3-2005

Estimating Performance Time for Air Force Military Construction Projects

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ESTIMATING PERFORMANCE TIME FOR AIR FORCE MILITARY CONSTRUCTION PROJECTS

THESIS

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AFIT/GEM/ENV/05M-05

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Wright-Patterson Air Force Base, Ohio

AFIT/GEM/ENV/05M-05

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THESIS

Presented to the Faculty

Department of Systems and Engineering Management

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Engineering Management

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March 2005

APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

AFIT/GEM/ENV/05M-05

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CONSTRUCTION PROJECTS

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Abstract

The prediction of construction time performance is a problem of interest to both researchers and construction industry practitioners. This research seeks to identify significant factors which may influence construction durations for Air Force Military Construction (MILCON) projects to establish a time prediction model. Data were collected for 856 MILCON projects completed between 1988 and 2004; this included both traditional facility and non-facility (e.g. airfield pavements, utilities) projects. These data were analyzed using Bromilow's time-cost (BTC) model (1969) as well as multiple linear regression. Neither model produced acceptable results for non-facility projects; however, the multiple linear regression model was found to provide the most acceptable time prediction model for facility projects.

As with the BTC model and previous research reported in the literature, there was a significant correlation between cost and duration. However, several other factors were also identified that resulted in significantly lower than average construction durations. These include projects completed within certain management groupings (referred to as Major Commands in the Air Force), projects where the Northwestern Army Corps of Engineers served as the construction agent, and projects completed using in-house design services. Several possible reasons may exist for these differences; therefore, it cannot be inferred that the results are indicative of the organizations' management processes.

The forecasting ability of the model was then evaluated using a set of 129 projects not used in the formulation of the model. The resulting model appears to provide a valid alternative for predicting construction durations for Air Force MILCON facility projects. Therefore, it may be used as a prediction tool or as a policy setting tool.

Acknowledgments

This research would not have been possible without the support of a variety of individuals. First, I would like to thank my thesis advisor, Dr. Alfred Thal, for providing the much needed guidance to steer me through this process. I would also like to thank my committee members, Lt Col Jeffery Weir, Major Andre Dempsey, and Major Timothy Webb, for all the advice and support provided along the way. A special thanks also goes out to Major Frank Simas at AETC Headquarters for proving the initial motivation for this research. I would also like to recognize David Huggins at Maxwell AFB/Gunter Annex for his support in gathering the data needed to complete this effort. Most importantly, I would like to thank my wife for her support and understanding throughout this process.

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ESTIMATING PERFORMANCE TIME FOR AIR FORCE MILITARY CONSTRUCTION PROJECTS

I. Introduction

Background

Importance of Construction Time Estimates

Cost, quality, and time are frequently identified as the three critical factors in defining the success or failure of a construction project. This classification often results in construction time estimates serving as benchmarks for measuring project performance (Walker, 1995: 263). Therefore, determining which factors influence construction duration has been the focus of many researchers and construction professionals, driving an increasing effort for reliable front-end predictions of construction duration. However, the ability to accurately estimate project completion times is often viewed as dependent on the skill, experience, and individual intuition of the planning engineer (Chan and Kumaraswamy, 1995: 319). In many cases, this dependence may lead to subjective estimates which are highly variable and easily influenced by external factors. This variability is magnified by many client-contractor relationships where time constraints prevent the completion of detailed construction time estimates (Ng et al., 2001: 166). Minimizing the subjective influence of the planning engineer or client on construction time estimates has been the goal of numerous empirical modeling efforts. Rather than relying on subjective measures, these models view construction duration as function of a number of significant time-influencing factors. These models enable both the client and contractor to benchmark the expected construction period more accurately, without negatively affecting construction time and budget constraints.

Bromilow's Time-Cost Model

The first empirical model of construction time performance was published in an Australian study conducted by Bromilow (1969). This model, often called Bromilow's time-cost (BTC) model, was developed as a means of providing a quick and quantitative construction time estimate using easily identified factors. The model predicted construction duration using the estimated final cost of the construction effort. Bromilow's model revealed that the construction time was highly correlated with the size of the project as measured by cost (Bromilow, 1969). Through use of a linear regression model, Bromilow was successful in providing a point estimate as well as upper and lower quartile limits of construction duration using historical project data.

Over the years, the BTC model has been subject to two principal criticisms which have driven both refinements and alterations to the model. The first criticism is the limited applicability of the model outside of the original study sample (Australian construction projects meeting specified criteria). This criticism has been the basis for multiple efforts to further calibrate the time-cost model for use across a variety of project types and project locations. The second principal criticism of the BTC model is that it may fail to consider factors in addition to cost when forecasting the construction time (Walker, 1994: 264). This criticism has been the basis for multiple studies seeking to refine the time-cost model in order to include additional quantitative, as well as qualitative, factors. In spite of these criticisms, the BTC model is widely recognized today as the standard for estimating the performance time of construction projects (Ng et al., 2001: 166).

Air Force Application

The ability to properly estimate construction time performance through the use of empirical models has practical application in the Air Force Military Construction (MILCON) program. The sole objective of the Air Force MILCON program is to provide quality facilities that meet user requirements both on time and within budget (U.S. Army Corps of Engineers, 2003:6). Air Force program managers are specifically tasked to meet these time and budget requirements (Department of the Air Force: Jan 2003).

Current Air Force Policy

The current method used to benchmark performance time for Air Force MILCON facility projects is based on the programmed amount (PA) of the project to be completed. Current duration goals were established through a U.S. Army Corps of Engineers Program Management Plan (U.S. Army Corps of Engineers, 2003: 8). In this plan, the goals for construction duration, defined as the time from the Notice to Proceed (NTP) to the Beneficial Occupancy Date (BOD), are determined using the following criteria.

- PA less than \$5M: construction duration is 365 days
- PA between \$5M and \$20M: construction duration is 540 days
- PA \$20M and greater: construction duration is 730 days

These duration goals were also published as Air Force guidance used to establish acceptable performance time targets as one of the criteria for the "Dirtkicker" award, an award designed to recognize superior Major Command (MAJCOM) MILCON programs (Department of the Air Force, Oct 2003). The primary goals remained unchanged; however, the Air Force guidance changed the construction durations to 455, 630, and 820 days, respectively, for overseas MAJCOMs.

While the Air Force uses specific guidance for the formulation of MILCON cost construction estimates, no such formal guidance currently exists for duration estimates. Under the current process, a construction duration estimate is required prior to contract award, with the Air Force project manager tasked to ensure that the specified construction performance period is adequate (Department of the Air Force, 2000: 7-3). The specific methods for both the estimation and verification of this estimate are left to the discretion of the Air Force project manager or Architect/Engineer (A/E) firm responsible for design.

Problems with Current Air Force Policy

While providing a basis for measurement, the "Dirtkicker" benchmarking method neglects complex factors which may influence project durations. These factors could include weather, site conditions, project complexity, environmental factors, and execution method among others. Forcing a project into a desired rather than realistic time mold created by an inaccurate initial estimate can create negative effects which may cause organizational problems in other areas. While underestimation may place extra demands on the organization by creating funding shortages which may negatively affect current projects, overestimation may create barriers to planning for developments in other areas (Khosrowshahi and Kaka, 1996: 377).

If program managers are tasked to deliver a project at cost and on schedule, it follows that duration goals set at the Air Force level must be reasonable and obtainable.

Therefore, a model providing accurate duration estimates based on significant factors would be both a useful policy setting and prediction tool; it would benefit program managers by providing a more comprehensive predictor of construction duration. This research seeks to develop a tool which can be used to estimate project durations easily, cost effectively, and at an early stage in the Air Force MILCON process.

Problem Statement

The current guidance used by the Air Force to both benchmark and estimate project performance time may not account for relevant factors which influence project duration. This research proposes to identify a model, or combination of models, which may be used to estimate performance time for Air Force MILCON projects.

Research Question

Given the specific problem stated above, this research seeks to answer the following question: What model, or combination of models, can be used to provide a statistically accurate prediction of project performance time for Air Force MILCON facility projects?

Investigative Questions

The following investigative questions will be addressed to answer the overarching research question.

1) Does the current Air Force guidance used to benchmark project performance provide a statistically accurate estimate of actual construction durations?

2) What models have been identified by experts in the field that have been successful in predicting durations for construction projects?

3) Is there a model, or set of models, which can be used to predict construction durations across a range of Air Force MILCON projects?

4) What is the predictive accuracy of the proposed model?

Limitations

The focus of this research is on those factors which may be used to predict construction duration for Air Force MILCON facility projects. Data collection will be focused only on Air Force projects, which limits the generalizability of the results. This limited data set dictates that the model be applied only to those projects whose characteristics fall within the range of those used in the development of the prediction model.

This research also focuses on macro level variables that can be identified early in the planning process without analyzing construction specific tasks (i.e., concrete pouring, framing, finishing, etc.). For this reason, the resulting model will be applicable only for front-end predictions of construction duration; it is not intended for estimating project durations once specific construction schedules are developed.

The effectiveness of the regression model may also be limited by the availability of data. Some factors identified as having an important impact on construction duration by previous studies may not be included due to a lack of Air Force MILCON project data. While factors relating to project scope will be more easily identifiable; many more qualitative factors to include management effectiveness, project relationships, and communication among others; may be harder to measure and include in a prediction model.

Proposed Methodology

This research will be completed in three phases. In the first phase, a subset of completed projects will be compared to the current project duration goals established by current Air Force policy. This phase will use a statistical methodology to determine whether or not the current Air Force construction duration goals are being met. Descriptive statistics will be used to compare actual and predicted duration values.

In the second phase, a literature review will be conducted in order to identify models which have been successful in predicting construction durations in past research. This phase will also include a discussion of factors which are viewed as universal indicators of construction duration and how these factors have been previously combined in various empirical models.

The third phase will collect data for Air Force MILCON projects contained within the Air Force Civil Engineering System Project Management (ACES-PM) database. A subset of this data will then be analyzed through a statistical methodology in order to identify the combination of model parameters which provide the most accurate prediction of construction duration. This analysis will be conducted either through linear or multiple linear regression, commonly viewed as the most widely used statistical procedure for determining relationships between dependent and independent variables (Chan and Kumaraswamy, 1999: 637). This methodology will allow the incorporation of as many models or parameters that are found to significantly influence the values of the dependent variable (construction time) and provide a measure of the goodness of fit of the proposed model. Once a model is identified, the predictive accuracy of the proposed model can then be analyzed by comparison of the predicted values to another subset of completed projects within the ACES-PM database.

II. Literature Review

Introduction

This chapter reviews the body of literature related to commonly accepted duration estimation models, specifically the Bromilow Time-Cost (BTC) model. Both refinements and additions to the original BTC model will be discussed in order to highlight the strengths and weaknesses of differing time-cost modeling efforts. Modeling efforts focusing on quantitative variables will first be discussed, followed by an overview of efforts designed to include more qualitative management-related variables. Also included is a discussion of those factors which have been identified through previous research as having a significant influence on construction durations. Finally, the Air Force Military Construction (MILCON) process will be discussed, along with the current construction duration guidelines set by current Air Force policy.

Construction Duration Estimation Methods

In practice, there are two common methods of estimating construction duration: 1) setting the project completion date based on the client's time constraints, e.g., occupancy need, or 2) conducting a detailed analysis of the work to be done and resources available (Ng et al., 2001: 166). Both methods have shown a tendency to produce problematic estimates. Method 1 can lead to unrealistic construction time estimates driven by external factors, usually in the form of a fixed date of occupancy. Estimates based on a fixed date of occupancy may slight actual project requirements in order to meet the occupancy need date, thereby resulting in an overly optimistic construction duration estimate. Additional problems with this optimistic estimate result when large portions of construction time are consumed by procedural issues, thus leaving little remaining time in which to meet the client's occupancy need date (Bromilow, 1969: 75). While method 2 provides a more comprehensive estimate of construction duration, it is often impractical because of the time and manpower limitations associated with estimating construction projects (Ng et al., 2001: 166). In addition, estimates may vary widely since this method is highly dependent on the skill and experience of the planning engineer (Chan and Kumaraswamy, 1996: 319). The ability to estimate individual construction tasks may also be limited during the planning phase, as many of these specific tasks and materials have yet to be determined. This inability to establish a complete estimate during the project planning stage is a major drawback of this duration estimation technique (Khosrowshahi and Kaka, 1996: 376). Regardless of the construction stage at which the duration estimate is completed, most organizations simply do not have the resources to produce this type of comprehensive estimate for multiple construction projects.

Inaccurate initial estimates may be magnified by processes within the contractor-client relationship. Client-produced duration estimates can be driven by the unrealistic external circumstances discussed previously, while contractors are many times unable to invest the time and money required to produce accurate initial estimates. These constraints lead many contractors to assume that the construction duration set by the client is reasonable in lieu of investing the necessary resources to either develop a revised estimate or review the client's initial estimate for accuracy (Ng et al., 2001: 165). This common contractor-client estimation process can lead to inaccurate duration estimates which are based on external factors rather than actual project requirements. The pitfalls found in the commonly accepted construction duration estimation process highlight the need for a simple, accurate tool which can be used to predict construction durations.

Bromilow's Time-Cost Model

Motivation

The first empirical mathematical model for predicting construction duration was developed by Bromilow (1969). Motivated by the observation that many actual construction durations did not align with estimates established early in the planning process, Bromilow investigated the time performance of 309 building projects completed in Australia between July 1964 and July 1967. His initial comparison revealed that only 37 projects (12 percent) were completed on or before the estimated completion time (Bromilow, 1969: 72). This discrepancy motivated Bromilow to identify general standards of performance which could be used to develop more accurate construction duration estimates.

Model Development

Bromilow initially intended to use building size as an indicator of construction duration; but after investigating various measures of building size, he concluded that final cost provided the best indicator of project size. Cost was determined to be the best predictor because it not only provided a measure of the physical size of the project, but it also reflected the complexity and quality of the work completed (Bromilow, 1969: 73). Because of this characteristic, cost could be used to account for multiple factors which may influence the duration of a construction project. Bromilow determined the relationship between construction duration and cost through the use of a regression model. After investigating several transformations of the data, he found logarithmic scales to reveal the most significant time-cost relationship as shown in Figure 1.

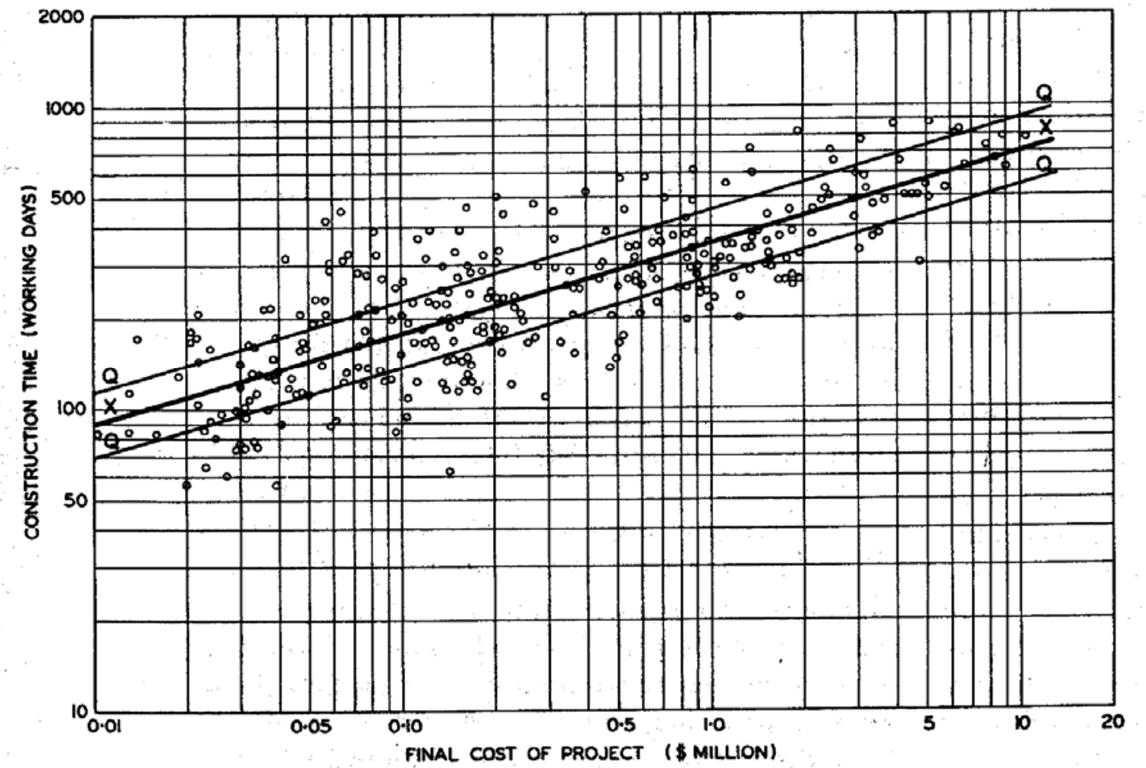


Figure 1. Bromilow's Double Log Graph (Bromilow, 1969)

Bromilow found the mean trend line (marked XX in Figure 1) to have the following time-cost relationship (Bromilow, 1969: 73),

$$T = K\, C^{B} \tag{1}$$

where

T = actual construction time in working days,

C = final cost of building in A$ million,

K = constant describing the general level of time performance for a $1 million project, and

B = constant indicative of the sensitivity of time performance as measured by cost.

Bromilow calculated K and B values of 313 and 0.3, respectively, resulting in the final relationship of

$$T = 313\ C^{0.3} \tag{2}$$

This nonlinear model, in the form of a power equation, is linear after applying a logarithmic transformation. The resulting equation using a natural log transformation is

$$\ln(T) = \ln(K\ C^{B}) = \ln(K) + B\ln(C) \tag{3}$$

Letting $y = \ln(T)$, $x = \ln(C)$, $\beta_0 = \ln(K)$, and $\beta_1 = B$ results in the standard linear regression equation

$$y = \beta_0 + \beta_1 x \tag{4}$$

Viewed in this form, K can be seen graphically as the average working time for a project costing $1 Million, and B can be seen as the slope of the regression line in Figure 1. While a B value of less then 1.0 indicates that the rate of increase of time required for construction decreases as the project size increases, a value larger than 1.0 would imply a longer construction time per unit cost as project size increases (Bromilow, 1969: 74). This relationship is better illustrated using the linear scale shown in Figure 2. The decreasing slope of line XX indicates that the rate of increase in construction time required decreases with increasing project size, as indicated by a B value of less than 1.0 in Equation 2.

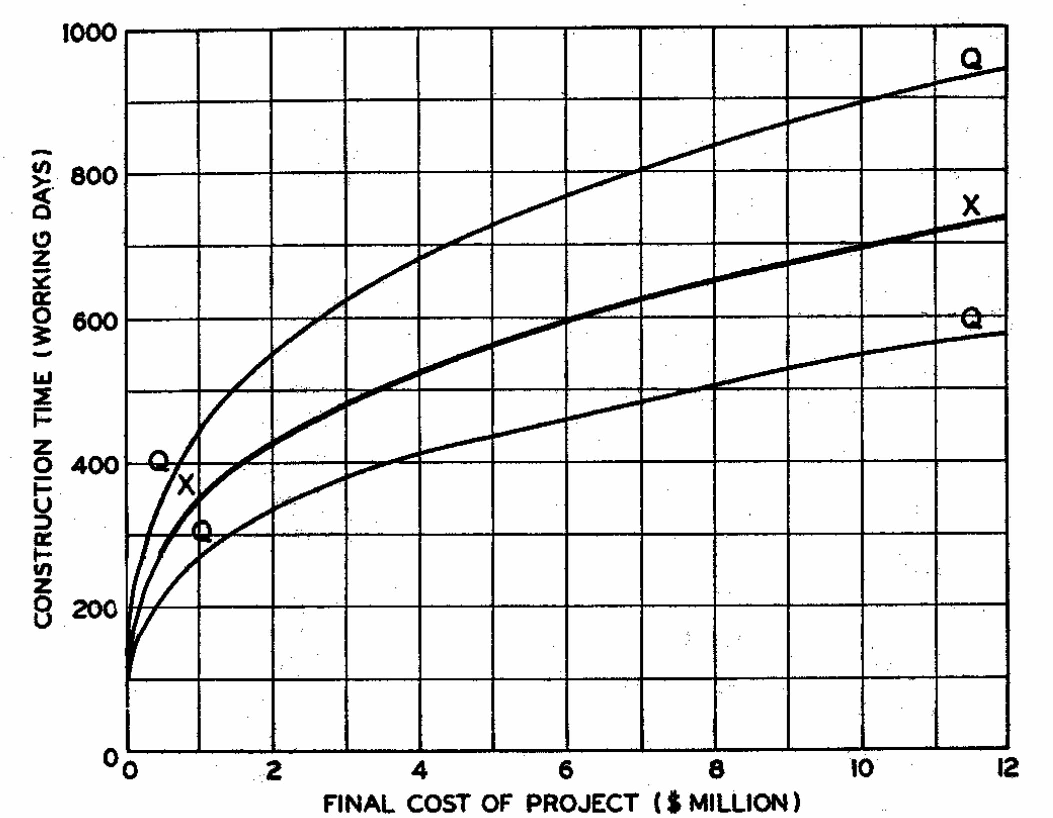


Figure 2. Bromilow's Time-Cost Graph (Bromilow, 1969)

Bromilow used quartile limits (mean +/- 0.674 standard deviations) as an indication of an individual project's departure from the mean. These limits, by definition, contain 50 percent of the actual construction durations for the sample projects. The upper and lower quartile limits (labeled QQ) are shown in Figures 1 and 2. These limits can be used to determine the relative time performance for a project, where an individual construction project can be considered within schedule if it is between the upper and lower quartile limits. A construction duration below the lower quartile would indicate exceptional time performance, while a project above the upper quartile would indicate substandard time performance. In this way, Bromilow (1969: 74, 76) was able to establish “norms of performance” which could be used to identify the performance level of the construction contractor. These norms are significant because they provide an objective, quantifiable, and defendable standard with which to specify construction durations and measure contractor performance.

