Acta Astronautica 93 (2014) 345–351

Contents lists available at ScienceDirect

Acta Astronautica

journal homepage: www.elsevier.com/locate/actaastro

What is wrong with space system cost models? A survey and assessment of cost estimating approaches ☆

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A R T I C L E   I N F O

Article history:
Received 2 January 2012
Received in revised form
14 May 2013
Accepted 5 July 2013
Available online 15 July 2013

Keywords:
Cost estimating
Cost models
Systems engineering management

A B S T R A C T

Despite several decades of research and refinement in cost estimating tools and practices, the final cost of US space programs continues to exceed initial cost estimates by an average of more than 45%. Thus, program cost models not only exhibit error, they are seriously biased. A structured review surveyed techniques, approaches, models and conceptual tools related to space program cost estimating, to understand cost in complex space systems. Analysis shows problems of cost estimating result from the growing complexity of space programs, failures in managing growth, and mission failures. Although there is greater expectation for the models to accurately predict program costs, the current models used for seeking funding for large space programs are inadequate due to (1) inability to predict future, (2) lack of insight, and (3) process replaces judgment in decision making.

1. Introduction

Space program cost overruns continue throughout the last 40 years despite better databases, models, estimators, and more stringent reviews [32]. The space community and agencies that audit and/or track performance like the US General Accountability Office continue to observe profound differences between cost model predictions at program project beginning and actual costs at program completions. Some say the tools are accurate but essential cost elements are missing. Others argue the tools are not adequate and a better approach is needed.

The research team at University of Alabama at Huntsville's Center for System Studies evaluated models currently being used to estimate cost of large space systems and scoured literature for other models and techniques in order to find a more effective means of estimating cost. Examining the techniques and the problem more closely, patterns emerged that made the approaches difficult to differentiate. Rather than a variety of approaches and models with distinct methodologies, all approaches were found to be basically derived from or fit to the same weight-based equation and associated cost estimating relationships that have been used for the last 50 years.

Interviewed sources maintain the problem of cost overruns and discrepancies does not appear to be the fault of the models; forecasting future costs of not-yet-done projects and missions based on historical data has always been outside the statistical capabilities of cost estimating. As discussed below, this may well be true. However, if program cost models are fundamentally unable to predict program cost, what is their purpose?

Based on research, problems of cost estimating have resulted from the growing complexity of space programs and projects and from failures in missions, in managing growth, and in controlling cost. The knee-jerk reaction to failure in Systems Engineering is to overcompensate by (1) having more oversight and review, and (2) "systemizing" or creating more processes and techniques. These observations of systems engineering apply equally to the problems

☆ 'This paper was presented during the 63rd IAC in Naples'.

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http://dx.doi.org/10.1016/j.actaastro.2013.07.014

of Space Systems Cost Estimating. Both have very good engineers and tools and therefore are not the problem.

This paper serves as a catalyst among the cost estimating community for broadening discussion of the expectations and limitations of current methods of cost estimating. The authors hope the issues highlighted will promote modifications, debate, and advances to state-of-practice in systems engineering. In the following sections, the hypothesis to be explored is the inadequacy of the current cost models used for seeking funding for large space programs is due to (1) inability to predict future, (2) lack of insight, and (3) process replaces judgment in decision making.

2. Parametric models only predict the past

What is cost estimating? Hamaker [14] describes cost estimating simply as "The translation of technical, programmatic and management specifications into cost." There are many methods of cost estimating; three most distinct and common methods are engineering build-up, analogy, and parametric. In practice, each is used at different stages of the project's lifecycle, and a thorough estimate will include all three in some combination. However, it could be argued that *all methods are basically the same*, and they are essentially parametric methods because they are statistical extrapolations of past experience into the future. Past experience is historical data which includes detailed work hours and bills of material (engineering build-up), the data is adjusted or extrapolated (analogy) for the similarities to current project, and is statistically fit to mathematical equations relating cost to one or more physical or performance variables associated with the item being estimated (parametric) [20,21].

