/

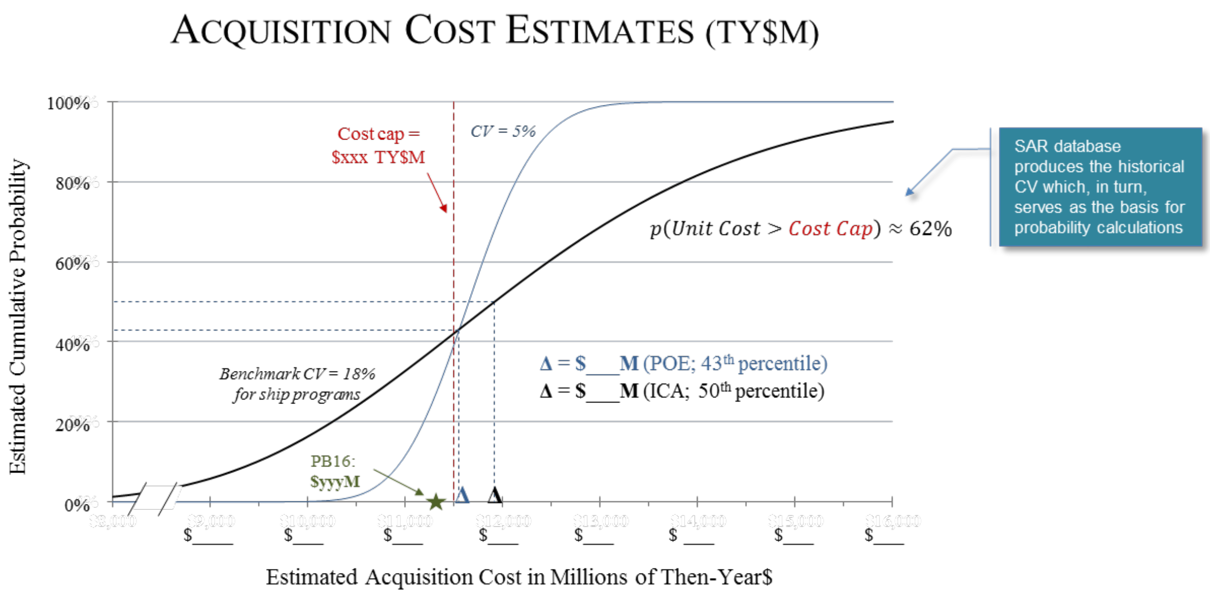

Figure 2

Conjectures

In keeping with past studies by Braxton and Flynn, and in lieu of suggestions made by USD(AT&L) that Better-Buying-Power (BBP) initiatives have led to less cost risk, it's useful to proffer these conjectures of the behavior of coefficients of variation (CVs):

- Consistency
  - CVs in current cost estimates are consistent with those computed from acquisition histories;
- Tendency to Decline During Acquisition Phase
  - CVs decrease throughout the acquisition lifecycle;
- Platform Homogeneity
  - CVs are equivalent for aircraft, ships, and other platform types;
- Tendency to Decrease after Normalization
  - CVs decrease when adjusted for changes in quantity and inflation; and
- Invariance of Secular Trend
  - CVs are steady long-term.

An assessment of the correctness of each of the above conjectures is enabled through a data collection and analysis effort, described below.

DATA COLLECTION

SAR Basics

To support the generation of realistic S-curves, this research entailed a data collection and analysis effort using Selected Acquisition Reports (SARs). The SARs contain raw data on cost outcomes of mostly completed major defense acquisition programs (MDAPs) but also a handful of on-going programs where cost growth has likely stabilized. As multiple studies have indicated, the SARs, while not perfect, are nevertheless a good, convenient, comprehensive, official source of data on cost, schedule, and technical performance of MDAPs. More importantly, they are tied to milestones, as are independent cost estimates (ICEs), and they present total program acquisition costs across multiple appropriations categories.

For a given program, the SAR provides two estimates of cost. The first is a baseline estimate (BE), usually made when the system nears a major milestone. The second is the current estimate (CE), which is based on best-available information and includes all known and anticipated revisions and changes to the program. For completed acquisitions, the CE in the last SAR reported is regarded as the actual cost of the program. SAR costs are reported in both base-year (BY) and then-year (TY) dollars, allowing for comparisons both with and without the effects of inflation.

The ratio of the CE to the BE is a cost growth factor, or CGF, reported as a metric in most SAR-based cost-growth studies. Computation of CGFs for large samples of completed programs serves as the basis upon which to estimate the standard deviation and the mean of acquisition cost outcomes, and hence the CV. An outcome, as measured by the CGF, is a percent deviation, in index form, from an expected value or the BE.

Prospective changes in acquisition quantity from a program baseline are generally regarded as beyond the purview of the cost analyst in terms of generating S-curves.[17] There are several ways for adjusting raw then-year or base-year dollars in the SARs to reflect the changes in quantity that did occur, including but not limited to the ones shown here below. The estimated cost change corresponding to the quantity change is denoted QΔE.

- “Paasche” index: Adjust baseline estimate to reflect current quantities
    - $CGF = \frac{CE}{(BE+Q\Delta E)}$; used in the SARs
- “Laspeyres” index: Adjust current estimate to reflect baseline quantities
    - $CGF = \frac{(CE-Q\Delta E)}{BE}$

[17] Performing what-if drills for alternative development and production quantities and schedules is, however, a legitimate and necessary undertaking.

- "Fisher" index = Square root of the product of the first two
    - $\sqrt{(Laspeyres * Paasche)}$

The first two formulae are analogous to the Paasche and Laspeyres price indices in economics, which are based on current and base year quantities, respectively. The third we dub "Fisher's" index which is the geometric mean of the first two. The Fisher index takes into consideration the reality that changes in quantity are typically implemented *between* the base year and current year rather than at either extreme. Deltas in CVs are typically negligible no matter which method of adjustment is used.[18]

Alternative Databases

Many databases have been developed over the years using the SARs. They range in size and scope from small, unpublished *ad hoc* files in Excel to more comprehensive products using sophisticated database software, with major efforts depicted in Figure 3.

In theory, it makes no sense for pockets of cost analysts to repeatedly and independently create their own SAR databases using the same underlying source of data. To compound this problem, the scope and quality of the databases vary in terms of data collected and validated, normalization techniques employed, and medium used for data storage.

Early on in this study, NCCA and the OSD CAPE recognized the need to develop <u>one</u>, <u>authoritative</u> database of numerical SAR data, carefully designed to meet universal requirements and to collect and store raw data, for subsequent use throughout the entire cost and acquisition communities. Note that the Congress and the Government Accountability Office (GAO) are big users of SAR data, too.

To leverage past work, this study culled historical data (pre-2012) from an existing NCCA database. It met the requirement to capture all variance categories, by type of appropriation. Not all SAR databases do.

A completely new design was conceived, however, involving the separation of raw and normalized data, use of a Change Log, built-in instructions, and the specification of business rules for normalization. The business rules, if they fit a certain need, can be tacked on to the database much like an application program interface. Details are provided in the last major section of this report, after an analysis of study findings.

[18] The Module 5 Inflation and Index Numbers of the Cost Estimating Body of Knowledge (CEBoK) provides additional details, courtesy of Brian Flynn.

Database Attribute	Database Source		
	NCCA	RAND	PA&E
Number of Observations (MDAPs)	300+	70	138
Method of Quantity Adjustment			
Beginning/End/Fisher	Fisher	Beginning	Not Made
Estimate of Dollar Value	SAR Value	Cost Improvement Curve	
Categories of Cost Change Captured in the Database	All seven from the SARs	Economic (Escalation) and Quantity (non-SAR)	Non-SAR:"Mistakes and Decisions"
Type of Information Stored			
SAR Summary Sheets	All	Unknown	Unknown
Individual SARs (PDFs)	All	Unknown	Unknown

Figure 3

RESULTS OF ANALYSIS

Overview

The new, authoritative database of normalized, numerical SAR data is already yielding insights to support realistic cost risk analysis. Benchmark CVs are producible from the raw cost growth factors, with an example shown in the radar graph (Figure 4) for predominately ship and submarine acquisition programs. The CGFs are based on then-year dollar calculations, adjusted for changes in quantity. The data are displayed in chronological order according to the date of the baseline estimate, or BE, beginning at true North and proceeding in clockwise fashion. That is, the newest acquisition appears first (Ship to Shore Connector) and oldest last (SSN-668 Submarines). The four imaginary quadrants correspond roughly to different decades of acquisition.

