Chapter 2
Early Life Cycle Cost Estimation: Fiscal Stewardship with Engineered Resilient Systems

Travis Moody, Robert Provine, Samantha Todd, Nicholas Tyler, Thomas R. Ryan, and Ricardo Valerdi

Abstract Organizations are constantly seeking to achieve earlier and more accurate cost estimates in order to make better trades space and design decisions, as well as minimize project cost and schedule overrun. These estimates facilitate decisions that are more informed – especially within the United States Department of Defense's engineered resilient systems (ERS) program. This paper will discuss the current methods used to achieve life cycle estimates, the role of estimation within ERS, and recommend a parametric life cycle cost estimation model that will support decision-making. In addition, this paper will focus solely on early life cycle engineering inputs that translate with Department of Defense's pre-Milestone A in order to create an early life cycle cost estimation model (ELCE). This model leverages the engineering inputs (design parameters) that are typically available early in the design process in the following five categories: hardware, software, systems engineering, project management, and integration. This paper will also highlight future research goals to determine values for factors of economies of scale, regression analysis with real data, limitations, and potential impacts of application.

Keywords Acquisition • DoD 5000.02 • Engineered resilient systems • Life cycle • Costing • Hardware estimation • Software estimation • Systems engineering estimation • Project management • Project management estimation • Integration • Integration estimation • COSYSMO • COCOMO II • Cost estimation relationships

---

T. Moody (✉) • R. Provine • S. Todd • N. Tyler • T.R. Ryan
United States Military Academy, West Point, NY, USA
e-mail: travis.moody@usma.edu

R. Valerdi
University of Arizona, Tucson, AZ, USA
e-mail: rvalerdi@arizona.edu

A.M. Madni et al. (eds.), *Disciplinary Convergence in Systems Engineering Research*, https://doi.org/10.1007/978-3-319-62217-0_2

2.1 Introduction

Estimating the life cycle cost of a new system, in a stage early enough to procure funding, is a difficult proposition. The Department of Defense (DoD) is at the forefront of military costing, but the institution as a whole needs to produce estimates that are more effective. For example, when the F-35 Lightning II Program was proposed for funding in October 2001, the total program cost was estimated to be $224.77 billion dollars for 2866 units. As of August 2013 after 121 months behind schedule, the total program cost had soared to $332.32 billion dollars. This constitutes an increase of 47% while producing 409 less units and a 72% increase in per unit cost from the original estimates [9]. This is unacceptable and breaches the trust between the citizens of the United States, the government, and the DoD [4, 5].

Engineered resilient systems (ERS) is one such DoD program attempting to help reduce cost-associated problems by attaching life cycle estimates to decision alternatives. ERS is housed within the US Army Engineer Research and Development Center (ERDC) and aims to provide a data-driven approach to building resilient systems through trade space analysis tools [10]. Within the ERS suite of tools, there exists a need for an embedded cost estimation component that is provided as an output to ERS users during the early stages (pre-Milestone A) of a system life cycle, as shown in Fig. 2.1. As design parameters are entered into the ERS tradespace tool, a SysML-like architecture is created, which allows for the generation of life cycle cost estimates. These estimates will then be attached to different design alternatives to aid engineers in the decision-making process.

Established methods for determining the cost of a system are described as top-down, bottom-up, and parametric [1, 15]. This research is concerned

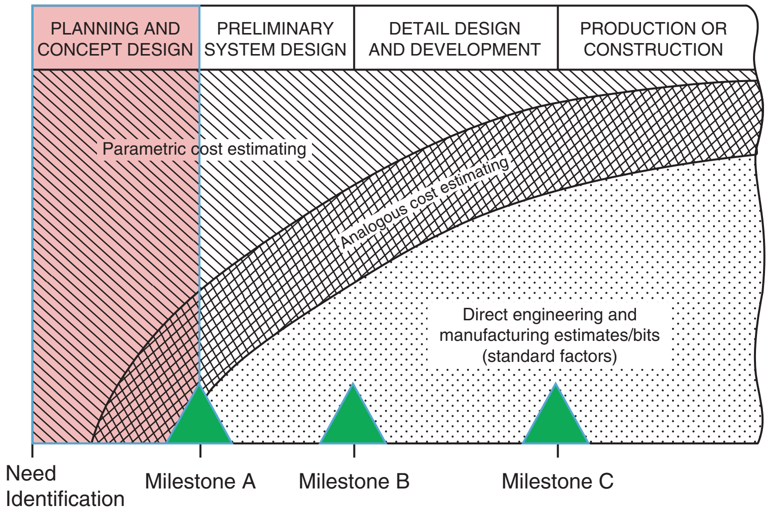

Fig. 2.1 DoD acquisition milestones overlaid on general cost estimating techniques by engineering phase. This depicts the three milestones of the DoD acquisitions process in relation to the systems phases. The *red* box outlines the boundary of the research in this paper [1, 6]