Model Contributions

The BTC model was successful in identifying a clear trend between project cost and project duration. While the sample data contained significant variability between projects due to differences in design, location, quality, administrative procedures, and other factors, the trend between the time-cost data was still clearly identifiable (Bromilow, 1969: 74). This trend is significant in that it suggests that, in spite of significant variability, construction duration can be adequately predicted using project cost during the early planning phase of a project.

BTC Model Refinements

Motivation for Refinements

While the BTC model was successful in predicting construction durations for projects within the original study sample (Australian construction projects constructed between 1964 and 1967), it had limited applicability outside of this set of projects. This lack of generalizability is a limiting factor in any regression model. Inaccuracies may result when regression models are used to extrapolate or predict values of the dependent variable for independent variables which are outside the population for which the original model was developed (McClave et al., 200: 651). Without the ability to extrapolate, the BTC model could not be used to predict construction durations in other years, countries, economic conditions, or construction methods; in effect, the model could only be applied to a very narrow range of Australian construction projects. This limited applicability has been the basis for multiple research efforts seeking to calibrate the BTC model for use across a range of differing project characteristics. These efforts do not attempt to develop a new empirical time-cost model, but rather seek to apply the BTC model to differing project types through an adjustment of the original model parameters (*K* and *B*).

Refinements

Multiple research efforts have been conducted in order to further refine the BTC model for use across multiple project characteristics. In fact, Bromilow was the first to recognize the need for refinements to the original model. In 1980, a total of 419 projects from both government and private sources completed between 1970 and 1976 were investigated using the time-cost relationship (Bromilow et al., 1980: 79). This research revealed the need to partition data in order to account for differences in project characteristics. In addition to partitioning projects by private and government works, Bromilow et al. (1980) also found it necessary to further separate those projects completed prior to 1974. This distinction was made in order to account for the "overheated" Australian economy of 1973 and the subsequent effect on the availability of materials, labor, and delays related to disputes (Bromilow et al., 1980: 81.) While the original time-cost model showed continuing validity, updates in parameter values were necessary. This observation led to the formulation of the models shown in Table 1.

Table 1. Model Results (Bromilow et al., 1980)

Project Type	Model
Pre-1974 Private	$T = 232\ C^{0.28}$
Pre-1974 Government	$T = 335\ C^{0.28}$
Post-1974 Private	$T = 243\ C^{0.37}$
Post-1974 Government	$T = 406\ C^{0.34}$

Ireland (1985) used the BTC model to predict construction times for high-rise building projects in Australia. From a sample of 25 buildings, Ireland determined the relationship between cost and average construction time to be:

$$T = 219\ C^{0.47} \tag{5}$$

This research marked the first attempt to apply the BTC model relationship outside of the range of projects contained in the original study through a re-evaluation of the *K* and *B* values. The resulting model gave an R^2 value of 0.576 (Ireland, 1985) and was successful in expanding the original bounds of the BTC model.

Kaka and Price (1991) conducted similar research to include projects for both building and roadwork construction completed between 1984 and 1989 in the United Kingdom. This research partitioned project data under two subgroups in order to determine whether different parameter values were justified. Projects were classified according to type of project, client type, form of contract, and type of competition (Kaka and Price, 1991: 385). Kaka and Price developed an empirical time-cost model similar to that developed in the original BTC model. The project type and client type were found to significantly influence the time-cost relationship, thereby justifying the need for differing parameter values. They concluded that even when significant variation in the estimated and actual values of construction durations existed, the relationship between time and cost remains highly correlated (Kaka and Price, 1991: 385).

Yeong (1994) conducted a study of the BTC model relationship for use in building projects in both Australia and Malaysia. By partitioning projects into both private and government projects, the models shown in Table 2 were developed. These results confirmed Bromilow's initial model, but also illustrated that significantly different parameter values could be used to model construction durations across a range of differing project characteristics.

Table 2. Model Results (Yeong, 1994)

Project Type	Model
Australian Private	$T = 161\ C^{0.367}$
Australian Government	$T = 287\ C^{0.237}$
All Australian	$T = 269\ C^{0.215}$
Malaysian Government	$T = 518\ C^{0.352}$

Kumaraswamy and Chan (1995) investigated the significant factors influencing construction duration for both building and infrastructure projects completed in Hong Kong. Projects were partitioned into public and private projects, and further subdivided by project type to include buildings, roads, and other civil engineering projects (Kumaraswamy and Chan, 1995: 211). They concluded that the empirical time-cost relationships derived as a result of their research were significantly correlated to the previous studies conducted in Australia (Kumaraswamy and Chan, 1995: 217).

Chan (1999) studied the time-cost relationship for building projects in Hong Kong and found the following relationship (Chan, 1999: 195).

$$T = 518\, C^{0.352} \qquad (6)$$

Chan (1995: 195) also concluded that the time-cost relationship offered an objective estimation alternative which would be a useful supplement to current estimation methods, and that the relationship would provide useful information to both project managers and clients during the construction process.

Ng et al. (2001) further refined the BTC model for use with a new set of Australian projects completed between 1991 and 1998. This research further verified the need for differing parameter estimates based on project characteristics. They partitioned the data into both public and private sector projects, as well as by contractor selection method, type of project, and contractual arrangements (Ng et al., 2001: 168). The only significant difference was found between project types, which led to the development of the two models below (Ng et al., 2001: 172). Their equation for non-industrial projects was

$$T = 152.5\, C^{0.362} \qquad (7)$$

And their equation for industrial projects was

$$T = 96.8\, C^{0.310} \qquad (8)$$

Ng et al. further illustrated the value of partitioning data based on differing project characteristics in order to develop multiple time-cost relationships, concluding that the BTC model provided the best measure of construction time as measured by project cost (Ng et al., 2001: 172).

Summary of Refinements

Several common themes can be identified across the research efforts to further refine the original BTC model for use across a range of project characteristics. First, Bromilow's original time-cost relationship is shown to consistently provide a valid measure of construction time as measured by project cost. The above studies also highlight the value of developing different model parameter values (K and B) in order to apply the model across differing project characteristics. This allows the modeler to account for multiple factors which may influence project durations through the development of differing parameter values for each significant project characteristic identified. Key to this process is the ability to partition data by relevant factors. While the resulting time-cost equation is relatively simple to determine, the challenge lies in the identification of factors which may be significant enough to warrant a time-cost relationship with differing parameter values. Identifying these break points will result in any number of separate models which, when taken as a whole, are able to account for a variety of factors which may influence construction duration.

BTC Model Additions

Motivation for Additions

While the BTC model was successful in predicting construction durations using time-cost data, a potential shortcoming of the model is the exclusion of other factors which may influence the completion time of construction projects. This potential shortcoming has been the basis of several studies to improve the accuracy of the BTC model through the inclusion of additional factors. These modeling efforts aim to incorporate as many predictor variables (factors) as are found to have a significant influence on the dependent variable (construction duration). These additional predictor variables may include both quantitative (scope-related) as well as qualitative (management-related) factors.

Scope-Related Factor Additions

Several research efforts have been conducted in order to determine additional scope-related factors which may have a significant influence on construction duration. Chan and Kumaraswamy (1995) have conducted multiple studies to investigate the relationship between project characteristics and construction duration for a subset of Hong Kong construction projects. Their studies focus both on macro level variables such as construction cost, total gross floor area, and number of stories, as well as micro-level variables related to specific construction tasks such as concrete pouring and finishing (Chan and Kumaraswamy, 1995: 320). These efforts led to the development of two empirical models, both similar in form to the original BTC model. The first model was

$$T = L\,A^{M} \tag{9}$$

where

T = actual construction time in working days,

A = total gross floor area in m^2, and

L and M = constants corresponding to the K and B constants of the BTC model.

The results of this research indicated that the floor area is a significant quantitative factor which influences construction duration. This model was applied to both public and private buildings with R^2 values of 0.66 and 0.48, respectively. A similar model was hypothesized using the number of stories; however, a significant relationship between the number of stories and construction duration was not discovered (Chan and

Kumaraswamy, 1995: 322). Finally, the research combined cost and floor area in the form

$$T = KC^{B} A^{M} \tag{10}$$

which was found to be significant for the sample size of Hong Kong building projects with an R^2 value of 0.63.

Khosrowshahi and Kaka (1995) conducted similar research in order to identify a combination of factors which may influence project durations for housing projects in the United Kingdom. A large number of variables were investigated for inclusion in the final model through the use of a multiple linear regression analysis. The factors shown in Table 3 were selected for use in the final regression model.

Table 3. Summary of Factors (Khosrowshahi and Kaka, 1995)

Factor	Definition
Cost	Total cost of the completed project
Operation	Project type (rehabilitation, refurbishment, revitalization, or renovation)
Sub-type	Type of project completed (bungalow, public or sheltered)
Abnormality	Indicative of any special or unique project features
Start Month	Indicative of weather considerations
Horizontal Access	Degree to which workers and materials are moved horizontally
Floors	Number of stories

The corresponding multiple linear regression analysis of these factors resulted in the formulation of the following model.

$$e^{(Duration)} = Constant + Log\ (Cost)*Cost\ coefficient + Horizontal\ access\ coefficient + Buildability\ coefficient + Scope\ coefficient + Operation\ coefficient + Frame\ coefficient + Units*Unit\ coefficient + Start\ month\ coefficient + Abnormality\ coefficient + Floor\ coefficient \quad (11)$$

Coefficients for the resulting model were determined using the categorizations in Table 4, with a separate multiplying coefficient for each category. The resulting model was successful in explaining a large portion of the variability within the sample projects with an R^2 value of 0.93. Once project characteristics for each factor below were known, the construction duration could be predicted using Equation 11.

Table 4. Factor Categorizations (Khosrowshahi and Kaka, 1995)

Operation	Frame	Units	Months	Abnormality	Floor
Refurbishment	Steel	Constant	Jan	Access	Concrete
Alteration	Brick		Feb	Comminication	Steel
Extension	Concrete		Mar	Mistake	Timber
New	Timber		Apr	Delays	Brick
			May	Stoppages	
			Jun	Speed up	
			Jul	Resource	
			Aug	Cost Limit	
			Sep	Occupied	
			Oct	Variations	
			Nov	Transport	
			Dec	Time Limit	
				Unknown	
				None	
				Others	

While this research was successful in including various scope-related factors in a multiple regression model, it also reinforced the continuing validity of the original BTC relationship. Khosrowshahi and Kaka (1995: 381) concluded that while other variables play a "considerable role" in determining construction duration, the dominating correlation was identified between project cost and duration.

Management-Related Factor Additions

There have also been several research efforts focusing on more qualitative, management-related factors. Ireland (1985) investigated the influence of managerial actions on the construction time performance in building projects. This was one of the first attempts to determine a direct relationship between management practices and construction duration. Ireland looked to improve on the original BTC model, citing the principal criticism that many aspects of the management process were too complex to be modeled using constant parameter values. His research concluded that client experience, form of building procurement, and project organizational structure are significant managerial factors which interact in a more complex model of project time performance (Ireland, 1985). However, due to high variability among projects, this research did not combine these management factors in an empirical model.

High levels of variability in management-related factor models were also noted by Walker (1995) and Nkado (1995). Through the use of a survey methodology, these studies concluded that many management and client related factors were viewed by project team leaders as having a significant influence on construction duration. Both studies were unsuccessful in quantifying the statistical impact of these factors, presumably due to their high dependence on managerial planning and control (Walker, 1995: 272). While these surveys revealed a good degree of consistency in responses and a relative ranking of important factors influencing project durations, both studies recognized the difficulty of combining these factors into any sort of empirical model. As a result of theses studies, those factors which are readily identifiable and directly quantifiable are generally viewed as having the most significant influence on construction durations (Nkado, 1995: 85).

Skitmore and Ng (2003: 1076) examined the relationship between construction time and other contract details, such as estimated construction cost, client sector, project type, contractor selection method, and contractual arrangement. This research collected data for 93 Australian construction projects to include company name, project name, project location, client sector, project type, contractor selection method, contractual arrangement, original contract period, actual contract period, original contract sum, and final contract sum (Skitmore and Ng, 2003, 1076). These data were then analyzed for significant trends using a multiple linear regression analysis, resulting in the final model with an R^2 value of 0.9406 in the form of

$$\begin{aligned} LATIME &= 0.207638 + 0.966737(LCTIME) \\ &+ 0.097269(LS) - 0.083980(OT) \end{aligned} \tag{12}$$

where

LATIME = log-actual time,

LCTIME = log-contract time,

LS = lump sum dummy variable, and

OT = "other" selection dummy variable.

The duration estimation model (Skitmore and Ng, 2002: 1080) is dependent on both the contract period and contract sum being known. While this may be valid in rare cases, contract period and contract sum are more often estimated from available information at the time of estimation. For this reason, the research further sought to examine how sensitive the model was to deviations from the initial contract time and period estimates. Results of this sensitivity analysis indicated that errors in the predicted construction time become smaller as the contract period increases (Skitmore and Ng, 2002: 1081).

Summary of Previous Research

Several common themes can be identified across the body of research seeking to improve the original BTC model through the inclusion of both quantitative and qualitative factors. First, it is commonly agreed upon that construction duration is influenced by numerous factors in addition to cost, and that many of these factors are management and client related. Modeling the subjective nature of these factors has been the challenge of many research efforts, as there is little consensus as to which combination of these more qualitative factors provides an accurate predictor of construction duration. Efforts to develop an empirical model have been further limited by the high variability associated with these more qualitative factors. In fact, the inclusion of such qualitative factors often presents an overwhelming source of variability when investigating regional effects on construction duration (Bromilow, et al., 1988: 4). Even when these factors are easily identified, it is usually difficult to quantitatively evaluate their impact on construction duration in an empirical form (Nkado, 1995: 84).

While many of these studies have suggested additional relationships between project duration and a variety of factors, they have also acknowledged the continuing validity of the time-cost relationship in the original BTC model. The BTC model is still widely recognized today as the standard for estimating the time period required for construction projects (Ireland, 1985: 137; RIRA, 1989). The dominating correlation between project cost and duration has been recognized across multiple research efforts, many of which have attempted to include additional factors in an empirical model (Khosrowshahi and Kaka, 1996: 95; Kaka and Price, 1991: 91; Ng et al., 2001: 172). A summary of these research efforts is shown in Table 5.

Table 5. Summary of Existing Models (Chan and Kumaraswamy, 2002)

Proposer(s)	Type of project surveyed	Country of project surveyed	Sample size	Type of model relationship	R^2 Value	Main parameters included in model		
						Project scope	Project complexity	Management attributes
Bromilow (1969)	Building	Australia	329	Log Linear	-	*		
Bromilow et al. (1980)	Public Building	Australia	277	Log Linear	-	*		
	Private Building	Australia	118	Log Linear	-	*		
Ireland (1985)	Commercial	Australia	25	Log Linear	0.576	*		
				Linear	0.730	*	*	*
Kaka and Price (1991)	Building	UK	661	Log Linear	0.610, 0.680	*		
	Roadworks	UK	140	Log Linear	0.970	*		
Nkado (1992)	Commercial	UK	29	Linear	0.790	*	*	
Walker (1994)	Non-residential	Australia	33	Log Linear	0.999	*	*	*
Yeong (1994)	Building	Australia	87	Log Linear	-	*		
		Malaysia	51	Log Linear	-	*		
Chan and Kumaraswamy (1995)	Public building	Hong Kong	37	Log Linear	0.656	*		
	Private building	Hong Kong	36	Log Linear	0.476	*		
	Civil works	Hong Kong	38	Log Linear	0.640	*		
Chan (1996)	Building	Hong Kong	110	Log Linear	0.850	*		
Khosrowshahi and Kaka (1996)	Housing	UK	54	Log Linear	0.927	*	*	
Ng et al. (2001)	Building	Australia	93	Log Linear	0.588	*		
Skitmore and Ng (2003)	Building	Australia	93	Log Linear	0.941	*		*

Table 5 illustrates several important concepts. Project scope (as measured by cost) can be seen as the dominant parameter selected across multiple research efforts. Attempts to include additional qualitative factors are limited; and when accomplished, they typically focus on a relatively small sample of projects due to the difficulty associated with the collection of data. Additionally, the log-linear relationship has been shown to provide the most revealing relationship between time and cost. These log-linear models have been successful in explaining significant portions of the data variability, with R^2 values ranging from 0.48 to 0.99. Due to the wide range of project characteristics associated with many of these studies, the resulting models may not be successful in explaining large portions of this variability. However, the models are still statistically significant, even in light of a low R^2 value. This variability in results can be expected for this type of model; however, it is important to note that the trend between construction time and a number of independent variables is still clearly defined.

Research has also recognized that the BTC model offers the principal advantage that multiple characteristics of a construction project can be expressed in a single unit of scope measurement, due to the fact that the total cost of the project is a function of other factors such as project complexity and quality (Walker, 1995). A second advantage of the BTC model is the ability to estimate construction durations at an early stage in the planning process. At the pre-contract stage when specific construction tasks and materials are yet to be determined, the BTC model requires only cost data to produce a valid duration estimate. Many factors identified as significant in addition to cost may not be known until the post-contract stage, when more of the risks and uncertainties associated with the client, contractor, and construction specific factors are known (Skitmore and Ng, 2003: 1076). While the inclusion of additional factors may be beneficial at this point, the BTC model still offers the most reliable model for front-end (pre-contract) predictions of construction duration.

Existing research reveals two distinct methodologies for estimating construction durations: 1) through data partitioning and the development of differing parameter values in the original BTC model and 2) through a multiple linear regression analysis of multiple predictor variables. While somewhat different in nature, both of these model types may be seen as adaptations of the original BTC model relationship. The selection of model type is many times dictated by the stage at which the construction duration estimate is to be completed and by the project data available at the time of estimation. For pre-contract estimates, when little or no project or contract specifics are known, the parameterized BTC model has been shown to provide valid results using readily available time-cost data. When some contract specifics have been determined, more complex multiple linear regression models have been shown to be beneficial (Skitmore and Ng, 2003).

Factor Selection

Importance

While previous research has identified cost as the dominant predictor of construction duration, an understanding of other significant factors is still beneficial. Even if these parameters are not included specifically in the empirical model (through multiple linear regression), these factors can be used to partition data in order to account for differing project characteristics. This allows the formulation of separate empirical models for significantly different project characteristics. The challenge lies in the identification of factors which may be significant enough to warrant a time-cost relationship with differing parameter values. In order to determine where these break points may lie, a review of time influencing factors identified by experts in the field is required. This section will focus on those commonly accepted factors, with an emphasis on those factors that can be identified early in the project process, during the estimation phase.

Commonly Accepted Factors

Researchers have been plagued by a lack of consensus when attempting to prioritize factors thought to influence construction duration. Nkado (1995) completed a survey of senior planners in construction firms in the United Kingdom in an effort to provide a prioritized listing of factors. He concluded that factors which influence construction duration can be prioritized, but also identified a lack of consensus in the literature regarding factor selection (Nkado, 1995: 85). The ten most important factors identified were the client's specified sequence of completion, contractor's programming of construction work, form of construction, client's and designer's priority on construction time, complexity of project, project location, buildability of design, availability of the construction management team, and timeliness of the project information and documents (Nkado, 1995: 84). Walker (1995) further developed similar factors into a model in order to illustrate the important influence of the construction management team on the process. As a result of a survey of 100 managers of Australian construction projects, he concluded that time performance was viewed as primarily dependent on the construction manager's ability to overcome problems related to project complexity, communication, project scope, and client characteristics (Walker, 1995: 268). The resulting model is shown in Figure 3.

In this model, the construction management team acts as a filter to all factors which may influence construction duration. The influence of individual components on subsequent components is illustrated by the arrow, while the strength of each influence is indicated by the number of positive signs. This research further highlighted the variability associated with the selection of factors by concluding that the individual characteristics of the project manager may influence which factors become significant during the construction process.

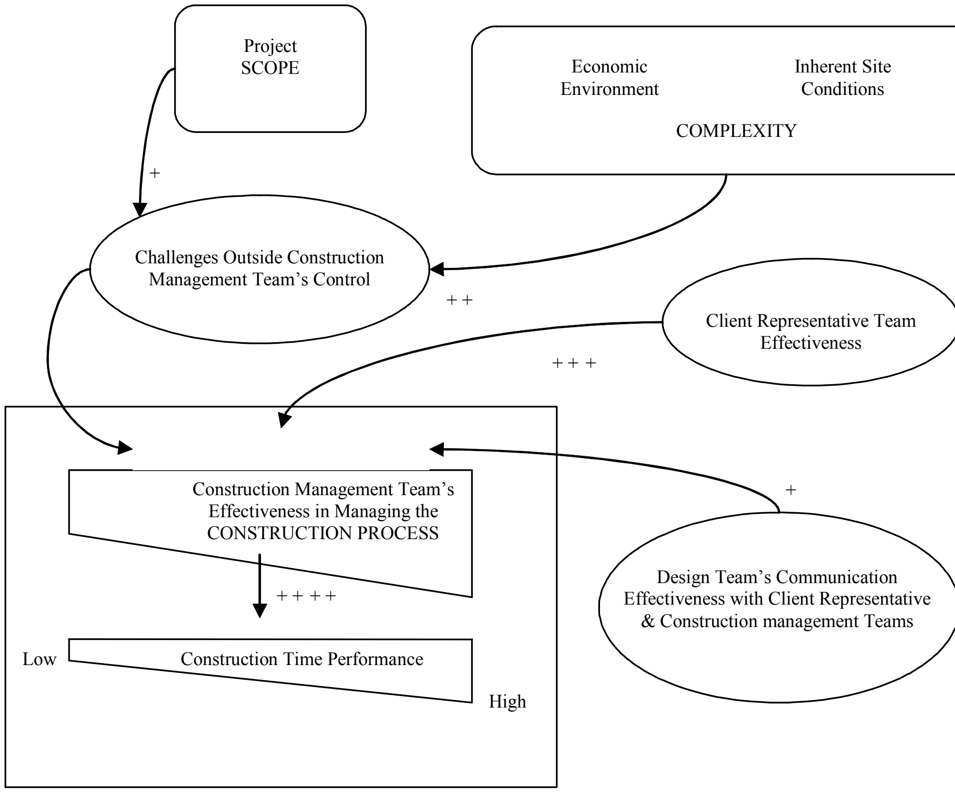


Figure 3. Model of Construction Time Performance Causal Factors (Walker, 1995)

The relative ranking of factors may also vary significantly based on the population surveyed. Assaf et al. (1995) conducted a survey of contractors, Architect/Engineer (A/E) firms, and owners to determine whether a consensus could be reached regarding which factors may influence construction duration. The causes of delay were grouped into nine major categories: materials, manpower, equipment, financing, environment, changes, government relations, contractual relationships, and scheduling and controlling. The causes of delay were ranked for each sample group as shown in Table 6. The results show agreement between all three groups in several areas; in particular, the financing group was ranked highest and environment lowest. However, this study also highlighted some significant differences in perceptions which exist between A/E firms and owners (Assaf et al., 1995: 50). While certain factors are viewed as influential regardless of the respondent perspective, it important to note that there are substantial differences in the perceived importance of many factors between the groups surveyed. The results of this research further highlight the lack of consensus which exists in the construction industry regarding the selection of important construction time influencing factors.