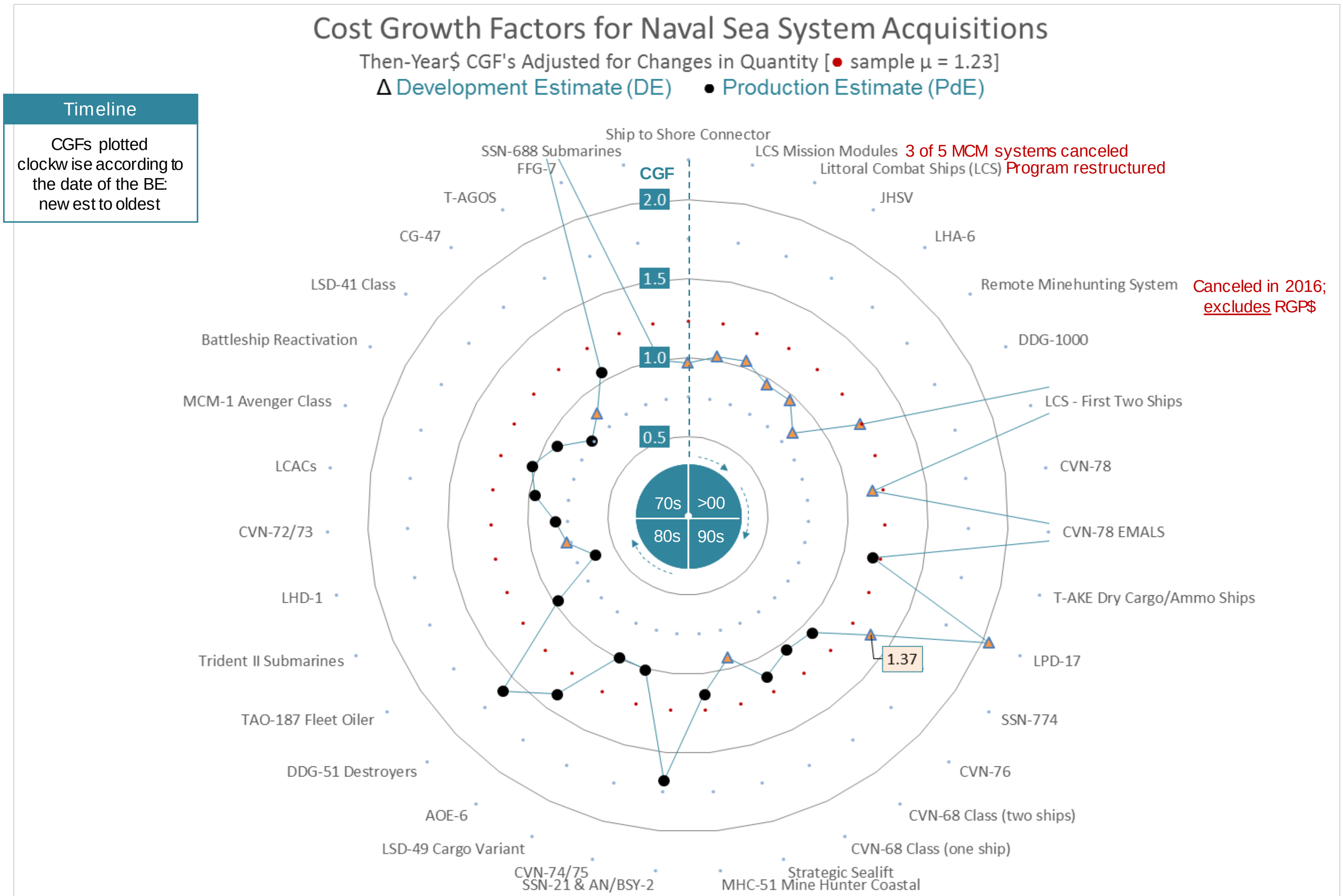

Figure 4

Average cost growth in the entire sample of development (DE) and production (PdE) estimates is 23%. Outliers and extreme outliers are clearly visible throughout acquisition history, in every decade. The

Littoral Combat Ship (LCS) program, with Congress mandating separate SAR reporting on the first two hulls in the ship class, provides a recent example. Another example is the Electro-Magnetic Aircraft Launch System (EMALS) for *Ford* Class carriers.

Interestingly, many of the acquisitions with baseline estimates in the late 1970s, such as LSD-41 Class ships, achieved negative cost growth. That is, costs came in less than estimated. This may have been due to the use of competitive acquisition strategies during this era. In the case of LSD-41 Class, six shipyards submitted bids in 1984 for a winner-take-all competition for the last five ships in the class. The yards bid on a survival basis, with Avondale the winner. Two of the six yards, Lockheed Seattle and General Dynamics/Quincy, filed for bankruptcy upon losing.

More recently, cost growth appears subdued, with a string of current acquisitions appearing near the 1.0 CGF iso-circle. USD(AT&L) notes the trend and proclaims that

> *"Not only is cost growth significantly lower than historical levels, but recent efforts have dramatically lowered cost growth further. Recent improvements focused on acquisition fundamentals and an empowered government workforce have been more successful than laissez-faire acquisition reforms of the mid-1990s or prior to the passage of Goldwater-Nichols and the Packard Commission reforms of the late 1980s."*[19]

However, careful interpretation of results is in order. Many current acquisitions will extend into the decades ahead. The jury is still out on their definitive outcomes. Further, the SARs don't always reveal the complete story of an acquisition. Littoral Combat Ship, for example, has been restructured because of issues with self-protection in the littoral.[20] Additionally, critical components of some of its mission modules have failed miserably and have been canceled, such as the Remote Minehunting System (RMS). To compound the problems, three of five systems planned for deployment from LCS's Knighthawk helicopter have similarly been canceled due to performance and platform integration issues, including the Rapid Airborne Mine Clearance System (RAMICS) and the Organic Airborne and Surface Influence Sweep (OASIS).[21]

In short, focusing simply on the SAR raw numbers, while important and useful, can lead to a misinterpretation of results and a misguided notion of the impact of policy. Every single acquisition in the graph merits its own analysis and interpretation.

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[19] Performance of the Defense Acquisition System: 2016 Annual Report; USD(AT&L); page xv.

[20] "In 2014, at the direction of Secretary of Defense Chuck Hagel, the program was restructured [citing survivability and mission effectiveness issues, in an emerging threat environment]," from *Navy Littoral Combat Ship (LCS)/Frigate Program: Background and Issues for Congress*, Ronald O'Rourke; Congressional Research Service 6 Mar 2016.

[21] "The first LCS MCM Package is due to be delivered around 2019, and three programs were eliminated: MH-60S helicopter tow [influence sled]; Rapid Airborne Mine Clearance System (RAMICS); and OASIS;" 2013 Mine Warfare Association Forum Update; posted on December 17, 2014.

Sample Data at Milestone B

Of the 35 programs in the sample of Naval Sea System Acquisitions, 17 were MS B estimates of total program acquisition cost (which includes development, production, and, less frequently, military construction). Platform types included surface combatants, carriers, amphibious assault vessels, and submarines. From the SAR summary sheets and individual SARs, the following data elements were captured: base year, baseline type, platform type, baseline and current cost and quantity estimates, changes to date by variance category, and date of last SAR, with costs in both base-year and then-year dollars. Results were analyzed, and the means, standard deviations, and CVs are displayed in Table 1.

Cost Growth Factors & CVs for DON Sea System MDAPs at MS B				
	(Without Quantity Adjustment)		(Quantity Adjusted)	
Statistics	Base-Year$	Then-Year$	Base-Year$	Then-Year$
Mean	1.61	1.97	1.18	1.30
Standard Deviation	1.11	1.54	0.38	0.61
CV	69%	78%	32%	47%

Table 1

Four CVs were tallied, corresponding to the four types of CGFs estimated. As adjustments for quantity and inflation were made, the CVs decreased, as expected. More specifically, the total delta in CVs from unadjusted in then-year dollars to quantity-adjusted in base-year dollars is 46 percentage points (78% - 32%. Of this amount, *after* adjusting for changes in quantity, inflation represents a full 15 percentage points (47% - 32%). Escalation, then, is an important element of uncertainty in defense acquisition.

Figure 5 shows CGFs adjusted for changes in quantity but not inflation. The histogram's skewness suggests a lognormal distribution, with the mean falling to the right of the median. Average cost growth is 30% with a CV of 47%, consistent with previous studies.[22]

[22] "Weapon Systems Acquisition Reform Act (WSARA) and the enhanced Scenario-Based Method (eSBM) for Cost Risk Analysis," Brian J. Flynn and Paul R. Garvey; presented to the 44th Annual Department of Defense Cost Analysis Symposium, February 2011, Williamsburg, Virginia; Published by the Naval Center for Cost Analysis, Washington, DC; April 2011

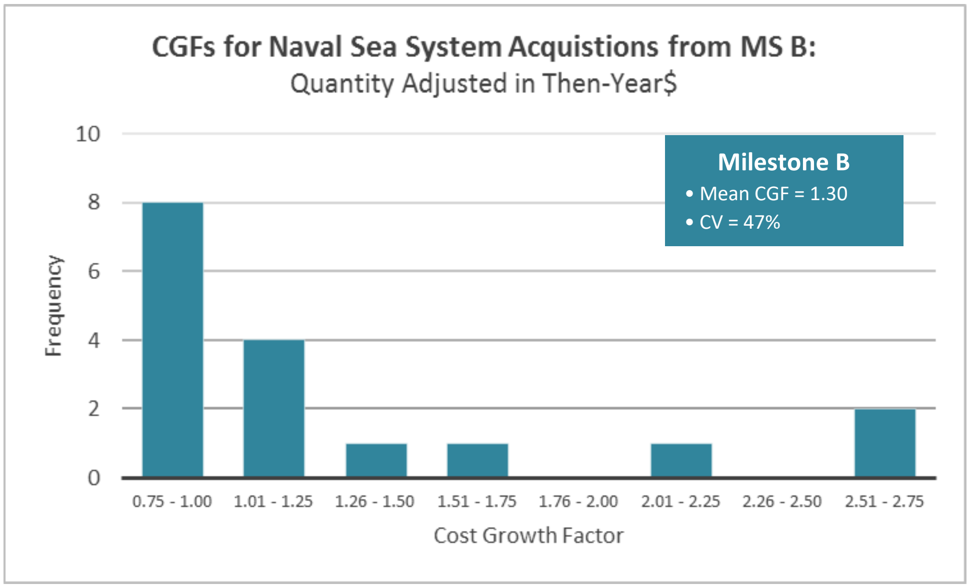

Figure 5

Sample Data at Milestone C

Turning to MS C, the SAR Production Estimate (PdE) is of total program acquisition costs, including the sunk cost of development. As expected, CGF and CV metrics exhibit an across-the-board drop from MS B estimates, as Table 2 shows. This decrease results not only from the inclusion of sunk development costs in the calculations, but probably also from increased program knowledge and program stability moving from MS B to MS C.

