AN EVALUATION OF GROWTH MODELS AS PREDICTIVE TOOLS FOR ESTIMATES AT COMPLETION (EAC)

THESIS

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Abstract

Efficient decision making mandates the accuracy of forecasted estimations of a contract's final value known within Earned Value Management (EVM) as the Estimates at Completion (EAC). Our research evaluates the prospect of nonlinear growth modeling as an alternative to the current predictive tools used for calculating EAC, such as the Cost Performance Index (CPI), the Schedule Cost Index (SCI), and the Composite Index methods. Our study uses the Gompertz growth curve to produce three EAC Models based on contract phase: A Production Model, a Development Model, and a Combined Model. Contract Performance Report (CPR) data are used to develop the models. Mean Absolute Percentage Error (MAPE) is used to evaluate and select the more accurate model's EAC. We compare along three datasets for performance evaluation: a model building dataset, an additional dataset, and a dataset of designated Over Target Baseline (OTB) contracts. For 63% to 79% of OTB contracts, depending on model and phase examined, our study shows all three growth models out perform all three Index-based methods. Our research shows growth models as a more accurate estimating tool for identified OTB contract's EAC as compared to the CPI, SCI, and Composite Index methods.

To being led by Curiosity instead of Limitations

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Elizabeth N. Trahan

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AN EVALUATION OF GROWTH MODELS AS PREDICTIVE TOOLS FOR ESTIMATES AT COMPLETION (EAC)

I. Introduction

General Issue

Over the last forty years, earned value (EV) evolved in the U.S. government acquisition process from hot topic to managerial best practice. Earned Value Management (EVM) is not a software program, it is a compilation of business management practices that provides a structured method to measure and analyze performance. Proper interpretation and application of EV measures serve as a warning tool for project managers on the status of their programs in the categories of cost, schedule, and performance. The Earned Value Management System (EVMS) provides a means of organization for project schedule, budget, and planning components that can produce forecasts and status determinations. EVMS equips program managers with the capability to forecast results used in the decision making process. The basis for project alterations necessary to meet established goals originates from a comparison of the current state of a program to the forecasted measure. Efficient decision making mandates the accuracy of the forecasted estimations. The measures highlighted by EVMS methodology provide the inputs for these forecasts, termed Estimates at Completion (EAC).

Grave program outcomes, such as cost overruns, schedule delays, and cancellations, have occurred due to poor decision-making based on inaccurate estimates. In a 1993 study, Calcutt noted that approximately 20 to 50 percent of completed contracts were over budget based on phase and type. In addition, programs projecting cost overruns by the 15 to 20 percent point are unlikely to complete the program with a decreased cost overrun (Christensen, 1994). Well-publicized program failures, such as the Navy's A-12 Avenger program, added to the "series of management disasters" that have shaped the necessity and desire for the Department of Defense (DoD) to spearhead the search for more accurate estimation methods (Abba, 1995).

Background

In 1991, the DoD culture revolved around the desire for accurate estimates and the preference for low cost alternatives with on-target reports. Decision makers began to appear to give favorable measures greater value than accurate ones. The Navy's A-12 Avenger program ran significantly over initial cost estimates and continued to spiral into poor management decisions and ineffective monitoring. In conjunction with the program cancellation, Secretary Cheney noted that he was unable to get a distinct price for the continuation of the program (Morrison, 1991). The cancellation of the Navy's A-12 Avenger program pushed the DoD to revise its monitoring and cost estimations for large acquisitions, as described by evolving federal regulations. Prior to this revision, the DoD had been operating on the Cost/Schedule Control Systems Criteria (C/SCSC) since 1967. While C/SCSC met with positive reviews and impressive results, it also carried some concern from the DoD and private industry to become more user-friendly (Fleming, 2000).

In 1995, the Management Systems Subcommittee of the National Defense Industrial Association met to review and rewrite the DoD's formal earned value criteria.

The new focus incorporated the needs of private industry and shed the stringent governmental verbiage that had discouraged full competition for contracts. The result was the EVMS accepted in 1996 by the then Under Secretary of Defense for Acquisition and Technology, Dr. Paul Kaminski. DoD Instruction 5000.2R incorporates EVMS guidelines and mandates inclusion for major acquisitions in accordance with the Office of Management and Budget (OMB), OMB Circular -11.

EVMS begins with a planning process and consistent monitoring when standards and regulations are in place. As outlined in the Federal Acquisition Regulation subpart 34.2, as a minimum, contracting officers shall require monthly EVMS reports from contractors in addition to the EVMS plan as part of their proposal. “Today’s DoD acquisition environment demands the use of EVM as an objective measure of a program’s performance from which informed management decisions can be made,” (USD, 2007). As of April 2008, DoD mandates EVMS compliance for cost and incentive contracts and subcontracts valued over $50 million or more. Contracts and subcontracts valued $20 million or less have the optional inclusion of a defined EVMS, hindering a risk-based process, while those over $20 million must contain a defined EVMS.

Specific Issue

The mandate for EVMS stems from the DoD’s desire to mitigate risk. Early detection serves as the most effective way to mitigate the risks associated with cost overrun. Accurate cost estimates are essential to effective budgeting and planning under limited resources because of these high risks to cost and schedule overruns. Christensen makes note in his 1993 study by concluding that, “without more realistic estimates, senior management may be lulled into a false sense of security about their programs and fail to take appropriate action."

The current practice for calculating the EAC involves program offices building estimates for acquisition contracts using different combinations of Contract Performance Report (CPR) data. Analysts use many combinations of CPR data to form factors used as prediction tools. Chapter Two documents numerous case studies that have shown the increasing fallacies in this factor process. Fallacies arise from inaccurate estimates leading to poor decision making. The fallacy occurs when reaching a plausible argument by using false inferences. The inaccuracies of the factor methodology in use leads decision makers to these false inferences. Proper identification of deviations from the EVM plan must be made to ensure effective responsive actions (Al-Jibouri, 2003). There is increasing interest on alternative methods for estimates displayed by developmental studies from Brown (2002), Singh(2005), and Tracy (2005) along with investigational studies by Christenson (1995), Nystrom (1995), and RAND, to name a few. Prior research shows that current measures rarely stay between 20 and 85 percent of the initial estimates (Singh, 2005). These findings show contracts tend to either perform within their expected estimates or are vastly misestimated.

An alternative to the factor method uses regression as a tool to forecast costs. Regression studies show linear regression techniques as a viable prediction tool for early detection but less effective in later stages of contract life cycles (e.g. Olsen, 1976; Tracy, 2005). Nonlinear capabilities in the form of growth modeling have not been thoroughly inspected concerning EAC. Growth models provide parameters that are intrinsically useful to analysts.

Research Objectives

Our research focuses on two main tasks. First we identify growth models as a feasible and intrinsically useful methodology for Estimates at Completion (EAC). Second we properly evaluate growth models for accuracy as compared to current practices. To perform a proper evaluation of growth models we both create models from existing data and compare their EAC accuracy to that of three commonly used Index-based EAC.

Scope and Limitations

Past political influences and assumptions combine with data accessibility to limit our research two fold. Past studies and practices are based on individual assumptions that will be detailed with their respective studies in Chapter Two. These assumptions may alter the interpretation of some of the variables and their uses. Highlighting these definitions and practices allow our findings to maintain a higher content validity. High content validity provides reassurance that what we define is what is being measured. To further support this effort, we remove designated Over Target Baseline (OTB) contracts from the model development stage but include OTB contracts as a separate dataset for the model evaluation stage.

The data limitations occur due to the developments in database management and upkeep. In July 2007, the Under Secretary of Defense distributed a memorandum that announced the full implementation of the automated Central Repository (CR). Chapter Three discusses the flow of information and data access, as well as, the multiple databases and exchange levels requiring secure access in order to analyze the data collected. While consolidated from previous methods, this process still provides many different security levels and interfaces to navigate. Data access limits our ability to build and evaluated models from a larger dataset. Chapter Three also comments more on the selection of data and structure of the databases used in this study. While dealing with a smaller dataset our models are evaluated extensively to provide more robust findings.

Additionally, EVMS criteria is particular to Acquisition Category (ACAT) I programs. This limits our generalizations to those contracts using these tracking tools. OSD dictates the scope of our presentable research findings for security purposes not specified. Due to these security features the information provided by our research reports only by program type: production or development. This restriction prevents individual program information and contract specific data's presence in this document.

Summary

DoD officials expect clear, effective decision-making from all program managers, both DoD based and contractors alike. The DoD and corporate industry recognize this fact and further respond with the development of the EVMS. However, this tool alone is not the only solution, all parties involved in the acquisition process demand better estimates. Our research aims to evaluate the prospects of nonlinear growth modeling as a solution to the shortcomings of current predictive tools for EAC and the desire for more descriptive models. The EAC represents the final cost estimation and is the most influential calculation in the program manager's analysis.

The next chapter contains a review of the literature pertaining to EAC and an introduction to growth modeling techniques. This review of the basics of EVMS includes current calculation methods for EAC and previous studies developing alternative methods to fulfill our first objective. Chapter Two also includes a brief introduction to nonlinear growth curves. The remaining chapters detail our findings for completion of our second objective: proper evaluation of growth curve predictive potential. Chapter Three presents our data and methodology. This portion of our research describes the separation of data subgroups and the evaluation process we use while incorporating an explanation of data screening procedures and the growth model fitting process, as well as, introducing the computing requirements and limitations associated with these methodologies. The fourth chapter presents our growth model results. The Final Chapter discusses the comparison and associated implications of our growth models to that of the Index-based models.

II. Literature Review

Basis for Study

The previous chapter highlighted the history and development of a management tool for decision makers, EVMS. While noted for its difficulties and controversy, the importance of measuring project success using defined criteria is undisputable (Baccarini, 1999; Liu et al, 1998). Likewise, the Under Secretary of Defense issued a memorandum stating that, " EVM is considered by many in the project management community to be the best option currently available for holding all parties accountable for the effective management of large and complex projects" (AT&L, 2007). This chapter covers the basics of EVMS to provide a common reference for prior research evaluations. Current practice and prior research have identified numerous methods for forecasting the completion costs for programs. This review of literature provides an overview of the factor studies as well as prior regression and alternative approaches taken to calculate the EAC. A brief introduction to growth models provides the basis for their perspective usefulness. The main objective of this chapter is to sufficiently identify the necessity and prospect of this study's methodology selection.

EVMS Metrics

From standards and regulation the EVMS process begins with a planning process and consistent monitoring practices. As outlined in the Federal Acquisition Regulation subpart 34.2, as a minimum, contracting officers shall require a monthly EVMS report from contractors on programs budgeting over $20 million in addition to the EVMS plan as part of its proposal (DoDI 5000.2). Additionally, the Defense Federal Acquisition

Regulation corresponding to EVMS details that the contractors must provide, “management procedures that provide for generation of timely, reliable, and verifiable information for the Contract Performance Report (CPR)” (CFR 48, 2008). Necessary to follow the past procedures and conclusions, the basics of EVMS allow understanding of the CPR variables.

The basics of EVMS fall into three core components: Planned Value (PV), Earned Value (EV), and Actual Cost (AC). The EVMS denotes PV as a point along a time-phased budget. Early projection takes form from the project baseline, also referred to as the Budgeted Cost of Work Scheduled (BCWS). The PV usually takes on a stretched-out S shape and is therefore referred to, by private industries, as the S-curve (Anbari, 2003). The Budget at Completion (BAC) represents the cumulative end point for this projection. Budgeted Cost of Work Performed (BCWP) captures EV by measuring the work accomplished. This measure fluctuates greatly between tasks and contractor practices.