Table 6. Rank of Causes of Groups of Delay Factors (Assaf et al., 1995)

Group	Owner Average Rank	Contractor Average Rank	A/E Average Rank
Material	6	2	2
Manpower	2	8	6
Equipment	7	7	7
Financing	1	1	1
Changes	3	4	4
Government relations	4	5	8
Scheduling and controlling	8	6	5
Environment	9	9	9
Contractual relationships	4	3	3

Additional studies have been conducted across a range of countries and project types in order to determine the major factors influencing project duration. Table 7 provides an overview of these efforts and highlights several significant factors which have been identified across a range of studies. Table 8 summarizes the frequency of which these factors have been selected across multiple studies. As such, this table provides an overview of multiple research efforts. Construction delays relating to variations in the project scope are most frequently identified, followed by shortages in both materials and productivity. Also identified as frequently occurring are management and site related issues. While this analysis provides an overview of the relative importance of factors identified through multiple research efforts, it does not seek to develop a combined model containing categorized factors.

Table 7. Major Factors Causing Construction Delays (Chan and Kumaraswamy, 2002)

	Country where survey was conducted and investigator(s)									
	US	UK	Developing Co	Turkey	UK	Nigeria	UK	Saudi Arabia	Hong Kong	Indonesia
Factors causing project delays	Baldwin et. al, (1971)	NEDO (1983)	Chalabi and Camp (1984)	Arditi et al, (1985)	NEDO, (1988)	Mansfield et al, (1994)	Naoum, (1991)	Assaf et al, (1995)	Chan and Kumaraswamy, (1997)	Kaming et al, (1997)
Inclement weather	*	*			*					
Labor shortage/low labor productivity	*			*				*		*
Poor subcontractor performance	*	*			*			*		
Variations		*		*	*			*	*	*
Unforseen ground conditions		*			*				*	
Materials shortages		*		*	*	*				*
Inadequate construction planning			*	*						*
Financial difficulties				*		*		*		
Delays in design work				*	*					
Poor site management					*	*		*	*	
Impractical design					*					
Poor communication					*			*	*	
Inapporopriate type of contract							*			
Lack of designer's experience							*			
Innaccurate Estimating										*

Table 8. Frequency of Factors Causing Construction Delays

Factors causing project delays	Frequency
Variations	6
Materials shortages	5
Labor shortage/low labor productivity	4
Poor subcontractor performance	4
Poor site management	4
Inclement weather	3
Unforseen ground conditions	3
Inadequate construction planning	3
Financial difficulties	3
Poor communication	3
Delays in design work	2
Impractical design	1
Inapporopriate type of contract	1
Lack of designer's experience	1
Innaccurate Estimating	1

Chan and Kumaraswamy (2002) expanded the survey to include the perceptions of industry practitioners in Hong Kong, to include clients, consultants, and contractors (Chan and Kumaraswamy, 2002: 28). Seeking to address the lack of consensus in literature regarding the selection of factors, they categorized the resulting factors into project scope, project complexity, project environment, management attributes, and other factors. These principal factors and sub factors are shown in Figure 4. Chan and Kumaraswamy (2002: 24) hypothesized that this categorization could serve as a more universal model, applicable in Hong Kong as well as in other countries. To date, this model offers the most complete categorization of commonly identified factors which are applicable to a variety of project characteristics. This model provides a useful partitioning of factors into easily identified categories for both quantitative (scope-related) as well as qualitative (management-related) factors.

Summary of Factor-Related Research

There are several common themes identified across the factor-related literature above. A general lack of consensus exists in identifying significant factors influencing construction duration. In spite of this lack of consensus, previous research has been successful in prioritizing these factors in order of relative importance. Previous research has also been successful in subdividing these factors into specific categories, most commonly into categories relating to management attributes, project scope, environment, and design issues. The challenge in the development of a duration estimation model lies in determining which of these factors can be identified and modeled using parameter values.

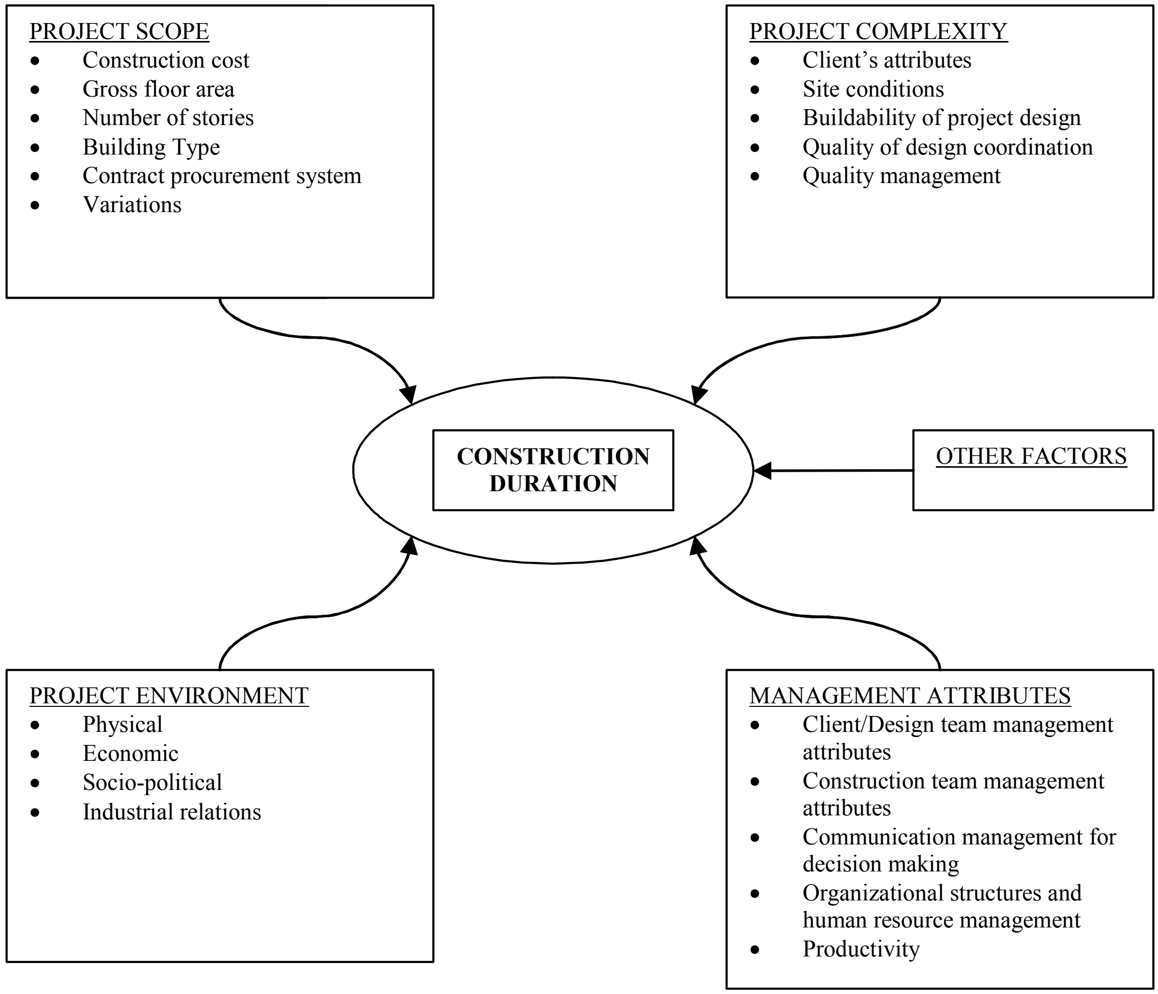


Figure 4. Factors Affecting Construction Duration (Chan and Kumaraswamy, 2002)

To be useful in predicting construction durations at an early stage, factors must be easily identifiable during the planning phase of a project. While many of the above factors have been identified as important, they may be difficult to determine during the planning phase of a project. Management-related issues are particularly hard to model and even more difficult to predict using preliminary project information. Issues related to design quality produce similar problems in modeling because many of these factors may not be known until well into the construction period. Project scope and environment issues are somewhat more suited for inclusion in a front-end modeling effort since they are known early in the construction planning process. Furthermore, multiple factors within in these two categories should be identifiable through either direct or proxy measures. By necessity, a model which is to be useful in predicting front-end construction durations must focus heavily on scope and environment related factors at the expense of more qualitative management-related factors which are not known during the planning phase.

United States Air Force Military Construction (MILCON) Overview

MILCON Definition and Objective

Military Construction is defined as any "construction, development, conversion, or extension of any kind carried out with respect to a military installation" (Department of the Air Force, Jan 2003: 21). This MILCON project classification includes all construction work exceeding $750,000 for buildings, roads, airfield pavements, and utility systems necessary to produce a "complete and useable" facility or improvement to an existing facility (Department of the Air Force, Jan 2003: 21). The objective of the Air Force MILCON program is to provide quality facilities to support Air Force missions (Department of the Air Force, Jan 2003).

Air Force MILCON Process

The Air Force MILCON process can be divided into four distinct stages as shown in Figure 5. The primary purpose of this sequential MILCON process is to confirm that the project scope, site location, and estimated construction costs are defined in sufficient detail to ensure successful project execution (Department of the Air Force, 2000: 1-3). Each phase in this process will be discussed in detail in the following sections.

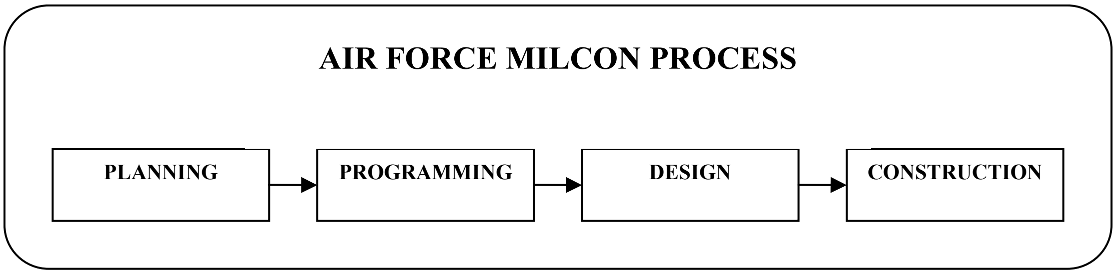


Figure 5. Air Force MILCON Process (Department of the Air Force, 2000)

Planning Phase

The Air Force defines effective planning as that which "establishes facility requirements critical for mission accomplishment and proposes the most effective and economical means of satisfying those requirements" (Department of the Air Force, Jan 2003: 6). Planning for Air Force MILCON projects is accomplished through a three-step process of determining requirements, evaluating alternative solutions, and initiating programming actions (Department of the Air Force, Jan 2003: 6). Each Air Force installation is tasked to identify facility needs and to determine which of these needs cannot be met with existing facilities. The installation commander is then responsible to review, validate, and prioritize these MILCON facility requirements. The installation must also determine the most economical and effective means of meeting facility needs and accomplish planning actions to account for environmental, siting, and security requirements. These planning actions are ensured through the completion of a Certificate of Compliance signed by the installation commander (Department of the Air Force, Jan

2003: 7). Once the need for a facility has been identified, validated, and properly planned, the Base Civil Engineer (BCE) is responsible for initiating the project programming phase.

Programming Phase

Air Force Instruction 32-1021 defines MILCON programming as "the process of developing and obtaining approval and funding for MILCON projects" (Department of the Air Force, Jan 2003: 21). Once a project has been validated through the planning phase, the BCE is responsible to prepare and submit a DD Form 1391 and other required documentation and enter the project into the Automated Civil Engineering System-Project Management (ACES–PM) database. This documentation requires the completion of an initial cost estimate, or Programmed Amount (PA), which must be developed in accordance with the Office of the Secretary of Defense (OSD) Pricing Guide or the Air Force Civil Engineering Support Agency (AFCESA) Historical Construction Handbook (Department of the Air Force, Jan 2003: 22). The Air Force also encourages the use of a parametric cost estimating system, such as the Air Force Parametric Cost Estimating System (Department of the Air Force, 2000: 2-3). The PA estimate is to be based on a thoroughly developed Requirements and Management Plan (RAMP).

A complete RAMP is developed through discussions of the project with the Major Commane (MAJCOM), Air Force installation, and facility user; it may be completed by the BCE, MAJCOM Civil Engineering staffs, or by an Architect/Engineer (A/E) firm under contract with the BCE (Department of the Air Force, Jan 2000: 2-2). The RAMP consists of two parts: the Requirements Document and the Project Management Plan (PMP). The Requirements Document includes the accurate definition of all project requirements and ensures that the scope is based on those requirements. When completed, this document serves as the basis for the parametric cost estimate (Department of the Air Force, Jan 2000: 2-2). The PMP is designed to outline the roles and responsibilities of the various management functions involved in the project; it also specifies certain project details such as risk, contract type, scheduling, project packaging, and design agent (Department of the Air Force, Jan 2000: 2-3).

MAJCOMs are responsible to compile and validate submitted MILCON projects and forward their commander-approved MILCON project listing to higher headquarters. The civil engineering representatives at this level are then responsible to review each MILCON project in order to validate need, feasibility, compliance with Air Force objectives, and project cost. Projects are then reviewed in order to develop the Integrated Priority List (IPL) which includes Air Force, Air National Guard, and Air Force Reserve Command MILCON projects. The IPL is used by the Air Force to submit a two-year MILCON budget to OSD and Congress each even numbered fiscal year (Department of the Air Force, 2000: 2-4). The MILCON budget is reviewed by OSD, and after approval, submitted to Congress as part of the President's Budget. Each even numbered year, a six-year Future Year Defense Plan (FYDP) is developed for the Program Objective Memorandum (POM) to provide an overview of needed resource and requirements for the next six years (Department of the Air Force, Jan 2003: 24).

MILCON projects are authorized by Congress through the Defense Authorization Bill, which is reviewed by both the House and Senate Armed Services Committees. After authorization, the Secretary of Defense requests appropriations for authorized MILCON projects. The House and Senate Appropriations Committees review the appropriation request before forwarding the bill to the President. After presidential signature, the request becomes law in the form of the Military Construction Appropriations Act. After authorization and appropriation, the Air Force is responsible for arranging funding of specific construction projects (Department of the Air Force, Jan 2003: 25)

<u>Design Phase</u>

Design involves the determination of specific project characteristics across all engineering disciplines. The design process is structured to produce a completed project which enhances the Air Force mission and ensure functionality, efficiency, and economy while meeting user expectations (Department of the Air Force, 1994). The process typically begins no later than 30 days prior to the completion of the RAMP. It begins with the issuance of the MAJCOM Field Design Instruction (DI) to the Air Force Project Manager (AF PM), signifying the authority to initiate design actions such as A/E selection and award, site investigation, and design (Department of the Air Force, 2000: 4-2). This process allows the Design Agent (DA), typically the U.S. Army Corps of Engineers (COE) or Naval Facilities Engineering Command (NAVFAC), to participate in the preparation of the PMP; it also allows initiation of the necessary administrative actions required before the start of design.

The DA may utilize either in-house personnel or an A/E firm to complete the design. The selection of an A/E firm is a complex procedure strictly controlled by policy and regulations (Department of the Air Force, 1994). The specific requirements associated with this process are beyond the scope of this research; however, this process ultimately results in the issuance of a Notice to Proceed to the selected A/E firm or in-house staff (Department of the Air Force, 2000: 1-4). The selected entity initiates the design effort after the Predefinition Conference, a process intended to establish design requirements to facilitate a clear exchange of product requirements between the design group and the government (Department of the Air Force, 2000: 4-6). Through this conference, the AF PM is specifically tasked to resolve any discrepancies which may exist regarding project criteria. This includes the critical need date, which is defined as the date established by the MAJCOM or the user as the last date the facility can be turned over to the user for occupancy without adverse mission impacts (Department of the Air Force, 2000: 4-7).

From this point forward, the design phase can be conceptually broken into two steps: Project Definition and Contract Document Development (Department of the Air Force, 2000: 1-5). During the Project Definition phase, project requirements and the parametric cost estimate are validated by the design group. The AF PM and DA are tasked to monitor the Current Working Estimate (CWE) during this stage of the design process, and the AF PM must ensure that any revised parametric cost estimate developed during this phase reflects actual project requirements (Department of the Air Force, 2000: 4-3). If the estimate is higher than the PA contained in the DD Form 1391, several actions may be taken to include redefinition, identifying additive bid items, reducing project scope or requirements, or reprogramming (Department of the Air Force, 2000: 5-11). The MAJCOM has authority to change the scope and target cost prior to submitting the project to Air Force level in response to the annual MILCON call letter. After submittal, only headquarters Air Force personnel may change the scope and PA during the MILCON approval process and subsequent submittal to OSD for inclusion in the

President's Budget (Department of the Air Force, 2000: 4-3). Changes in scope after this point are accomplished through updates to the CWE; however, these changes may require approval from higher authorities subject to the conditions shown in Table 9.

Table 9. MILCON Scope Change Authority (Department of the Air Force, 2003)

Situation	Approval Authority
Scope decrease greater than 25% of authorized scope	Congress
Scope decrease less than or equal to 25% or authorized scope	MAJCOM/CE
Scope increase no greater than 10% of authorized scope	MAJCOM/CE
Scope increase greater than 10% but no greater than 25% of authorized scope	HQ USAF/ILEC
Scope increase greater than 25% of authorized scope	Congress

The Contract Document Development stage begins with the MAJCOM authorizing the DA to proceed with design through the issuance of a Field Design Instruction. During this stage, conceptual documents are used to develop working drawings and specifications which serve as the basis for the contract documents used to solicit construction bids (Department of the Air Force, 2000: 1-5). This process is completed through specified design process submittals. These submittals, intended to clarify and identify the user's needs early in the design process, (Department of the Air Force, 2000: 5-21) are defined using the milestones below (Department of the Air Force, 2000: 5-22)

- Project Definition (15% design complete)
- Early Preliminary Design Submittal, if required (30% design complete)

- Preliminary Design Submittal, if required (60% design complete)
- Pre-Final Design Submittal (90% design complete)
- Corrected Final Design Submittal (100% design complete)
- Ready-to Advertise Submittal (RTA)

There are various requirements associated with each submittal; however, common to each phase is a cost estimate requirement, with the RTA submittal requiring an Independent Government Estimate completed by the DA.

Cost and scope changes during design are controlled through several processes. New requirements or scope changes are to be added after the Project Definition submittal only when unforeseen extenuating circumstances exist (Department of the Air Force, 2000: 5-24). Additionally, the MAJCOM has limited opportunities to adjust the PA shown on the DD Form 1391 once it is submitted to Air Force level as discussed above. After the President's Budget is submitted, changes to the PA are not permitted.

Performance periods are also essentially fixed during this stage of design, since critical need dates are established during the Predefinition Conference. It is important to note that the A/E firm or in-house design staff will usually be responsible for establishing the construction duration estimate prior to this stage in design. However, the AF PM is still specifically tasked to ensure that the construction performance period is adequate to accomplish the project and meet any critical occupancy dates regardless of the performance period which may be selected by the DA (Department of the Air Force, 2000: 5-26).

Construction Phase

Construction is defined as "the erection, installation or assembly of infrastructure or facilities and supporting amenities, signage, landscaping, etc., or any alteration or additions thereto" (Department of the Air Force, 2000: Glossary-4). For Air Force MILCON projects this period can be defined as the time from the construction Notice to Proceed (NTP) to the Beneficial Occupancy Date (BOD). The authority to advertise a selected project to prospective construction contractors is granted at the Air Force level when all of the following criteria are satisfied (Department of the Air Force, Jan 2000: 6-5).

1) Project included in the authorization and appropriation bills signed by the President

2) Project at least 95% designed as reported in ACES-PM

3) Basic CWE/PA is not greater than 110%

4) Overall MAJCOM fiscal year MILCON program CWE/PA ratio does not exceed 100%

5) Environmental Impact Analysis Process (EIAP) is completed and reported in ACES-PM

The construction bid process is largely managed by the Contracting Officer. Specific details of this process are beyond the scope of this research; however, the basic steps of the process are outlined below.