Why are parametric models used? "Parametric cost models relate quantifiable characteristics of a system such as flight hardware weight, power, data rate, thrust, and nontechnical variables such as schedule, team experience, and new technology to an estimated cost" [14]. This technique performs a series of regression analyses to determine which inputs are the "drivers" of the project's outcome (cost). The drivers are controllable system design or planning characteristics which have a causal effect on system cost. Parametrics then use those few important parameters that have the most significant cost impact on the project to provide a ballpark estimate for funding, or to do tradeoff studies [21]. With such a description of the ability of parametric models to identify which system elements drive cost, it is easy to see why it was universally adopted by space agencies and governments.

Parametric models can be classified by base metric. For weight-based models, a curve is developed to describe the relationship between mass and cost, and can be modified with a series of multipliers that range from team experience to material selection. Prince argues weight is not a driver, because it is not a cause of cost. Weight is convenient because it follows the *law of scale*: the intuition that scaling up a design ought to increase its cost. As a cost predictor, "weight can get us into the ballpark, but does not tell us what seat we are in" [22]. Most of the models are variations of the original, now 50 years old, weight-equation: cost scales with weight.

It is worth noting, however, that Collopy and Curran [7] have shown that part costs scale more closely with surface area than with weight. A portion of the argument is worth recapitulating here.

(1) Almost all the cost of aerospace systems is labor at some point in the supply chain. Weight does not cause cost just because more mass is more expensive than less mass. It can only cause cost insofar as more mass requires more labor.
(2) Volume is a stronger driver than weight. When part cost is corrected for material content, most of the correction is division by material density, to convert weight to volume. If there were two parts, identical in shape and manufacturing process, but one is made of lead and the other of aluminum, should the lead part cost four times as much just because lead weighs four times as much as aluminum?
(3) When aerospace parts are compared which are identical in form, differing only in size, the larger ones cost more. However, the cost does not scale with the third power of the change in linear dimensions, which it should if cost was caused by weight. Instead cost fits with the 2.2 power of linear scale, closer to 2 (scaling with surface area) than 3 (scaling with volume).

A more recent contribution to the parametric model is the complexity-based equation. Instead of weight, regression curves relate an artificial complexity value to the historical costs of systems. There is no doubt that design information, measured according to Shannon information theory, is a cost driver, at least at the part level [8], and complexity is sometimes synonymous with Shannon information measures. Also, incorporating complexity measures has increased the fit of cost models with historical data [14,29], but most of these models do not explain how complexity causes cost any more than weight does. The reason for this is the models share similar cost estimating relationships and historical data. They do not provide any additional understanding of a model which is based on historical data. The complexity factors are used as a fudge-factor substitute for weight, or as additional variables and modified coefficients. Basically, they are analogy strategies.

Rush and Roy [25] have noted parametric tools are good at predicting within the bounds of similar projects, but when "new technology is introduced, the systems fall down or are severely limited in their predictive capability." Additionally, they note parametric models are built on underlying assumptions and relationships between variables which do not necessarily reflect reality. It is the cost estimator and their expertise that ultimately controls the output of any model.

An excerpt from the 1995 NASA parametric handbook:

When a parametric model is applied to values outside its database range, the credibility of the resulting estimate becomes questionable. In cost estimating, one rarely finds large, directly applicable databases, and the source document has to be evaluated to determine if the parametric can be applied to the current estimate. However, it is possible to develop parametric tools that relate cost based on generic complexity values or tables. Such generalized parameters, can be related to the task at hand by an experienced modeler that results in a good cost model, but a parametric model always needs to make sense for the present estimate. Additionally and before using, one should validate models based on expert opinion [21].

Stated simply, parametric models are like investment advertisements: "past performance does not guarantee future results", no matter how it is tweaked or repackaged.

3. Cost models lack insight

Given parametric methods are the accepted tools for developing a cost estimate, the next point of contention is how parametric cost models are used. Literature reveals the main use for them is to obtain funding. As an early or conceptual estimate, "a history-based equation is a grossly accurate sanity check" [23]. However, for budget estimates, the model is expected to predict the actual cost, and then criticized when actuals exceed predicted. "The general problem in space project cost estimating is predicting the cost of projects early in their formulation phase in order to make accurate commitments on what the project is likely to cost. These commitments are made to the project stakeholders who include NASA management, the Office of Management and Budget and Congress, among others" [17].