The method of measuring should be predetermined and consistently followed. Contractors incorporate EV through various breakouts based on project beginning and project completion (Anbari, 2003). While earned valuation is specific to each situation, contractors commonly use the 50/50 rule, which symbolizes 50 percent EV at schedule beginning and 50 percent EV at completion, for many contracts. Previous research shows that very detailed breakouts (Fleming, 2000) and larger contracts (Kerzner, 2001) need to be incorporated to prevent distortions to the budget. Kerzner’s research also shows that alternative rules, such as 0/100 work better for smaller projects (2001). The type of work being completed determines the best course of EV accounting whether it be 10/90, 20/80, 25/75, or any other rule. Some tasks have preparation matters that equate to a larger up front accounting for earned value merely by the beginning of the activity (Anbari, 2003). Since each contract that requires an EVMS mandates validation by the government, the EV data collected through the CPR are also considered valid (Smirnoff, 2006). Chapter Three further addresses the implications of this assumption.

Our final key measure represents the actual costs incurred. AC or Actual Cost of Work Performed (ACWP) has no relation to how work accomplished is measured. The calculation of the EAC relies on an analysis of ACWP in relation to the other measures described above. Figure 1 is a graphic representation of the Performance Measurement Baseline to demonstrate the comparison between variables (Christensen, 1993).

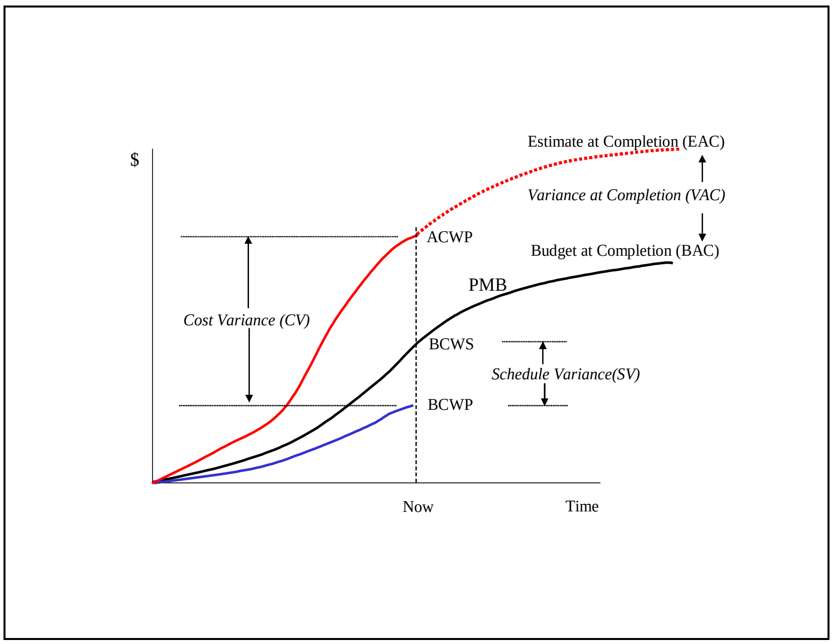


Figure 1: The Performance Measurement Baseline (PMB)

Included are variance factors used to describe risk and discrepancies between the EVMS variables. The Schedule Variance (SV) denotes the difference between BCWP and BCWS, a favorable SV will be positive showing that BCWS is less than BCWP. The Cost Variance (CV) denotes the difference between BCWS less ACWP; a favorable CV will be positive showing that ACWP is less than BCWS (DoDI 5000.2). The variables collected and variances calculated work to provide the decision making tools for program managers (PMs). Appendix A: DSMC Gold Card, 2006 contains the DSMC Gold Card for an additional visual display and description of EVM analysis and development of management reports. The Gold Card acts as consolidated quick reference for EVM users. This reference includes a handy acronyms section for terminology unique within EVM (DSMC Gold Card, 2008). PMs most commonly compare the EAC to the BAC to perform project status evaluations by obtaining a Variance at Completion or VAC. PMs strive to minimize the VAC. More accurate EACs assist efficient and effective decision making when adjusting the budgeting and/or cancelling a contract or program.

Political Influences

An overarching theme found in the literature limits effective data handling by political influences. Christensen conducted several studies associating to narrow in on the events surrounding the A-12 cancellation. While Christensen found no difference in the effectiveness of the CPI calculation, there were many other reporting differences noted between the types and handling procedures for the contracts (1993). Christensen's later study published in 1996, shows that the cumulative CPI-based EAC chosen most frequently represents the low bound option (1996). Program managers and researches of organizational culture also noted the lack of cultural acceptance for accurate numbers (Eskerod, 2007). Initial controversies arose from the lack of attention given to the more accurate estimates in the A-12 scenario. The major disagreement was that Defense Secretary Cheney could not get anyone to tell him the bottom dollar (Morrison, 1991), while the most accurate estimates were available and being repressed (Beach, 2000) by project participants for appearance purposes (Eskerod, 2007). Ruter included as an externality to his 2007 study on cost overruns that a "major culture change should be encouraged inside DoD" in order to fix the problems. Alternative political differences were found with GAO and RAND reports and briefings which list cost estimates at fault for major program failures.

Acquisition reforms have given notable increases to the monitoring process but have not significantly changed the accuracy of program outcomes to estimates. Christensen's study comparing pre and post A-12 cancellation programs show a significant decrease in cost overruns; however, Holbrook's thesis in 2003 examined additional reform efforts with no significant improvements found. Holbrook comments that estimation practices could be the leading factor in overruns due to the monitoring improvements noted by the reform effects from Christensen's pre/post A-12 comparison. Holbrook's findings support the suggestion that estimates are to blame for poor decision making and cost overruns. Smirnoff revisited the topic of acquisition reform in 2006 and presented the first and only contrary findings, stating that reform measures have positively affected cost estimation.

The Office of the Under Secretary of Defense notes the lack of participation in EVMS as a contributor to the issues arising in program management (AT&L, 2007). The timeliness of contractor CPR submissions is essential to adequately representing the contract performance. Pletcher and Young (1994) point out the limitations associated with lack of tail-end submissions, CPRs after the 75% complete mark, of data within the Defense Acquisition Executive Summaries. The specific limitations of the data used in this study will be addressed in chapter four along with its collection procedures. These political influences cannot be fixed overnight. Ensuring the most accurate estimates along with the efficient means to convey them are available will allow for a smooth transition (Bryde, 2007; Ng, 2007). Overcoming political influences starts with effective applications of accurate estimates. The smooth transition occurs, first, by showing the existence of improved measures and then by presenting a politically acceptable means of conveying the methodology.

Factor Methods

PMs and contractors primarily rest their EAC projections, and consequentially their decisions regarding the status of their projects, on the use of factors or indices. Equation 1 of Table 1 displays "the generic index-based formula" (Christensen, 1995). Numerous studies have been conducted to show the inaccuracies caused by the use of these methods (Tracy, 2005; Brown, 2002; Christensen, 1995; Singh, 2004). Each of these studies cites literature and rationale for the exploration into new methods of calculating the EAC. Index based studies have looked at comparisons of accuracy between four groups of *performance indices* before trying to create their own. Table 1 presents Equations 2 through 5 which display these *performance indices* with respect to the EVMS variables. Equation 5 of Table 1 involves the use of weights which usually sum to one with each being an amount between zero and one (Christensen, 1995). Previous studies show the mix support for each of the Index-based factors.

Analysts form reservations about the ease of transfer to program managers and decision makers. These reservations result from looking at methods outside of factor based processes due to their complex and hard to follow nature (Tracy, 2005; Anbari, 2003). In response to this fact, most EAC research conducted either comparing index-based methods or evaluating potential weights or adjustments for them (Christensen, 1995).

Table 1: Index Formulas

EAC = ACWP + (BAC – BCWP) / Index	(1)
Cost Performance Index (CPI) = BCWP/ACWP	(2)
Schedule Performance Index (SPI) = BCWP/BCWS	(3)
Schedule Cost Index (SCI) = SPI * CPI	(4)
Composite Index = W1 * SPI + W2 * CPI	(5)

Initial comparison papers show the CPI demonstrating the best predictive index (Busse, 1977; Karsch, 1976). These studies established the conclusion for focusing on sensitivity within a constrained model. A later study concludes with the cumulative Schedule-Cost Index (SCI) as the *best* predictor (Terry and Vanderburgh, 1993). Nystrom's (1995) Air Force Institute of Technology (AFIT) thesis compares 12 Index-based methods to 4 regression methods to show the Composite Index-method as a more accurate and stable prediction tool. Nystrom's composite Index-method used weights of 0.20 and 0.80 on SPI and CPI, respectively.

In 1995, Christensen and others from the AFIT performed a comparison of the little known research done on EAC methodology. In this study, Christensen was able to collect 25 papers to review, including an assortment of unpublished working papers. Two main conclusions formed from the diverse set of studies reviewed: "(1) The accuracy of regression-based models over index-based formulas has not been established… [and] (2) The accuracy of index-based formulas depends on the type of system, and the stage and phase of the contract" (Christensen, 1995).

These conclusions base their responses from small sample sizes, the smallest being one contract, as with Karsch (1974) and Singh (2004). Other studies sampled did not vary by type of contract, consisting either of all production or all development contracts (Christensen, 1995). Support for the index-based methods has been published along with insights noted by thesis works such as the guidelines suggested here:

> "1. Because the CPI will not vary by more than ten percent after the contract is more than 20 percent complete, a TCPI greater than the CPI is suspect (Christensen and Payne, 1992; Christensen and Heise, 1993).
> 2. The cumulative CPI estimated EAC is a reasonable lower bound to actual CACs (Christensen, 1996).
> 3. The final cost overrun will not be less than the current overrun (Christensen, 1999)." (Tracy, 2005)

While many of the researchers were gaining published exposure with preferences of index-based formulas, regression initiatives were working hard on the side, but were deemed too rigorous or lengthy at the time of their introduction. Our study includes an examination of the CPI, SCI and Composite Index-based methods to alleviate any conflict of practice and preference between them. Reviewing past regression attempts provides insight to the reservations found with regression and hurdles we may face in applying nonlinear growth modeling techniques.

Regression & Alternative Approaches

Compelling outcomes from regression analysis pose great insight to EAC computations (Christensen, 1995). Simple regression studies came as an answer to transforming the index-based methods. Time-series analysis has been utilized to investigate this opinion. Olsen (1976) and Chacko (1981) apply time-series combined with computer programs and smoothing techniques but were seemingly only effective for their specific contracts. No comparison of these models has been performed. Tracy (2005) identified five models to span varying phases of a contracts completion. This approach supports the notion that no one method could be useful for the entire life of a contract (Christensen, 1993).

Karsch (1974) incorporated nonlinear regression into an index-based analysis which launched the investigation into the validity of his derived method. Busse (1977) later used a similar equation but found that a focus on its sensitivity was necessary. The most compelling argument for methods outside of index-based based on the normalized S-curve methodology (Christensen, 1995). The outcome of such a methodology could be used for comparative and predictive purposes and, while complicated, was able to provide a cumulative cost growth for 22 development programs (Weida, 1977). This study launched an assortment of regression studies on development contracts (Watkins, 1982; Dukovich, 1999; Unger, 2001; Brown, 2002).

The regression analysis follows a tendency towards linear applications, focusing the efforts on adapting the Rayleigh-Norden model (Watkins, 1982) and subsequently the Weibull model (Dukovich, 1999). While this method shows potential when applied to the formulation of budgets (Unger, 2001) when adapted to predict EAC the Rayleigh method is greatly out performed by the Index-based methods (Nystrom, 1995). Additional studies looked into regression as an improved method over index-based calculations of EAC. Heydinger (1977) uses the Erlang equation along with the Space and Missile Systems Organizatiori (SAMSO) to show regression's capabilities as a preferred method to index methods, but Covach proves the instability of these findings years later in his comparative study (1981). Further details on the methods not evaluated in this study can be found using the references cited.