The issuance of the Authority to Advertise (ATA) begins the construction bid process. The contracting officer begins solicitation by notifying prospective offerers through the Commerce Business Daily with the publication of either an Invitation for Bid or Request for Proposal. After bids are received and reviewed, a construction contract is awarded to the apparent low bid, which becomes the basis for the CWE (Department of the Air Force, 2000: 6-9). Once an acceptable bid is received, the MAJCOM is granted authority to award the contract, thereby signaling the end of the construction bid process.

The selected contractor is authorized to start actual construction through the NTP issued by the Contracting Officer. This notice both authorizes the contractor to allocate funds and establishes the start date for the contract performance period (Department of the Air Force, 2000: 7-3). Once construction begins, the CA (COE or NAVFAC) is responsible for construction surveillance; however, construction inspection and quality control are largely the responsibility of the contractor (Department of the Air Force, 2000: 7-4). The contractor is also tasked to prepare the construction schedule detailing how the contract completion dates will be met, while the Contracting Officer is responsible to review and approve the schedule (Department of the Air Force, 2000: 7-7). Changes to this approved schedule may be required by the Air Force when dictated by mission changes (Department of the Air Force, 2000: 7-7). Construction contract modifications are closely managed throughout the construction process, as these additions frequently add time to the construction schedule and may cause an increase to the CWE (Department of the Air Force, 2000: 7-10).

Project completion is signaled by the DD Form 1354, Transfer and Acceptance of Military Real Property, which establishes the legal transfer of ownership of government real property (Department of the Air Force, 2000: 7-16). After final inspection and completion of the DD From 1354, the Air Force may accept the facility from the Contracting Agent. This acceptance procedure indicates that the facility is ready for user occupancy, which is commonly referred to as the Beneficial Occupancy Date (BOD), and serves as the completion date for the construction contract.

Important Aspects of the Air Force MILCON Process

There are several aspects of the Air Force MILCON process which are important regarding the formulation of a construction duration estimate. For instance, the MILCON process dictates that estimates for both construction time and cost are established early, reaching a final estimation stage well before the final design is complete. Cost estimates are subjected to a rigorous verification process, and a largely complete and verified cost estimate is required at the beginning of the programming phase for inclusion in the DD Form 1391. These cost estimates are verified through use of historical project data in accordance with the OSD pricing guide or other historical cost data. Cost overruns are strictly controlled and, in extreme cases, can lead to restricting award, redesign, re-bidding, or reprogramming (Department of the Air Force, 2000: 6-9).

Initial time estimates are set during the programming phase through the PMP. These estimates are most often completed by the A/E firm, but the AF PM is tasked to ensure that the construction performance period is adequate, specifically in terms of any critical occupancy need dates (Department of the Air Force, 2000: 7-3). However, the time estimation process is not determined through a comparison with historical data or subjected to the same rigorous verification process. While critical need dates may be an important consideration, using them to drive construction duration estimates may be problematic. This process may have a tendency to lead to construction duration estimates which are driven by external circumstances rather than actual project requirements. This problem has been identified by Bromilow (1969: 75) as creating problems associated with forcing a project into a desired, rather than realistic, time mold. These situations may also lead to negative effects which may lead to organizational problems in other areas (Khosrowshahi and Kaka, 1996: 377).

Air Force Construction Duration Goals

Air Force construction duration estimates are controlled largely through benchmark goals and are not subject to the same strict procedural controls as cost estimates. The current method used to benchmark performance time for Air Force MILCON facility projects is based on the programmed amount (PA). Current duration goals were established through a U.S. Army Corps of Engineers MILCON Program Management Plan (U.S. Army Corps of Engineers, 2003: 8). In this plan, the goals for construction duration, defined as the time from the Notice to Proceed (NTP) to the Beneficial Occupancy Date (BOD), are determined using the following criteria.

- PA less than $5M: construction duration is 365 days
- PA between $5M and $20M: construction duration is 540 days
- PA $20M and greater: construction duration is 730 days

These duration goals were also published in Air Force guidance used to establish acceptable performance time targets as one of the criteria used for the "Dirtkicker" award, an award designed to recognize superior MAJCOM MILCON programs (Department of the Air Force, Oct 2003). However, the Air Force guidance changed the construction durations to 455, 630, and 820 days, respectively, for overseas MAJCOMs.

Additionally, the Air Force specifies goals for construction schedule growth, which is defined as the performance days (i.e., NTP to BOD) relative to the original performance days specified in the contract. Schedule growth goals are specified through the U.S. Army Corps of Engineers MILCON Program Management Plan at 10% or less (U.S. Army Corps of Engineers, 2003: 8). These goals are further refined for use as "Dirtkicker" award criteria, with award points being prorated based on the percentage of MAJCOM projects in each category below (Department of the Air Force, Oct 2003: 3).

- High: ≤ 10% Schedule Growth
- Middle: > 10% and ≤ 25% Schedule Growth
- Low : >25% Schedule Growth

Air Force MILCON Duration Estimation Problems

Accurate MILCON construction time estimates are encouraged by policy formulation through the use of the Air Force goals above; however, this benchmarking method may neglect complex factors which may influence project duration. It is clear that Air Force MILCON project managers are charged to deliver projects meeting both cost and schedule constraints. While cost constraints are sufficiently defined historically and verified through the MILCON process, duration estimates are subject to less stringent control. If schedule growth is to be monitored, it follows that duration goals set at the Air Force level must be reasonable and obtainable. Therefore, a model providing accurate duration estimates based on significant factors would be a useful policy setting tool for use in specifying construction duration goals. A model of this type would also benefit Air Force program managers by providing a means to either produce or evaluate the accuracy of a front-end duration prediction.

III. Methodology

Introduction

This chapter explains the two primary methodologies used to estimate construction durations in more detail. The previous research outlined in Chapter II revealed two distinct methodologies, both based on the original Bromilow Time-Cost (BTC) model, for estimating construction durations: 1) using simple linear regression with partitioned data to develop differing parameter values in the original BTC model, and 2) using multiple linear regression analysis to identify predictor variables. Since both methodologies have been shown to provide accurate predictions of construction duration, a comparison between models of each type is warranted. Therefore, this section discusses the steps involved in both linear and multiple linear regression models of construction duration and the assumptions associated with these models. Also discussed are various methods for determining goodness of fit and predictive accuracy. These methodologies will be combined in order to meet the objectives of this research.

Simple Linear Regression Methodology

General Method

Simple linear regression seeks to fit a straight line to a set of data, thereby resulting in a simple linear function of the form (McClave et al., 2000: 458)

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{13}$$

where

y = Dependent or response variable (variable to be modeled),

x = Independent or predictor variable (used as a predictor of y),

ε =- Random error component,

β_0 = Y intercept of the line, and

β_1 = Slope of the line.

Illustrated graphically in Figure 6, β_0 and β_1 can be seen as the y intercept (8.547) and slope (-0.994), respectively, while ε can be seen as the difference between the observed data points and the fitted regression line. This figure provides an illustration of the resulting probabilistic model, made up of both the deterministic portion (illustrated by the straight line) as well as a random error term.

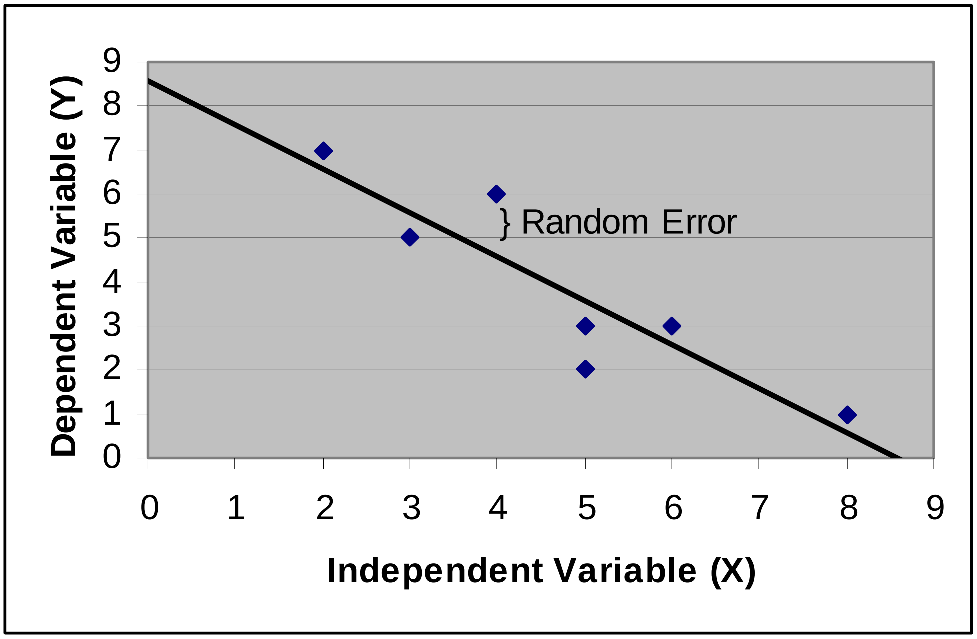


Figure 6. Simple Linear Regression Example Graph

McClave et al. (2000) summarize simple linear regression with the four-step process shown in Figure 7. Each step in this process will be discussed in detail in the following paragraphs.

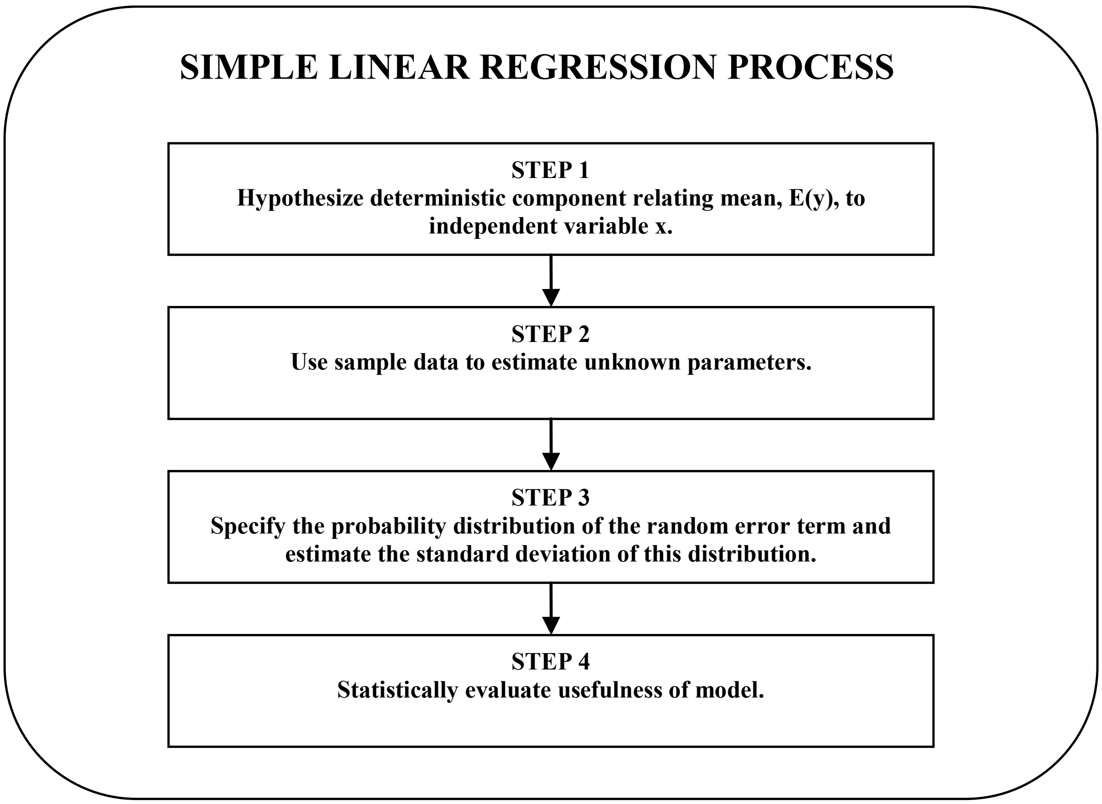


Figure 7. Simple Linear Regression Process (McClave et al., 2000)

Step 1: The first step is to hypothesize a relationship for the deterministic (straight line) portion of the model. In other words, the mean of the dependent variable *y* is hypothesized to be equal to the deterministic portion of the regression equation shown in Equation 13. This is reflected by the equation

$$E(y) = \beta_0 + \beta_1 x \tag{14}$$

At this point, both the slope (β_1) and y intercept (β_0) will be known only if the entire population of (x,y) measurements are known (McClave et al., 2000: 458).

Step 2: This step focuses on estimating the unknown y-intercept and slope terms. This estimation process is accomplished through the method of least squares, a general method of finding estimated (fitted) values of parameters. Estimates are found such that the sum of the squared differences between the fitted values and actual values is as small as possible. The resulting regression line is positioned such that the sum of the squared vertical distances between the observed points and the fitted line, illustrated by the random error term in Figure 6, is minimized (McClave et al., 200: 461). The regression line has the following two properties: 1) the sum of the errors equals 0 and 2) the sum of the squared errors is smaller than any other possible linear model (McClave et al., 2000: 462).

Step 3: This step seeks to specify both a probability distribution and standard deviation for the random component (ε) of the probabilistic model. The following four basic assumptions are required in order to specify the probability distribution (McClave et al., 2000: 473).

1) The mean of the probability distribution of ε is 0.
2) The variance of the probability distribution of ε is constant.
3) The probability distribution of ε is normal.
4) The values of ε for differing values of y are independent.

The variability of the random error ε (as measured by its variance σ^2) has a direct effect on the estimation errors of the model parameters β_0 and β_1. Since σ^2 is generally unknown, its value must be estimated using available data. The best estimate of σ^2 is obtained by dividing the sum of squares of the error (SSE) term discussed above by the number of degrees of freedom (n) associated with the error variance estimate (McClave et al., 2000: 474). The estimated value of σ^2, or s^2, is thus calculated by

$$s^2 = SSE / (n-2) \tag{15}$$

The estimated value of σ is the square root of this number. These two quantities are commonly referred to as the Mean Square Error (MSE) and Root MSE.

Step 4: This step determines the usefulness of the model for predicting the dependent variable y. One measure of model utility tests the null hypothesis that the linear model is not valid for the prediction of y (McClave et al., 2000: 480). This test focuses on the slope β_1 through the following hypotheses.

$$H_o : \beta_1 = 0 \tag{16}$$

$$H_a : \beta_1 \neq 0 \tag{17}$$

This hypothesis test uses the t statistic through either one or two-tailed test. If the calculated t-value falls within the rejection region, the null hypothesis is rejected, indicating that the slope is not equal to 0. The same result can be obtained by using the observed significant level (p-value). A p-value less than the specified significance level, α, leads to the rejection of the null hypothesis (McClave et al., 2000: 481).

Another measure of model utility is to determine how well the proposed model fits the actual data, i.e., determine goodness of fit. For simple linear regression models, goodness of fit is commonly measured using the coefficient of determination (R^2). If all the data points lie on the regression line, R^2 is 1; if there is no direct linear relationship, R^2 is 0 (Chan, 1999: 193).

Simple Linear Regression in Construction Duration Modeling

Multiple research efforts have utilized simple linear regression for the purpose of modeling construction durations. Two slightly different methodologies have been adopted by the research described in Chapter II. The first methodology utilizes the classic simple linear regression approach discussed above. Using a slight variation, the second methodology seeks to partition the available data based on factors thought to have a significant influence on construction duration. This partitioning is used to develop separate simple linear regression models with varying regression coefficients.

The classical simple linear regression approach was first introduced by Bromilow (1969). A detailed explanation of this research may be found in Chapter II. Using a log transformation, Bromilow was successful in modeling construction durations using project cost as the independent variable. This non-partitioned methodology has been further developed and validated by further research conducted by Ireland (1985) and Chan (1999).

Data partitioning was first introduced by Bromilow et al. (1980). This research recognized the distinction between government and private projects, as well as completion year by proposing separate linear regression models for each. This partitioning methodology has been further validated by multiple research efforts to include Kaka and Price (1991), Yeong (1994), Kumaraswamy and Chan (1995), and Ng et al. (2001). These efforts were successful in explaining more of the variability associated with construction durations by partitioning the collected data based on public versus private sector, contractor selection method, type of project, and type of contract. These studies utilized an iterative process in analyzing partitioned data for significant difference in means or variances through analysis of variance (ANOVA) tests (Ng et al., 2001: 169). After identifying significantly different factors, these research efforts produced simple regression models which, when taken as a whole, were successful in explaining a significant amount of the variability associated with construction duration estimation.

The ANOVA test is a commonly accepted method for identifying differences between means (McClave et al., 2000: 825). This test evaluates the null hypothesis that all means are equal as shown in the following equations.

$$H_o : \mu_1 = \mu_2 = \ldots = \mu_n \tag{18}$$

$$H_a : \text{at least two means differ} \tag{19}$$

A p-value less than the pre-selected significance level, α, leads to the rejection of the null hypothesis. If the ANOVA reveals significant differences among the residuals of the pooled data when partitioned by specified subgroups, these subgroups can be assumed to be reasonable partition limits (Ng et al., 2001: 168). If there are differences in groups with more than two sample means, a multiple comparison test may be used to determine which subgroups significantly differ. Three basic assumptions must be satisfied for valid ANOVA results (McClave et. al 2000: 825).

1) The probability distribution of the populations sampled must all be normal.
2) The probability distributions of the populations of responses must have equal variances.
3) The samples selected must be random and independent.

JMP software offers several different tools for comparing means. A comparison circle plots provides a visual representation of the group means. Means comparison circles are illustrated with the confidence intervals of their respective group means for either the Student's t or Tukey HSD (honestly significantly different) comparison. Means diamonds may be used in conjunction with comparison circles as shown in Figure 8.

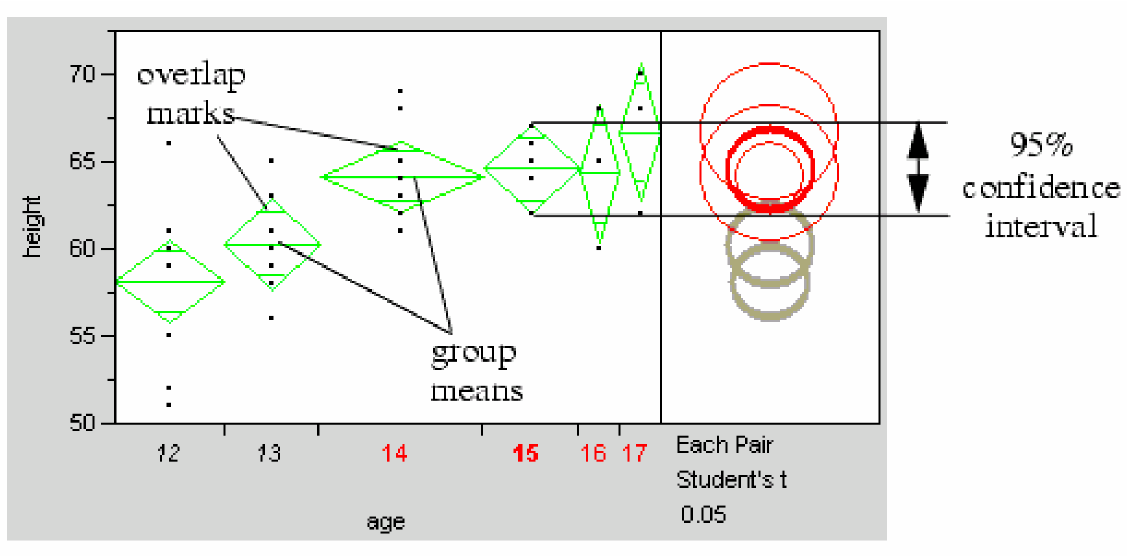


Figure 8. Means Comparison Methods (SAS Institute, 2003)

A means diamond illustrates a sample mean and 95% confidence interval. The line across each diamond represents the group mean. The vertical span of each diamond represents the 95% confidence interval for each group. Overlap marks for each diamond are computed using the group mean +/- the confidence interval. Overlap marks in one diamond that are closer to the mean of another diamond than that diamond's overlap marks indicate that those two groups are not different at the 95% confidence level (SAS Institute, 2003). Means can also be examined visually for differences by examining how the comparison circles intersect. The outside angle of intersection may be used to determine whether group means are significantly different. This relationship is shown in Figure 9. This relationship is also summarized in JMP through use of the connecting lines report. This report shows a letter-coded report where means not sharing a letter are interpreted as significantly different (SAS Institute, 2003).

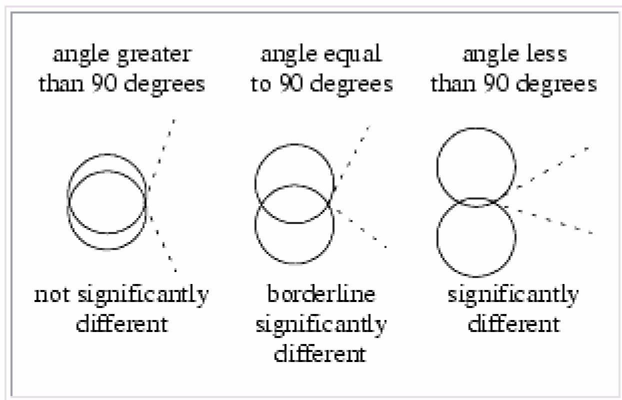


Figure 9. Angle of Intersection Schematic (SAS Institute, 2003)

Multiple Linear Regression Methodology

General Method

Multiple regression models are those which seek to include a combination of multiple independent variables, thereby resulting in a regression model of the form (McClave et al., 2000: 534)

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \qquad (20)$$

where

y = Dependent or response variable (variable to be modeled),

x_1, x_2, x_k = Independent variables,

ε = Random error component, and

β_i = Respective regression coefficients.

McClave et. al (2000) summarize multiple linear regression with the five-step process shown in Figure 10. Each step in this process will be discussed in detail in the following section.