Cost Growth Factors & CVs for DON Sea System MDAPs at MS C				
	(Without Quantity Adjustment)		(Quantity Adjusted)	
Statistics	Base-Year$	Then-Year$	Base-Year$	Then-Year$
Mean	1.02	0.95	1.09	1.05
Standard Deviation	0.28	0.27	0.14	0.23
CV	28%	29%	13%	22%

Table 2

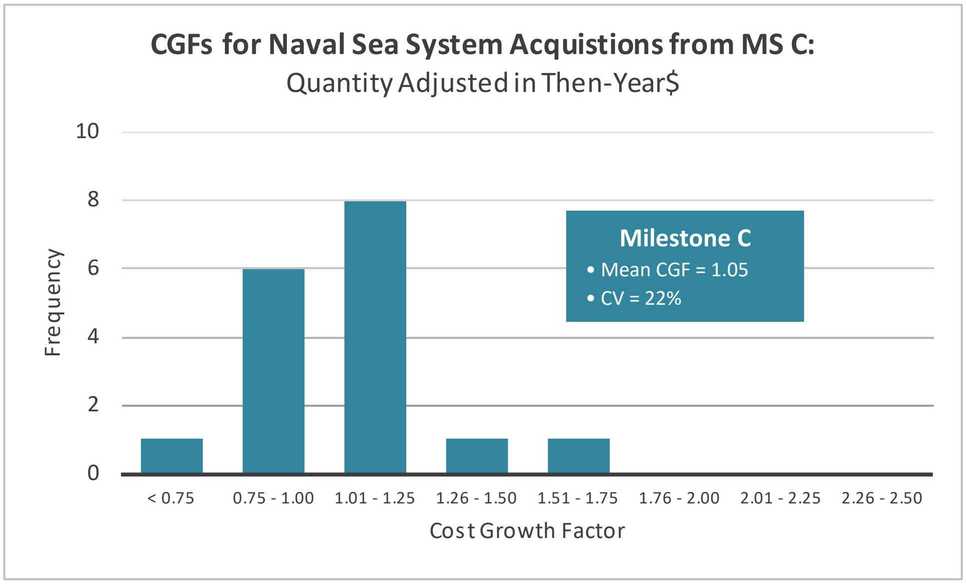

Figure 6

Secular Trends at Milestones B and C

Turning now to the conjecture of constant CVs over lengthy periods, Table 3 shows a pronounced decrease in average cost growth for Milestone B estimates. But there's no statistically-discernable differences in the CVs. The sample contains EMALS but excludes the SAR for the first two hulls of LCS. The latter was technically a Planning or Milestone A estimate.

CVs at Milestone B for Date of BE ≥ Yr2000				
Statistics	(Without Qty Adjustment)		(Quantity Adjusted)	
	Base-Year$	Then-Year$	Base-Year$	Then-Year$
Mean	1.16	1.31	1.08	1.20
Standard Deviation	0.81	1.05	0.41	0.55
CV	70%	80%	38%	46%

CVs at Milestone B for Date of BE < Yr2000				
Statistics	(Without Qty Adjustment)		(Quantity Adjusted)	
	Base-Year$	Then-Year$	Base-Year$	Then-Year$
Mean	2.13	2.73	1.31	1.41
Standard Deviation	1.23	1.73	0.34	0.69
CV	58%	63%	26%	49%

Table 3

Including both LCS and EMALS yields the results of Table 4, with almost identical CGFs pre- and post-2000, and with the current CV now higher than before.

CVs at Milestone B for Date of BE ≥ Yr2000 (with EMALS and LCS#1 &2)				
Statistics	(Without Qty Adjustment)		(Quantity Adjusted)	
	Base-Year$	Then-Year$	Base-Year$	Then-Year$
Mean	1.33	1.48	1.25	1.39
Standard Deviation	0.94	1.14	0.68	0.79
CV	71%	77%	54%	57%

Table 4

Turning now to Milestone C, a paucity of observations requires an examination of secular trends pre- and post-1990 rather than a decade later. This makes sense relative to Milestone B (pre- and post-2000) in the acquisition life cycle since the former is a development rather than a production estimate. As Table 5 shows, the CVs are identical between the two time periods.

CVs at Milestone C for Date of BE ≥ Yr1990				
	(Without Qty Adjustment)		(Quantity Adjusted)	
Statistics	Base-Year$	Then-Year$	Base-Year$	Then-Year$
Mean	1.07	1.06	1.18	1.21
Standard Deviation	0.23	0.26	0.12	0.24
CV	21%	24%	10%	20%

CVs at Milestone C for Date of BE < Yr1990				
	(Without Qty Adjustment)		(Quantity Adjusted)	
Statistics	Base-Year$	Then-Year$	Base-Year$	Then-Year$
Mean	0.99	0.89	1.05	0.96
Standard Deviation	0.32	0.27	0.14	0.19
CV	32%	31%	13%	20%

Table 5

Conjectures of CV Behavior

Returning to the conjectures of CV behavior, with statistical details available from the authors, these observations are offered:

- Consistency
    - Conjecture: CVs from ICEs and cost assessments accord with acquisition experience
    - Finding: CVs appear underestimated too often by program offices, as evidenced in briefings to the DON Cost Review Board. The authors, for example, have witnessed program-office CVs of 5% at Milestone A, and, almost unbelievably, a CV of ½ of one percent at Milestone C. These values are far below the CVs shown in the Tables 3 and 5

- Tendency to Decline During Acquisition Phase
    - Conjecture: CVs decrease throughout acquisition lifecycle
    - Finding: Strongly supported by evidence, as noted in Milestone B to C transitions (Tables 3 and 5)

- Platform Homogeneity
    - Conjecture: CV are the same across platform types
    - Finding: Under study

- Tendency to Decrease after Normalization
    - Conjecture: CVs decrease when adjusted for changes in quantity and inflation
    - Finding: Strongly supported by the evidence, as shown in Tables 3, 4, and 5. Logically, CGFs decrease in value when sources of cost variation are eliminated.

- Invariance of Secular Trend
    - Conjecture: CVs steady long-term

- For estimates at Milestone B, results are mixed, and dependent open the inclusion of two key observations. With EMALS included, CVs are essentially unchanged. For estimates at Milestone C, on the other hand, there's no evidence that CVs have decreased in value.[23]

THE NEW SAR DATABASE ARCHITECTURE

Introduction

The diverse set of analysts and organizations that use defense cost databases and analytical tools have innumerable and often unique requirements, and it would be impossible to predict every way a user may want to visualize, normalize, and analyze data. Further, needs change over time. The threat changes, requirements change, and the Congress makes statutory changes to defense acquisition. Analysts respond to the new environment. The goal of developing a new SAR database was to accommodate this uncertainty with an authoritative design that could be adapted to meet any present and future analytical needs.

The process of developing a functional SAR database began as a task in 2012 to support the Naval Center for Cost Analysis' S-Curve Tool by developing its database backbone. The database development process was largely a manual one and prone to human error, given the data discontinuities.

While the scope of the current redevelopment effort is to support an update to the NCCA S-Curve Tool, our research and innovations are a test of implementing design requirements for a single-source, authoritative, and standardized database, as envisioned by NCCA and the OSD CAPE in their Cost Assessment Data Enterprise (CADE) initiative. Figure 7 shows the progression from 2007 to present day of SAR data collection, processing, and storage in support of calculating CGFs and CVs. It also shows how this current effort has planned for a future vision of better data management. This better data management allows for easier updates to the database and it standardizes the raw and normalized datasets for improved usability via application programming interfaces. What follows Figure 7 is an analysis of the SAR database design. The discussion and analysis will highlight the implications of our automation and reproducibility standards on support to analysts and organizations in the broad defense cost community.

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[23] This result should be viewed with caution, as the sample size is small.