Most models mentioned thus far focused on development contracts due to their history of identified tendencies and have not been expanded to make them more generalizable to other types of contracts (Christensen, 1995). Research has also spanned into the realm of cost growth specifically, not to be confused with the EAC (Lucas, 2004; Ruter, 2007). Our study incorporates contributions from overrun studies regarding inflation, reform initiatives, and phase effects (Cross, 2006; Gautier, 2004; Ruter, 2007; Smirnoff, 2006). These studies suggest future studies include findings that are both user-friendly and accurate method of forecasting costs (Christensen, 1996; Brown, 2002; Tracy, 2005). Many of these new methods with greater accuracy were met with great controversy. Growth models stand out with their predictive nature that stems from nonlinear regression while also providing intrinsically useful parameters.

Sigmoidal Growth Models

Many areas of study produce sigmoidal or "S-shaped" growth curves. As previously mentioned, our study focuses on one of these types of data. "Such curves start at some fixed point and increase their growth rate monotonically to reach an inflection point, after this the growth rate decreases to approach asymptotically some finale value," (Ratkowsky, 1983). There are several mathematical methods describing the sigmoidal curvatures with varying levels of complexity.

In general, growth models contain an ‘α’ denoting the asymptote, a ‘β’ denoting the y-intercept, and a ‘ γ’ denoting the rate of change four-parameter growth models add a ‘δ’ to increase flexibility in the model. JMP provides nonlinear templates solving for these parameters, for full details see Appendix D: JMP Nonlinear Modeling Templates* using the following substitutions: $\theta_1 = \alpha$, $\theta_2 = \beta$, $\theta_3 = \gamma$, and $\theta_4 = \delta$. The Gompertz growth and the logistic models represent three-parameter sigmoidal curves, while the Richards and Weibull-type models represent four-parameter variations. Table 2 illustrates the formulas for these curves.

Table 2: Growth Model Formulas

3- Parameter	Logistic	$Y = \alpha / [\ 1 + \exp\ (\beta - \gamma X)\ ]$
	Gompertz	$Y = \alpha \exp\ [-\exp\ (\beta - \gamma X\ )]$
4 -Parameter	Richards	$Y = \alpha / [\ 1 + \exp\ (\beta - \gamma X)]^{1/\delta}$
	Weibull-type	$Y = \alpha - \beta \exp\ (-\gamma X^{\delta})$

Our study narrows growth models to examine the Gompertz and Richards growth models. “In 1825 Benjamin Gompertz published a paper in the Philosophical Transactions of the Royal Society, *On the Nature of the Function Expressive of the Law of Human Mortality,*“ producing a method of calculating the relationship of increasing age on mortality (Winsor, 1932). It was not until 1931 that Charles Winsor adapted the Gompertz equation into a more expansive growth formula (1932). In Winsor’s evaluation he shows the similarities of the Gompertz and logistic methods.

Although the Gompertz and logistic models are similar, their differences make them applicable to several different fields. Vieira and Hoffman (1977) suggest that while the logistic curve became widespread in use, the Gompertz curve could prove a better fit in phenomena in fields such as biology and economics. For these reasons, our study selected the Gompertz growth model to represent the three-parameter sigmoidal curve estimation methodology in this evaluation. In addition, the previously discussed Rayleigh methodology represents a derivation of the Weibull-type model that has been already evaluated. Nystrom (1995) previously found the index methods to perform better than the Rayleigh. While some studies found the Rayleigh model useful (Unger, 2001), our study aims to evaluate predictive tools for EAC not the budgeting arena. For these reasons, the Richards growth model will represent the four-parameter sigmoidal curve in our study.

Summary

This chapter covers the basics of the EVMS and its variables. Finding the preferred mechanism for calculating a contract's EAC requires this understanding. Past research shows a history of development of index-based methods, as well as, the prospect of regression accuracy. The next chapter describes the collection process and inherent limitations of the data. Our collection presents the data's natural fit to the S-curve described by previous researchers as validation for the methodology selection. This chapter also details the methodology used to fit and evaluate the growth models selected. The forth chapter presents the application of methodology, while the comparison is reserved for Chapter Five to include a discussion of the implications it causes. We attempt to aid our methodology in remaining user-friendly and easily transferable to allow inexperienced personnel to follow and interpret.

III. Data and Methodology

Introduction

This chapter describes the procedure followed to evaluate the growth models as predictive tools for Estimates at Completion (EAC). The objective of this evaluation is to determine if a growth model performs better than the commonly used Index methods, including the CPI, the SCI, and the Composite Index. This chapter begins with a description of the data source and criteria for screening the data. The previous chapter selects Gompertz growth and Richards growth as the focus of this evaluation. This chapter provides the methodology required for solving these models. This portion includes the introduction of software utilized in this study and the models selected for evaluation. Finally, we present the tools used to determine the *better* EAC.

Database Structure

Our research examines the major participants, as shown by Figure 2 of the Defense Coat and Resource Center's (DCARC) illustration of data interfaces. We then discuss each participant's influences to the data collection and review portions of our analysis. DCARC provides the primary housing of DoD cost data. Established in 1998 as a replacement to the Contractor Cost Data Report Project Office, DCARC is part of the Office of the Secretary of Defense (OSD) Program Analysis and Evaluation (PA&E), which collects current and historical Major Defense Acquisition Program cost and software resource data. DCARC manages two systems for cost analysts: Defense

Automated Cost Information Management System (DACIMS) and the EVM Central Repository.

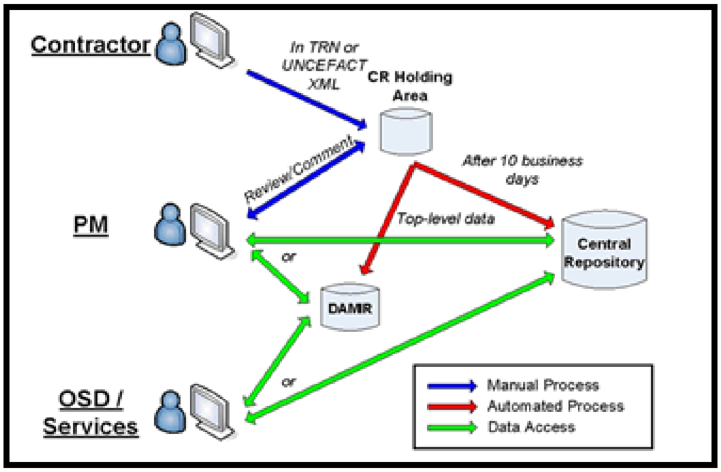


Figure 2: Earned Value Databases

The Defense Acquisition Management Information Retrieval (DAMIR), highlighted in the center of Figure 2, provides the interface for retrieving data between PMs and OSD. The DAMIR gathers information directly and indirectly from all participants in the acquisition process through DAES and CPR data. Chief responsibility for valid data belongs to the contractor and should be verified by the PM and DCMA. While not completely addressed in past literature and acquisition policy. Analysts of EVMS assume valid, consistent, and reliable data within these repositories. Appendix B displays the logic and consistency checks utilized by EVMS analysts to support the analysts' assumptions previously mentioned.

Data Screening

Despite the multitude of participants in the recording process described in the previous section, data access presents a lack of follow-up and full completion of earned value records. Incomplete contract data and patchy record keeping present numerous limitations in this study. Data screening for use in this research follows three steps past the access and collection stages. OSD provides access to DAMIR from which we pull completed program and contract data. OSD grants access but can restrict the release of that data. Our research uses data from program and contract level. However, OSD limits our findings in this study to portfolio statements or Air Force as a whole. Data Screening consists of three stages: data manipulating, data reviewing, and data sorting.

We collect our initial database comprising of archived DAMIR records from 1960 to 2007. In whole, 430 contracts consisting of 5482 CPR entries comprise the initial data set. The initial data set contains numerous errors and holes. Our research fails to see any formal revisit at the completion of a contract made to clean and verify the entries placed into archives. We commence data reviewing by identifying errors and abnormalities in the data set. We correct discrepancies which present rational conclusions correctable errors found include typos, such as an entry of 00 for the year 2000 electronically converting to 1900. When we found double entries made to correct the previous amounts or other information present, we kept the latter of the two. Typos, such as the one mentioned previously, that could be easily understood provide easy corrections. Our study did not attempt to correct typos requiring great lengths of reasoning or document specific knowledge. In addition, we deem entries lacking essential EV numbers as useless in this study.

Converting the programs into comparable data involves some data manipulation. OSD limits our study to releasing results by portfolio or AF level which requires a formatting conducive to multiple magnitudes of programs. Our study uses the creation of a percent time variable to present programs of varying magnitude on the same range. We use the reported Work Start Date, Submit Date, and Completion Date to calculate a count for the present time and range of time. Table 3 shows the formulation of the percent of time complete. In addition, Appendix C: VBA Coding for Percent of Time Complete contains coding for a Visual Basic Application macro for Excel that provides a user-friendly means of calculating percent of time complete.

Table 3: Percent Time Formulation

$\% \text{ time complete} = \dfrac{PC}{Range}$	PC : Present Count = Submit Date
	CCDate : End Count = Completion Date * Use latest recorded
Range = CCDate - WSDate	WSDate : Begin Count = Work Start Date * Use earliest recorded

EV analysis evaluates the completion of tasks over time. Percent time complete corresponds with percent task complete. Our study also requires the Total Cost, hereafter referred to as TC, for evaluation purposes. In many cases this data is not provided in which case the cumulative ACWP from the last CPR entry represents the TC. Percent complete refers to task completion and measures the amount completed as compared to the budgeted activities. Table 4 presents the formula and corresponding acronyms for the percent complete equation.

Table 4: Percent Complete Formulation

$\% \text{ complete} = \dfrac{ACWP}{BAC}$	ACWP: Actual Cost of Work Performed
	BAC : Budget at Completion
	CBBASE: Contractor Budgeted Base
BAC = CBBASE – MR	MR: Management Reserve

Data sorting involves the separations of development and production programs as well as the span check on entries. Chapter Two presents the previous research that supports our segregation of production and development phase contracts. Past research shows a distinct difference in the cost patterns associated with production and development contracts. We next check the span of each contract's CPR entries, this refers to the span between the first EVMS entry and the last EVMS entry for a contract. We note the lack of follow-up, but the data presents a lack of complete documentation on both ends for many contracts. Due to the inherent limitations in the CPR process, we do not expect to obtain CPR data at 100% but recognize the utility if this data were obtainable. Our study requires a complete, full span of entries to achieve the goal of forming a method that can relate to the entire life of a contract. Table 5 contains a summary of the data using percent time and percent complete as comparable measures of each contract's entries and recorded span.

Table 5: Data Summary after Reviewing

		First Entry		Last Entry		Entries per Contract	
Type	Contracts	Percent Time	Percent Complete	Percent Time	Percent Complete		Entries
Production	195	0.362787	0.310997	0.842614	0.8864	11.44615	2232
Development	156	0.291139	0.313112	0.826521	0.866748	13.98077	2181
Total	351	0.326963	0.312054	0.834567	0.876574	12.71346	4413

As Table 5 shows, the average contract' s last entry occurs at 87% complete which does not include a complete set of data points to span the contract from beginning to 100% complete. Our study requires a sufficient span of data. To appease this requirement we desire a span of no more than 10% complete at the first entry and at least 90% complete by the last entry. Providing useful EAC calculations requires contract information prior to the 10%. Decision makers need accurate tools that provide early detection and evaluation of the status of projects.

Ideally, 100% complete details the TC point, however, many contracts exceeded this point as well. Excluding all of these contracts severely limits this research. Those that denote an over target baseline (OTB) date were excluded from the model building dataset due to their particular nature and increased difficulty in addressing EAC calculations. To properly account for OTB evaluations, we create a separate dataset of designated OTB contracts for comparison to the Index based methods. We attempt to capture the trends of standard contracts by this initial exclusion. The Department of the Air Force details that in exceptional cases a contractor is "authorized to implement and report to a baseline that exceeds the cost of authorized work" (1993). The Index method usually continues to influence decisions after OTB designation, however these specific contracts require outside adjustments and judgment calls. Additional exclusions occur when the BCWS, BCWP, or ACWP decreases between reporting periods. This occurrence causes a decreasing cost parameter making an index calculation not possible (Nystrom, 1995).