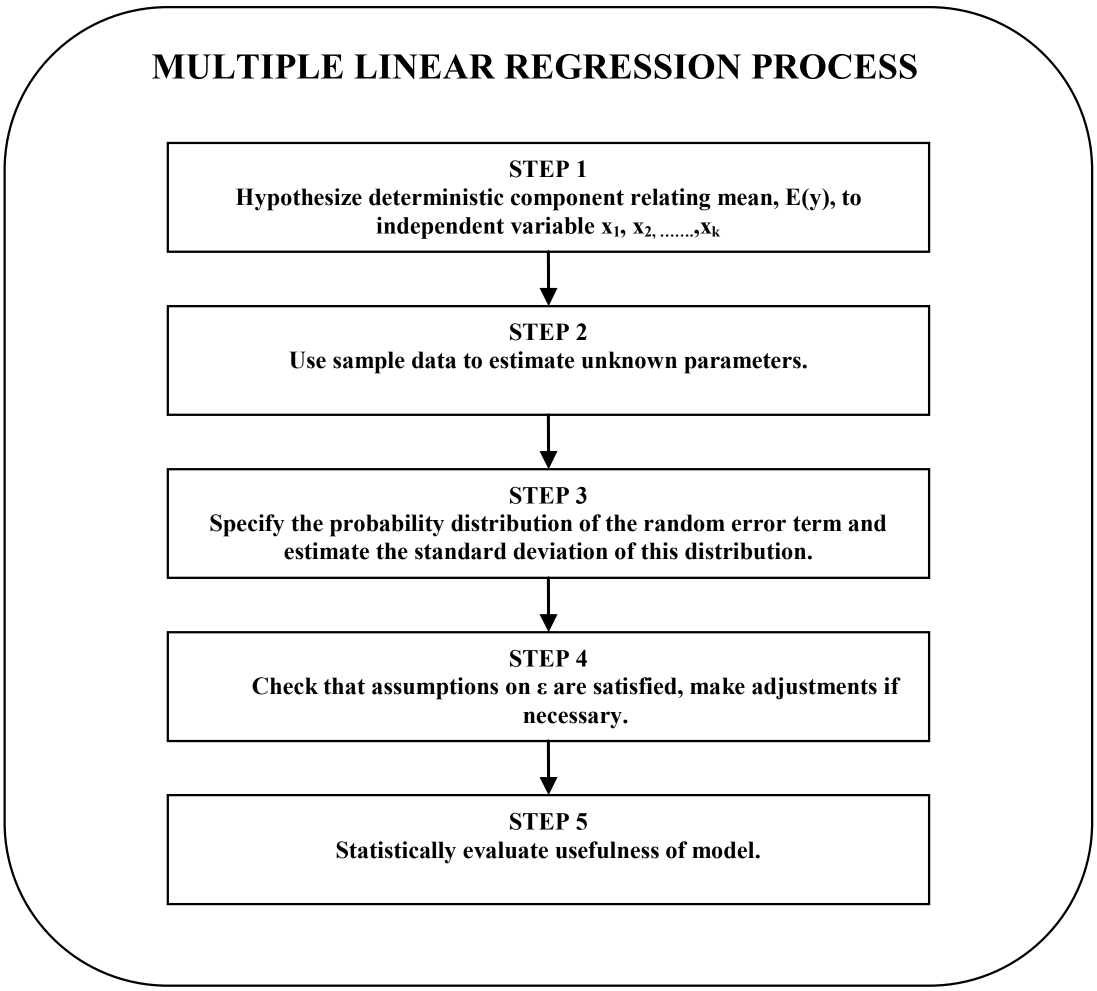


Figure 10. Multiple Linear Regression Process (McClave et al., 2000)

Step 1: This first step involves the selection of which independent variables to include in the model. Depending on the response variable to be modeled, multiple regression models may include a combination of first order terms, higher order terms, coded variables (representing a qualitative variable), and interaction terms (a combination of variables). If the model is to contain qualitative variables, these variables must be coded to allow their inclusion in a prediction model. These coded variables are called dummy variables due to the arbitrary nature of the selection of the numbers assigned to each qualitative variable level (McClave et al., 2000: 594). A typical coding method for these dummy variables involves the use of 0-1 coding. In order to represent a particular level, the dummy variable takes on a value of either 0 or 1. Using this method, the number of dummy variables is always one less than the number of levels the qualitative variable can take on (McClave et al., 2000: 596).

Step 2: This step estimates the unknown regression parameters through the method of least squares. This process is identical to the method described previously for simple linear regression. The primary difference is the difficulty of the numerical solution since multiple linear regression may require solving a large number of simultaneous equations (McClave et al, 2000: 536). The end result of this step is parameter estimates for each β coefficient.

Step 3: This step establishes a probability distribution for the random error term ε in Equation 27 above. As in simple linear regression, since σ^2 is generally unknown, its value must be estimated using available data. The best estimate of σ^2 is obtained by dividing the sum of squares of the error (SSE) term by the difference between the sample size and the number of estimated β parameters $\beta_0, \beta_1, \ldots \beta_k$ (McClave et al., 2000: 543). The estimated value of σ^2, or s^2, is thus calculated by

$$s^2 = SSE / (n-(k+1)) \tag{21}$$

Step 4: This step focuses on the verification of the assumptions regarding the random error term ε as discussed for simple linear regression, as well as recognizing the need for any model adjustments. These model assumptions are most easily verified through residual analysis. To perform this analysis, residuals should be plotted on the vertical axis against the independent variable (x) as well as predicted values. If the random error assumptions are correct, the residuals should be randomly distributed around the 0 line. If a non-random pattern is observed, the random error assumptions may not be justified; this pattern may suggest a need for changes in the model to include additional variables or a transformation of either the independent or dependent variable data. Residual analysis is also useful for identifying outliers, or observations which deviate significantly from the regression model. Extreme outliers may bias the results by influencing the regression line in a particular direction. Approximately 95% of the residual can be expected to lie within 2 standard deviations of the 0 line, and essentially all should lie within 3 standard deviations (McClave et al., 2000: 638).

Step 5: This step seeks to determine the usefulness of the model for predicting the dependent variable y using the same procedure discussed in simple linear regression above. One measure of model utility tests the null hypothesis that the linear model is not valid for the prediction of y (McClave et al., 2000: 480). This test focuses on the slope β_1 through the hypotheses shown in Equations 23 and 24 above. This hypothesis test uses the t statistic with either a one or two-tailed test. If the calculated t-value falls within the rejection region, the null hypothesis is rejected, indicating the slope is not 0 (McClave et al., 2000: 544).

The overall utility of the model must also be verified. While the coefficient of determination (R^2) may provide some indication of goodness of fit, it is valid only if the sample contains substantially more data points than the number of β parameters in the model (McClave et al., 2000: 556). For this reason, R^2 may provide a goodness of fit measure that tends to be too optimistic when multiple linear regression is utilized and may be forced to 1 with the addition of enough β parameters. The adjusted R^2 accounts for this problem by adjusting for both the sample size (n) and the number of β parameters in the model; for this reason, it is the preferred measure of model utility for multiple regression (McClave et al., 2000: 557).

Another useful test for determining overall or "global" model utility is the F test. This test is useful in determining whether any of the β coefficients are useful in predicting the value of the dependent variable y by testing the following hypotheses (McClave et al., 2000: 558)

$$H_o : \beta_1 = \beta_2 = \ldots = \beta_k = 0 \tag{22}$$

$$H_a : \text{At least one } \beta \neq 0 \tag{23}$$

The F test may be used as a first step in determining overall model utility. Once the model utility is verified, one or more t tests can be conducted on the individual β parameters as discussed above.

Multiple Linear Regression in Construction Duration Modeling

The use of multiple linear regression as a tool for modeling construction time has been validated by several studies. This procedure has been recognized as the most widely used statistical procedure for deriving relationships between a large number of independent variables and has been noted as such by multiple studies (Chan and

Kumaraswamy, 1999: 637; Khosrowshahi and Kaka, 1996: 379). Khosrowshahi and Kaka (1996) selected independent variables for inclusion in the regression process based on the perceptions of industry practitioners regarding which variables were seen as likely to be most influential in controlling project durations. This analysis used a multiple linear regression analysis methodology to determine duration estimates for housing projects in the U.K. The results of this research are covered in detail in Chapter II (Khosrowshahi and Kaka, 1996: 379).

Chan and Kumaraswamy (1995) used a multiple linear regression procedure to model construction durations for building projects in Hong Kong. They utilized a stepwise selection procedure with a significance level of 5% to determine which variables should be included in the model. These variables were sequentially added and the regression model re-run; changes to the R^2 value and the significance level of the variables were then observed. Only variables with a *p*-value of less than 5% were included in the final regression equation (Chan and Kumaraswamy, 1995: 637). Skitmore and Ng (2003) used the same methodology to forecast construction durations for Australian construction projects. Independent variables were selected for possible inclusion in the model based on those factors identified as essential variables through previous research (Skitmore and Ng, 2003: 1076).

Hybrid Construction Duration Modeling Methodology

This section explains the hybrid methodology used in the development of a predictive model. As discussed above, differing methodologies have been successful depending on the characteristics of the data to be modeled. This research uses a combination of these existing models to develop a hybrid methodology shown in Figure 11 below. This basic model building process is based on a similar model developed by Cole (2003).

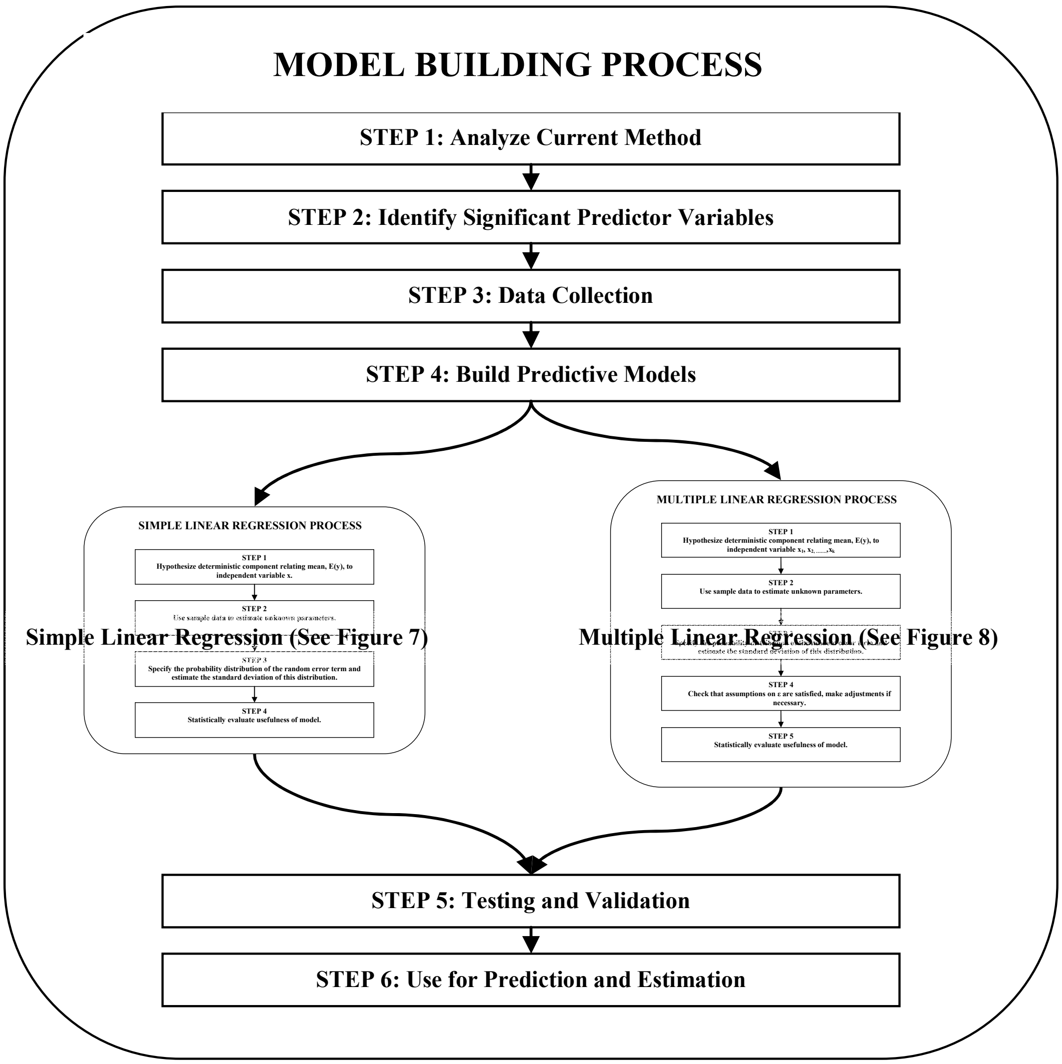


Figure 11: Hybrid Construction Duration Modeling Process

Step 1: The first step in this process is the identification of the need for a model. This need may be identified through a comparison between actual and planned values of construction duration for existing estimation methods. Bromilow (1969) identified the need for an empirical mathematical model for predicting construction duration by noting significant differences between these values which indicated the need for an improved estimation process (Bromilow, 1969: 72).

Since the Air Force currently specifies construction duration limits based on both the "Dirtkicker" criteria and Architect/Engineer (A/E) estimate outlined in Chapter II, the need for an improved model may be identified through a comparison of actual durations with these values. Significant variation from these benchmark goals may indicate the need for a more comprehensive model to predict construction durations in a more accurate manner.

Step 2: Before a model can be developed, predictor variables thought to have a significant influence on the independent variable must be identified. Therefore, Step 2 focuses on determining potentially significant predictor variables for possible inclusion in the final model. These potentially significant variables may be identified either through direct polling of industry professionals (Chan, 1999: 192), through a review of factors identified by previous predictive models (Skitmore and Ng, 2003: 1076), or through the use of intuition and common sense (Chan and Kumaraswamy, 1999: 354).

A discussion of factors identified by previous research was covered in detail in Chapter II. This step seeks to organize this previous research to reach a consensus regarding possible significant factors influencing construction durations for Air Force Military Construction (MILCON) projects. Chan and Kumaraswamy (2002) summarized previous research into the four main categories of Project Scope, Environment, Complexity, and Management Attributes as shown in Figure 4. This model will be used as a tool to guide the selection of Air Force specific factors. The results of this step will facilitate more efficient data collection by focusing only on the selection of those predictor variables thought to significantly affect the response variable (construction duration). The selected variables will be evaluated in the next step as the predictive models are developed.

Step 3: The significant predictor variables identified in Step 2 may now be used to drive the data collection process. This step focuses on data collection from a specified sample population, which for this research is limited to Air Force MILCON projects. While the data for the identified significant factors may come from a variety of data sources, previous research has shown that the selected data are most effective when readily identifiable from project information and directly quantifiable by the contractor (Nkado, 1995).

The Air Force tracks all such project information using the Automated Civil Engineering System-Project Management (ACES-PM) database. This database includes initial planning, cost, contract, design, and environmental data for Air Force projects across every Major Command (MAJCOM); it is required to be relevant and current, reflecting the most current project conditions. This database will serve as the primary source of data for this research. Additional project characteristics which are not contained within this database may be obtained through other sources as either direct or proxy measures.

Step 4: Once data has been collected, the next step is to build a duration prediction model using statistical regression analysis. The predictive models in this step will follow the methodologies presented in Figures 7 and 8 for either simple or multiple linear regression, which are recognized through previous research as the most widely used statistical procedures for deriving relationships between independent and dependent variables (Chan and Kumaraswamy, 1999: 637; Khosrowshahi and Kaka, 1996: 379). The end result of this step should be a number of proposed predictive models which utilize the selected predictor variables to estimate values of the independent variable.

Step 5: Once various predictive models have been proposed, the results of each must be evaluated in order to select the most appropriate model. The selected model must then be evaluated to ensure accuracy and validity. While this step has been recognized as a crucial step in regression modeling (McClave et al., 507), measuring predictive ability through *a priori* testing has not been a focus of many previous research efforts for construction duration estimation (Kenley, 2001: 759). The most common method of measuring predictive accuracy is to set aside a portion of the original data to use during the testing and validation phase. Since historical data is used, the actual construction durations are known, allowing the predictive model(s) to be tested to ensure the estimated construction durations are close to the actual recorded duration. If estimated values are used in the final model, sensitivity analysis may be necessary. For example, if the prediction of actual construction time is based on an estimated cost, it is necessary to examine how sensitive the prediction models are when the actual construction cost varies from this estimate (Skitmore and Ng, 2003: 1080).

Step 6: The last step is to use the model for the intended purpose of prediction. If the selected model proves to be valid through Step 5, this predictive model may be successful in providing the Air Force with a justifiable and repeatable process for estimating construction duration times. The resulting model may be useful for making predictions at the installation or MAJCOM level, and as a policy setting tool at the Air Force level.

IV. Research Results

Introduction

This chapter details the steps in the development of a predictive model of construction duration for Air Force Military Construction (MILCON) projects. The steps to retrieve data from the Automated Civil Engineering System-Project Management (ACES-PM) database and additional data sources are explained. The steps to analyze the data are then discussed, using the six-step methodology covered in the previous chapter to develop two separate duration prediction models. Finally, this chapter discusses the steps taken to select the most appropriate model for use in predicting construction durations for Air Force MILCON projects.

Step 1: Analyze Current Method

This step evaluated the effectiveness of current Air Force processes to both benchmark and predict construction durations for MILCON projects. As discussed in Chapter II, the Air Force currently establishes benchmarks for acceptable construction duration times through the "Dirtkicker" award limits. Construction durations are specified prior to contract award, usually in the form of an estimate completed by the Architect/Engineer (A/E) and verified by the design agent. This step evaluated the effectiveness of both the current "Dirtkicker" criteria and design agent duration estimates in terms of recently completed Air Force MILCON projects.

To evaluate the current "Dirtkicker" award limits, 332 projects with construction midpoint dates ranging from 2001 to the present were selected for analysis. All projects costs were normalized to 2004 dollars by using the Building Cost Index (McGraw Hill Construction, 2004), which will be discussed in detail in subsequent sections. Of these projects, 94 (28%) fell within the specified "Dirtkicker" benchmark limits based on total project cost. The remaining 238 (72%) failed to meet the "Dirtkicker" benchmark goals. While this analysis provided a relative indication of the projects meeting Air Force goals, additional analysis was required to determine the extent to which the benchmark goals were either met or exceeded. This was accomplished by calculating the total percentage of projects falling under or over the limits by a specified number of months. The results of this analysis are shown in Table 10. Only 18% of projects fall within two months of the specified duration criteria (9% under and 9% over), and 38% exceed the limits by more than 4 months.

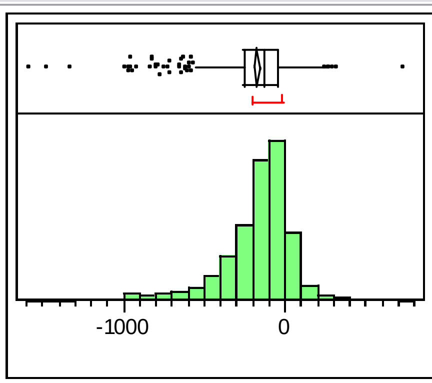
Table 10. "Dirtkicker" Benchmark Limits Analysis

	Months Under/Over	Total Projects	% of Total Projects	Cumulative %	Decumulative %
Months Under	12+	1	0%	0%	100%
	6-12	21	6%	7%	93%
	4-6	14	4%	11%	89%
	2-4	28	8%	19%	81%
	0-2	30	9%	28%	72%
Months Over	0-2	30	9%	37%	63%
	2-4	51	15%	53%	47%
	4-6	34	10%	63%	37%
	6-12	65	20%	83%	17%
	12+	58	17%	100%	0%

Another indication of the accuracy of current Air Force MILCON project duration estimates may be determined by examining the accuracy of the planner's estimate for completed projects. For this analysis, 575 projects were selected, and comparisons were conducted between the planner's duration estimate (defined as the original performance period on the contract) and the actual duration as determined by the beneficial occupancy date. The difference between the planner's estimate and actual duration was calculated for each project, with the distribution of this difference being shown in Figure 12. As shown in this figure, the planner's estimate is between 1573 days under to 750 days over the actual construction duration. The mean is 167 days under actual completion times, with a standard deviation of 224. These results indicate that many of the planned duration estimates fail to predict actual performance, and consistently underestimate construction durations.

Distributions

Planned-Actual



Quantiles

100.0%	maximum	750
99.5%		312
97.5%		166
90.0%		35
75.0%	quartile	-41
50.0%	median	-123
25.0%	quartile	-237
10.0%		-427
2.5%		-782
0.5%		-1331
0.0%	minimum	-1573

Moments

Mean	-167.1005
Std Dev	223.89074
Std Err Mean	9.3368894
upper 95% Mean	-148.7619
lower 95% Mean	-185.4391
N	575

Figure 12. Planned – Actual Duration Distribution

Clearly, a large number of projects are falling outside both the benchmark goals established by the "Dirtkicker" criteria and the duration estimate specified during the planning phase. These results indicate that the realities of construction duration for Air Force MILCON projects are well removed from the expectation, both in terms of "Dirtkicker" criteria and planner established estimates. Since the "Dirtkicker" criteria are designed to recognize superior performance, it is difficult to examine the overall validity of these limits; however, it appears that a majority (72%) of current projects are failing to meet these benchmark limits. Additionally, it is not possible to examine the inputs to the planning estimate as they may be based on a variety of factors not included within the ACES-PM database. This makes a complete analysis of the planning estimate difficult. Despite this, it is reasonable to assume that additional factors may be causing at least a portion of the variability in duration estimates.