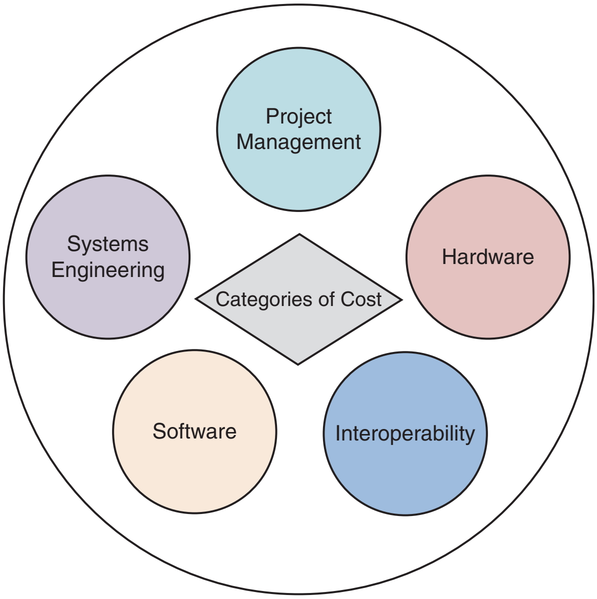

Fig. 2.2 Five categories of system level costs. The inputs for a parametric model are derived from more general areas of cost. The areas of cost identified in this research are software, hardware, project management, systems engineering, and integration. Parametric models currently exist for each area except integration [2, 13, 15, 17]

particularly with pre-Milestone A (pre-MS A), a program review between the conceptual and preliminary design phase in the DoD 5000.02 acquisition process. Referring to Fig. 2.1, most cost decisions are made with parametric models or a more subjective top-down method pre-MS A. Parametric cost estimation uses inputs, also called parameters, to help shape the mathematical relationships that will produce a more accurate estimate [15]. Currently there is no complete parametric model that accounts for total system costs; the existing models are discrete cost categories. This research is aimed at developing a parametric model that can be used to develop a total system cost pre-MS A.

When estimating the total costs of a system, it is intuitive to consider factors that specifically drive the cost of software, hardware, project management, systems engineering, and integration, as shown in Fig. 2.2. This exists because most systems are made up of some combination of the five categories [7]. The goal of this paper is to introduce a comprehensive parametric model which utilizes inputs that are available early in a system's life cycle, already contained within pre-existing models, that can be used to generate an effort output associated with cost. The aggregate of these costs will enable ERS users to make better tradespace decisions.

2.2 Background

In the current paradigm of cost estimation, there exists different estimation models specifically for the various types of systems; however, those models remain limited to their corresponding areas of cost, which therefore limits cost estimators' ability

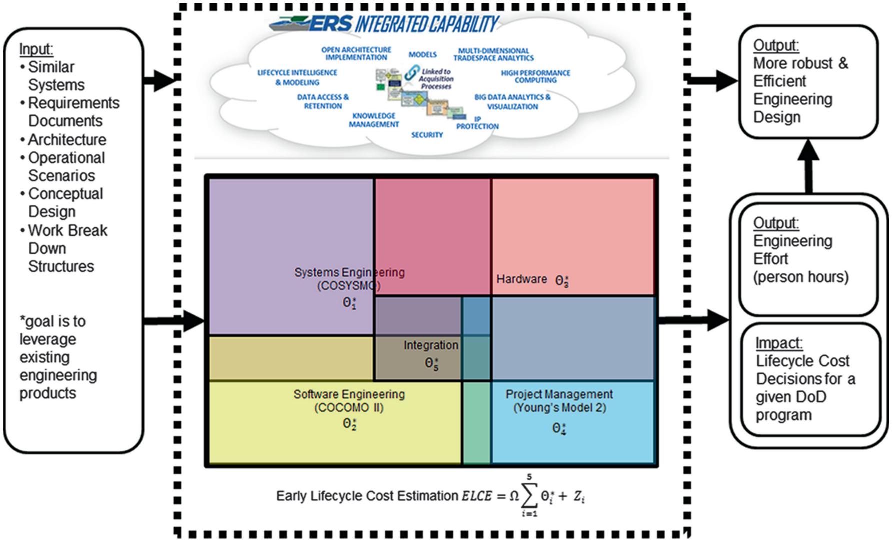

Fig. 2.3 The graphic depicts the five categories of cost, with their perceived overlaps, and the interaction between engineering inputs and ERS outputs [2, 3, 8, 10, 13, 15, 17]