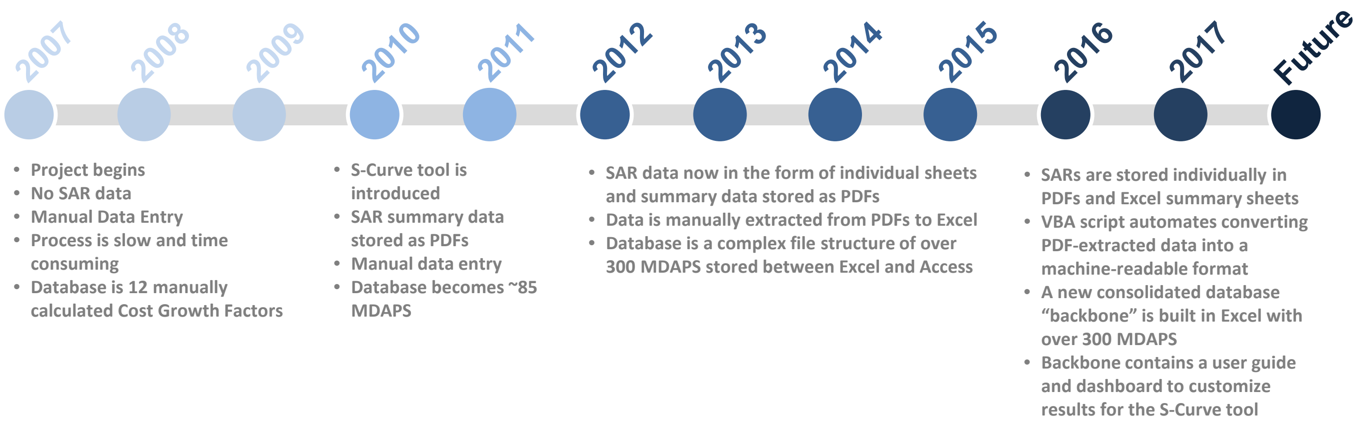

Figure 7

Evaluating the 2012 NCCA SAR Database

To begin evaluating the 2012 SAR database, we had to understand how SAR data was stored and what procedures were required to transfer the SAR data from an individual file into a database. SAR data exists in three different states: SARs dating from 1969 through 1997, stored digitally as photocopies of physical documents in a non-machine readable form; as individual SARs, dating from today back to 1997, stored in a standard digital format that are not natively machine-readable; and stored as summary-level, multi-programmatic reports, stored in a database-compatible format.[24]

The key differences between these types of reports are how the data is stored, and the contents of the data. Individual SARs, including both the pre- and post-1997 reports, include cost variance data and a detailed program breakdown structure that highlights the existence of subprograms, if applicable. An example of a subprogram or system is the engine for Joint Strike Fighter (JSF), now accounted for separately in the SARs. The summary-level data is stored in a format compatible with a database; however, the absence of cost variance data in these files render them insufficient, alone, to derive CGF and CV results at the appropriation level, such as Research, Development, Test and Evaluation (RDT&E) and Procurement, as Figure 8 illustrates.

[24] DAMIR has a back-end relational database used to generate the SAR PDFs "on demand," like a bank statement. The SAR PDFs contain tables of data. These are digital but are not machine-readable because a computer would struggle to access the tabular information even though they are human readable. The equivalent tables in a format such as a spreadsheet would be machine readable. These transformations can be achieved using Application Program Interfaces (APIs)

Program	Base Year	Baseline Type	Baseline Estimate			Current Estimate		
			Base-Year Dollars	Then-Year Dollars	Quantity	Base-Year Dollars	Then-Year Dollars	Quantity
Army:								
AH-64E	2010	PdE	2,307.0	2,510.4	56	2,031.9	**2,522.7**	63
AH-64E	2010	PdE	10,468.7	11,896.6	639	12,658.6	14,597.1	639
AMF JTRS	2008	DE	7,141.3	8,334.0	25,124	2,907.1	3,493.4	14,222
AMPV	2015	DE	10,724.8	13,944.8	2,936	10,749.8	13,842.4	2,936

Summary BY $M (AH-64E-New-Build_437_SAR_2015)					
Item	**RDT&E**	**Procurement**	**MILCON**	**Acq O&M**	**Total**
Current Changes	--		--	--	
Economic	--	17.8	--	--	17.8
Quantity	--	0.0	--	--	0.0
Schedule	--	5.3	--	--	5.3
Engineering	--	0.0	--	--	0.0
Estimating	--	5.3	--	--	5.3
Other	--	0	--	--	0
Support	--	-78.5	--	--	-78.5
Subtotal	--	96.3	--	--	96.3
Total Changes	--	12.3	--	--	12.3
Current Estimate	--	2522.7	--	--	**2522.7**

Excerpts of metatags of program entries in summary-level data (Above) versus metatags for a cost variance table for the same program (Left). Note how the cost variance table for the program is more detailed, and the current estimate (highlighted in yellow) matches the value in the summary-level table.

Figure 8

Because pre- and post-1997 SARs with cost variance data were not available in a machine-readable format, the 2012 effort opted to manually recreate cost variance tables. This effort involved extracting the data tables from over 1,600 individual SARs, usually by copying and pasting from PDFs into Excel, and then formatting the entries to place the numbers in their proper bins. Sometimes, manual data entry was required. This methodology elevated the risk of human error and the use of erroneous observations. Knowing this risk, the first step of development in the new SAR database was to validate and verify the existing data.

Multiple versions of the previous database were discovered. These databases contained conflicting data for some identical observations, and the lack of documentation on each version of the databases made it difficult to discern which observations were the finalized variants. Our solution was to standardize the metatags in each version of the SAR database to enable cross-referencing. Our assumption was that by cross-referencing all versions of the previous build, we could identify if a program had been added and when, which data had been changed and when, and if a program was broken into subprograms and when. With this process, we could back into the finalized database used in 2012 as well as establish an audit trail to illuminate how data was normalized. The resulting "de-normalized" database was used as a baseline for raw SAR data dating back to 1986.[25] Final SAR submissions of this vintage, it's important to note, reflect baseline estimates dating back to the 1970s, or the early days of the modern Defense Acquisition System with milestone reviews.

[25] SARs before 1986 were not digitally recreated in the 2012 effort.

Summary-level data is limited to the Baseline Estimates (BE) and the Current Estimates (CE) for a program for all available milestones, whereas individual SARs present BE and CE cost variance tables as well. A Current Estimate reflects changes from the BE, bucketed into these cost variance categories, as shown in Table 6: Economic, Quantity, Schedule, Engineering, Estimating, Other, and Support. Because, in theory, the totals for the BEs and CEs found in summary-level data equal the totals derived from the cost variance data, we performed a second cross-reference between summary-level data and the "de-normalized" raw data to verify if the manually entered cost variance data for a program summed to the correct total values for the same program. This effort identified all erroneously-entered observations. Corrections were made to maintain data quality.

Table 6

Cost Category	Definition
Economic	A change that is solely due to price-level changes in the economy
Quantity	A cost variance that is due to a change in the number of units of an end item of equipment
Schedule	Costs resulting from a change in a procurement or delivery schedule, completion date, or intermediate milestone for development or production
Engineering	Cost increases or decreases that are due to an alteration in the physical or functional characteristics of a system or item delivered
Estimating	Changes that are due solely to the correction of previous estimating errors or to refinements of a current estimate
Other	Cost variances that are due to unforeseeable events not covered in any other category (e.g., natural disaster, strike)
Support	Any change in cost, regardless of reason, associated with support equipment for the major hardware item (defined as any Work Breakdown Structure (WBS) element not included in flyaway, rollaway, or sailaway costs)

Descriptions of standard SAR cost variance categories. These categories were converted into metatags for the database.

Between cross-referencing, validation, and verification techniques, we successfully cleansed the 2012 SAR database of most blemishes and established an authoritative resource for SAR data dating back to a base year of 1986. This data was used as the groundwork for the new SAR database.

The New Database Architecture

The 2012 SAR database was built upon architecture that emerged as problems with the raw data emerged, meaning the database files existed in isolation from each other, requiring manual interaction to produce results. Ultimately, this posed no issue when CGFs and CVs were derived to support the NCCA S-Curve Tool in 2012, but the lack of a pre-conceived architecture rendered the 2012 database insufficient as a baseline for a new SAR database. It was not designed with annual updates in mind, making database maintenance significantly more difficult than an updated design allows. We concluded that an overhaul of database architecture was required to meet the standards of a modern and functional database.

We decided on five core database architecture requirements for the new SAR database:

1. The architecture must isolate raw data;
2. The architecture must normalize raw data separately to preserve the integrity of raw data;
3. The architecture must maintain an audit trail of all changes or modifications to raw data;
4. Calculation threads must be separated from raw and normalized data; and
5. All normalization and calculation steps must be shown separately and transparently.

The goal of this architecture design was to develop an authoritative, modular, and transparent system that could suit the needs of any analyst or organization.

With the architecture determined, the next step was to organize raw data. The simplest solution can often be the best; we therefore decided to preserve the metatags found in cost variance tables and summary-level spreadsheets. In addition, we added metatags to support labeling the commodity class (Aircraft, Submarine, Missile, etc.) of each program and to generate a unique identification string for each observation. The next step was to import raw data into the new database.

Extracting SAR Data

Populating the new SAR database with data from existing and new sources was not as simple as "copying and pasting." The raw data from the 2012 SAR database was first converted back to the original structure found in SARs, and a script was written to import the data without manual data entry. While this import was seamless, we still had to retrieve SARs produced since the 2012 effort.

To retrieve the SARs, we explored two options:

- Manually download the required SARs from the Defense Acquisition Management Information Retrieval (DAMIR) system, where individual observations are stored.[26]
- Use the existing but incomplete APIs for DAMIR to automate SAR retrieval and cost variance table extraction.

Due to time constraints on the scope of this effort, we estimated that fully developing the APIs for DAMIR required more time than manually downloading the required SARs. However, we concurrently tested a "proof of concept" using the existing APIs, and demonstrated feasibility in automating cost variance table data extraction.

As discussed, individual SARs post-1997 contain cost variance tables, but are not stored in a format compatible with our database architecture. When natively extracted into a spreadsheet, the cost variance tables contained numerous formatting errors, rendering the data incompatible with the metatags associated with the raw data.[27] Figure 9 shows the results when a post-1997 SAR is natively converted into a spreadsheet. Note the numerous formatting errors.

[26] "Defense Acquisition Management Information Retrieval," (DAMIR), Department of Defense, 2017. DAMIR is a DoD initiative that provides enterprise visibility to Acquisition program information. DAMIR is the authoritative source for Selected Acquisition Reports (SAR), SAR Baselines, Acquisition Program Baselines (APB), MAIS Annual Reports (MAR), MAIS Original Estimates (MAIS OEs), and Assessments.