The Government Accountability Office (GAO) issues Cost Estimating Guides for agencies seeking funding. It states "the purpose of a cost estimate is determined by its intended use, and its intended use determines its scope and detail. Cost estimates have three general purposes: (1) to help managers evaluate affordability and performance against plans, as well as the selection of alternative systems and solutions, (2) to support the budget process by providing estimates of the funding required to efficiently execute a program" [31], and (3) to help engineers design more affordable systems.

Hamaker sums up the purpose of cost models in an excerpt from his dissertation, Improving the Predictive Capability of Spacecraft Models:

The trade space for decisions regarding space projects obviously includes many technical considerations (e.g., the available onboard electrical power, the required data rate, the choice of stabilization method, the selection of structural materials, the level of redundancy, the level of autonomy that the spacecraft should possess, the type of reaction control, the type of propulsion system, the type of communication system, and other such technical decisions). Managers and engineers are generally aware their choices on these matters have large implications for the cost, schedule and risk of their missions [14].

It is crucial to have a grasp of the cause and effect of technical variables such as listed above, in order to have credible estimates for schedule and risk. However, the models don't provide enough insight for causal relationships because they are too general-purpose, intended for Rough Order of Magnitude estimate, or "black-box" due to their proprietary protection.

The most commonly used models, NAFCOM, PRICE-H, and SEER-H are basically the only parametric models sufficient in size and scope to model space projects, and based on interviews at Marshall Space Flight Center (MFSC), provide generally equivalent answers in the form of a cost and probability of a given cost outcome.

Two other models evaluated are a discrete event-like approach to cost estimating: P-Beat by Boeing and NASA, and a Process-Based cost model by SAIC. They were both developed for NASA, are built with process catalogs, and are time-phased [27,29]. Data was collected for the processes of each activity from design though manufacturing, similar to activity-based cost estimating. This greater level of detail provides more insight in a representational model, fine-tuning the fidelity of the output. Ultimately, the models are still founded on parametric equations—one weight-based, the other complexity-based. The effect of these models is to modify either the base-metric or the coefficients of the curve fit to the base metric. Neither was adopted for use by the NASA. This research determined they require too much detailed data processing to produce timely estimates.

Hamaker [16] observes more details do not imply better accuracy. The purpose of detailed approach is for decision-making; however, he notes they tend to have over-optimistic labor cost estimates. In addition, "the deeper one goes into WBS, the more unsure one is of data" due to noise or "village watchmen syndrome", which is inconsistent data reporting.

Improvements to modeling techniques include complexity factors which attempt to capture new technology and increasing interfaces between contractors. Hamaker's QUICKCOST model is a parametric model which includes only non-technical parameters: engineering management and new technology. Its transparency and simplicity allows ease of use and understanding with cost results as good as NAFCOM [17]. These additional inputs; complexity, engineering management, team experience and new technology, have been a major improvement in NAFCOM within the last decade, and have followed suit in PRICE and SEER.

Prince [22] attests that when these models incorporated the above non-technical input parameters, the output was impressively improved. However, he cites the critic's continued complaints of these parametric models are:

(1) Predict past better than future;
(2) Limited support for technical design trades;
(3) Limited support for management and process trades, and;
(4) Small, imperfectly understood data sets.

The latter complaint is the major reason why parametric models fail. As technologies, computer capabilities, requirements and new management processes evolve; there is a time lag between the estimate and the true impact of these developments on the resulting project. Prince [22] calls this time lag a temporal/cultural/technology gap, meaning "the lack of real data to fill in the gap means the knowledge base used to adjust the parametric estimate is theoretical; adding more technical or programmatic input variables are not feasible." Newer methods must be pursued to address the advancements mentioned above, anticipate the questions about how the estimate was formed, how it addresses the unknowns, and explain why the estimated cost is realistic.

However, this complaint does not satisfactorily explain the persistent bias between initial program estimates and actual program costs. Why are the actuals, on average, 45% higher than the estimates? Do technology and culture over time make programs less efficient and more expensive? Why would the government invest in technology that always makes development less productive?