Table 6: Data Collection Breakout

Number of Contracts		Dataset Subgroups			Percent Complete			limited entries	
Phase Type	**Total**	**Model**	**Addtn**	**OTB**	**First <.1**	**Last >.9**	**Both**	**1**	**2 - 3**
Production	195	30	80	9	60	120	33	12	5
Development	156	20	47	19	59	90	32	10	7
Total	351	50	127	28	119	210	65	22	12

The separation of the three evaluation subgroups and the descriptive break out of the collect data displays in Table 6. Where possible, contracts containing CPR entries after the 90% completion point are evaluated within the Additional dataset subgroup. The OTB dataset contains the designated OTB contracts which can also be evaluated but not included in the Model dataset. The dataset subgroups provide the additional evaluation capabilities necessary for general application conclusions. Table 6 provides the categories of our final research datasets. We develop our models from the 30 production and 20 development programs comprising our model building dataset, while we evaluate our models across the 205 contracts contained in all three datasets. Contracts with limited entries, less than three CPRs, would normally drop from previous regression methods (Olsen, 1976; Chacko, 1981). However, the robust nature of our method allows solving of EAC for these contracts. The limited contracts that provide an assumed TC are included in the additional dataset. Our analysis suggests that the multiple repositories, lack of follow-up, and history of regulatory changes lead to the high magnitude of unsalvageable data. Current initiatives by DoD (2007) expect to resolve some of these issues by providing a central repository. The model selection process uses the compilation graphs of these programs in order to select a form fitting replication.

Model Fitting Process

Our methodology uses the statistical discovery software JMP® for the computationally rigorous process of nonlinear model fitting. SAS Institute Inc developed JMP in October 1989 but does not claim it as part of their SAS System. “JMP is designed to be a point-and-click, walk-up-and-use product that harnesses the power of interactive statistical graphics to serve the analysis needs of the researcher," (SAS Institute Inc., 2005). Due to the screening and methodologies selected JMP does not represent any limitations to our study.

A representative program chosen from each of the datasets provides a visual comparison to select from sample models. JMP provides 33 nonlinear model formulas with sample graphs and allows for users to input their own formulas. For further details, Appendix D provides Table 20.2 from the SAS Institute Inc.'s Guide for nonlinear modeling templates (2005). Extensive details on this function can be found in the referenced Guide and at the website <www.jmp.com>. Chapter Two discusses the rational for choosing the Gompertz and Richards methods for this study. Within its nonlinear fitting platform, JMP refers to forms of these models as Model H and Model P, Gompertz growth and Richards growth models respectively.

The nonlinear fitting process follows three main criteria. First, we define the column parameters and starting values. For this step, we use the recommended starting values of the designated software, unless known or calculated estimates exist. Next, we select the nonlinear fit platform using JMP. Nonlinear models differ from linear models by the way their parameters enter the model. In linear models the parameters appear in linear fashion in that they directly multiply or add to the model, for example $Y = \theta X + \epsilon$. In nonlinear models, the parameters appear nonlinearly, for example $Y = X^{\theta} + \epsilon$.

Linear and nonlinear regression models are similar in that they both use least squares to estimate their parameters. However, nonlinear approximation by these means lends to elements of bias, non-normality, and excessive variance that can decrease as sample size increases (Ratkowsky, 1983). Least squares refer to the process of minimizing the square of the residual amount created by the difference between the predicted values and the actual values used to fit the model.

The least squares estimate is all about finding the point on the expectation surface closest to the actual point and then finding the parameter which corresponds to that point. For linear models this process is fairly straightforward, but for nonlinear models these steps can prove very difficult. Difficulty with finding the first set of points corresponds to the curvature of the expectation surface making it hard to solve for the desired point. The second step is difficult because mapping points is only easily done in one direction, from the parameter plane to the expectation surface (Bates, 1988). To overcome these difficulties we use iterative methods to determine the least squares estimate. JMP uses the Gauss-Newton method of least squares approximation.

For, “linear models, the sum of squares surface has a single minimum and the Gauss-Newton method will find that minimum in a single iteration for any set of initial parameter estimates,” (Ratkowsky, 1983). This method solves by running the expectation function to iteratively improve an initial guess for the parameter and keeps improving the estimates until there is no change. “This process is repeated until convergence is obtained, that is, until the increment is so small that there is no useful change in the elements of the parameter vector,” (Bates, 1988).

Gauss-Newton finds convergence with close-to-linear models rapidly without depending strongly on the initial parameters. Nonlinear models do not solve without considerable computational effort which can still lead to pitfalls, such as bias, non-normality, and excessive variance (Ratkowsky, 1983). As the model’s inherent nonlinearity increases, solving for the parameters becomes increasingly difficult and convergence may not occur. In these cases, there may be several minimums present on the response surface. When working with intrinsically nonlinear functions, those that cannot be transformed into linear functions, it is important to obtain good initial estimates for the iteration process (Ratkowsky, 1983). Our study takes into account the intrinsically nonlinear nature of the Gompertz growth by selecting initial values representative of our data. In addition to the Gauss-Newton iterative method, JMP applies another criterion for convergence in that the relative change in the sum of squares on successive iterations return smaller (Bates, 1988). The Iteration Control panel performs these tasks within the JMP software.

The Iteration Control Panel completes the Nonlinear fitting platform by using the model specified. We begin with starting parameters and use the computing power of JMP to perform a step estimation taken to solve for the parameters providing the smaller residual values. The parameters are adjusted by iterations until a smaller value of residuals is not found. Once the residuals are minimized the function is said to converge to that set of parameters. Upon convergence we provide the growth formula parameters and their confidence limits, Lower CL and Upper CL. An additional set of iterations produces the Lower CL and Upper CL. These values represent the "lower and upper $100(1 - \alpha)$ percent confidence limits for the parameters," (SAS, 2005). This alpha refers to the analyst's desired significance level. Our study uses $\alpha = 0.05$ so that the confidence limits provide a range for 95% of the possible parameter responses.

> "The upper and lower confidence limits are based on a search for the value of each parameter after minimizing with respect to the other parameters that produces a SSE greater by a certain amount than the solution's minimum SSE. The goal of this difference is based on the *F*-distribution. The intervals are

sometimes called *likelihood confidence intervals* or *profile likelihood confidence intervals* (Bates and Watts 1988; Ratkowsky 1990) "(SAS, 2005).

Chapter Four discusses the models and variables showing how the parameters enter the Gompertz growth curve with an input of the percent time complete variable. The model solves for the estimate of the percent complete measure at that point in time and for an estimate of value multiples by the BAC. The EAC is calculated by an assumption of X=1 or 100% time complete.

Table 7: EAC Formula Using Growth Model

Gompertz Growth :	$GG(X) = \alpha(\exp(-\exp(\beta-\gamma*X)))$
EAC :	$EAC(X) = ACWP(X) +[(GG(1)-GG(X))*BAC]$

Table 7 provides the equation for EAC when we use this assumption and give credit to current state by subtracting the estimated completion and adding the actual costs. Evaluation procedures commence using this formula in comparison to the popular Index methods described earlier to evaluate the efficiency of growth models as predictive tools. The EAC calculation uses the Index-based EAC formula with the Index values for the CPI, SCI, and Composite methodologies as introduced in Chapter Two.

Comparison Procedures

The EAC aims to provide a reliable means of managing a program throughout its existence. Selecting the best methodology identifies itself with maintaining values that diverge the least from the actual values. This accuracy provides decision makers with the best estimations. Error terms or residuals contain these deviations or differences between the actual values and the estimated values. Mean Squared Error (MSE) measures the distance between the model values and actual values while neutralizing the effects of a positive or negative sway. Nahmias (1993) insists that MSE dissolves in utility across series due to magnitude.

Table 8: Comparison Formula

Absolute Percentage Error	APE = Abs [(EAC – TAC) / TAC]
Mean Absolute Percentage Error	MAPE = (∑ APE) / n
EAC = Estimate at Completion; TAC = Total at Completion; n = number of contracts	

Mean Absolute Percentage Error (MAPE) allows for magnitude to be proportionally distributed and thus can fully compare multiple series regardless of magnitude (Land, 1980; Nahmias, 1993). The calculation of the MAPE stems from the Absolute Percentage Error (APE) computation. Table 8 illustrates these formulas and their inputs. Prior research shows cumulative CPI and Composite Index methodologies perform *better* than 8 other index and 4 regression based EAC methods by comparison of contracts using MAPE (Nystrom, 1995). More accurate performance is associated with a lower MAPE value.

Application of Methodology

This chapter presents the screening process that our study uses to find sufficient data for modeling. Steps illustrated for the growth model methodology apply to this data producing the analysis portion. Chapter Four details the development for both type and combined contract growth models. Our research discusses how the contract TC contrasts with the predicted EAC for each method to comprise the calculations previously described. Using the MAPE and APE, we present the performance comparison of our growth model EAC to that of the three Index-based EAC, the CPI, the SCI, and the

Composite Index. Our research deems the *better* model to have the smaller MAPE value over the course of averages and total individual contract evaluations (Land and Preston, 1980; Nystrom, 1995). The final chapter discusses these results and their implications to our hypothesis and DoD policy.

IV. Results and Analysis

Growth Model Results

This chapter details the results of the nonlinear model fitting and EAC computation using the growth model outputs. JMP provides output that is comparable between the two nonlinear methods selected, Gompertz growth and Richards growth. Our study prefers a model with the smaller sum of squared error (SSE) or squared difference between the estimate and actual values. This represents an estimated cost closer to the actual cost. JMP provides the SSE which shows the residual sum of squares error, the DFE for the degree of freedom for error, the MSE defining the mean squared error measuring variance, and the RMSE which estimates the standard deviation of the residual error as shown in Table 9.

Table 9: Regression Error Results

Type	Model	SSE	DFE	MSE	RMSE
Production	Gompertz	22.052	497	0.04437	0.21064
	Richards	22.0324	496	0.04442	0.21076
Development	Gompertz	6.7982	392	0.01734	0.13169
	Richards	46.9026	394	0.11904	0.34502
Combined	Gompertz	30.9447	892	0.03469	0.18626
	Richards	Convergence not attained			

The SSE from Table 9 shows that we can predict a more accurate model of percent completions over percent time for Development contracts using the Gompertz Growth Model vice the Richards Model. We select the Gompertz growth for comparison in production programs due to the negligible difference in error results. When models perform relatively similar then we prefer the one with the fewer parameters for ease of calculation. Appendix E and F provide full JMP output to both nonlinear fitting platforms and type contracts for the Production Model and the Development Model. Appendix G provides the output for the Combined Model using the Gompertz growth model, as JMP fails to find convergence using the Richards growth model.

The Gompertz model is defined by $Y=\alpha*Exp(-Exp(\beta-\gamma t))$, where Y is the percent complete at time t, α represents the final value, or asymptote, as t approaches infinity. The parameters β and γ adjust both slope and point of inflection of the curve (Gille, 2004). The first derivative (growth rate) is defined by $Y'=\alpha* Exp(-Exp(\beta-\gamma t))*\gamma*Exp(\beta-\gamma t)$. The coordinates of the point of inflection are $t_i=\beta/\gamma$ and $Y_i=\alpha/e$, where e is the Eulerian number (Gille, 2004). "The last formula demonstrates that the point of inflection is always at a fixed proportion of the [final] value. Note: The Gompertz growth curve can be applied to sigmoid growth processes in which the point of inflection is localized approximately at 1/3 of the [final] value," (Gille, 2004). Due to distinct differences in the patterns of production and development contracts, we analyze each set individually and once in combination. In the next sections, we present the developed models for Production, Development, and Combined applications.