[27] If one were to attempt to natively extract the cost variance tables, it is easy to understand why one may opt to pursue manual data entry as a quick-turn solution.

Summary TY $M				
Item	RDT&E	Procurement	MILCON	Total
SAR Baseline (Production Estimate)	5468.4	617.3	--	6085.7
Previous Changes				
Economic	+118.0	+49.4	--	+167.4
Quantity	--	+946.0	--	+946.0
Schedule	+1329.0	-61.8	--	+1267.2
Engineering	+202.6	--	--	+202.6
Estimating	+383.8	+1497.3	--	+1881.1
Other	--	--	--	--
Support	--	--	--	--
Subtotal	+2033.4	+2430.9	--	+4464.3
Current Changes				
Economic	-6.3	-2.0	--	-8.3
Quantity	--	--	--	--
Schedule	--	--	--	--
Engineering	+60.7	+14.0	--	+74.7
Estimating	+11.6	-5.8	--	+5.8
Other	--	--	--	--
Support	--	--	--	--
Subtotal	+66.0	+6.2	--	+72.2
Adjustments	--	--	--	--
Total Changes	+2099.4	+2437.1	--	+4536.5
Current Estimate	7567.8	3054.4	--	10622.2

Summary TY $M					
Item	RDT&E	Procurement	MILCON	Acq O&M	Total
SAR Baseline (Development Estimate)	5468.4	617.3	0		6085.7
Previous Changes					
Economic	118	49.4	0		167.4
Quantity	0	946	0		946
Schedule	1329	-61.8	0		1267.2
Engineering	202.6	0	0		202.6
Estimating	383.8	1497.3	0		1881.1
Other	0	0	0		0
Support	0	0	0		0
Subtotal	2033.4	2430.9	0.0	0.0	4464.3
Current Changes					
Economic	6.3	2.0	0		8.3
Quantity	0.0	0.0	0		0.0
Schedule	0.0	0.0	0		0.0
Engineering	60.7	14.0	0		74.7
Estimating	11.6	5.8	0		5.8
Other	0	0	0		0
Support	0	0	0		0
Subtotal	66.0	6.2	0.0	0.0	72.2
Total Changes	2099.4	2437.1	0.0	0.0	4536.5
Current Estimate	7567.8	3054.4	0.0	0.0	10622.2

	RDT&E ($TY)						
Program	**SAR Baseline**	**Quantity**	**Schedule**	**Engineering**	**Estimating**	**Other**	**Support**
AEHF_SV	73.8	0	0	0	0.2	0	0
AEHF_SV	5468.4	0	0	60.7	11.6	0	0
AGM-88E(AARGM)_368_SAR_2015	600.3	0	2.1	0	-0.1	0	0
AH-64E-New-Build_437_SAR_2015	0	0	0	0	0	0	0
AH-64E-Reman_202_SAR_2015	1664.7	0	0	0	33.5	0	0
AIM-9X-BlockII_442_SAR_2015	175.7	0	0	0	32	0	0
AMDR_384_SAR_2015	1911.1	0	0	175	-22.7	0	0
AMF-JTRS_421_SAR_2015	1764.2	0	0	0	126.2	0	0
AMF-JTRS_SALT_421_SAR_2015	177.6	-2.2	0	0	-129.9	0	0
AMPV_471_SAR_2015	1073.8	0	0	0	-1.5	0	0
AMRAAM_185_SAR_2015	1350.6	0	0	0	-882.6	0	0

We developed a script that automated the extraction of cost variance tables from SARs and reformatted the data in two ways: The first output (top right) recreated the cost variance table in a spreadsheet, preserving the original format; the second output (bottom) converted cost variance data for a program into a single database entry. The database format allowed us to combine all programs into a single spreadsheet.

Figure 9

However, modernizing the SAR database architecture meant avoiding manual data entry at every opportunity. To resolve formatting errors, we developed a script to automate cost variance data extraction and reformatting. The script accomplished two goals:

- To maintain digital copies of each cost variance table for our records (the script recreated each cost variance table in a spreadsheet while preserving the original formatting); and
- To reformat the entire cost variance table into a single data entry that corresponded to the metatags in our database.

With the script complete, in a matter of seconds, all cost variance data was extracted, reformatted, and imported into the new SAR database.[28] This exercise proved that most of the manual effort to extract, clean, and reformat data for a SAR database could be automated. While we were unable to commit to

[28] An important detail to note: While this automatic process could have been done for the data in the 2012 build, SARs pre-1997 do not exist in a machine-readable state. They are photocopied documents stored as images and required a mass digitization effort in 2012 to be converted into a digital form.

fully developing the APIs to retrieve cost variance tables from DAMIR, our "proof of concept" demonstrated feasibility, meaning that future iterations of the SAR database architecture could directly link into DAMIR, completely automating the process of updating and maintaining the raw SAR data.

Normalizing SAR Data

Different analysts and different organizations may have competing preferences on what constitutes a valid methodology to normalize data. Moreover, in the case of SARs, a raw observation may not accurately describe the program it is attempting to describe, and there may be an objective way to normalize the observation.

For example, one user may require incomplete programs to be excluded from calculation threads fearing that they would confound cost-growth calculations for a purer set of fully completed programs. Another user may require incomplete programmatic data because they may consider it valid in their normalization process and want to reflect the most and latest data available. The validity of each preference notwithstanding, the underlying SAR data to support either normalization method is the same.

Typically, data are cleaned and normalized before being input into a calculation. We added more steps to the process:[29]

- First, raw data is extracted and its integrity is preserved separately from all other functions;
- Second, if amendments to raw data are required, all changes are logged and the original observations are preserved parallel to the amended entries to maintain an audit trail;
- Third, normalization is treated in separate modules, stored separately from raw data, and presented as transparently as possible so an analyst can easily examine all steps in a normalization process; and
- Fourth, we constructed a dashboard so a user can select which normalization modules they wish to apply to the data, if any at all, and control the thresholds of how strictly modules are applied.

In the next section, we will review the key differences between normalization in the 2012 SAR database and in the new SAR database, as well as discuss the benefits of our innovative methods.

[29] There are three states of data: raw (uncorrected), raw (corrected), and normalized. Correction can be viewed as just a non-controversial form of normalization.

Normalization in the 2012 SAR database

The normalization effort for the 2012 SAR database was almost entirely manual and normalized data was mixed in with the raw data. As discussed, this necessitated “de-normalizing” all data in the 2012 SAR database to recreate the series of authoritative raw data for the new SAR database. The following are the normalization techniques used in the 2012 build:

Manual Assessment of Completeness Factor: Queries were run as a heuristic to assess the “completeness factor” of a program for the most recent SAR available for a program. Completeness was graded one through five, where one equated to a program being the most incomplete, and five being the most complete.[30] The criteria were as follows:

1. Program is in Phase A[31], with the CE being the Milestone A or Planning Estimate (PE), or was cancelled
2. Program has had fewer than six SARs reporting in Phase B, with the CE being the Milestone B or Development Estimate (DE) and none reporting in Phase C
3. Program has had fewer than six SARs reporting in Phase C, with the CE being the Milestone C or Production Estimate (PdE)
4. Program has six or more SARs reporting in Phase C (PdE), including a current SAR[32]
5. The program has previously reported at Milestone C (PdE), but is no longer reporting due to completion.

After queries were run, results were manually scrubbed to make exemptions for completed production programs without a Milestone C (PdE). This occurred for many ship acquisition programs.

Manual Check for Subprograms: As cost variance tables were analyzed and manually recreated as a database, each SAR was checked for the existence of subprograms. New observations were created using the cost variance data from the subprogram. These data entries were assigned different program names and program numbers (PNOs) identified by an alphanumeric string instead of a numeric code.[33]

[30] Like EVM and CSDRs, SARs can stop reporting at mostly complete.

[31] We use current milestone and phase terminology for simplicity. While the precise names and designations of the milestones and phases have changed over the decades, they haven’t remained consistent enough for straightforward equivalence (e.g., Milestone II became Milestone B).

[32] The annual SARs are effective as of the end of each calendar year, but they are usually not released on DAMIR until around April of the following year. Thus, as of this writing the most recent SARs are December, 2015.

[33] DAMIR uses a three-digit numerical code called a PNO as the unique identifier for MDAPs. For MAIS programs, the first character of the three-character PNO is a letter instead of a number.

Manual Assessment of Subprogram Validity: As subprograms were identified, they were also assessed to determine if they were "valid." Meaning, in some cases, what a SAR denoted as a subprogram may not actually constitute a subprogram.

Manual Review for Milestone Transition Errors: For most programs, passage through an acquisition milestone entails a transition from one baseline estimate to another: PE to DE, or DE to PdE. To correctly calculate cost growth, the Current Estimate from the latest SAR, in whatever acquisition phase, should be used. For example, cost growth for DDG-51 Class destroyers at Milestone B should use the latest DDG-51 PdE's Current Estimate. The latter number is the best guess of total acquisition cost for the entire ship-construction program. This validation step checks that the calculations are executed using the correct values.

Manual Review for "Interphase growth": In the milestone transition, it is sometimes the case that the most recent CE of the previous phase does not match the new BE of the current phase. In this case, the difference is classified as "Interphase growth." Programs were manually reviewed to check for the existence of Interphase growth, as shown in Figure 10.