Having exhausted the available contemporary models used in space industry, failing to find how they provide insight, the next search was for *elusive cost drivers* cost modelers think are still out there and not accounted for. "Most of the work that has gone on over the years to improve the models has been focused on adding technical cost drivers to try to explain the cost behavior of space projects [2]. It seems the thinking has been that if enough engineering nuances are reflected by the cost models, the costs will line up on a regression line (so to speak)" [14].

Cost Estimating handbooks (GAO, 2009) [20,21,31] caution that cost over-runs will result from omission of key cost drivers if there are improperly defined Work Breakdown Structures (WBS), incorrect WBS categories, and bad data. The Work Breakdown Structure is a hierarchical decomposition of the tasks that make up a development project. Hamaker [14] chides "there is no such thing as a good WBS, just look for the least evil WBS." The WBS is all about data—having the right data, use of statistics, and accounting for uncertainty.

Others [18] assert that if the "un-modelable" variables are addressed, the real drivers of cost will be captured. Wertz identifies these following ideas as variables to consider modeling:

(1) Performance—"what the space mission is all about, the reason we′re there. Thus, what we would really like is a cost model that treats life-cycle cost as a function of system performance." This is the basic objective of analyzing mission utility, yet this type of model is difficult to create.
(2) Organizational culture—the way of doing business for the organization that designs and plans a project is different than the one that manufactures it.
(3) Organizational size—case studies show smaller organizations are able to build spacecraft for less money, but it depends on the spacecraft. Several examples point to "size matters" but no indication of how to take it into account.
(4) Willingness to accept risk—many case studies show a key ingredient to success of low-cost satellite programs is their willingness to be innovative, try new approaches, and yet accept possibility it might not work; this dramatically reduces space systems cost [18].

In an interview at MFSC with Andy Prince, he relies on his nearly 30 years of experience as a NASA cost analyst to claim organizational culture drives 80% of cost at NASA. Hamaker observes the same phenomena: "At Johnson Space Center, Hum Mandell, assisted by Richard Whitlock and Kelley Cyr, initiated analyses of this problem. Making imaginative use of the PRICE model, they found NASA′s culture drives cost and that the complexity of NASA projects had been steadily increasing, an idea also advanced by Gruhl. Mandell argued persuasively to NASA management for a change in culture from the exotically expensive to the affordable. At the same time, he argued that estimates of future projects needed to account for the steadily increasing complexity of NASA projects" [13].

The conclusion about parametric methods is (1) they are statistically limited in ability to extrapolate beyond past programs, and (2) they do not explain cause and effect of design change to cost change. Therefore, they do not provide the level of insight necessary for decision-making.

The first half of this paper focused on parametric methods as an inadequate tool. However, when challenged with the question "what else is there?", the problem of cost estimating became inadequacy of the person(s) using the cost models. The problems with cost estimating are very similar to the problems of systems engineering in that expert judgment is being replaced by processes.

4. Expert judgment vs. process

The following definition for Systems Engineering, given by Mike Griffin [12], "Space System Engineering is the art and science of developing an operable system capable of meeting mission requirements within imposed constraints including (but not restricted to) mass, cost, and schedule." Similarly, Society of Cost Estimating Analysts (SCEA) defines cost estimating as "the art of approximating the probable cost or value of something, based on information available at the time" [26]. These definitions bring to mind Frosch′s observations of systems engineering in NASA, "We have lost sight of the fact that engineering is an art, not a technique; technique is a tool" [10].

Techniques, procedures, documentation, elaborate mathematical decision-theoretic analyses, computer aided techniques/models have "led to greater *diffusion of responsibility for decisions*", which has led to "systemizing" the process. The italicized portion of Griffin′s [12] discussion about use of models in systems engineering decision is a clue to why NASA culture accounts for Prince′s 80% cost idea. Program managers pressure cost estimators to seek and justify lowest cost estimate, over performance, and creates a culture which avoids wanting to know what something really costs [23]. As a result, cost estimators conform to a rule of duplicating a previously accepted proposal or manipulating the model until it delivers a predetermined number.

Similarly in systems engineering there is pressure from program and project management to complete the job on schedule and within budget, to do what was accepted last time. "Present methods of systems management tend to focus attention on what is required, rather than what is important; i.e., 'doing things right' vs. 'doing the right things', rather than just legally defensible designs" [11].