Step 2: Identify Significant Predictor Variables

Various factors have been identified through the literature review as having a significant influence on the duration of construction projects. Therefore, this section focuses on those factors that can be used in the development of a predictive model for Air Force MILCON projects. This analysis does not seek to include all relevant factors in a predictive model, but rather identify the most important factors for which data collection is feasible.

As discussed in Chapter II, Chan and Kumaraswamy (2002) have provided the most comprehensive model of duration-influencing factors to date (see Figure 4). Since the current research focuses on the establishment of duration estimates early in the planning process, factors must be easily identifiable. For the Air Force MILCON process, this means that selected factors must be available during the planning, programming or early design phases as discussed in Chapter II. Using this guidance, factors identified through previous research were selected which can be expected to influence construction durations for Air Force MILCON projects. These factors, shown in Table 11, were divided into the categories previously developed by Chan and Kumaraswamy (2002).

Table 11. Summary of Factors

Factor	Definition	Category (Chan and Kumaraswamy, 2002)
Design/Construction Agent	Agency responsible for construction management	Management Attributes
Design Type	Method used for project design	Management Attributes
Complexity	Project buildability	Project Complexity
Weather	Weatehr during project construction	Project Complexity
Location	Physical location of construction project	Project Environment
Economic Conditions	Economic conditions at time of project construction	Project Environment
Materials Availability	Availability of materials needed for construction	Project Environment
Price	Total cost of completed project	Project Scope
Execution/Design Method	Method of contractual arrangements	Project Scope
Type Work	Type of work associated with majority of project	Project Scope
Changes	Changes introduced after initial design	Project Scope
Facility Type	Primary functional use of completed facility	Project Scope

As expected, many of the identified factors fall within the project scope or project environment category. Factors in these categories should be readily identifiable during or before the design phase of the project. For instance, the location, price, execution/design method, type work, and facility type are all determined or estimated during the planning or early design phase. The remaining scope and environment factors in these categories (economic conditions, materials availability, and changes) may be possible to determine using historical data or through interaction with individual project managers.

Management-related and design quality issues are largely excluded because they are particularly hard to model, and even more difficult to predict using preliminary project information. Management and complexity related factors that can be determined or reasonably forecasted during the design or programming phase were included. The design/construction agent, design type, and some measure of project complexity should be known early enough to include these factors in the prediction model. Weather effects may be possible to model using historical data for the project region. Limiting the model to the selected factors above should allow planners to utilize the model before contract award. Additionally, a model using these factors may be used after construction completion to measure performance in the same manner as the current "Dirtkicker" criteria.

Step 3: Data Collection

While the factors selected above are likely to be significant based on previous research, their inclusion in the model-building process may be limited by the availability of Air Force MILCON project data. Therefore, this section discusses the steps to identify data which may serve as either a direct or proxy measure for the factors.

ACES-PM Data Collection

The majority of the data for this research was taken from the ACES-PM database. ACES-PM was implemented in 2001 for the programming, design, and construction management of Air Force projects (AFCESA, 2003:18). Most data is contained within specified tabs sorted by various categories to include Programming, Facility Investment Metric (FIM), Environmental, Design, Contract Management, and Funding. Oracle software was utilized to retrieve and analyze data of interest within the database. The fields shown in Appendix A were queried for all completed MILCON projects and sorted by specified tabs. These fields were selected for use as either predictor variables or in screening data for later use. After an initial analysis of the selected data, it was clear that certain data fields contained incomplete, missing, or inaccurate information. Therefore, many of the queried data fields were deleted from this analysis. Table 12 provides an explanation for each selected or filtered data field.

Additional Data Collection

Additional factors were identified for possible inclusion in the final model through other sources, many times through further development of the categorizations identified through the ACES-PM data above. These additional factors included Major Command (MAJCOM) size, Army Corps of Engineers (COE) regions, facility category, year of construction, weather effects, and economic influences. The collection procedures for each of these factors are described below.

MAJCOM Size: MAJCOM size was determined by comparing the ACES-PM MAJCOM field with the MAJCOM size categorization provided by the "Dirtkicker" award criteria. These categorizations are shown in Table 13.

Table 12. ACES-PM Data Field Selection

Tab	Field Title	Kept/Eliminated	Explanation
General	Project Title	Kept	Used to differentiate projects, not used for analysis
	Fiscal Year	Eliminated	Did not always represent fiscal year of actual project construction
	Installation	Kept	Used to differentiate project locations
	Type	Kept	Used to screen MILCON projects, not used for analysis
Programming	MAJCOM	Kept	Used as a possible predictor variable
	Programmed Amount	Kept	Used for analysis of final model
	Status	Kept	Used to screen for completed projects
	Category Code	Kept	Used as a possible predictor variable
	IRR Facility Class	Kept	Used as a possible predictor variable
	Scope	Eliminated	Not consistently completed
	Unit of Measure	Eliminated	Not consistently completed
	Type Work	Kept	Used as a possible predictor variable
Supplemental	Design Agent	Kept	Used as a possible predictor variable (along with Construction Agent)
	Construction Agent	Kept	Used as a possible predictor variable (along with Design Agent)
Design	Project Delivery Method	Kept	Used as a possible predictor variable
	Designer/ A-E Firm	Eliminated	Not consistently completed
	Method of Design	Kept	Used as a possible predictor variable
Contract Management	Method of Contract	Eliminated	Not consistently completed
	Construction Method	Eliminated	Not consistently completed
	Number of Modifications	Eliminated	Not consistently completed
	Notice to Proceed	Kept	Used to determine actual construction duration
	Contract Days	Eliminated	Not consistently completed
	Project Contract Total Cost	Kept	Used as a possible predictor variable
	Modified Days	Eliminated	Not consistently completed
	Total Days	Eliminated	Not consistently completed
	Cost of Contract Mods	Eliminated	Not consistently completed
Milestones	Design Start Actual	Eliminated	Not consistently completed
	Design Complete Actual	Eliminated	Not consistently completed
	Construction Start Estimated	Eliminated	Not consistently completed
	Beneficial Occupancy Estimated	Eliminated	Not consistently completed
	Beneficial Occupancy Actual	Kept	Used to determine actual construction duration

Table 13: MAJCOM Size Categories (Department of the Air Force, 2003)

Large MAJCOM	Small MAJCOM
ACC	11 WG
AETC	AFSOC
AFMC	USAFA
AFSPC	AFRC
AMC	
PACAF	
USAFE	

<u>COE Region</u>: Projects were assigned to COE regions by deferring to map shown in Figure 13 (USACOE, 2003). COE regions which contain significantly different project durations may be selected as variables for inclusion in the final model.

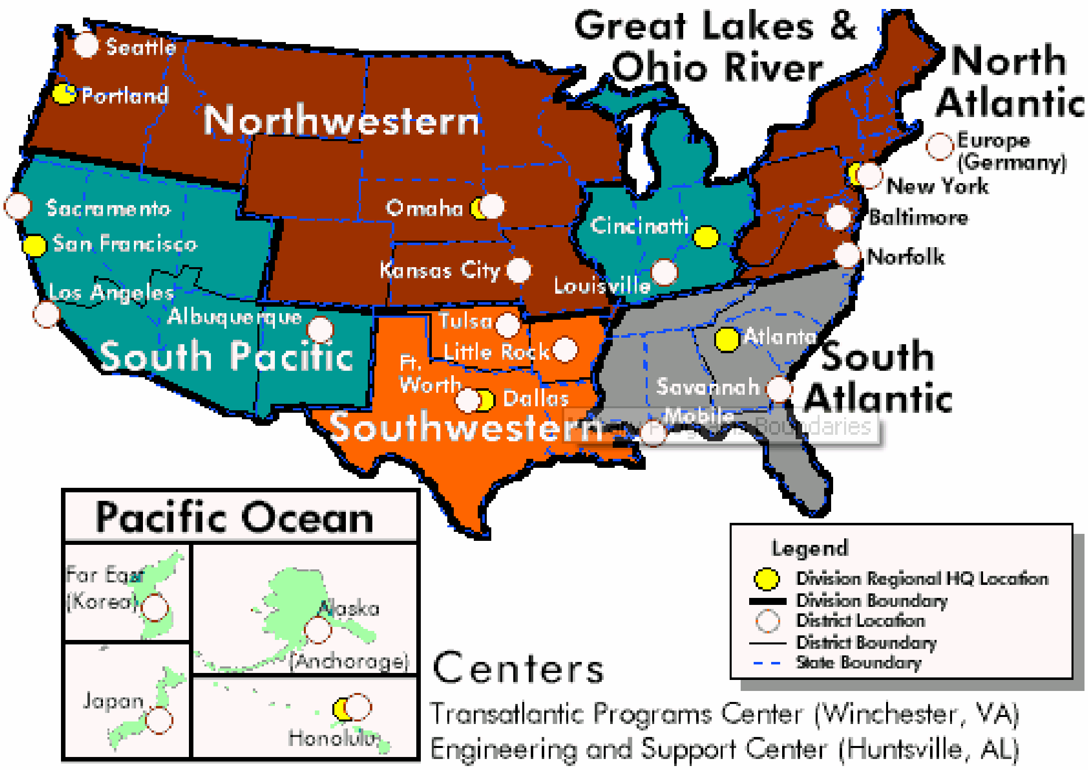


Figure13. U.S. Army COE Military Districts (USACOE, 2003)

Facility Categories: Facility types were further subdivided using the Air Force facility category code field contained within ACES-PM. This factor was included in order to identify possible differences in construction durations among facility types. For category code classifications, the first two digits of the category code were used to determine the category group (Department of the Air Force, 1996: 259). The most significant facility classifications (if any) will be selected for inclusion in the final model.

Year of Construction: The construction midpoint was calculated as the midpoint between the notice to proceed and beneficial occupancy data contained in ACES-PM. This date was used to determine the year of construction for each project. This factor was included to identify any significant differences which may occur between differing construction years.

Weather Effects: Three different weather data types were investigated for possible inclusion in the model. The mean daily minimum temperature, mean annual rainfall, and mean annual days of rainfall were collected for each installation location through the World Metrological Organization (2004). Definitions for each weather data factor are given below.

- Mean Daily Minimum Temperature: Average of daily minimum temperature (degrees C) over a yearly period.
- Mean Annual Rainfall: Average yearly rainfall (mm).
- Mean Number of Precipitation Days: Mean number of days with at least 1 mm of precipitation (precipitation includes both rain and snow).

The data were based on the climatologically averages for a 30-year time period at each project location specified by the installation field within ACES-PM. When data for exact installation locations were not available, the weather data for the next closest city was selected.

Economic Indicator: Labor supply, defined as the number of workers able to work at a give time in a given occupation or industry, is commonly viewed as an important influence on productivity regardless of industry (Baumol and Blinder, 1985: 676). Because labor productivity can be directly related to construction speed, labor supply was considered a possible factor influencing construction durations. To provide a measure of labor supply, total full time and part time employment for the construction industry were collected from the Bureau of Economic Analysis (BEA). Employment can be measured either as a count of workers, where each employed worker is counted only once, or as a count of jobs, where all jobs held by the worker are counted (Bureau of Economic Analysis, 2004). The BEA reports the number of jobs for specific industries through the Regional Economic Indicator System; it reports employment and income data for the construction industry, at the county level, from 1969 to the present. Total construction industry full time and part time employment numbers were collected for each county containing an Air Force installation. Due to the difficultly in obtaining equivalent economic data for overseas projects, these project types were not included in the analysis. Therefore, economic conditions will only be investigated as a possible predictor variable for projects completed within the United States.

Data Formatting

Once data collection was complete, much of the data required manipulation in order to be included in a predictive model; therefore, this section discusses the steps to format the following raw data.

Construction Duration: The independent variable used for this analysis was the total construction duration in days. The Air Force defines construction duration as the time between the Notice to Proceed and Beneficial Occupancy dates in calendar days. This variable was calculated as the difference between the beneficial occupancy and notice to proceed fields contained in the ACES-PM database.

Project Cost: The total cost of each selected project was measured using the contract total cost as contained in the ACES-PM database. Previous research has identified the importance of normalizing construction costs across multiple years through the use of cost indices (Bromilow, 1969; Khosrowshahi and Kaka, 1996; Ng et al., 2001). All projects costs were subsequently normalized to 2004 dollars by using the Building Cost Index published in *Engineering News Record*. The Building Cost Index contains both materials and labor components based on the price and labor data for 20 United States cities (McGraw Hill Construction, 2004). While not directly applicable outside the United States, these same values were applied to overseas projects using the assumption that errors introduced by this universal application would be negligible.

Construction Year: Construction years were divided into three-year increments based on the midpoint date of construction. Six year groupings were used to divide projects within these three-year increments beginning with 1988.

Weather Effects: Temperature effects were divided into three categories based on average annual minimum temperatures. Quartile limits were used to roughly determine break points, with the upper 25% of temperatures representing high, lower 25% representing low, and the remaining 50% representing medium temperature levels. This same process was used to determine categorizations for precipitation levels and rain days.

These categorical values were used to determine differences using the analysis of variance (ANOVA) tests; however, continuous values were used for multiple linear regression analysis.

Economic Conditions: To provide a measure of the possible influence of labor supply on the construction industry, the concept of labor supply elasticity was utilized. For this research, labor elasticity is defined as the percentage change in the quantity of available labor within the construction industry with respect to the available labor supply in the previous year. Mathematically, labor supply elasticity measures the extent to which a labor supply is able to respond to changes in demand; i.e., high labor elasticity equates to a large quantity of available workers, which could be expected to result in decreased construction durations. Labor supply elasticity values were calculated for each year at the county level using the labor supply data collected from the BEA. Quartile limits were used to roughly determine break points for categorizations, with the upper 25% representing high, lower 25% representing low, and the remaining 50% representing medium labor elasticity levels. Continuous values for labor supply elasticity will be used for multiple linear regression analysis.

Summary of Selected Factors

The factors discussed above were investigated for possible inclusion in the selected regression model. Table 14 provides a summary of these factors, and Figure 14 shows these factors in relation to the construction duration model developed by Chan and Kumaraswamy (2002). It is important to note that the link between model factors and possible influences on construction duration for which data is collected is notional; it does not provide an explanation of all possible influences within an individual factor.

For example, COE regions are presented as indicator of regional variability; however, differences between COE regions could also indicate a difference in management attributes between regions. Therefore, the COE region could be used to represent management attributes instead of regional variability. Thus, a direct definitive tie to an influence behind each factor may not be possible.

Step 4: Build Predictive Models

This section discusses the steps to apply both the Bromilow Time Cost (BTC) and Multiple Linear Regression (MLR) models to the collected project data. For the BTC model, this analysis also included steps to identify significant factors influencing construction durations. Once identified, these factors were used to apply the BTC model to partitioned data sets. Both the BTC and MLR were developed using the following assumptions, which must be verified in order for valid regression results.

1) The mean of the probability distribution of ε is 0.
2) The variance of the probability distribution of ε is constant.
3) The probability distribution of ε is normal.
4) The values of ε for differing values of y are independent.

The resulting models were then compared to determine the most appropriate one for the data set.

Table 14. Independent Variables for BTC Model

Factor	Measure	Categories
Total Cost	Project Contract Total Cost	None
Project Delivery Method	Project Delivery Method	Traditional
		Design Build
		Other
Location	COE Region	Northwestern
		South Pacific
		Southwestern
		Great Lakes and Ohio River
		North Atlantic
		South Atlantic
		Pacific Ocean
		Other Overseas
Type Work	Type Work	New Construction
		Addition/Alteration
Design Method	Design Method	In-House
		AE
		Other
Design/Construction Agent	Design/Construction Agent	COE
		NAVFAC
		In-House
Facility Class	Air Force Category Code	11 - Airfield Pavements
		12 - Petroleum Dispensing and Operating Facilities
		13 - Communication, Nav Aids, and Airfield Lighting
		14 - Land Operations Facilities
		17 - Training Facilities
		21 - Maintenance Facilities
		41 - Liquid Fuel Storage
		42 - Explosives Facilities
		44, 45 - Storage Facilities
		5X, 442 - Medical and Medical Support
		61 - Administrative Facilities
		72 - Dormitories, Officer Quarters, and Dining Halls
		73 - Personnel Support
		74 - Morale, Welfare and Recreation - Indoors
		75 - Services - Outdoors
		81 - Electricity
		82, 83, 84 - Heat, Sewage, and Water
		85, 86 - Roadway Facilities, Railroad Trackage
		87 - Ground Improvement Structures
		31 - Research and Development Facilities
		88, 89 - Fire and Other Alarm Systems, Miscellaneous Utilities
MAJCOM	MAJCOM	11 WG
		ACC
		AETC
		AFMC
		AFRC
		AFSOC
		AFSPC
		AMC
		PACAF
		USAFA
		USAFE
MAJCOM Size	MAJCOM Size	Small
		Large
Construction Year	Midpoint Construction Year	1988 and less
		1989-1991
		1992-1994
		1995-1997
		1998-2000
		2000 and greater
Weather: Temperature	Average Annual Minimum Temperature	Low
		Medium
		High
Weather: Precipitation Level	Average Yearly Precipitation	Low
		Medium
		High
Weather: Rain Days	Average Rain Days	Low
		Medium
		High
Economic Conditions	Labor Elasticity Level	Low
		Medium
		High

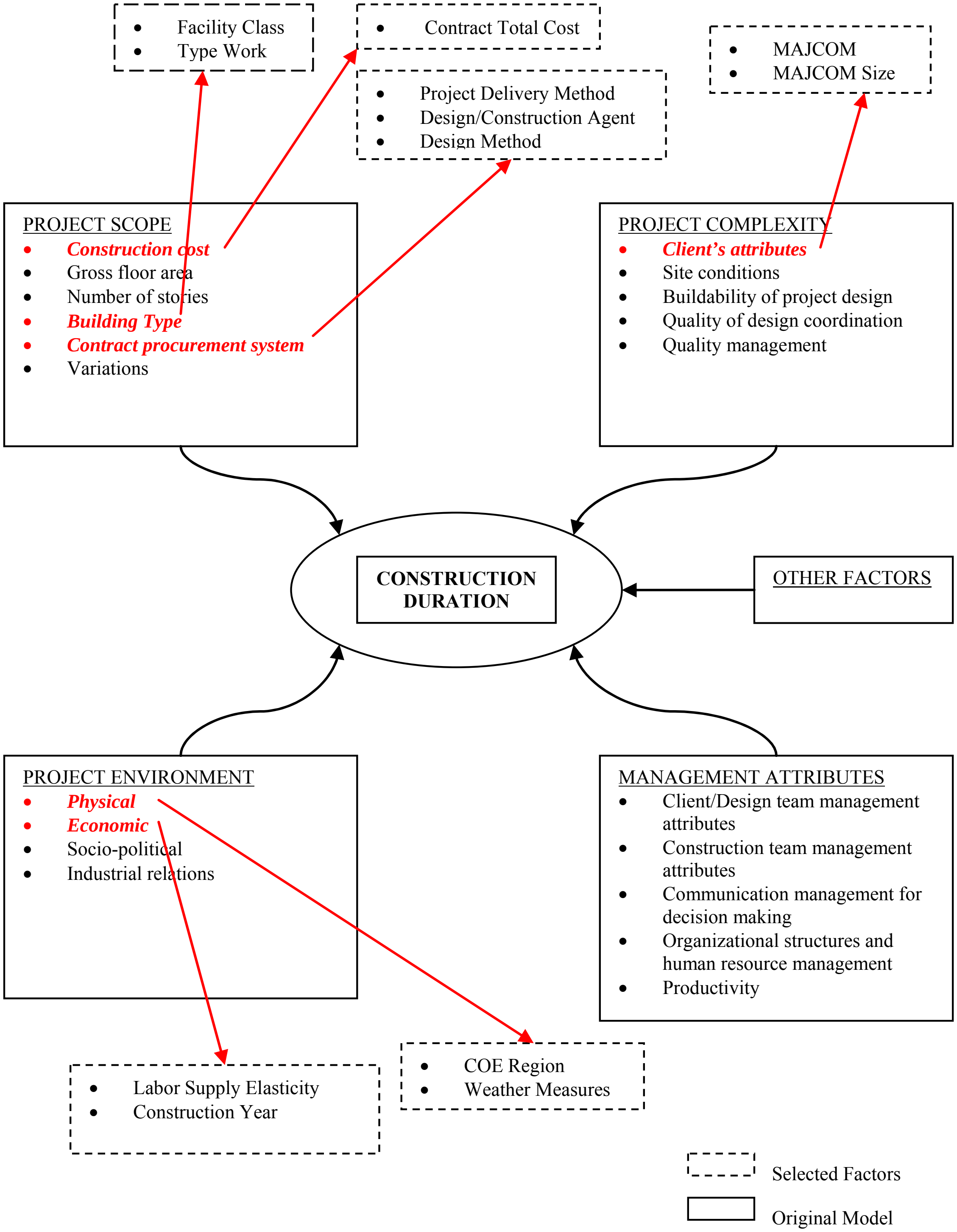
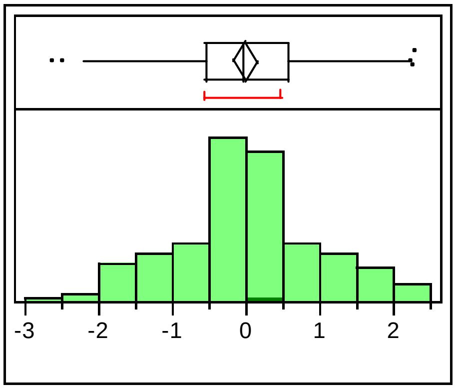


Figure 14. Selected Factors Model Summary

BTC Model Preparations

As discussed in Chapter II, the BTC model has typically been applied to a homogenous set of construction projects. The Air Force MILCON program presents a problem in that it contains a wide variety of projects ranging from utilities and pavements to facility renovation and new construction. Before the BTC model was applied, steps were taken to limit a portion of this variability. Projects were first divided into two major classifications: facility and non-facility projects. Facility projects included all work on traditional building structures. Non-facility projects included all pavements, utilities, liquid fuels storage, and pipeline projects. This initial segregation resulted in 616 facility projects and 129 non-facility projects. The BTC model was then applied to all projects in each category. Before presenting the resulting models though, the categories were screened for influential cases (i.e. outliers). This was accomplished by examining the studentized residuals in a manner similar to that used by Chan and Kumaraswamy (1999). The resulting studentized residual distributions for the non-facility and facility projects are shown in Figures 15 and 16, respectively. For non-facility projects, seven projects were identified as outliers and removed, leaving a sample size of 122. For facility projects, 36 projects were identified as outliers, leaving a sample size of 580.