Change Summary Then-Year $M					
	RDT&E	Proc	MILCON	O&M	Total
SAR Development Estimate	548.7	5087.7	0.0	0.0	5636.4
Previous Changes					
Economic	-24.6	-450.8	--	--	-475.4
Quantity	+153.0	+988.2	--	--	+1141.2
Schedule	--	+198.0	--	--	+198.0
Engineering	+226.0	+780.6	--	--	+1006.6
Estimating	+402.4	+2569.4	--	--	+2971.8
Other	--	--	--	--	--
Support	+70.2	+638.9	--	--	+709.1
Subtotal	+827.0	+4724.3	0.0	0.0	+5551.3
Current Changes					
Economic	+3.4	+144.8	--	--	+148.2
Quantity	--	--	--	--	--
Schedule	--	-8.2	--	--	-8.2
Engineering	--	--	--	--	--
Estimating	-0.3	-6.9	--	--	-7.2
Other	--	--	--	--	--
Support	--	+75.5	--	--	+75.5
Subtotal	+3.1	+205.2	0.0	0.0	+208.3
Total Changes	+830.1	+4929.5	0.0	0.0	[illegible]
Current Estimate	1378.8	10017.2	0.0	0.0	$\boxed{11396.0}$

Summary Then Year $M				
	RDT&E	Proc	MILCON	Total
SAR Baseline (Prod Est)	1375.7	10049.0	--	$\boxed{11424.7}$
Previous Changes				
Economic	-10.1	-164.0	--	-174.1
Quantity	--	+1385.4	--	+1385.4
Schedule	--	+100.7	--	+100.7
Engineering	+188.7	+46.9	--	+235.6
Estimating	+113.5	[illegible]	--	+1352.1
Other	--	--	--	--
Support	--	-83.4	--	-83.4
Subtotal	+292.1	+2524.2	--	+2816.3
Current Changes				
Economic	+0.2	-12.2	--	-12.0
Quantity	--	--	--	--
Schedule	--	+9.2	--	+9.2
Engineering	+17.0	+0.3	--	+17.3
Estimating	-4.2	+76.8	--	+72.6
Other	--	--	--	--
Support	--	+71.8	--	+71.8
Subtotal	+13.0	+145.9	--	+158.9
Total Changes	+305.1	+2670.1	--	+2975.2
CE - Cost Variance	1680.8	12719.1	--	14399.9
CE - Cost & Funding	1680.8	12719.1	--	14399.9

The value of current estimate of the SAR from period 1 (Left) is less than the baseline estimate in the SAR for period 2 (Right). We label this incongruity as "Interphase Growth."

Figure 10

Manual Scrub for Un-rebaselining: Observations were scrubbed for cases where a program had been rebaselined due to cost growth. For these observations, the estimates for the observation were modified to reflect the "unrebaselined" estimates.

Other Issues

While not normalization steps, it's useful to describe two shortcomings of the 2012 Excel database which the current effort fixes:

> **Semi-Automated Cost Growth Factor Calculations:** The 2012 SAR database can calculate CGFs automatically if the architecture of the database is not changed. Moreover, these calculations are not dynamic, meaning outputs will not update if source data is amended.
>
> **Semi-Automated Coefficient of Variance Calculations:** Much like how CGFs are calculated, the 2012 SAR database can calculate CVs automatically if the architecture of the database is not changed. Moreover, these calculations are not dynamic, meaning that outputs will not update if source data is amended.

Normalization in the new SAR database

There are two primary differences in how the new SAR database normalizes data versus the 2012 database. First, the new SAR database treats normalization using separate mathematical modules. This separation not only preserves the integrity of the raw data, but provides a transparent, step-by-step process of how the modules decide if raw data requires normalization, and the mathematical procedures for that normalization. Second, most of the normalization is automated. For example, as raw data is imported into the database, normalization modules will update automatically to ensure that results are always up to date. The following are descriptions of the normalization techniques and modules implemented in the new SAR database:

Automated Determination of Most Recent Program Observation: This module identifies and labels the most recent SAR available for a program by overall most recent observation, and by most recent observation by milestone.

Automated Completeness Factor Determination: Raw data is scored against the same criteria as detailed in the 2012 SAR database, the primary difference being all program entries are scored for completeness rather than just the most recent observation per program. The model is also able to interpret if a program had a Milestone C production estimate (PdE) without a Milestone B estimate (DE). This sometimes occurs with historical ship acquisition programs such as LSD-41 Whidbey Island class.

Manual Assessment of Subprogram Existence: Because the DAMIR APIs were not fully developed in this effort, subprograms still require a manual assessment from the SARs. However, we expedited this by leveraging knowledge of subprogram existence provided in the 2012 effort.

Automated Milestone Transition Error Adjustments: Assisted by the module that identifies most recent program observation, the milestone transition error adjustment module automatically identifies if the BE of the most recent milestone for a program does not equal the quantity adjusted CE in the previous milestone. If the module identifies an incongruity, the model will communicate with an NCCA inflation index and adjust the values appropriately. (See section "*Case Study: Milestone Transition Error*" for a detailed outline on this process.)

Automated Interphase Growth Detector: This module expands upon other normalization modules to check for the existence of interphase growth when a program transitions milestones. If interphase growth is detected, this module will notify the user and will calculate the value.

Dynamic Outlier Threshold: This normalization module allows a user to set how many standard deviations from the mean constitute an outlier. The model will automatically calculate how many outliers are present in a sample, and notify the user.

Exclusion Dashboard: This module contains a dashboard that allows a user to exclude any observation from the normalization and calculation threads, as well as provide a space for the user to provide justification for the exclusion. The dashboard will also notify the user of how many observations, normally included in a calculation thread, are being omitted.

Statistical Significance Check: This module examines the implications on hypothesis testing of using small sample sizes. The model notifies the user of results.

Manual Scrub for "Un-Rebaselining": Programs were scrubbed for cases where a program has been rebaselined due to cost growth, such as Joint Strike Fighter. For these observations, the estimates were modified to reflect cost growth from the original baseline. Results are captured in the Change Log.

Raw Data Change Log/Audit Trail: A detailed Change Log was developed concurrently with the new SAR database to allow users to make modifications to raw data without the repercussions of removing the original observation for other users. (See section "*Auditing Changes to SAR Data*" for a detailed outline on this process.)

Automated Cost Growth Factor Calculations: Calculation threads for CGFs are automated to update dynamically as raw data is added into the database, as well as when changes are made to normalization modules.

Automated Coefficient of Variation Calculations: Calculation threads for CVs are automated to update live as raw data is added into the database, as well as when changes are made to normalization modules.

Automated Conversion to S-Curve Tool: The normalization and calculation threads in the new SAR database produce an output spreadsheet containing metadata that is compatible with the NCCA S-Curve Tool. Previously, the metadata for the NCCA S-Curve Tool were computed in a standalone file. The "interface sheet" approach remains the same. The improvement is that it is now part of the self-contained database. For the moment, the entire SAR database is not contained in the S-Curve Tool, though NCCA may decide to go that route.

Business Rules

We classified some of the normalization modules as "business rules." These business rules are specialized and automated normalization modules that check for specific incongruities in data and work to correct them. The two business rules included in the new SAR database are correcting for milestone transitions errors and flagging interphase growth.

Because not all users of the new SAR database architecture may agree with the use of correcting for milestone transitions and for interphase growth, these normalization modules are separated from the raw and amended data, and users can see what the resulting CGFs, as well as CVs, would look like if these normalization techniques were not applied. This study will outline the process of the milestone transition error module as a case study.

Case Study: Milestone Transition Error

Sample of SARs for DDG-51 Destroyers										
		Baseline Estimate			Current Estimate			Quantity Changes	
Base Year	Milestone	Base-Year$	Then-Year$	Qty.	Base-Year$	Then-Year$	Qty.	Base-Year$	Then-Year$
1987	PdE	$16,953.70	$20,117.50	23	$66,840.90	$106,846.50	86	$37,019.70	$64,220.00
1984	DE	$12,454.40	$18,479.60	18	$15,887.80	$20,117.50	23	$3,098.20	$4,097.00
1981	PE	$6,443.50	$10,953.50	9	$12,454.40	$18,479.60	18	$1,691.80	$2,590.90

Source: DAMIR; Department of Defense; Naval Center for Cost Analysis.

Excerpts of observations from the new SAR database for the DDG-51 program. Note that the Current for the 1984 DE observation does not match the Baseline Estimate for the 1987 PdE observation Estimate.

Table 7

Typically, after a program transitions milestones, the Current Estimate (CE) of the original milestone becomes the Baseline Estimate (BE) of the subsequent milestone. This convention holds true in Table 7, where the $20.1B TY$ CE in DE becomes an identical $20.1B TY$ BE in PdE. So far, so good. But, the BY$ estimates don't hold, since a three-year gap ensues. $15.9B becomes $17.0B. Hence, BY$ calculations using data from the PdE need to be adjusted for the amount of inflation occurring between 1984 and 1987.

The milestone transition error normalization module will detect this type of incongruity and will communicate with NCCA inflation indices to generate an appropriate inflator value to, in this case: first, set the 1987 BE to the 1984 CE values; and second, apply the inflator to convert the 1984 CE values to 1987 dollars.[34] This inflator is necessary because the new BE inserted by the module is set to 1987

[34] Naval Center for Cost Analysis. *NCCA Inflation Indices and Joint Inflation Calculator*. 29 Feb. 2016. Raw data. 1000 Navy Pentagon, Washington, D.C.

dollars, and both the BE and the CE must be represented by the same dollar-years for consistency in the estimate.

First, this study will review the resulting CGFs for this program if the milestone transition error normalization module did not exist to adjust the estimates. After, this study will review identical calculation threads but performed with data normalized by the module.