Furthermore, the processes, algorithms, and other analytical tools must be used as tools to supplement, not replace sound engineering judgment or decision-making. “There will come a time in any system development when educated human judgment and understanding will be worth more than any amount of computer analysis. This in no way demeans the importance of detailed analysis and the specialists who perform it, but, applied without judgment or conducted in an atmosphere of preconception and prejudice, such analysis can be a road to failure” [12]. “The judgment of the systems engineer must be the final decision mechanism in such cases. An engineer′s work consists of the decisions he makes, and must be willing to stand behind them” [12].

The search for better tools, the pressure to do what worked last time, and the growing number of processes, are rooted in a fear of failure. Griffin observes, “Aversion to all failure has resulted in substitution of abundant processes, analysis, and band aids to prevent us from failing at every step along the way. Systems engineers have often substituted that for the real creative process, leadership, and discipline in accomplishing what was set out to do” [28].

Fear of failure greatly contributes to the cost growth spiral. For instance, fear of mission failure leads to extra precaution. This leads to increased design work, increased mission assurance, additional testing, redundant systems, and endless reviews; which all lead to higher costs. At the same time, fear that a program′s high cost estimate will result in rejection cause program managers to justify the lowest cost estimate possible.

GAO′s 2009 Cost Estimating Guide contains a twelve step process that ensures, if followed, realistic cost estimates are developed for adequate funding. Despite more processes and focus on realistic cost, cost overruns continue and expectation of accurate cost prediction dwindles. Estimators simply do not have a reliable method of providing information about the value of the estimate other than as a bottom-line, negative number.

Brathwaite and Saleh [3] observe “by choosing to focus on and minimize cost, decision-makers may constrain the performance of the system, and… limit its value creation potential.” Furthermore, they assert “Investments in space systems are substantial, with characteristics similar to high-risk investments. Traditional approaches to system design, acquisition, and risk mitigation are derived from a cost-centric mindset, and as such, they incorporate little information about the value of the spacecraft to its stakeholders” [4]. They suggest a change in philosophy of cost estimating. “An engineering system in general, and a launch vehicle in particular, is a value delivery artifact. Value delivered, or the flow of service that system is likely to deliver over its lifetime, whether tangible or intangible, deserves as much effort to quantify as the systems′ costs” [3].

5. Endogenous cost growth

As noted above, space programs tend to grow in projected cost between inception and completion or cancellation. In fact, this trend can be observed in all large aerospace and defense development programs. The specific elements of cost growth on which this paper focuses are development cost and unit production cost. These two cost elements are estimated in the earliest weeks of conceptual design, and estimates are updated until the space system is launched, or the product development program is completed and manufactured articles are rolling off a full-rate production line.

In 90% of programs, these costs grow during development [1]. Average cost growth, according to Augustine, is about 50%, although this figure is capped by cancellation of most of the worst-offending programs. Numerous studies attempt to explain cost growth as a product of requirements changes, program funding profiles, and engineering mistakes [5,24]. However, initial cost estimates are based on documented results of earlier programs′ requirements, funding changes, and engineering mistakes unique to each program. Thus, the cost of these problems is built into the original estimate. They could account for the size of variances in estimate errors, but in no way do they explain a 50% average increase in the cost of programs over their original estimates.

Only three causes can logically explain the observed cost growth:

(1) Cost estimators are stupid. Those who prepare estimates always err on the low side, refusing or unable to learn from experience.
(2) Cost estimators are liars. Initial project costs are deliberately set to be an average of 35% or so below what the estimators believe the program will cost in order to obtain political support for the program from stakeholders who would not favor the program if they were told the truth. Note, if this actually occurred, it would be criminal fraud.
(3) Cost growth is an endogenous process. The methods used to develop complex aerospace and defense systems causes the cost of these systems to grow relative to initial estimates.

Even a minimal amount of observation of actual programs is sufficient to discredit explanations (1) and (2) above. Cost estimates for major US aerospace and defense systems are usually prepared by cost professionals, often from independent organizations like RAND or the Aerospace Corporation, who have substantial expertise supported by historical data and sophisticated mathematical models. They are not stupid, and they have no motivation or inclination to lie.