Studentized Resid Ln Duration



Quantiles

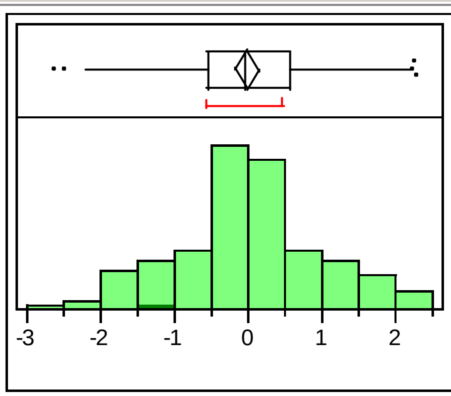
100.0%	maximum	2.321
99.5%		2.321
97.5%		2.256
90.0%		1.428
75.0%	quartile	0.582
50.0%	median	-0.040
25.0%	quartile	-0.527
10.0%		-1.330
2.5%		-2.086
0.5%		-2.596
0.0%	minimum	-2.596

Moments

Mean	0.0002255
Std Dev	1.0039568
Std Err Mean	0.0883935
upper 95% Mean	0.1751271
lower 95% Mean	-0.174676
N	129

Figure 15. Studentized Residual Distribution for Non-Facility Projects

Studentized Resid Ln Duration



Quantiles

100.0%	maximum	2.321
99.5%		2.321
97.5%		2.256
90.0%		1.428
75.0%	quartile	0.582
50.0%	median	-0.040
25.0%	quartile	-0.527
10.0%		-1.330
2.5%		-2.086
0.5%		-2.596
0.0%	minimum	-2.596

Moments

Mean	0.0002255
Std Dev	1.0039568
Std Err Mean	0.0883935
upper 95% Mean	0.1751271
lower 95% Mean	-0.174676
N	129

Figure 16. Studentized Residual Distribution for Facility Projects

BTC Model Results for Non-Facility Projects

The simple linear regression results for non-facility projects using are shown below in Figure 17 and represented by the following equation.

$$y = 4.25 + 0.134x_1 \tag{24}$$

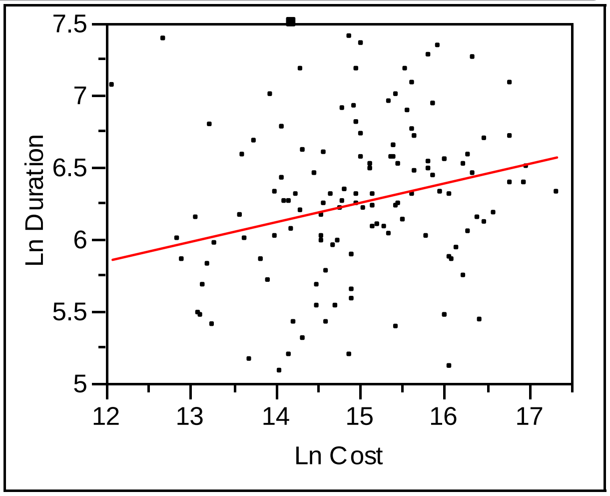
where

y = Project construction duration (ln days), and

x_1 = Project total cost (ln \$).

The overall model is significant at the conventional 5% significance level ($F = 8.975$, $p = 0.003$); however, the model explains little of the variability within this project group ($R^2 = 0.070$). The estimated regression coefficients for the slope and intercept terms are both significant ($p < 0.001$ and 0.003, respectively). These results indicate that while the model is significant, there is a large amount of variability in these types of projects that is not explained by the overall regression model; therefore the model was not considered to be effective as a prediction tool. Partitioning of the data was investigated to determine possible sources of this variability.

Regression Plot



Summary of Fit

RSquare	0.069586
RSquare Adj	0.061832
Root Mean Square Error	0.512383
Mean of Response	6.262238
Observations (or Sum Wgts)	122

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	2.356210	2.35621	8.9748
Error	120	31.504368	0.26254	Prob > F
C. Total	121	33.860578		0.0033

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	4.2482086	0.673884	6.30	<.0001
Ln Cost	0.1341835	0.044791	3.00	0.0033

Figure 17. BTC Model Results for Non-Facility Projects

BTC Model Results for Facility Projects

The simple linear regression results for facility projects are shown in Figure 18 and represented by the following equation.

$$y = 3.29 + 0.202x_1 \tag{25}$$

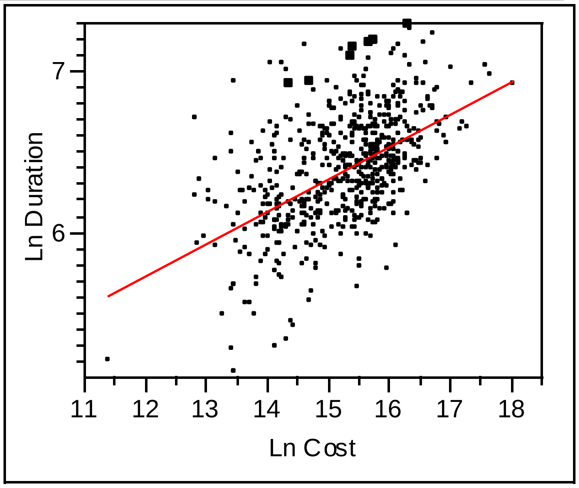
where

y = Project construction duration (ln days), and

x_1 = Project total cost (ln \$).

The overall model is significant at the conventional 5% significance level ($F = 295$, $p < 0.0001$) and explains a moderate portion of the variability within the data ($R^2 = 0.338$). The estimated regression coefficients for the slope and intercept terms are both significant ($p < 0.0001$). While these results suggest a significant relationship between variables, the majority of the variability among projects is not explained by the model. This result is not unexpected for the data as the projects vary widely in location, building type, and a variety of other factors. Partitioning of the data may be successful in explaining larger portions of this variability.

Regression Plot



Summary of Fit

RSquare	0.337942
RSquare Adj	0.336797
Root Mean Square Error	0.254114
Mean of Response	6.384217
Observations (or Sum Wgts)	580

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	19.051554	19.0516	295.0356
Error	578	37.323631	0.0646	Prob > F
C. Total	579	56.375185		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.2893727	0.180487	18.23	<.0001
Ln Cost	0.2020136	0.011761	17.18	<.0001

Figure 18. BTC Model Results for Facility Projects

Data Partitioning

Both the non-facility and facility data above seem to be influenced by additional variability which is not explained within the BTC models. Partitioning the data and re-applying the BTC relationship may explain larger portions of this variability. Analyzing the residuals of the pooled above may reveal some of the significant factors influencing construction durations. As discussed in Chapter III, the ANOVA test is a commonly accepted method for identifying differences between means. If the ANOVA reveals significant differences among the residuals of the pooled data when partitioned by specified subgroups, these subgroups will be assumed to be reasonable partition limits.

Partitioned BTC Model Results for Non-Facility Projects

This section discusses the steps to identify significant factors in addition to cost which may influence construction durations for non-facility Air Force MILCON projects. The significant factors were used to develop multiple BTC models using the partitioned data sets. To determine potential significant factors, the residuals of the pooled data were analyzed for each possible factor, with the exception of project cost, listed in Table 14. The ANOVA results for the Facility Class are shown in Figure 19. The resulting *p* value is 0.133; therefore, the null hypothesis could not be rejected, indicating that there were not significant differences between duration residuals in terms of facility type.

Analysis of Variance

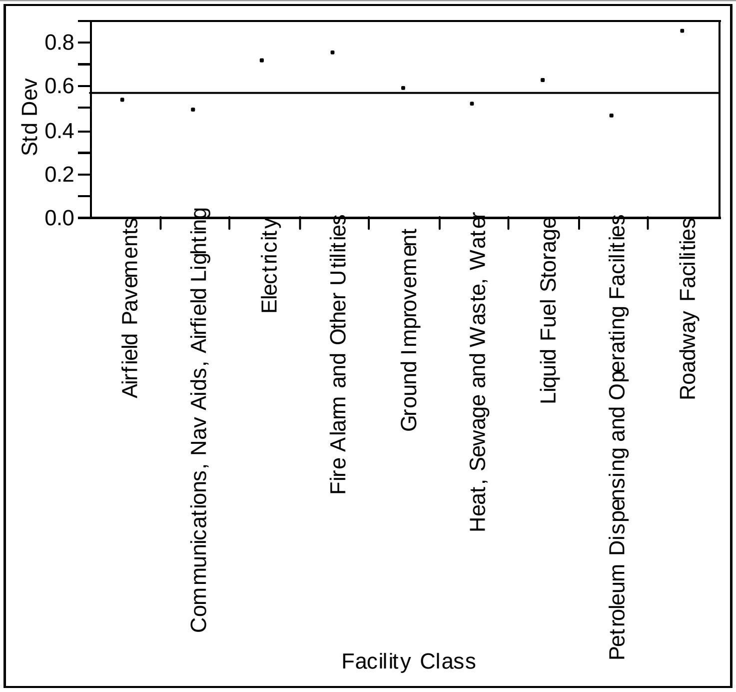
Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Facility Type	8	3.204242	0.400530	1.5993	0.1327
Error	113	28.300126	0.250444		
C. Total	121	31.504368			

Figure 19. ANOVA Results for Facility Type

To ensure the validity of the ANOVA results, the three basic assumptions were tested. The normal assumption was verified through the Shapiro-Wilks W test. This test indicated no evidence against a normally distributed population ($W = 0.988$, $p = 0.365$). The equal variance assumption was verified using Levene's test, with the results being shown in Figure 20. A p-value less than the conventional 0.05 indicates sufficient evidence to reject the null hypothesis and assume the variances are not equal. In this case, the p-value of 0.194 indicates that the constant variance assumption cannot be disproved. When non-constant variances are detected, the Welch ANOVA test for non-constant variances must be utilized to determine significant differences in the means. This test is interpreted in the same manner as the ANOVA analysis detailed above.

The ANOVA analysis was repeated for each possible factor as shown in Appendix B, with the results being summarized in Table 15. All p-values for the selected factors were above 0.05, indicating that these factors did not appear to influence construction durations for non-facility projects. Therefore, further partitioning of the data based on these factors would not be successful in explaining additional variability.

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Airfield Pavements	39	0.5222764	0.4031338	0.4032193
Communications, Nav Aids, Airfield Lighting	3	0.4844825	0.3532354	0.4203776
Electricity	8	0.7021053	0.5274397	0.5221014
Fire Alarm and Other Utilities	4	0.7441363	0.6253295	0.6253295
Ground Improvement	10	0.5812859	0.3831958	0.3454650
Heat, Sewage and Waste, Water	42	0.5046980	0.3893304	0.3885021
Liquid Fuel Storage	6	0.6151459	0.5215222	0.5215222
Petroleum Dispensing and Operating Facilities	7	0.4555025	0.3245745	0.3302413
Roadway Facilities	10	0.8429454	0.7069619	0.7069619

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	1.4118	8	120	0.1983
Brown-Forsythe	1.3778	8	120	0.2130
Levene	1.4223	8	120	0.1940
Bartlett	0.8449	8	.	0.5628

Warning: Small sample sizes. Use Caution.

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
1.7121	8	18.069	0.1632

Figure 20. Equal Variance Test for Facility Type

Table 15. ANOVA Results for Non-Facility Projects

Factor	ANOVA F	df	p	Levenes' test p	Welch ANOVA F	p
Facility Class	1.60	8, 113	0.133	0.090	-	-
Type Work	0.44	1, 120	0.506	0.793	-	-
MAJCOM	1.45	8, 113	0.185	0.287	-	-
MAJCOM Size	1.32	1, 120	0.253	0.134	-	-
COE Region	1.31	7, 114	0.253	0.380	-	-
Design/Construction Agent	0.28	2, 119	0.754	0.623	-	-
Project Delivery Method	1.78	2, 119	0.173	0.546	-	-
Design Method	1.04	2, 119	0.358	0.718	-	-
Year Group	1.47	4, 117	0.216	0.017	2.66	0.117
Weather: Temperature	0.03	2, 119	0.966	0.375	-	-
Weather: Precipitation Level	1.45	2, 119	0.239	0.536	-	-
Weather: Rain Days	0.40	2, 119	0.674	0.686	-	-
Labor Elasticity Level	0.19	2, 97	0.828	0.074	-	-

While the relationship between time and cost was significant for the non-partitioned data, the model was not successful in explaining much of the variability in projects. This may be due to the large variety of project types; as expected, these projects likely share very few similar characteristics and project requirements. The low R^2 value and lack of significant differences among factors after partitioning the data indicates that the BTC model does appear to be appropriate for non-facility Air Force MILCON projects.

Partitioned BTC Model Results for Facility Projects

This section discusses the steps to identify significant factors in addition to cost which may influence construction durations for Air Force MILCON facility projects. The significant factors were used to develop multiple BTC models using partitioned data sets. To determine potential significant factors, the residuals of the pooled data were analyzed for each possible factor, with the exception of project cost, listed in Table 14.

The ANOVA results for each possible factor were analyzed using the same procedure detailed for non-facility projects. The results of this analysis are summarized in Table 16; specific output for this analysis may be found in Appendix C.

Table 16. ANOVA Results for Facility Projects

Factor	ANOVA F	ANOVA df	ANOVA p	Levenes' test p	Welch ANOVA F	Welch ANOVA p
Facility Class	1.08	10, 569	0.3761	0.3314	-	-
Type Work	0.70	1, 578	0.4016	0.0430	0.65	0.4227
MAJCOM	2.23	10, 569	0.0151	0.0086	2.01	0.0483
MAJCOM Size	0.13	1, 578	0.7162	0.8658		
COE Region	5.83	7, 572	<.0001	0.0162	6.43	<.0001
Design/Construction Agent	4.97	2, 577	0.0072	0.9354		
Project Delivery Method	1.00	2, 577	0.3703	0.2699		
Design Method	0.84	2, 577	0.4308	0.0895		
Year Group	0.92	5, 574	0.4679	0.0958		
Weather: Temperature	5.94	2, 577	0.0028	0.9574		
Weather: Precipitation Level	1.42	2, 577	0.2424	0.4749		
Weather: Rain Days	2.04	2, 577	0.1314	0.7673		
Labor Elasticity Level	2.46	2, 479	0.0868	0.0254	2.01	0.1396

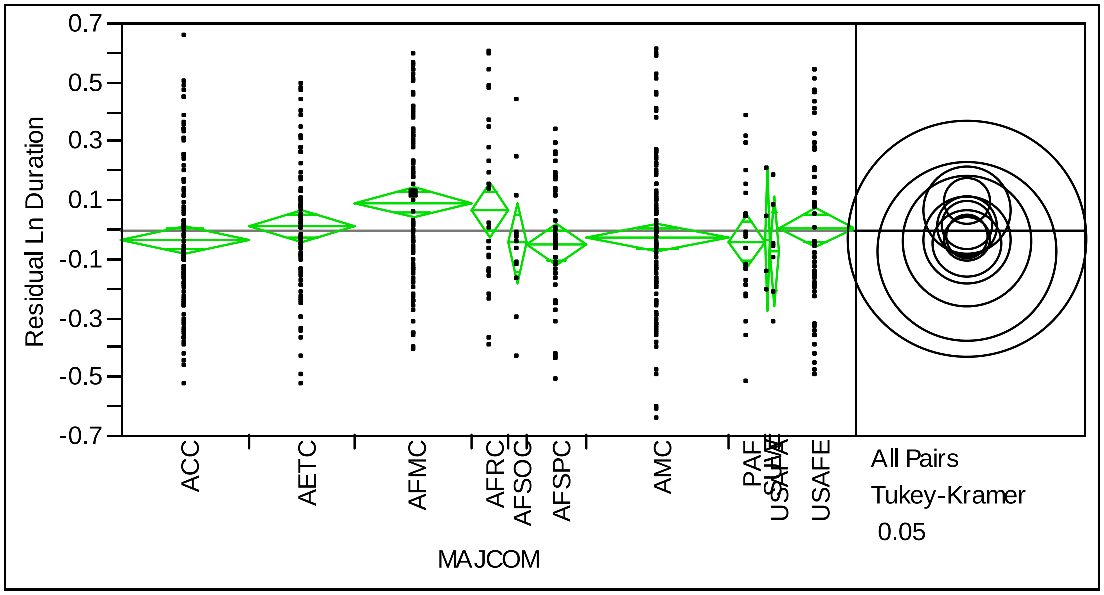
The results of this analysis revealed several factors expected to cause significantly different construction duration means (shown in bold in Table 16). These factors were MAJCOM (p = 0.015), COE Region (p < 0.0001), Design Construction Agent (p = 0.007), and Temperature (p = 0.003). Violations of the constant variance assumption were detected through Levine's test, and the Welch ANOVA test was used for any p-value of 0.05 or less. There were no violations of the assumption in terms of a normally distributed population distribution (W = 0.997, p = 0.463). These factors were further investigated to determine possible partition groups.

These results are significant in that they revealed a variety of factors which do not appear to influence construction durations for Air Force MILCON facility projects.

Construction duration residuals within subgroups including facility class, type work, MAJCOM size, project delivery method, design method, year group, precipitation level, rain days, and labor elasticity level did not show significant differences in means. This indicates that construction durations within the sample data are not significantly influenced by building type, type of construction, various contract procurement and design methods, construction year, precipitation effects, or prevailing economic conditions. Particularly interesting is the apparent lack of influence of both facility class and type work, both of which are traditionally thought to have significant influence on both construction methods and subsequent durations.

While the ANOVA procedure was successful in identifying groupings which may contain at least two significantly different means, it did not specify which combination within these subgroups may have significantly different means. To determine which project types within each subgroup differ significantly (e.g., which MAJCOM are significantly different), means comparison were conducted in conjunction with the Tukey Honestly Significantly Different (HSD) test. This test offers the principle advantage of providing a conservative comparison among differing sample sizes (SAS Institute, 2003). Actual project groupings were determining by looking for groups of similar projects based on sample size, similar means, and intuition. Sample size is important in that some project types did not contain enough data points to partition samples. The means comparisons were used to provide a rough indication of these groups, but the actual selection of groups remained somewhat subjective. For this reason, some classifications were made through the use of intuition, or common sense, grouping like projects together when means were similar. The use of intuition in this type of procedure has been validated by previous research (Chan and Kumaraswamy, 1999: 354). This procedure was used to further investigate project types identified as having at least two significantly different means through the initial ANOVA analysis (MAJCOM, COE Region, Design/Construction Agent, and Temperature).

The means comparisons results for differing MAJCOMs are shown in Figure 21. While the initial ANOVA analysis suggested a difference between at least two MAJCOMs, the means comparison revealed very few differences. AFMC projects appeared to behave significantly different from projects completed within the combined group of the remaining MAJCOMs. These observations were used to develop the MAJCOM groupings listed in Table 17.



Level			Mean
AFMC	A		0.0927610
AFRC	A	B	0.0646217
AETC	A	B	0.0116633
USAFE	A	B	0.0059435
AMC		B	-0.0299986
SUW	A	B	-0.0329977
ACC		B	-0.0343415
PAF	A	B	-0.0397290
AFSOC	A	B	-0.0446270
AFSPC		B	-0.0528691
USAFA	A	B	-0.0743579

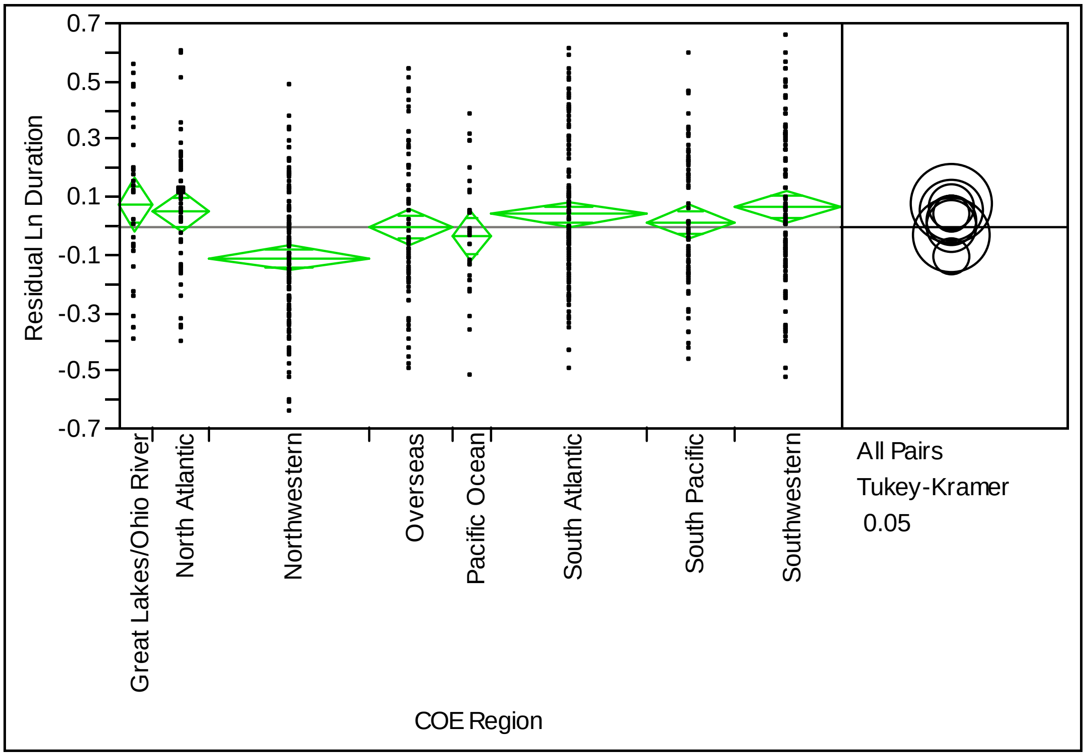
Levels not connected by same letter are significantly different

Figure 21. Means Comparison for MAJCOM Groupings

Table 17. MAJCOM Groupings

MAJCOM	n	Mean (Ln Days)	Group
AFMC	93	0.0928	1
AFRC	29	0.0646	2
AETC	83	0.0117	2
USAFE	59	0.0059	2
AMC	112	-0.0300	2
11 WG	4	-0.0330	2
ACC	103	-0.0343	2
PACAF	29	-0.0397	2
AFSOC	13	-0.0446	2
AFSPC	48	-0.0529	2
USAFA	7	-0.0744	2

Means comparisons for projects in differing COE regions are shown in Figure 22. These results indicated that the durations for projects in the Northwestern region were significantly less than the mean for the majority of facility projects. The majority of COE regions did not differ significantly in terms of construction duration residual mean values. It was not clear whether Pacific Ocean and Overseas regions belong in the same group with the Northwestern region or as members of the larger combined group. For this analysis, these projects were combined with the Northwestern region. The final COE region groupings are shown in Table 18.