Production Growth Model

JMP's nonlinear fitting platform converges after 8 iterations as detailed in Appendix E. Figure 3 illustrates the static or widespread variation that appears to detract from a tight pattern. Each point in the model Figures 3 through 5 represents a CPR entry for any given contract. The comparison is made between the percent time and percent complete variables. While the parameters attempt to capture a portion of the trend, there are numerous functions present across the spectrum of data. Tight clusters allow for convergence in the growth model, however, Figure 3 allows the analysis to see the wide variance of points present. The growth model $GG(X) = 1.1101 * \exp(-\exp(1.4376 - (3.8065 * X)))$ denotes the formula for the production contracts.

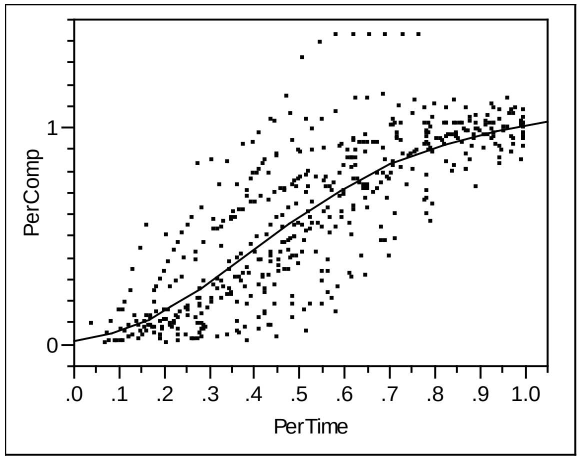


Figure 3: Production, Fitted Growth Model

Fitting a growth model to this data requires a wide range of adjustment to the parameters as noted in the confidence limits. The upper and lower confidence limits, provided in Table 10, describe a 95% confidence band of our parameters. Confidence Limits associate a degree of confidence that the estimated parameter lies within the Upper and Lower bounds. Setting an acceptable alpha, or significance level typically 0.05, allows the analysis to determine a threshold for prediction variance.

Table 10: Gompertz Parameter Estimates, Production

Type	Parameter	Estimate	Lower CL	Upper CL
Production	**α**	1.1100915505	1.02156497	1.23685939
	β	1.4376028332	1.23297772	1.68671739
	γ	3.8065483743	3.07051754	4.61890912

This model solves for an output of percent complete with an input of percent time past. The asymptote suggests that as time reaches infinity production contracts will reach 111% complete. That represents a cost overrun of 11% on these type contracts. Using the confidence limits, the lower bound still anticipates a 2.16% cost overrun at completion. The inflection point occurs at 38% time past, close to the one third of other sigmoidal curves. The growth rate adjusts due to the first derivative. Table 11 shows an initial growth rate of 0.26, meaning for every 1% of time that passes percent complete grows by 0.26%. This growth rate increases until the inflection point, approx PerTime = .4, where the when time passes by 1% the completion grows by 1.55%.

Table 11: Growth Rates, Production

Production Model	
PerTime	**Growth Rate**
0	0.26399581
0.1	0.68422951
0.2	1.16286183
0.3	1.48115127
0.4	1.54906527
0.5	1.41592132
0.6	1.1803973
0.7	0.92404729
0.8	0.69292655
0.9	0.504567
1	0.36010502

Development Growth Model

The Nonlinear Fitting Platform for Development contracts converges in 8 iterations as well. The function produces a generally good fit but Figure 4 shows the appearance of a separate growth pattern above the general mass fitted with the model. Separating this into two trends might provide a deeper look into the effectiveness of growth modeling on this set of data. The minor grouping consists of only two contracts that unfortunately do not seemly have anything in common. Without a commonality present the separation of models cannot be effectively utilized with extraneous data.

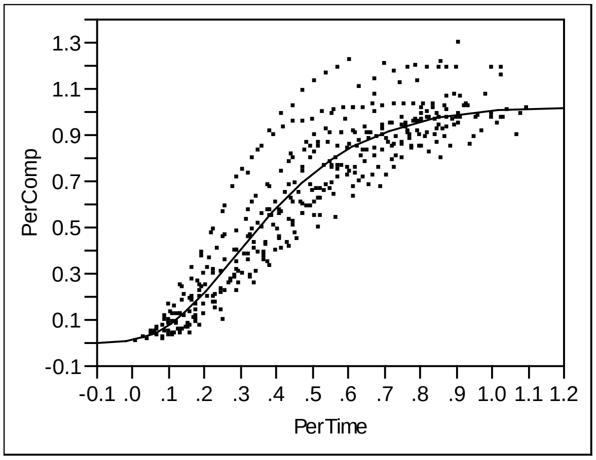


Figure 4: Development, Fitted Growth Model

The Development model expresses as GG(X) = 1.0287* exp (-exp (1.4641– (5.1090* X))), Table 12. The growth model displays an asymptote for development contracts at 103% complete. The confidence limits include 1 within its upper and lower bounds, which means that, unlike with production contracts, the growth model anticipates development contracts to complete at their BAC. This does not mean that there is a 95% chance of this event happening, but that we are 95% confident that the actual highest completion value is 1. In other words, we have 95% confidence that there is no difference in the correct α parameter and 1. This effectively leads to the possibility of 100% completion. The confidence limits span as high as 1.07 or 107% complete as well.

Table 12: Gompertz Parameter Estimates, Development

Type	Parameter	Estimate	Lower CL	Upper CL
Development	**α**	1.0286948876	0.98932688	1.07413186
	β	1.4640952401	1.31141111	1.63659679
	γ	5.1090380118	4.51915989	5.75679388

Parameters β and γ adjust the slope and inflection point. Chapter Three describes the adaption of parameters β and γ to provide the utility of growth rates and inflection points. The development contracts reach their inflection point noticeably earlier than the production contracts, 29% time complete. Table 13 presents the growth rates as these parameters reflect for development contracts. The development growth models also accelerate more quickly beginning with an initial growth rate of 0.3 and reaching 2.85 by the inflection point. This growth rate represents a percent completion increase of 2.85% for each 1% passing of time for that period in the development contract's life cycle.

Table 13: Growth Rates, Development

Development Model	
PerTime	**Growth Rate**
0	0.30112424
0.1	1.16040311
0.2	2.23854092
0.3	2.85122226
0.4	2.8309454
0.5	2.42068132
0.6	1.89238811
0.7	1.40192412
0.8	1.00559922
0.9	0.70748571
1	0.49200126

Combined Growth Model

A Combined Model fulfills our attempt to develop a model for cross-phase contracts. By evaluating a more robust model, we increase the potential utility in supplying a model that can encompass all contract phases and types. PMs and EVM

Analysis deal with a variety of contracts and programs for which they use the Index-based methods to produce their EAC, this is what we use to compare our models to in the final chapter. Figure 5 illustrates the Combined Model results from a combination of the model building datasets from both the production and development contracts.

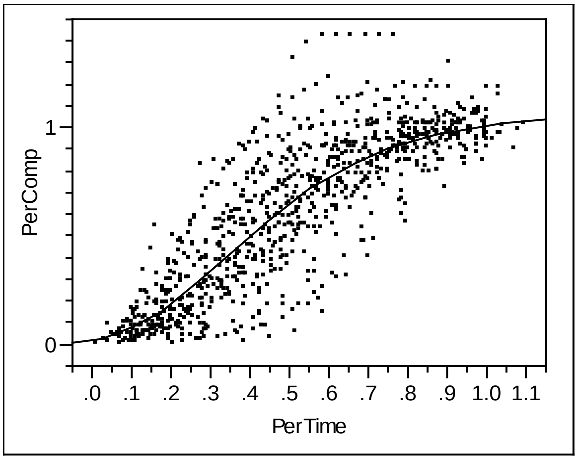


Figure 5: Combined, Fitted Growth Model

The model expresses as GG(X) = 1.0725*exp (-exp (1.4025- (4.1914*X))) with parameters displayed in Table 14. This model shows the anticipated max value of a contract's TC to be 107% of its BAC. The confidence limits enhance our ability to see the range of expected asymptotes, shown in Table 14. Interestingly the lower bound hovers around the expected asymptote for the development contracts and the limits contain the production model estimate.

Table 14: Gompertz Parameter Estimates, Combined

Type	Parameter	Estimate	Lower CL	Upper CL
Combined	**α**	1.0725171856	1.02242268	1.13304678
	β	1.4024548609	1.26606734	1.55615821
	γ	4.1913890863	3.69098225	4.7297462

The Combined Model anticipates an inflection point at 33% time complete along with Table 15's growth rates. At the beginning of any contract a PM should anticipate a 0.31 growth rate using this model. The Combined Model growth rates show a steady increase to the inflection growth rate, approximately 1.84, along with a steady decrease in growth rate until the asymptote.

Table 15: Growth Rates, Combined

Combined Model	
PerTime	**Growth Rate**
0	0.31358912
0.1	0.86202975
0.2	1.47135737
0.3	1.8357393
0.4	1.86380603
0.5	1.65246402
0.6	1.3401619
0.7	1.02501195
0.8	0.75433105
0.9	0.54123704
1	0.38192172

Summary

This chapter displays the regression and analysis of the nonlinear fitting platform results of our look into the use of growth models as predictive tools. Tables and figures support the findings and provide resources for ease of model interpretation. The final chapter describes the MAPE comparison outcomes and the evaluation between our growth models and the current index-based practices of calculating EAC along with a discussion of implications. Our conclusion includes a revisit of our research purposes and presents our recommendations.

V. Discussion & Conclusion

Hypothesis Revisited

This study aims to bring light on the use of growth models as predictive tools for computing EAC. Our study discusses the past research and current practices that program managers and contractors use for Estimates at Completion (EAC). We begin by addressing the findings of other studies to bring light on the necessity for accurate estimates and the potential for growth modeling techniques to satistfy our first objective. Chapter Three details the process and tools that our study uses to create and evaluate the potential of growth model methods. In Chapter Four, we present the formulated growth models and their parameter estimates and valuable interpretations. Finally, to fulfill our second objective of a thorough evaluation, we conclude with a discussion of the associated implications of our comparison findings along with some recommendations for policy makers and future researchers in this field.

Discussion of Comparison

This portion provides a direct comparison of APE and MAPE values using the methodology from Chapter Three. We deem the smaller of the two compared MAPE values to reflect a more accurate EAC. Our evaluation provides percentages for overall performance based on the number of contracts for which the growth model had the lower MAPE value, as compared to the respective Index-based method. These percentages offer the effective usefulness of our growth models as they compare to the Index methodology currently in use by program managers. Our comparison uses the three dataset subgroups for performance evaluation. Our discussion hereafter refers to each database subgroup as Model, Additional, and OTB. Where the Model dataset contains the contracts used to create the models, the Additional dataset contains partial contract entries that include an entry above 90% completion in order to present a substitution for TC comparison, while excluding the OTB contracts for reasons Chapter Four outlines. The OTB dataset contains the designated Over Target Budget (OTB) contracts which also include an entry with Percent Complete >90%, for the assumed TC. Our study aims to find the most robust use of growth models. We include the evaluation of the OTB dataset due to the reality that these contracts begin like any other contract for EAC and other handling purposes, later to be designated as OTB and transition to special measures. Our comparison contrasts the three Models created, Production, Development, and Combined, amongst the three dataset subgroups for their corresponding type contracts. Our results present contract and entry level evaluations.

Production Model Evaluation

Our initial comparison using the Model dataset subgroup shows the growth method to perform *better* than the CPI method on 7 of the 30 contracts, additional details provided in Appendix H. Our further analysis compares additional contracts in the database that were not included in the fitting platform. These contracts may not contain early data points causing them to be excluded from the initial formatting procedures. While the overall comparison performs over the index methods on over a third of the contracts, surprisingly a glance at the comparison of the OTB contracts demonstrates a potential application for these growth models. The OTB comparison shows the growth model preferred on over two thirds of the contracts.