This leaves explanation (3): endogenous cost growth. In contrast to (1) and (2), endogenous cost growth is completely consistent with the data on historical programs. Augustine and others have documented exponential growth over time in costs of a variety of aerospace and defense systems, including tactical fighters, strategic bombers, aircraft carriers, and battle tanks. The exponential curve is the telltale manifestation of endogenous growth, whether in population biology, economics, chemistry, or in any other domain. The exponential function is the solution to differential equations of the form the rate of growth of x is proportional to y.

What is endogenous cost growth? A network of design teams responds to a prediction of product cost, A, by designing a product with cost alpha times A, where alpha is greater than one. Such a process could be a simple additive effect of the independent behavior of each design team, or it might critically depend on the network connecting design teams and the way in which information and guidance is communicated across the network.

One possible element of endogenous growth of product cost has been identified by Collopy [6]. While it is possible this effect is sufficient to explain the cost growth observed on most programs, it could be that much or most cost growth is brought about by other, yet undiscovered processes. Quantitative observation of the detailed design phases of actual development programs could illuminate this question.

In summary, there is strong evidence to suggest endogenous cost growth is a fundamental characteristic of current space development programs and is therefore essential to understanding program cost estimation. Fine tuning cost models without addressing the unnerving tendency of actual cost to diverge from predicted cost can only be pointless and frustrating.

6. Conclusions

This paper demonstrates the problems of cost estimating result from the growing complexity of space programs and projects and from failures in missions, managing growth, and controlling cost. Current methods and approaches to cost estimating space systems are inadequate is due to (1) inability to predict future, (2) lack of insight, and (3) process replaces judgment in decision making. This is the main contribution of this research effort.

The first section highlighted the statistical limitations of parametric models′ ability to extrapolate beyond past programs. The second section demonstrated several reasons why parametric models lack insight needed to understand causal relationships between cost and design variables. Among them were lack of data, unknown or un-modelable cost drivers, and the models are too general, intending to capture everything. The models which give more insight are difficult to use and time intensive. The third section showed, in an effort to avoid failure in predicting and managing cost, processes, techniques and models have replaced sound engineering judgment and decision-making. Insight and accuracy appear to be less important than providing a number that will be approved by senior management and the Office of Management and Budget. Lastly, the idea of endogenous cost growth was explored.

The authors hoped to find a better understanding of what causes cost. Instead, the literature highlighted barriers to that understanding. The research also provided ideas to improve cost estimating, such as removing excessive, constraining requirements which affect performance, cost, and schedules, and instead creating goals (Kennedy′s simple vision to "…land a man upon the moon and return him safely to the Earth"). Another is considering the delivered value of a space program or project; bringing value to customers or stakeholders is an important aspect of engineering design. Lastly, there is need for more support and training of good leaders and engineers who have ability to make, communicate, and stand behind decisions.

As a final thought, consider the following: How can program cost estimates provide any value in the face of endogenous cost growth? What if cost estimating is like the computer game in which you try to put your finger on a blue circle on the touch screen, but the circle deliberately moves away from under your finger? That is, what if cost estimating is a game that, in principle, cannot be won? If we cannot win, we must change the rules. Perhaps we need to move away from a paradigm of cost estimation, leading to cost achievement, and toward a new paradigm of cost control. Control theory shows that we can control system attributes, like the level of a surge tank, which cannot be predicted in open loop. Perhaps the future of this discipline will focus on methods of controlling program cost, rather than the futile attempt to predict it.

Acknowledgments

The authors thank the following members of the University of Alabama at Huntsville′s Center for Systems Studies research team for their contributions to this research effort: Jeff Little, Ian Maddox, and Angie Rush. In addition, the authors thank the following: Joey Shelton, Chief Technical Officer of Trivector Services, Inc, for facilitating interviews and NASA reviews, Christian Smart, Director of Cost Estimating and Analysis at Missle Defense Agency for sharing the Process Based Cost Model and explanations of its development, and Andy Prince, Cost Analyst at Marshall Space Flight Center, for sharing his insights about cost estimating at NASA.

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