to generate total life cycle cost estimates [2, 13, 15]. The models being leveraged to account for the four of the identified cost categories are constructive cost model (COCOMO II), the constructive systems engineering cost model (COSYSMO), Young's model 2 for project management, and SEER hardware (SEER-H). Currently, we are exploring that the integration component can be generated by the overlap of the other four categories of cost, as depicted in Fig. 2.3. Each of these cost models takes into account many different engineering inputs, which shape a system's cost, but are limited in that those inputs are for the whole life cycle and assume that everything about the system is known. The pre-existing models, for the most part, allow cost estimators to generate a life cycle cost estimate with what is known as pre-MS A. The goal of this research is to identify the parameters that are *known* early in the design tradespace process, for those existing models, and then combine them to create a total life cycle cost estimate. This is the fundamental difference between simply collecting cost estimates for the five cost categories and creating a parametric cost model which accounts for limited parameter availability [16]. Finally, as opposed to estimating for a specific system, this model aims to be more encompassing. A holistic cost model will provide a more complete picture of life cycle cost and will shed light on the interactions between cost elements which will increase its applicability within ERS.

2.3 Methodology

The methodology used by Valerdi (2008) in the development of COSYSMO leveraged a seven step process for building parametric models similar to what Boehm, et al. (2000) utilized in developing COCOMO II [2, 15]. This research will adapt some of those steps beginning with analyzing existing literature to understand the factors that influence life cycle cost. After reviewing the literature, next in the process is to leverage experts within the cost estimation field to refine any insight gained with research. Finally, this paper will explore how to model the concepts which will lead to the creation of an early parametric life cycle cost model.

Discussion with experts suggests that life cycle cost can be summarized into the five categories identified earlier in the paper [7]. The first step is to identify existing models that can be leveraged for each of these five categories of cost. The second step is to proceed with identifying which of the engineering inputs in these models will fit best early in the life cycle. The third step is to identify a method to account for cost categories that are not able to be represented by an existing parametric model. The fourth and final step is to analyze the model for integration. This step is necessary to determine overlap, if any, between parameters of the five individual categories of cost.

2.4 Preliminary Results and Analysis

Based on the methodology described above, the inputs available early in the life cycle were determined to focus the development of the initial early life cycle costing parametric model. This will allow engineers and decision makers to generate a parametric cost estimate earlier in the acquisition process. ERS with the added costing component enables decisions based off of differentiation of alternatives relative to this model.

2.4.1 Initial Model

The proposed cost estimating relationship (CER) for the early life cycle cost estimation (ELCE) model includes a combination of discrete cost models for each of the cost categories, referenced in Fig. 2.1. Current practice of creating parametric models dictates that the life cycle cost can be calculated by adding the outputs of the individual models and adjusting the CER with a scale factor as follows:

$$\text{ELCE} = \text{Scale Factor}^* \big(\text{COCOMO II} + \text{COSYSMO} + \text{SEER-H} + \text{PM} + \text{Integration} \tag{2.1}$$

$$\text{ELCE} = \Omega \sum_{i=1}^{5} \Theta_i^* + Z_i \tag{2.2}$$

Θ_1* = COCOMO II with factors only ascertainable post milestone A suppressed
Θ_2* = COSYSMO with factors only ascertainable post milestone A suppressed
Θ_3* = SEER-H with factors only ascertainable post milestone A suppressed
Θ_4* = Integration factor with factors only ascertainable post milestone A suppressed
Θ_5* = Young's model 2 with factors only ascertainable post milestone A suppressed
Z_i = Average cost of suppressed factors by model Θi
Ω = Model adjustment factor based on product line historical data heuristics

2.4.2 Inputs

Determining the inputs of each cost component that are available early on is important because the separate models assume everything is known about a system [2, 15]. Leading up to pre-Milestone A, relatively little is known about a system. It is for this reason that we must identify the parameters that are available to cost estimators.