Table 16: Production Model Performance Results

Production		Total	CPI		SCI		Composite	
	Model	30	7	23.33%	5	16.67%	5	16.67%
	Additional	80	29	36.25%	31	38.75%	29	36.25%
	OTB	9	7	77.78%	6	66.67%	6	66.67%
	Total	119	43	36.13%	42	35.29%	40	33.61%

Development Model Evaluation

Table 17 shows our growth model produces a more accurate EAC than the CPI-based method on 10 of the 20 development contracts, 50% of the Model dataset. Appendix I displays the outcome of the development model's comparison to the index based method along with details of MAPE comparison. While our method produces a more accurate EAC on less than half of the Additional dataset, it performs overwhelmingly better on the OTB dataset. Over the entire grouping of datasets the development growth model achieves *better* EACs on over half of the contracts as compared to all three Index-based methods. While the small dataset available limits our findings, our comparison shows consistent superiority of our growth model to the top three index methods.

Table 17: Development Model Performance Results

Development		Total	CPI		SCI		Composite	
	Model	20	10	50.00%	9	45.00%	10	50.00%
	Additional	47	21	44.68%	22	46.81%	21	44.68%
	OTB	19	14	73.68%	12	63.16%	13	68.42%
	Total	86	45	52.33%	43	50.00%	44	51.16%

Combined Model Evaluation

The Combined Model EAC falls short of accurate when comparing it to the CPI-based EAC on the Model dataset, detailed in Appendix J: Combined Model Comparison Results. However, Table 18 shows where the Combined Method well exceeds performance across all three index methods on the OTB datasets. From this we provide overall results using the three growth models. The Combined Model provides a more accurate EAC to that of the CPI and Composite Index methods on 71% of OTB contracts. This provides a much desired tool for these previously avoided and excluded specifically designated contracts.

Table 18: Combined Model Performance Results

Combined		Total	CPI		SCI		Composite	
	Model	50	17	34.00%	15	30.00%	15	30.00%
	Additional	127	52	40.94%	49	38.58%	48	37.80%
	OTB	28	20	71.43%	18	64.29%	20	71.43%
	Total	205	89	43.41%	82	40.00%	83	40.49%

To evaluate the efficiencies of the Combined Model, we break out the datasets to investigate the individual phase performance results, Table 19. The breakout of the Combined Model demonstrates the robust utility of a combined model when using growth models. The Combined Model still out performs the Index-based Methods on Development contracts and all OTB contracts. Overall, our evaluation of the growth model methodology demonstrates unexpected yet useful results. While the Production Model produces favorable EAC on over a third of the production contracts, the Development Model produces favorable EAC on over half of the development contracts.

The Combined Model supersedes the cumulative Index-based methods for computing EAC on OTB contracts.

Table 19: Combine Model Breakout

Combined Model		CPI		SCI		Composite	
Model	**Prod**	6	20.00%	5	16.67%	5	16.67%
	Devel	11	55.00%	10	50.00%	10	50.00%
Additional	**Prod**	29	36.25%	28	35.00%	26	32.50%
	Devel	23	48.94%	21	44.68%	22	46.81%
OTB	**Prod**	6	66.67%	5	55.56%	6	66.67%
	Devel	14	73.68%	13	68.42%	14	73.68%
	Total	89	43.41%	82	40.00%	83	40.49%

We show consistent performance by comparing our model to all three index methods and examining across different datasets. The Combined Model displays similar performance to that of the Production and Development Models. We highlight in Table 19 that our growth models provide improved accuracy as compared to the index methods for both production and development OTB contracts. These results show that the when evaluating production contracts it is best to use the Combined Model as it compares to the Production and Index models.

Application and Policy Recommendation

Earned Value remains a leader in program management tools, but what good is a tool that is not properly used? DoD notices the necessity to streamline the process and further proctor database access (DODI, 2007). Our findings support our hypothesis that growth models are a viable option for the EAC methodology tool bag within the realm of designated OTB contracts. All of our growth models perform overwhelmingly better than the current practices for specially designated OTB contracts. All our growth models show an increased accuracy of EAC for OTB contracts in both the production and development phases. We provide mixed results for development phase contracts alone. Growth models do provide utility in their parameter translations, such as inflection points and growth rates. These findings should be incorporated into development contract analysts' evaluation criteria, as our methodology provided limited accuracy at 50%. These parameters can also be further explored as early detection tools for OTB contracts prior to designation for all phase contracts. Appendix K: VBA Coding for EAC Using Growth Models provides Excel VBA coding for a user defined function in order to present a user-friendly application of these models. Should further research find the growing proportion of OTB contracts and their frequency becoming the norm for EVMS contracts; our models should be included in EAC assessment efforts and further be explored for their predictive capabilities.

This study also highlights several shortcomings of DoD's EVM tracking systems and bookkeeping. The lack of follow up and accurate record keeping prevent any kind of accurate and sustainable measuring tool for efficient evaluation. Our study aims to provide an accurate evaluation within the limitations of the datasets made available. One major convention found in this study was DoD and the decision maker's revolving blame put on cost estimators and their methodologies. Past research finds that the Index method, while not always the best solution provides a good estimate that requires detailed knowledge to tweak. Future decision makers and program managers need to focus on their bookkeeping and expert knowledge of their programs in order to aide cost estimators. The political influences present in the acquisition process create undue hardship on the proper allocation of resources and responsibility when blaming estimates for poor tracking or program performance. This study provides a more robust methodology, while continuing to support the inclusion of the Index methodology amongst the spectrum of EAC methods.

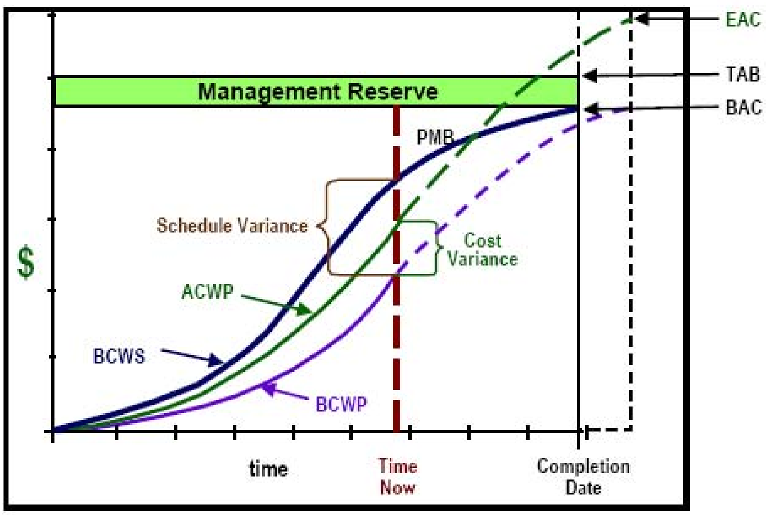
Summary & Future Research

Our study presents the successful evaluation of growth models and the predictive possibilities that growth models hold in EAC computation. No best model exists but our growth models present a *better* model than the popular index-based methods currently in use for estimating OTB contracts specifically. Extended evaluations could measure the cross-service capabilities of our models to access any increase predictive uses for growth curve methodologies. Future studies should also focus on the process and conventions of gathering the information necessary to gain effective inputs. With bad data, such as incomplete, poorly maintained, and inaccessible data, estimators and program mangers only produce bad estimates. Although our research involves a limited dataset, we appropriately segregated a model building datasets versus evaluation datasets to provide the robust capabilities of our model's application. This new methodology adds a unique perspective and consistently performs more accurately compared to the CPI, SCI, and Composite Index-based on an average of 71% of unique OTB contracts. These findings offer program managers and decision makers new models showing accuracy and overall utility when evaluating OTB contracts.

Appendix A: DSMC Gold Card, 2006

Defense Acquisition University

Earned Value Management 'Gold Card'



VARIANCES Favorable is Positive, Unfavorable is Negative

Cost Variance	CV	= BCWP – ACWP	CV % = (CV / BCWP) * 100
Schedule Variance	SV	= BCWP – BCWS	SV % = (SV / BCWS) * 100
Variance at Completion	VAC	= BAC – EAC	

OVERALL STATUS

% Schedule = $(BCWS_{CUM}$ / BAC) * 100
% Complete = $(BCWP_{CUM}$ / BAC) * 100
% Spent = $(ACWP_{CUM}$ / BAC) * 100

DoD TRIPWIRE METRICS Favorable is > 1.0, Unfavorable is < 1.0

Cost Efficiency CPI = BCWP / ACWP
Schedule Efficiency SPI = BCWP / BCWS

BASELINE EXECUTION INDEX (BEI) (Schedule Metric)
BEI = # of Baseline Tasks Actually Completed / # of Baseline Tasks Scheduled for Completion

CRITICAL PATH LENGTH INDEX (CPLI) (Schedule Metric)
CPLI = (Critical $Path_{Baseline}$ Duration + Float Duration) / Critical $Path_{Baseline}$ Duration

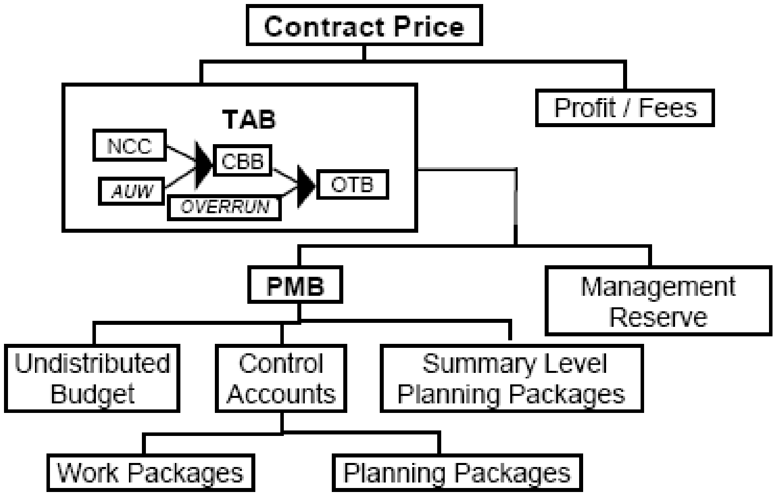
TO COMPLETE PERFORMANCE INDEX (TCPI) # §
$TCPI_{EAC}$ = Work Remaining / Cost Remaining = (BAC – $BCWP_{CUM}$) / (EAC – $ACWP_{CUM}$)

ESTIMATE AT COMPLETION #

EAC = Actuals to Date + [(Remaining Work) / (Efficiency Factor)]
EAC_{CPI} = $ACWP_{CUM}$ + [(BAC – $BCWP_{CUM}$) / CPI_{CUM}] = BAC / CPI_{CUM}
$EAC_{Composite}$ = $ACWP_{CUM}$ + [(BAC – $BCWP_{CUM}$) / (CPI_{CUM} * SPI_{CUM})]

\# To Determine a Contract Level TCPI or EAC; You May Replace BAC with TAB

§ To Determine the $TCPI_{BAC,LRE}$ Replace EAC with either BAC or LRE



TERMINOLOGY

NCC	Negotiated Contract Cost	Contract price less profit / fee(s)
AUW	Authorized Unpriced Work	Work contractually approved, but not yet negotiated / definitized
CBB	Contract Budget Base	Sum of NCC and AUW
OTB	Over Target Baseline	Sum of CBB and recognized overrun
TAB	Total Allocated Budget	Sum of all budgets for work on contract = NCC, CBB, or OTB
BAC	Budget At Completion	Total budget for total contract thru any given level
PMB	Performance Measurement Baseline	Contract time-phased budget plan
MR	Management Reserve	Budget withheld by Ktr PM for unknowns / risk management
UB	Undistributed Budget	Broadly defined activities not yet distributed to CAs
CA	Control Account	Lowest CWBS element assigned to a single focal point to plan & control scope / schedule / budget
WP	Work Package	Near-term, detail-planned activities within a CA
PP	Planning Package	Far-term CA activities not yet defined into WPs
BCWS	Budgeted Cost for Work Scheduled	Value of work planned to be accomplished = PLANNED VALUE
BCWP	Budgeted Cost for Work Performed	Value of work accomplished = EARNED VALUE
ACWP	Actual Cost of Work Performed	Cost of work accomplished = ACTUAL COST
EAC	Estimate At Completion	Estimate of total cost for total contract thru any given level; may be generated by Ktr, PMO, DCMA, etc. = EAC$_{Ktr / PMO / DCMA}$
LRE	Latest Revised Estimate	Ktr's EAC or EAC$_{Ktr}$
SLPP	Summary Level Planning Package	Far-term activities not yet defined into CAs
TCPI	To Complete Performance Index	Efficiency needed from 'time now' to achieve an EAC

EVM POLICY: DoDI 5000.2, Table E3.T2 . EVMS in accordance with ANSI/EIA-748 is required for cost or incentive contracts, subcontracts, intra-government work agreements, & other agreements valued ≥ $20M (Then-Yr $). EVMS contracts > $50M (TY $) require that the EVM system be formally validated by the cognizant contracting officer. Additional Guidance in Defense Acquisition Guidebook and the Earned Value Management Implementation Guide (EVMIG). EVMS is discouraged on Firm-Fixed Price, Level of Effort, & Time & Material efforts regardless of cost.