Cost Growth Factor Calculations for Milestone B (DE) Without Milestone Transition Adjustments (Quantity Adjusted):

Laspeyres:

Base-Year$:

$$\frac{CE - Q\Delta}{BE} = \frac{\$15{,}887.80 - \$3{,}089.20}{\$12{,}454.40} = 1.03$$

Then-Year$

$$\frac{CE - Q\Delta}{BE} = \frac{\$106{,}846.50 - \$64{,}220.00}{\$20{,}117.50} = 0.87$$

Paasche:

Base-Year$

$$\frac{CE}{BE + Q\Delta} = \frac{\$15{,}887.80}{\$12{,}454.40 + \$3{,}098.20} = 1.02$$

Then-Year$

$$\frac{CE}{BE + Q\Delta} = \frac{\$20{,}117.50}{\$18{,}479.60 + \$4{,}097.00} = 0.89$$

Fisher:

Base-Year$

$$\sqrt{(Laspeyres * Paasche)} = \sqrt{(1.03 * 1.02)} = \sqrt{1.04} = 1.02$$

Then-Year$

$$\sqrt{(Laspeyres * Paasche)} = \sqrt{(0.87 * 0.89)} = \sqrt{0.77} = 0.88$$

Cost Growth Factor Calculations for Milestone C (PdE) with Milestone Transition Adjustments (Quantity Adjusted):

Before performing the calculation with adjusted results, the normalization module will first generate an inflator using a series of NCCA inflation indices. In this case, the DDG-51 program was classified in the database as a ship program, and therefore uses a Shipbuilding and Conversion, Navy (SCN) inflation index. Of these there are two, the standard OMB-prescribed values and a unique value based on indices from the Bureau of Labor Statistics. We choose to use the latter. The resulting inflator was 1.09 to inflate 1984 dollars to 1987 dollars.[35]

$$\frac{SCN\ Raw\ Index\ (1987)}{SCN\ Raw\ Index\ (1984)} = \frac{0.5618}{0.5146} = 1.0916$$

Table 8 shows the amended values for the 1984 DE observation of the program after the normalization module applies the inflator. In short, the DE Current Estimate now uses the latest CE available in the SARs, as of 31 December 2015. This is the PdE's CE in TY$. Note that the $66.8B current estimate in BY$ has been deflating to $61.2B for the corresponding value in the DE.

Sample of SARs for DDG-51 Destroyers (DE Adjusted)

		Baseline Estimate			Current Estimate			Quantity Changes	
Base Year	Milestone	Base-Year$	Then-Year$	Qty.	Base-Year$	Then-Year$	Qty.	Base-Year$	Then-Year$
1987	PdE	$16,953.70	$20,117.50	23	$66,840.90	$106,846.50	86	$37,019.70	$64,220.00
1984	DE	$12,454.40	$18,479.60	18	$61,226.44	$106,846.50	86	$37,008.34	$68,317.00
1981	PE	$6,443.50	$10,953.50	9	$12,454.40	$18,479.60	18	$1,691.80	$2,590.90

Source: DAMIR; Department of Defense; Naval Center for Cost Analysis.

Excerpts of observations from the new SAR database for the DDG-51 program. The Current Estimate of the 1984 DE observation has been adjusted to reflect the current estimate of the 1987 PdE observation.

Table 8

[35] The Milestone Transition Error Module utilizes a specific Ship Construction: Navy (SCN) index for ship-classified programs (Such as for the DDG-51 program in this case) and a generalized *Else* inflation category for non-ship class programs. This decision was based on the scope of the database to fit the needs of the NCCA.

Below are CGF calculations, but performed through the normalization module.

Laspeyres:

Base-Year$:

$$\frac{CE - Q\Delta}{BE} = \frac{\$61{,}226.44 - \$37{,}009.34}{\$12{,}454.40} = 1.94$$

Then-Year$

$$\frac{CE - Q\Delta}{BE} = \frac{\$106{,}846.50 - \$68{,}317.00}{\$18{,}479.60} = 2.0$$

Paasche:

Base-Year$

$$\frac{CE}{BE + Q\Delta} = \frac{\$61{,}226.43}{\$12{,}454.40 + \$37{,}008.34} = 1.24$$

Then-Year$

$$\frac{CE}{BE + Q\Delta} = \frac{\$106{,}846.50}{\$18{,}479.60 + \$68{,}317.00} = 1.23$$

Fisher:

Base-Year$

$$\sqrt{(Laspeyres * Paasche)} = \sqrt{(1.94 * 1.24)} = \sqrt{2.41} = 1.55$$

Then-Year$

$$\sqrt{(Laspeyres * Paasche)} = \sqrt{(2.08 * 1.23)} = \sqrt{2.57} = 1.60$$

Results

This example aimed to demonstrate that there is a quantifiable difference between CGFs calculated using raw data versus data normalized for milestone transition errors.

The milestone transition error normalization module corrects raw data by ensuring that observations maintain their TY$ CEs as they transition milestones. If there is an error, the module will query for the correct CE and apply those values to the appropriate observations while also communicating with an inflation index to adjust the values to maintain dollar-year consistency.

This module runs automatically and in the background, even when raw data is imported into the database. As we continue to emphasize, this normalization module is separated from raw data to preserve raw data integrity. Additionally, the "unnormalized" CGF calculations are displayed beside the normalized variants, so a user can verify the quantifiable difference between results. This transparent assessment of the effects of normalization allows a user of the new SAR database to decide if they wish to use a normalized result or not.

CGF Results. Raw vs. Normalized

	Base-Year$	Then-Year$
Raw Data		
Laspeyres	1.03	0.87
Paasche	1.02	0.89
Fisher	1.02	0.88
Normalized		
Laspeyres	1.94	2.08
Paasche	1.24	1.23
Fisher	1.55	1.60

1/ Inflator used for normalization: 1.09
Source: DAMIR; Department of Defense; Naval Center for Cost Analysis.

Cost Growth Factor results comparing raw and normalized data. Note how normalized data results in higher CGFs.

Table 10

Auditing Changes to SAR Data

A primary goal of the new SAR database architecture was to engineer transparency at its core. As discussed, one way this was accomplished was by separating data normalization from the raw data, and separating calculation threads from the normalization modules—this way a user can analyze data and results at any step of the process, for any program at any milestone. However, even though our architectures preserve the integrity of raw data, not all raw observations had integrity to begin with.

For instance, not all programs or subprograms in the new SAR database clearly aligned with the taxonomy of commodity classifications (e.g., aircraft, submarine, electronics, etc.). Because of ambiguity, some programs, including those imported from the 2012 database, were reclassified to be more accurately represented within the database. Other amendments made to raw data included making corrections to: Program name, milestone mislabeling, missing base years, adjusting SAR years, Program Number (PNO), and in rare cases, cost variance data.[36]

When we "de-normalized" the data from the 2012 SAR database, we backed into an audit trail of how original raw data observations changed over time. In some cases, we had to reevaluate the validity of changes to raw data, as well as assess whether some unchanged raw data required amendments. Our rationale notwithstanding, we understood that not every user or organization may agree with our justifications for amending observations, or leaving other observations unchanged. This led to another core innovation in the new SAR database architecture—a thorough change log—developed concurrently with the new SAR database to not only preserve the integrity of raw data, but to establish an audit trail in cases where other users require different changes, or wish to revert changed observations to unchanged versions.

To achieve transparency, we added a rigorous documentation process for all amendments made to raw data. The change log was stored separately from the raw data and normalization modules, but also within the database for accessibility and accountability. The change log records the name of the user that makes a change, when a change was made, and what the change is. The changelog stores the original observation for preservation purposes, and displays the amended entry next to it while highlighting the differences. The change log will also record when new observations are added to the database.

The result is an authoritative audit trail of all modifications to the database, as well as detailed records to revert original entries if required.

[36] Typically, in the rare cases where cost variance data was adjusted, the raw data had been rebaselined to hide actual cost growth. As noted in the section *Normalization in the new SAR database*, we manually assessed whether a program required its cost variance data to be "un-rebaselined" to reflect actual cost growth.

IMPLICATIONS

Modular Architecture

While the new SAR database fulfilled its basic mission to support the update of the NCCA S-Curve Tool, the new database architecture also succeeded in outlining requirements for an authoritative architecture for other databases. These requirements are not exclusive to SAR databases, rather they establish architectural design standards for databases, normalization, and analysis.

While our innovative normalization modules and change log were scoped to support the mission of NCCA, they maintain some limitations that prevent them from being adapted by all potential users. For instance, while another user of the SAR database may require interphase growth adjustments, they may require using a unique inflation index not produced by NCCA. Our normalization module only communicates with an index provided by NCCA. There also may be other normalization methods a user would prefer that do not exist in the new SAR database. This is why it is critical for normalization processes to be built as separate modules that interact with databases, so that if a new user or organizations desires a new or alternative normalization module, it can be developed to integrate with the raw data portion of the architecture. Regardless of the normalization modules in the case of SAR data, the underlying SAR data remains the same.

Data is finite and "binary"—it either exists or it does not. This philosophy holds for SAR data as well. Therefore, developing a database to suit the needs of a particular analysis is short-sighted and unnecessarily restrictive. Once all raw data is compiled into a single authoritative source, what can and cannot be done with the raw data is limited to the data itself. Data is finite, but the present and future needs of an analyst are infinite; an analyst may need to perform a certain function, but that does not mean the data to support that effort exists.