The category-specific cost models we will use are COCOMO II (software), COSYSMO (systems engineering), SEER-H (hardware), and Young's project management model 2. Possible methods to account for integration costs include determining the function points of a system or utilizing the parameters identified by Ford and Shibata [8, 14]. Looking at the engineering inputs that feed into each model, we determined which inputs are identifiable early on in the life cycle similar to the COCOMO II early design model [2].

COSYSMO factors available pre-MS A include the size drivers of *number of requirements* and *number of operational scenarios*, both rated on a scale of easy, nominal, or difficult. The cost drivers that can be derived early in the life cycle are *stakeholder team cohesion*, *personnel/team capability*, *personnel experience/continuity*, and *technology risk* [15]. Each cost drivers rated on a scale that ranges from very low, low, nominal, high, to very high [15].

Project management inputs that are identifiable early in the life cycle and are independent of systems engineering drivers were derived from Young's model 2. The effort factor parameters applicable to early estimations are *requirements* and *scope*, *project complexity* and *risk*, *project constraint*, *stakeholder cohesion* and *multisite coordination*, and *documentation* and *communication level*. The efficiency multipliers, identifiable early in the life cycle, for the above factors are *people capability*, *process maturity*, and *tool support* [17].

COCOMO II has three parameters that can be estimated early in the systems life cycle. They are project size in terms of *source lines of code (SLOC)*, *number of function points*, and the *adaptability* and *reuse of the system* [2].

For hardware costs, this model will utilize a cost estimation relationship based on a few high-level parameters within the SEER-H suite that are related to hardware costs. These inputs are *operating environment*, *material composition*, *certification level*, *classification*, and *developer capability and experience* [13, 15]. They are ascertainable early in the life cycle due to their conceptual nature and provide a starting point for formulating a hardware cost estimate.

There is an absence of a pre-existing model for the integration cost of a system. There is limited research on this subject; however, Ford has generated some research that there are approximately six measures of effectiveness, which can impact the integration cost of a system. These measures are personnel requirements, level of systems cost, functional area performance, supporting-to-supported ratio, reconstitution capability, and satisfaction of the organization's priorities [8]. The inputs that are likely available early in a system's acquisition process are *personnel requirements*, *the level or magnitude of the systems cost*, *the systems anticipated functional area performance*, and *the ratio of supporting systems to supported systems*. We also anticipate that the number of function points is an additional cost driver. It is inherent that as the number of function points for a system increases, so does the subsequent cost of integration. The inputs suggested by Ford in conjunction with the number of function points of the system will help to provide a more accurate integration cost estimate [8].

2.5 Discussion

The nature of the research causes the creation of a robust parametric model and identification of specific engineering inputs by pre-MS A to be quite challenging. Several limitations to the research exist which add to the complexity of creating a parametric cost model that is robust and accurate enough for the ERS suite of tools. When creating this parametric model, it was identified that there should be an adjustment factor included for each category of cost. These factors would depend on how prevalent that category of cost is within the overall system's life cycle cost, the availability of historical project data, and the amount of uncertainty that specific category of cost experiences.

Within the above models, there exists overlap for multiple inputs, especially those related to systems engineering. For example, function points or system requirements might be present in multiple portions of the model. Such overlap can be problematic because it can lead to double counting, which results in an inflated estimate. However, repetition in inputs may not necessarily cause overlap in the model because they account for different sources of effort for the system. It will be necessary to determine a method to account for this redundancy in the model similar to how Wang, et al. decoupled overlaps between software and systems engineering cost drivers [18].

If a cost input is accounted for in multiple categories, then the decision must be made about which category that cost actually belongs in. The same inputs can represent separate levels of work in different categories. For example, a project manager and systems engineer might be working on the same portion of a system but generate separate efforts, each with distinct costs. This perceived overlap could create a more accurate cost estimate, as it might account for gaps in the model.

The ELCE model, both in its conceptual and mathematical forms, is the first step in developing a parametric life cycle cost estimate which can be integrated into ERS's tradespace analysis tool. To continue research and development of this model, we will collect data about different systems to validate the model. Subsequently, we will apply the parametric model to the data in order to test its accuracy. This will also help to determine the robustness of the model across different types of systems. Once the model has been tested, it will be adjusted for any identified inaccuracies. This process will be repeated until the model reaches an acceptable level of confidence.