EVM CONTRACTING REQUIREMENTS:

Non-DoD FAR Clauses – Solicitation – 52.234-2 (Pre-Award IBR) or 52.234-3 (Post Award IBR)
Solicitation & Contract – 52.234-4

DoD(≥ $20M) DFAR Clauses - 252.242-7001 for solicitations and 252.242-7002 for solicitations & contracts

Contract Performance Report – DI-MGMT-81466A * 5 Formats (WBS, Organization, Baseline, Staffing & Explanation)

Integrated Master Schedule – DI-MGMT-81650 * (Mandatory for DoD EVMS contracts)

Integrated Baseline Review (IBR) - Mandatory for all EVMS contracts

* See the EVMIG for CPR and IMS tailoring guidance.

Appendix B: EVMS Logic and Consistency Checks

EVMS Logic and Consistency Checks

First Criteria	and Second Criteria		ERROR	ACTION
Current BCWP and	No current BCWS	Work accomplished was scheduled for earlier or later period		Verify that work is not being done in advance of the work package being opened.
Current BCWS and	No current BCWP	Work scheduled was completed in earlier period or postponed until later period		
Current BCWP and	No current ACWP	Work performed at no cost		Determine reason
Current ACWP and	No current BCWP	No budget value could be earned, or work was not performed, or residual actual costs after work complete		Determine reason
Cumulative BCWP and	No cumulative BCWS	Work accomplished was scheduled for later period or work was earned against unopened work package		Verify that work is not being done in advance of the work package being opened.
Cumulative BCWS and	No cumulative BCWP	Work scheduled to begin has not yet started		
Cumulative ACWP and	No cumulative BCWP	Work charged to unopened work package (if BCWS = 0); or earned value could not be claimed (if BCWS > 0)	BCWS=0	Verify that work is not being charged to unopened work package
Cumulative ACWP and	No cumulative BCWS	Work charged to unopened work package		Verify that work is not being charged to unopened work package
Cumulative BCWP and	No cumulative ACWP	No actual costs have been reported for work performed		Determine reason
Cumulative BCWS = BAC		Work should be finished		
Cumulative BCWP = BAC		Work is finished		
Cumulative ACWP = BAC		Actual costs = budget; remaining effort is overrun		
Cumulative BCWS > BAC		Cumulative time phased budget should be ≤ total budget		Correct error
Cumulative BCWP > BAC		Cumulative work accomplished should be ≤ total budget		Correct error
Decrease in BCWS		Work scheduled to date has decreased		Determine reason -- replanning?
Decrease in BCWP		Work previously performed has been reduced		Determine reason -- replanning?
Decrease in ACWP		Previously reported costs reduced		Determine reason -- should be to fix accounting error only
Current ACWP > 0; Current BCWP = 0, and	Cum BCWP = BAC	Task already completed, but actual costs charged to completed task		Correct error or determine if they are residual costs being billed
Cum ACWP > EAC and	Cum BCWP = BAC	Task complete, but actuals exceed EAC		Adjust EAC to actual costs
Cum ACWP > EAC and	Cum BCWP < BAC	Actuals exceed EAC		Calculate more realistic EAC
TCPI-EAC significantly > CPI		EAC may be unrealistically low based on performance to date		Calculate more realistic EAC
TCPI-EAC significantly < CPI		EAC may be unrealistically high based on performance to date		Calculate more realistic EAC
TCPI-EAC < 0		Cum ACWP exceeds EAC		Calculate more realistic EAC
MR < 0		Negative MR		Correct error
UB < 0		UB contains contract change that results in credit		
MR is included in EAC column and	EAC = BAC	Included to balance total EAC to BAC		Remove MR from EAC column
MR is included in EAC column and	EAC is not equal to BAC	(Possible reason) Shows intended application of MR to risks		Understand basis for including MR in EAC

Appendix C: VBA Coding for Percent of Time Complete

Step 1: Enable Visual Basic Application within Excel
Step 2: Create New Module
Step 3: Enter Coding (below)
Step 4: Save and Use

```
Function PerTime (PMSubmit As Date, PMStart As Date, PMEnd As Date)

     'Coding practice to declare intermediate variable
    Dim Current_Count As Variant
    Dim Range_Count As Variant

    'Get count between Submit and Start Dates for current count
    Current_Count = PMSubmit - PMStart

    'Get count between Start and End Dates for range count
    Range_Count = PMEnd - PMStart

    'Calculate count/range to get percent time elapsed
    PerTime = Current_Count / Range_Count

End Function
```

Appendix D: JMP Nonlinear Modeling Templates*

Table 20.2 Guide to Nonlinear Modeling Templates

Data Reference	Formula	Model
Meyers (1988), p. 310	$\frac{\theta_1 x}{\theta_2 + x}$	A Michaelis-Menten
Draper and Smith (1981), p. 522, L	$\theta_1[1 - \exp(\theta_2 x)]$	B
Draper and Smith (1981), p. 476	$\theta_1 + (0.49 - \theta_1)\exp[-\theta_2(x - 8)]$	C
Draper and Smith (1981), p. 519, H	$\mathrm{xp}\left\{-\theta_1 x_1 \exp\left[\theta_2 \cdot \left(\frac{1}{x_2} - \frac{1}{620}\right)\right]\right\}$	D
Draper and Smith (1981), p. 519, H	$\theta_1 x^{\theta_2}$	E
Bates and Watts (1988), p. 310	$\theta_1 + \theta_2\exp(\theta_3 x)$	F Asymptotic Regression
Bates and Watts (1988), p. 310	$\frac{\theta_1}{\theta_2 \exp(\theta_3 x)}$	G Logistic
Bates and Watts (1988), p. 310	$\theta_1\exp[-\exp(\theta_2 - \theta_3 x)]$	H Gompertz Growth
Draper and Smith (1981), p. 524, N	$\theta_1[1 - (\theta_2 e)^{\theta_3 x}]$	I
Draper and Smith (1981), p. 524, N	$\theta_1 - \ln[1 + \theta_2\exp(-\theta_3 x)]$	J Log-Logistic
Draper and Smith (1981), p. 524, P	$\theta_1 + \frac{\theta_2}{x^{\theta_3}}$	K
Draper and Smith (1981), p. 524, P	$\ln[\theta_1\exp(-\theta_2 x) + (1 - \theta_1)\exp(-\theta_3 x)]$	L
Bates and Watts (1988), p. 271	$\frac{\theta_1\theta_3\left(x_2 - \frac{x_3}{1.632}\right)}{1 + \theta_2 x_1 + \theta_3 x_2 + \theta_4 x_3}$	M

*(SAS Institute Inc, 2005)

Table 20.2 Guide to Nonlinear Modeling Templates *(continued)*

Bates and Watts (1988), p.310	$\dfrac{\theta_2\theta_3 + \theta_1 x^{\theta_4}}{\theta_3 + x^{\theta_4}}$	O Morgan-Mercer-Florin
Bates and Watts (1988), p. 310	$\dfrac{\theta_1}{[1 + \theta_2 \exp(-\theta_3 x)]^{\frac{1}{\theta_4}}}$	P Richards Growth
Bates and Watts (1988), p. 274	$\dfrac{\theta_1}{\theta_2 + x_1} + \theta_3 x_2 + \theta_4 x_2^2 + \theta_5 x_2^3 + (\theta_6 + \theta_7 x_2^2) x_2 \exp\left(\dfrac{-x_1}{\theta_8 + \theta_9 x_2^2}\right)$	S

*(SAS Institute Inc, 2005)

Appendix E: Growth Model Regression Results, Production

Response: % comp, Predictor: Model H (Gompertz growth model, 3P)

Control Panel

Solution

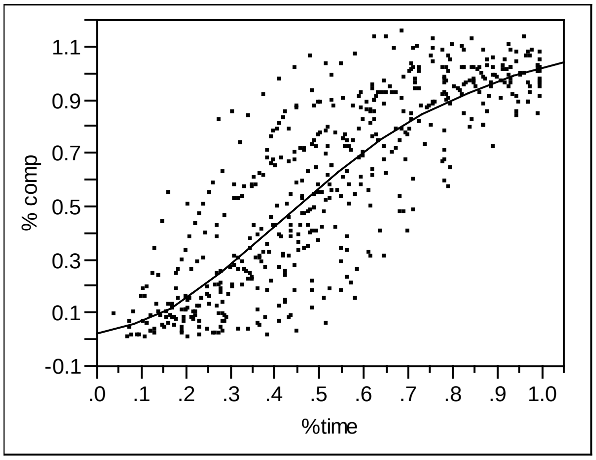
Criterion	Current	Stop Limit
Iteration	8	60
Obj Change	9.368885e-12	1e-15
Relative Gradient	7.3062953e-7	0.000001
Gradient	1.4189912e-7	0.000001

SSE	DFE	MSE	RMSE
22.05199648	497	0.0443702	0.2106424

Edit Alpha
0.050 Convergence Criterion
0.00001 Goal SSE for CL
.

Converged in Gradient

Plot



Parameter	Estimate	ApproxStdErr	Lower CL	Upper CL
theta1	1.1100915505	0.0535876	1.02156497	1.23685939
theta2	1.4376028332	0.11555117	1.23297772	1.68671739
theta3	3.8065483743	0.39795521	3.07051754	4.61890912

Response: % comp, Predictor: Model P (Richards growth model, 4P)

Control Panel

Solution

Criterion	Current	Stop Limit
Iteration	52	60
Obj Change	8.280463e-11	1e-15
Relative Gradient	6.1381767e-6	0.000001
Gradient	7.514406e-7	0.000001

SSE	DFE	MSE	RMSE
18.306851508	516	0.0354784	0.1883571

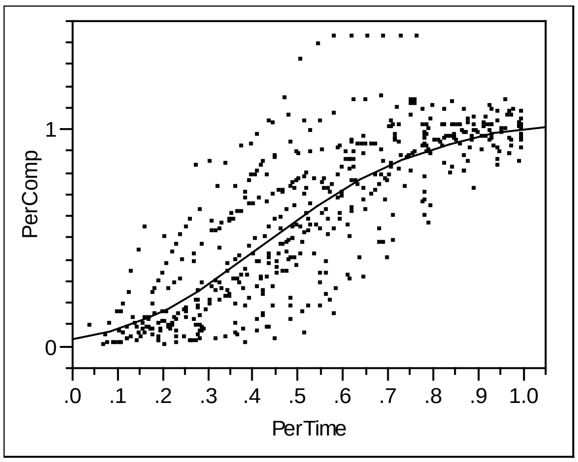
Parameter	Estimate	ApproxStdErr
theta1	1.061918655	0.0742053
theta2	2.8562172937	7.0391437
theta3	4.8076483432	1.65527359

Edit Alpha
0.050Convergence Criterion
0.00001Goal SSE for CL

Converged in Gradient

.