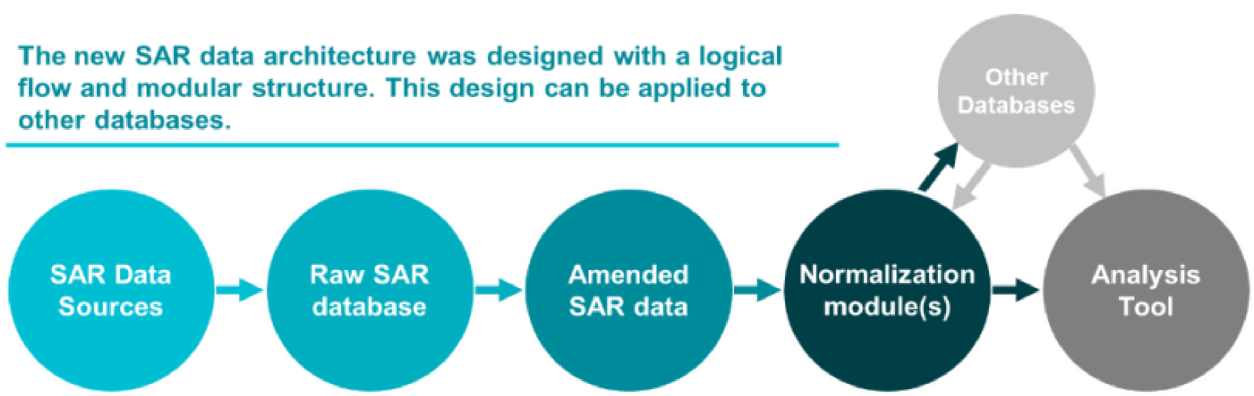

__Figure 11:__ The design for how a user would interact with a future SAR database system: SAR data is imported into a database that stores only raw data; The user can then amend data or utilize other states of amended data; Next, the user can select normalization modules, if any, to normalize the raw or amended data. Normalization methods may require interaction with other databases, or could support normalization methods for other databases; lastly, the user uses an analysis tool to produce results, which may also communicate with other supporting databases.

Understanding the limitations of single-source data, it is our conclusion that the goal of a future SAR database, or any other database in general, is to compile all existing data, and then determine what can be done with it afterwards. If an analyst's desired task is not possible given the limitations of a single source of data, then the next step is not to add more data into the existing database, but about what other databases need to exist in order to support the analyst's task. Assuming a new database is built using the architecture outlined in this study, an analyst can then focus on deciding what normalization modules and analysis tools need to be developed to marry multiple databases together to meet the needs of the task. This methodology is why the NCCA inflation indices are separated from the raw SAR data, and the milestone transition error normalization module uses both databases to produce results.[37] In theory, a normalization module for a database unrelated to the new SAR database could utilize the same NCCA inflation indices, which is why it is critical these databases are maintained separately from each other.

Additionally, it is our philosophy that raw data compiled in a future database must be maintained as such. This is critical for the integrity of database architecture, necessary to meet the unknown needs of all potential users. This is because, regardless of the normalization processes for a given series of data, the underlying data is the same in every scenario. Our modular database enforced the separation of raw data from normalization. This architecture allows for flexibility—built to interact with any or all necessary external components to meet every need of an analyst or organization. Figure 11 outlines our modular design.

What this philosophy infers is that some analysis may require the existence of other databases to support deriving results. In the case of SAR data analysis, interphase growth normalization requires inflation data; this data should be provided as a separate database. It would then be the goal of a normalization module or analysis tool to determine which indices are used to correctly deflate or inflate SAR data. To be clear, it is not the goal of a future SAR database to encompass data that does not exist in SARs alone. Rather, normalization modules and analysis tools should be developed to marry different databases together to meet the needs of an analyst. In sum, by using these principles, any database developed anywhere has the potential and capability to interact with any other database via a normalization module or tool.

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[37] The NCCA inflation indices that communicate with the new SAR database, as discussed, represent only SCN and *else* categories. It was not in the scope of this study to redevelop the NCCA inflation database to align its architecture with the architecture of the new SAR database. If the NCCA inflation indices were redeveloped with our architectural philosophy in mind, a normalization module would have access to all potential indices rather than those selected specifically for this effort.

Automated Architecture

We believe future iterations of normalization modules, analysis tools, as well as the technology that updates and maintains a SAR database, can be fully automated.

As discussed, we successfully tested a "proof of concept" to automatically retrieve and import cost variance data into a SAR database by using DAMIR APIs. If these APIs are properly developed, it is possible to not only retrieve cost variance data from individual SARs stored on DAMIR, but detect for the existence of subprograms within the SARs, and generate unique observations. It's important to note that:

- DAMIR has in place "outgoing" APIs for almost everything except the variance tables; and
- Plans are underway for DAMIR to develop these APIs "quid pro quo" with CADE developing its own outgoing APIs.

Both the Cost and Acquisition Communities are moving toward effective data exchange. Additionally, using metadata stored in the SARs, the API can determine the commodity classification of the program and subprograms, removing the need of a human to manually classify the commodity of a program.

Automation unlocks metatagging possibilities that were either impossible, or prohibitively time consuming in the 2012 or new SAR database. For instance, metatags capturing parent-child relationships between programs and subprograms can be automatically assigned while data is imported, or machine reading can generate a detailed taxonomy for program classifications (i.e., what is classified as "aircraft" in the new SAR database, could be broken into rotorcraft, fixed-wing, tilt-rotor, etc.) without the need for a human to manually determine a program classification. Database metatagging, presently limited to an analyst's specific needs, would become limited only to the full capabilities of data.

Normalization modules would no longer be fixed as they are in the new SAR database. A future database composed of all existing raw data becomes a data platform for any analyst or organization to develop their own normalization tools to suit their needs. And with transparency in mind, it is possible that these normalization modules would be open source, meaning an analyst can choose from a suite of all existing normalization modules, or have the tools to develop their own, using parts of existing modules if desired.

We also believe that all normalization that requires manual input can be fully automated. For instance, determining the existence of a subprogram can be done in the data extraction process, since our "proof of concept" test with DAMIR APIs identified cost variance tables for subprograms within a SAR; when this data is extracted and automatically imported into the SAR database, an algorithm would ensure that subprograms receive their own entries, and the parent-child relationship between the subprograms and their parent programs are labeled.

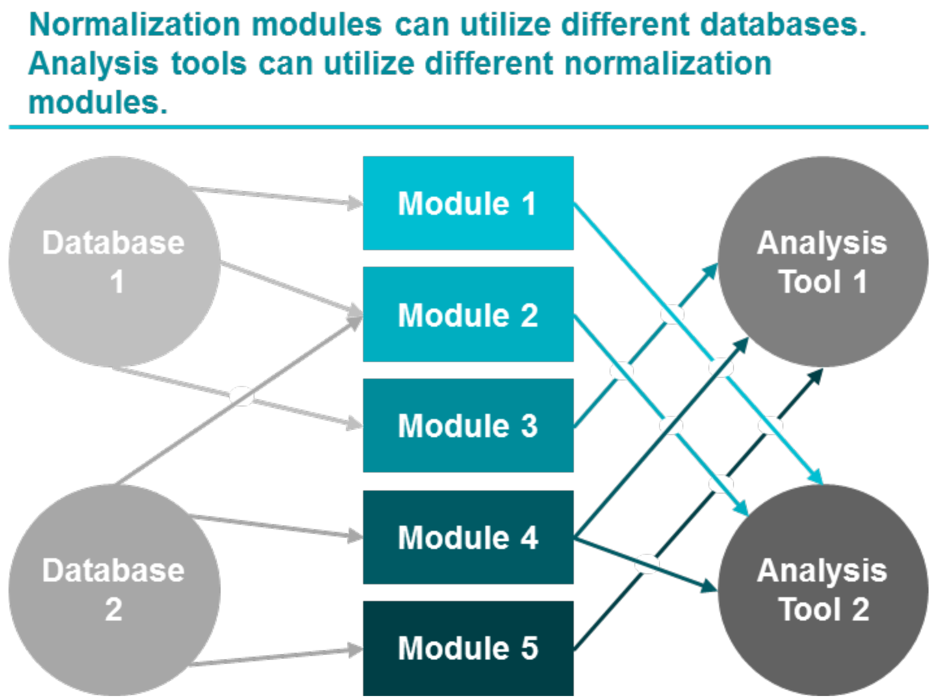

Figure 12: A modular data architecture could unlock unlimited possibilities for users, while simultaneously integrating complete transparency.

With the construction and maintenance of a SAR database and normalization fully automated, the tools used to analyze data can be far more powerful. For example, the scope of this study was centered on updating the metadata for the NCCA S-Curve Tool. The S-Curve Tool is a separate file from the SAR database utilizing CVs generated from the SAR database's normalization modules as a backbone. However, the limited nature of the NCCA S-Curve tool restricts what the tool can and cannot do. The tool, for instance, can identify how many outliers are in a sample, but cannot identify what programs those outliers are, additionally, the S-Curve tool was designed to primarily support risk assessments for the Navy rather than for all service branches. Because the new SAR database supports normalized CVs for all commodities, services, and milestones, a future S-Curve tool can be redesigned to not only automatically uplink to a future SAR database, but to also be modular to fully utilize any data from any database to support advanced risk analysis that exceeds the limitation of SAR data alone.

As database maintenance, normalization, and analytical tools approach full automation, will the future of the cost analyst be in jeopardy? Perhaps not, but the role of analyst will certainly change; with full automation, the function of an analyst might be to make amendments to raw data, verify calculation accuracy by using the transparency features in the architecture, and to piece together analytical tools using normalization modules to reveal new insights.

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