2.6 Conclusion

The research described in this paper aims to build a comprehensive parametric model that takes the inputs from multiple cost paradigms and generates a life cycle estimate. By leveraging the inputs available early in a system's life cycle, we aim to provide ERDC ERS with a pre-MS A cost estimation tool. Once fully developed, this tool can be integrated into ERS's high-powered computing tradespace analysis platform in support of the DoD acquisitions process. This research will assist ERS users to perform better analysis and comparison of alternatives. This research will be applied to data on existing DoD systems and analyzed against their actual, completed, life cycle costs in order to refine and calibrate the model. By contributing to the tradespace analysis tool, this research will provide a cost estimation method other than current DoD acquisitions methods.

References

1. Blanchard BS, Fabrycky WJ (2011) Chapter 17: Design for affordability (life cycle costing). In: Fabrycky WJ (ed) Systems engineering and analysis, 5th edn. Prentice Hall, Upper Saddle River, p 566
2. Boehm BW, Abts C, Brown AW, Clark BK, Horowitz E, Madachy R, Reifer D, Steece B (2000) Software cost estimation with COCOMO II. Prentice Hall, Upper Saddle River
3. Cabrera D, Cabrera L (2015) In: Powers E (ed) Systems thinking made simple: new hope for solving wicked problems. Odyssean Press, p 59

4. Carter A (2010) Better buying power: mandate for restoring affordability and productivity in defense spending [memorandum]. Department of Defense, Washington, DC
5. Carter A (2015) Message from secretary ashton carter to all department of defense personnel. Department of Defense
6. Department of defense instruction (2015) Operation of the defense acquisition system (Instruction No. DoDi 5000.02). Under Secretary of Defense for Acquisition, Technology, and Logistics (USD(AT&L)), Washington, DC
7. Farr J, Valerdi R, Goerger S, Dabkowski M (2016) Conversation between subject matter experts in field of cost estimation on paradigms of cost for generic systems. West Point
8. Ford TC (2008) Interoperability measurement. Air Force Institute of Technology Wright-Patterson Air Force Base, Ohio. Graduate School of Engineering and Management
9. GAO (2014) F-35 lightning II program (F-35) (Assessments of Major Weapons Programs No. 14-340SP). Washington, DC: US Government Accountability Office
10. Goerger SR, Madni AM, Eslinger OJ (2014) Engineered resilient systems: a DoD perspective. Conference on Systems Engineering Research
11. Holland JP (2016) Engineering for resilience. SciTech Presentation, San Diego. Slide 7
12. Under Secretary of Defense (AT&L) (2015) Operation of the defense acquisition system (No. DoDI 5000.02). Under Secretary of Defense (AT&L)
13. SEER-H® Documentation Team: MC, WL, JT, KM (2014) SEER for hardware detailed reference – user's manual. United States of America: Galorath Incorporated (User's Manual)
14. Shibata JT (2010) A space acquisition leading indicator based on system interoperability maturity, No. AFIT/GSE/ENV/10-D02DL. Air Force Institute of Technology Wright-Patterson Air Force Base, Ohio. Graduate School of Engineering and Management
15. Valerdi R (2008) In: Muller D (ed) The constructive systems engineering cost model (COSYSMO): quantifying the costs of systems engineering effort in complex systems. VDM Verlag, Saarbrucken
16. Valerdi R, Ryan TR (2016) Total cost of ownership (TOC): an approach for estimating UMAS costs. In: Caras JR, Dickmann JQ (eds) Operations research for unmanned systems, 1st edn. Wiley, Hoboken, pp 207–232
17. Young L, Wade J, Valerdi R, Farr J, Kwak YH (2010) An approach to estimate the lifecycle cost and effort in project management for systems centric projects. International Forumn on COCOMO and Systems/Software Cost Modeling
18. Wang G, Valerdi R, Roedler GJ, Ankrum A, Gaffney JE (2012) Harmonising software engineering and systems engineering cost estimation. Int J Comput Integr Manuf 25 (4–5):432–443. doi:10.1080/0951192X.2010.542182

Springer

http://www.springer.com/978-3-319-62216-3

Disciplinary Convergence in Systems Engineering Research
Madni, A.M.; Boehm, B.; Ghanem, R.; Erwin, D.; Wheaton, M.J. (Eds.)
2018, XIV, 1201 p. 384 illus., 244 illus. in color., Hardcover
ISBN: 978-3-319-62216-3