Plot



Appendix F: Growth Model Regression Results, Development

Response: % comp, Predictor: Model H (Gompertz growth model, 3P)

Control Panel

Solution

Criterion	Current	Stop Limit
Iteration	8	60
Obj Change	2.360702e-12	1e-15
Relative Gradient	1.6642454e-7	0.000001
Gradient	3.0473171e-8	0.000001

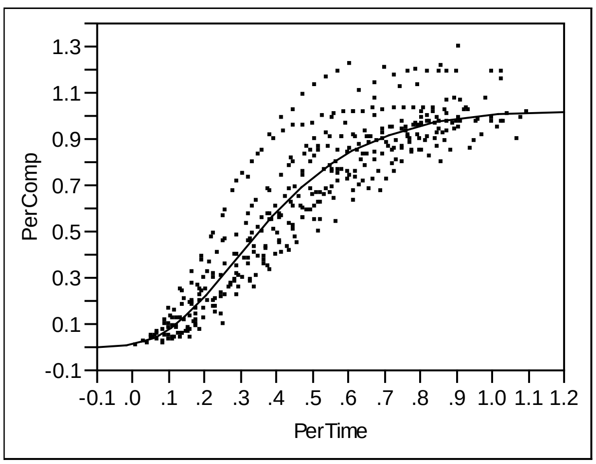
SSE	DFE	MSE	RMSE
6.798204157	392	0.0173424	0.1316904

Edit Alpha
0.050 Convergence Criterion
0.00001 Goal SSE for CL

Converged in Gradient

.

Plot



Parameter	Estimate	ApproxStdErr	Lower CL	Upper CL
theta1	1.0286948876	0.02124721	0.98932688	1.07413186
theta2	1.4640952401	0.08276051	1.31141111	1.63659679
theta3	5.1090380118	0.31268361	4.51915989	5.75679388

Response: % comp, Predictor: Model P (Richards growth model, 4P)

Control Panel

Solution

Criterion	Current	Stop Limit
Iteration	5	60
Obj Change	0.0000250035	1e-15
Relative Gradient	1.106055e-15	0.000001
Gradient	1.106055e-15	0.000001

SSE	DFE	MSE	RMSE
46.902573144	394	0.1190421	0.3450247

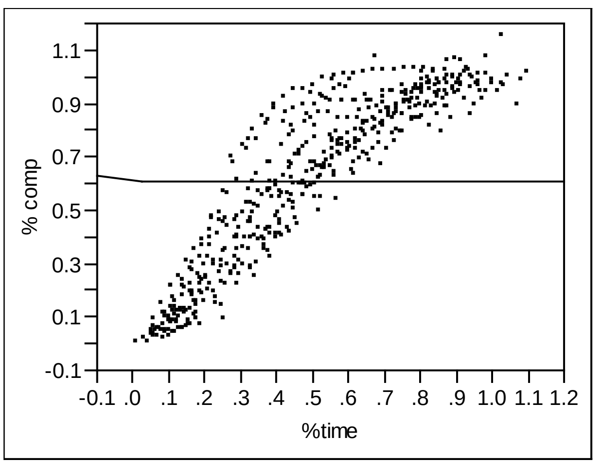
Parameter	Estimate	ApproxStdErr
theta1	0.6264657661	0.01736008
theta2	-5592.323859	0
theta3	17320259.541	0

Edit Alpha
0.050 Convergence Criterion
0.00001 Goal SSE for CL

Converged in Gradient

.

Plot



Appendix G: Growth Model Regression Results, Combined

Response: % comp, Predictor: Model H (Gompertz growth model, 3P)

Control Panel

Solution

Criterion	Current	Stop Limit
Iteration	2	60
Obj Change	2.27177e-10	1e-15
Relative Gradient	2.4251042e-6	0.000001
Gradient	4.6266593e-7	0.000001

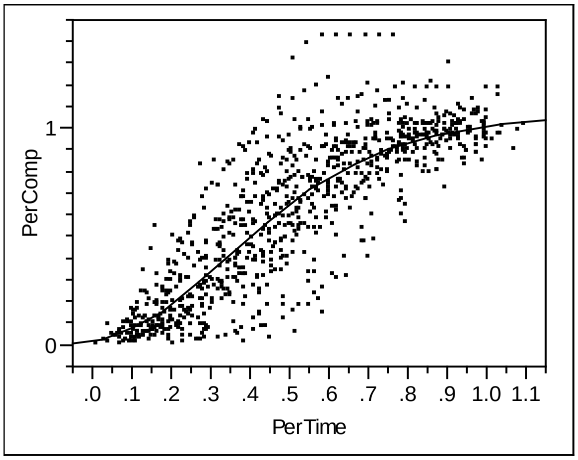
SSE	DFE	MSE	RMSE
30.944655372	892	0.0346913	0.1862561

Edit Alpha
0.050 Convergence Criterion
0.00001 Goal SSE for CL

Converged in Gradient

.

Plot



Parameter	Estimate	ApproxStdErr	Lower CL	Upper CL
theta1	1.0725171856	0.02810195	1.02242268	1.13304678
theta2	1.4024548609	0.0744987	1.26606734	1.55615821
theta3	4.1913890863	0.2673218	3.69098225	4.7297462

* Convergence efforts failed when solving for the Richards Growth Model

Appendix H: Production Model Comparison Results

Production Model Evaluation			
MAPE Values	**CPI**	**Gompertz**	**GG Better**
1	0.323025	0.411614	
2	0.184729	0.172613	YES
3	0.178261	0.158811	YES
4	0.061447	0.209233	
5	0.075876	0.152464	
6	0.073732	0.27412	
7	0.083785	0.136916	
8	0.145392	0.135245	YES
9	0.086357	0.160832	
10	0.070556	0.11937	
11	0.163241	0.126614	YES
12	0.095154	0.158299	
13	0.095154	0.158299	
14	0.035971	0.220933	
15	0.089265	0.307682	
16	0.021724	0.103886	
17	0.329718	0.204843	YES
18	0.052799	0.070716	
19	0.069839	0.258497	
20	0.045473	0.21795	
21	0.263655	0.202945	YES
22	0.029214	0.272923	
23	0.169799	0.304305	
24	0.060037	0.117187	
25	0.044969	0.043177	YES
26	0.093109	0.145791	
27	0.178438	0.189471	
28	0.124079	0.256773	
29	0.051723	0.110307	
30	0.321524	0.352838	
Average/ Total	**0.120601**	**0.191822**	**7**

Appendix I: Development Model Comparison Results

Development Model Evaluation			
MAPE Values	**CPI**	**Gompertz**	**GG better**
1	0.0636	0.1414	
2	0.1498	0.2344	
3	0.1121	0.146	
4	0.0636	0.1295	
5	0.2347	0.2016	YES
6	0.1053	0.0468	YES
7	0.0869	0.0541	YES
8	0.2597	0.1605	YES
9	0.1522	0.1123	YES
10	0.3651	0.2987	YES
11	0.1609	0.2177	
12	0.0609	0.0847	
13	0.2069	0.2626	
14	0.1425	0.0994	YES
15	0.262	0.2564	YES
16	0.0459	0.1213	
17	0.1886	0.1548	YES
18	0.1775	0.2489	
19	0.0944	0.1641	
20	0.5311	0.4135	YES
Average/ Total	**0.1732**	**0.1774**	**10**

Appendix J: Combined Model Comparison Results

Combined Model Evaluation							
MAPE Values	**CPI**	**Gompertz**	**GG better**		**CPI**	**Gompertz**	**GG better**
1	0.323025	0.433624		**26**	0.093109	0.168847	
2	0.184729	0.197465		**27**	0.178438	0.176029	YES
3	0.178261	0.18921		**28**	0.124079	0.291283	
4	0.061447	0.246495		**29**	0.051723	0.111617	
5	0.075876	0.184757		**30**	0.321524	0.368894	
6	0.073732	0.307001		**31**	0.063553	0.094823	
7	0.083785	0.175624		**32**	0.149752	0.195401	
8	0.145392	0.155189		**33**	0.112129	0.10577	YES
9	0.086357	0.175803		**34**	0.063563	0.094593	
10	0.03952	0.10585		**35**	0.234747	0.161034	YES
11	0.070556	0.139498		**36**	0.10532	0.099978	YES
12	0.163241	0.148192	YES	**37**	0.086897	0.079166	YES
13	0.095154	0.185612		**38**	0.259711	0.16411	YES
14	0.035971	0.25388		**39**	0.152244	0.160212	
15	0.089265	0.345064		**40**	0.365146	0.282861	YES
16	0.021724	0.137585		**41**	0.160944	0.179309	
17	0.329718	0.226561	YES	**42**	0.060892	0.029105	YES
18	0.052799	0.04306	YES	**43**	0.206858	0.22001	
19	0.069839	0.21456		**44**	0.142465	0.095077	YES
20	0.045473	0.178002		**45**	0.26203	0.232183	YES
21	0.263655	0.230964	YES	**46**	0.045915	0.168947	
22	0.029214	0.231093		**47**	0.188602	0.166803	YES
23	0.169799	0.256806		**48**	0.177529	0.210851	
24	0.060037	0.132562		**49**	0.094368	0.12525	
25	0.044969	0.039752	YES	**50**	0.531085	0.482889	YES

Average/ Total	**CPI**	**Gompertz**	**GG better**
	0.140523	**0.187985**	**17**

Appendix K: VBA Coding for EAC Using Growth Models

```
Function GG(PerTime As Double, ACWP As Double, BAC As Double, Model As
Single)

   'Declare intermediate variables
   Dim theta1 As Double
   Dim theta2 As Double
   Dim theta3 As Double
   Dim Base As Double
   Dim Now As Double

   'Zero out variables
   theta1 = 0
   theta2 = 0
   theta3 = 0
   Base = 0
   Now = 0

   'Insert conditional thetas for Production Model: Type 1
   If Model = 1 Then theta1 = 1.1100915505
   If Model = 1 Then theta2 = 1.4376028332
   If Model = 1 Then theta3 = 3.8065483743

   'Insert conditional thetas for Development Model: Type 2
   If Model = 2 Then theta1 = 1.0286948876
   If Model = 2 Then theta2 = 1.4640952401
   If Model = 2 Then theta3 = 5.1090380118

   'Insert conditional thetas for Combined Model: Type 3
   If Model = 3 Then theta1 = 1.0725171856
   If Model = 3 Then theta2 = 1.4024548609
   If Model = 3 Then theta3 = 4.1913890863

   'Define base model for GG(1)
   Base = theta1 * Exp(-Exp(theta2 - theta3))

   'Solve for GG(X)
   Now = theta1 * Exp(-Exp(theta2 - (theta3 * PerTime)))

   'Solve for EAC
      GG = ACWP + ((Base - Now) * BAC)

End Function
```

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14. ABSTRACT

Efficient decision making mandates the accuracy of forecasted estimations of a contract's final value known within Earned Value Management (EVM) as the Estimates at Completion (EAC). Our research evaluates the prospect of nonlinear growth modeling as an alternative to the current predictive tools used for calculating EAC, such as the Cost Performance Index (CPI), the Schedule Cost Index (SCI), and the Composite Index methods. Our study uses the Gompertz growth curve to produce three EAC Models based on contract phase: A Production Model, a Development Model, and a Combined Model. Contract Performance Report (CPR) data are used to develop the models. Mean Absolute Percentage Error (MAPE) is used to evaluate and select the more accurate model's EAC. We compare along three datasets for performance evaluation: a model building dataset, an additional dataset, and a dataset of designated Over Target Baseline (OTB) contracts. For 63% to 79% of OTB contracts, depending on model and phase examined, our study shows all three growth models out perform all three Index-based methods. Our research shows growth models as a more accurate estimating tool for identified OTB contract's EAC as compared to the CPI, SCI, and Composite Index methods.

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