Level			Mean
Great Lakes/Ohio River	A		0.0735207
Southw estern	A		0.0648271
North Atlantic	A		0.0501617
South Atlantic	A		0.0392949
South Pacific	A		0.0133958
Overseas	A	B	-0.0039132
Pacific Ocean	A	B	-0.0351121
Northw estern		B	-0.1123064

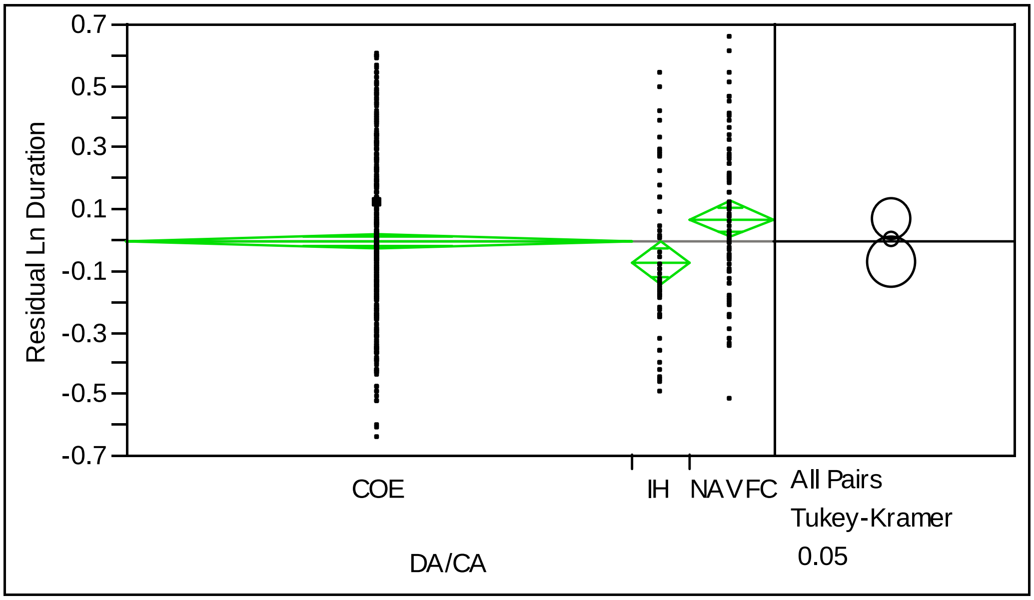
Levels not connected by same letter are significantly different

Figure 22. Means Comparison for COE Region Groupings

Table 18. COE Region Groupings

COE Region	n	Mean (Ln Days)	Group
Great Lakes and Ohio River	28	0.0735	1
Southwestern	85	0.0648	1
North Atlantic	46	0.0502	1
South Atlantic	125	0.0373	1
South Pacific	70	0.0134	1
Other Overseas	67	-0.0039	2
Pacific Ocean	31	-0.0351	2
Northwestern	128	-0.1123	2

The means comparisons results for differing design/construction agents are shown in Figure 23. These results indicate that Naval Facilities Engineering Command (NAVFAC) managed projects appeared to have significantly different durations than in-house managed efforts; however, it was not clear how COE managed projects should be partitioned. For this analysis, COE projects were treated as a separate project type. This resulted in three partition groups for the three design/construction agent options as shown in Table 19.



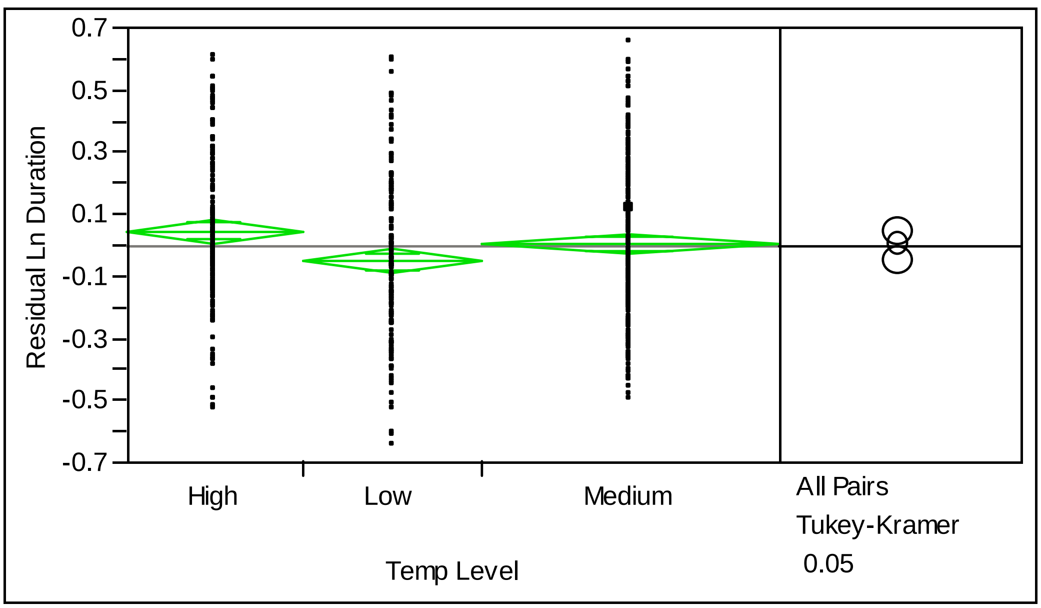
Level			Mean
NAVFC	A		0.0678075
COE	A	B	-0.0028259
IH		B	-0.0745612

Figure 23. Means Comparison for Design/Construction Agent Groupings

Table 19. Design/Construction Agent Groupings

Design/Construction Agent	n	Mean (Ln Days)	Group
NAVFAC	75	0.0678	1
COE	454	-0.0028	2
In-House	51	-0.0746	3

The means comparisons for projects in different temperature categories are shown in Figure 24. Projects completed in areas with few days below 0 degrees C appeared to have residuals significantly above the mean when compared with other temperature levels. Since the medium temperature environment appeared to be equally split between the low and high groups, these projects were treated as a separate partition group. The final temperature level groupings are shown in Table 20.



Level			Mean
High	A		0.0443530
Medium	A	B	0.0053123
Low		B	-0.0522535

Figure 24. Means Comparison for Temperature Level Groupings

Table 20. Temperature Level Groupings

Temperature Level	n	Mean (Ln Days)	Group
High	157	0.0444	1
Medium	263	0.0053	2
Low	160	-0.0523	3

The various factor groupings identified above were used to fit separate regression models for each selected grouping. The detailed results may be found in Appendix D, with a summary being provided in Table 21. Each of the resulting 12 models was tested for overall model significance, as well as individual coefficient validity using *F* and *t* tests. The results indicated that all models and associated regression coefficients (slope and intercept values) were significant at the $\alpha = 0.05$ significance level, with all *F* and *t* test values less than 0.0001. With the exception of the In-House model for Design/Construction Agent grouping ($R^2 = 0.459$), none of the regression models exhibited a significantly higher explained variance than the combined model ($R^2 = 0.338$). Therefore, even though the factors above were found to have significantly different mean values, the differences did not appear to explain any more of the variability than the non-partitioned BTC model. These results indicated a dominating correlation between time and cost, as other factors in addition to cost explained little additional variability. This primary time-cost relationship is consistent with results of previous BTC model research.

Table 21. Final BTC Models for Facility Projects

Regression Model	n	Model F Ratio	$p > F$	Slope	t Ratio	p > t	Intercept	t Ratio	$p > t$	R^2	R^2 (adj)	Shapiro Wilks W	$p < W$
All Facility Projects	580	295.0	<.0001	0.202	17.2	<.0001	3.29	18.2	<.0001	0.338	0.337	0.991	0.001
MAJCOM Models													
AFMC	93	45.6	<.0001	0.2145	6.8	<.0001	3.19	6.5	<.0001	0.334	0.326	0.980	0.164
AFRC, USAFE, AETC, 11WG, PACAF, AFSOC, USAFA, AMC, ACC, AFSPC	487	232.8	<.0001	0.191	15.3	<.0001	3.43	17.9	<.0001	0.324	0.323	0.981	<.0001
COE Region Models													
Great Lakes, SW, NA, SA, SP	354	212.0	<.0001	0.216	14.6	<.0001	3.12	13.7	<.0001	0.376	0.374	0.987	0.004
Overseas, Pacific Ocean, NW	226	86.8	<.0001	0.170	9.3	<.0001	3.72	13.3	<.0001	0.279	0.276	0.995	0.605
Design/Construction Agent Models													
NAVFAC	75	37.2	<.0001	0.213	6.1	<.0001	3.19	5.9	<.0001	0.338	0.328	0.991	0.886
COE	454	186.7	<.0001	0.190	13.7	<.0001	3.47	16.2	<.0001	0.292	0.291	0.992	0.012
In-House	51	41.6	<.0001	0.210	6.5	<.0001	3.09	6.4	<.0001	0.459	0.448	0.954	0.046
Temperature Level Models													
High	157	84.7	<.0001	0.204	9.2	<.0001	3.31	9.8	<.0001	0.353	0.349	0.979	0.018
Medium	263	138.6	<.0001	0.219	11.8	<.0001	3.04	10.6	<.0001	0.347	0.344	0.985	0.007
Low	160	81.2	<.0001	0.187	9.0	<.0001	3.47	10.9	<.0001	0.339	0.335	0.992	0.480

It is worth noting several violations of regression assumptions at this point. Each model was analyzed to detect departures from normality in the residual distribution, and six models did not meet the Shapiro Wilks test ($p < 0.05$). These projects were analyzed graphically, and for the purpose of this research, departures from normality were considered minimal. However, these departures from normality were considered in the selection of the final model.

Discussion of ANOVA Results

While the partitioned data sets resulting from the ANOVA test did not appear to explain more variability than the non-partitioned model, several of the ANOVA results offer some insight into which factors may have a significant influence on construction durations for Air Force MILCON projects. From a MAJCOM perspective, there appears to be little practical difference between differing MAJCOMs in terms of construction durations. These results indicated that the increased durations allowed for Pacific Air Force (PACAF) and United States Air Force in Europe (USAFE) projects under the current "Dirtkicker" criteria may not be warranted, as Air Force Materiel Command (AFMC) projects were the only MAJCOM group identified as having a significantly higher duration mean. The COE region analysis revealed that the Northwestern COE region had significantly lower construction durations in comparison to other regions. It is not possible to determine whether this result is due to regional concerns, management practices, or other factors, but the difference is significant. In-house design efforts appeared to produce lower than average construction durations; however, these results may not be indicative of the quality of the design effort. One possible explanation for this observation is the tendency for in-house managed projects to be less complex in nature, which could result in decreased construction durations. Low temperature projects have negative residual values, indicating shorter construction durations in these environments. One possible explanation for this observation may be the shortened construction seasons in cold weather regions which may lead to decreased construction durations.

MLR Model Preparations

The same factors identified for the BTC model above were investigated for inclusion in the MLR model. No new data collection was required, and the majority of the data remained unchanged from that presented for the development of the BTC model. However, categorical designations were no longer required for temperature, precipitation level, and rain days; these factors were modeled as continuous variables in the MLR model. The remaining categorical variables of project delivery method, COE region, type work, design method, design/construction agent, facility class, MAJCOM, MAJCOM size, and construction year group were modeled with dummy variables using a 0-1 coding method. As discussed previously, labor supply elasticity was not included in this analysis due to a lack of overseas data. The exclusion of this factor was not expected to negatively influence results, as the ANOVA analysis above revealed labor supply elasticity as an insignificant influence on construction durations for projects completed within the United States. A summary of the factors investigated for inclusion in the MLR model is shown in Table 22.

Table 22. Independent Variables for MLR Model

Factor	Measure	Categories
Total Cost	Project Contract Total Cost	None
Project Delivery Method	Project Delivery Method	Traditional Design Build Other
Location	COE Region	Northwestern South Pacific Southwestern Great Lakes and Ohio River North Atlantic South Atlantic Pacific Ocean Other Overseas
Type Work	Type Work	New Construction Addition/Alteration
Design Method	Design Method	In House AE Other
Design/Construction Agent	Design/Construction Agent	COE NAVFAC In-House
Facility Class	Air Force Category Code	11 - Airfield Pavements 12 - Petroleum Dispensing and Operating Facilities 13 - Communication, Nav Aids, and Airfield Lighting 14 - Land Operations Facilities 17 - Training Facilities 21 - Maintenance Facilities 41 - Liquid Fuel Storage 42 - Explosives Facilities 44, 45 - Storage Facilities 5X, 442 - Medical and Medical Support 61 - Administrative Facilities 72 - Dormitories, Officer Quarters, and Dining Halls 73 - Personnel Support 74 - Morale, Welfare and Recreation - Indoors 75 - Services - Outdoors 81 - Electricity 82, 83, 84 - Heat, Sewage, and Water 85, 86 - Roadway Facilities, Railroad Trackage 87 - Ground Improvement Structures 31 - Research and Development Facilities 88, 89 - Fire and Other Alarm Systems, Miscellaneous Utilities
MAJCOM	MAJCOM	11 WG ACC AETC AFMC AFRC AFSOC AFSPC AMC PACAF USAFA USAFE
MAJCOM Size	MAJCOM Size	Small Large
Construction Year	Midpoint Construction Year	1988 and less 1989-1991 1992-1994 1995-1997 1998-2000 2000 and greater
Weather: Temperature	Average Annual Minimum Temperature	None
Weather: Precipitation Level	Average Yearly Precipitation	None
Weather: Rain Days	Average Rain Days	None

Using the same assumptions applied to the BTC model project data, projects were first divided into two major classifications: facility and non-facility projects. Facility projects include all work on traditional building structures, while non-facility projects include all pavements, utilities, liquid fuels storage and pipelines. This initial partitioning resulted in 616 facility projects and 129 non-facility projects. A MLR model was then applied to all projects contained within each category.

MLR Model Development

A stepwise selection procedure was used to identify statistically significant variables for inclusion in the model, as was the case in studies by Walker (1995) and Chan and Kumaraswamy (1999). A forward stepwise procedure was conducted using JMP software. This procedure adds variables one at a time, re-calculates the regression model at each step, and notes the changes to the R^2 value (SAS Institute, 2003). To use this procedure, *p*-values must be specified by which variables are either entered or removed from the model. The *p*-value to enter the model is the significance probability that must be attributed to a regression term for it to be considered as a forward step and added to the model. The *p*-value to leave the model is the significance probability that must be attributed to a regression term for it to be considered as a backward step and removed from the model (SAS Institute, 2003). For the final model selection, only those variables with a *p*-value of less that 0.05 were selected for inclusion. This procedure was applied to both non-facility and facility project data.

MLR Model Results for Non-Facility Projects

Variables selected during the stepwise procedure were next investigated individually for inclusion in the final regression model using *p*-values. Those variables with a p-value of less than 0.05 were removed one at a time and the regression model recalculated. This iterative process was repeated until all model variables had p-values less than 0.05. The detailed results of this analysis are shown in Appendix E, with the final model output being shown in Figure 25.

Summary of Fit

RSquare	0.11853
RSquare Adj	0.097375
Root Mean Square Error	0.570882
Mean of Response	6.269047
Observations (or Sum Wgts)	129

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	5.478012	1.82600	5.6029
Error	125	40.738280	0.32591	Prob > F
C. Total	128	46.216292		0.0012

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.2763449	0.059238	105.95	<.0001
Electricity Dummy	0.4679603	0.210887	2.22	0.0283
AFSOC Dummy	0.4415588	0.210424	2.10	0.0379
Northwestern COE Dummy	-0.316063	0.127292	-2.48	0.0144

Figure 25. MLR Model Results for Non-Facility Projects

As Figure 25 indicates, three significant factors were identified for inclusion in the final model (Electricity facility variable, AFSOC MAJCOM variable, and Northwestern COE variable). The final model equation is shown below.

$$y = 6.28 + 0.468x_1 + 0.442x_2 + -0.316x_3 \quad (26)$$

where

y = Project construction duration (ln days),

x_1 = Electricity Facility dummy (1 if electrical facility project, 0 if not),

x_2 = AFSOC MAJCOM dummy (1 if AFSOC, 0 if not), and

x_3 = Northwestern COE Region (1 if Northwestern Region, 0 if not).

Analysis of the regression coefficients revealed additional information regarding expected project durations based on the selected variables. Northwestern COE region projects, with a negative regression coefficient, can be expected to have lower than average construction durations. AFSOC and electricity facility projects, with positive regression coefficients, can be expected to have higher than average construction durations. The remaining variables did not reveal any significant differences between construction durations.

The resulting model explained very little of the variability within projects (R^2 = 0.12), even though both the parameter estimates were significant ($p < 0.05$). This indicated that projects within these variable classifications were significantly different from other projects; however, with only three qualitative regression variables and no cost term, the model has little practical use for forecasting construction durations. The lack of a cost variable indicates that projects can be expected to have the same construction duration regardless of the cost of the project; this finding is obviously counterintuitive. Due to the low R^2 value and lack of a cost variable, this model was not investigated further, as it has no practical application for Air Force MILCON projects. As discussed in the BTC model formulation earlier, the significant variability associated with these non-facility projects appears to prevent the formulation of a valid prediction model.

MLR Model Results for Facility Projects

A stepwise procedure identical to that described for non-facility projects was completed for facility projects. The resulting model was then tested for the presence of any influential data points (outliers). Following previous studies by Chan and Kumaraswamy (1999), the model was tested using studentized residuals, with residuals exceeding 2.0 being investigated for removal from the model. It was assumed that projects selected for removal represent unique project circumstances not included within the factors selected for the model (i.e., natural disasters, contract disputes, etc.). Before removal though, potential outliers were reviewed to ensure they did not contain any common project characteristics which might indicate a unique population that should not be removed. Using this criteria, 21 projects were removed as outliers. A complete overview of the regression model steps described above may be found in Appendix F. The final selected model equation was.

$$y = 3.44 + 0.198x_1 + -0.059x_2 + -0.070x_3 + -0.222x_4 + -0.193x_5 + -.0146x_6 \qquad (27)$$

where

y = Project construction duration (ln days),

x_1 = Project total cost (ln \$),

x_2 = ACC MAJCOM dummy (1 if ACC, 0 if not),

x_3 = AETC MAJCOM dummy (1 if AETC, 0 if not),

x_4 = AFSOC MAJCOM dummy (1 if AFSOC, 0 if not),

x_5 = Northwestern COE Region (1 if Northwestern Region, 0 if not), and

x_6 = In-House Design/Construction Agent dummy (1 if In House, 0 if not).

The final model output is shown in Figure 26.

Summary of Fit

RSquare	0.374385
RSquare Adj	0.368002
Root Mean Square Error	0.263201
Mean of Response	6.387387
Observations (or Sum Wgts)	595

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	24.376188	4.06270	58.6460
Error	588	40.733687	0.06927	Prob > F
C. Total	594	65.109875		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.4406122	0.192648	17.86	<.0001
Ln Cost	0.1976649	0.012468	15.85	<.0001
ACC MAJCOM Dummy	-0.059409	0.0291	-2.04	0.0416
AETC MAJCOM Dummy	-0.070215	0.032457	-2.16	0.0309
AFSOC MAJCOM Dummy	-0.222033	0.069783	-3.18	0.0015
Northwestern COE Dummy	-0.193163	0.026872	-7.19	<.0001
IH DA/CA Dummy	-0.146322	0.039724	-3.68	0.0003

Figure 26. MLR Model Results for Facility Projects

The final model was considered statistically significant from the *F* test statistic (p < 0.0001). Additionally, the *t* test for parameter estimates revealed that all parameters were significant ($p < 0.05$). The resulting least squares model was successful in explaining almost 40% of the sample variation ($R^2 = 0.374$). This R^2 value was comparable with that of previous research and was considered acceptable, particularly given the wide range of project types included in the sample data. These results indicated that the model was successful in identifying significant relationships between project duration and a number of independent variables. The substantial spread of the results was not unexpected for building projects of this nature, particularly when buildings vary widely in location, design, administrative procedures, and facility type among other factors. While this variability was substantial, it is important to note that regardless of project differences, a clear trend was identified between duration and a variety of factors by the model.

Even the variables not selected for inclusion in the final model provide additional insight into the Air Force construction process. Project delivery method, type work, design method, facility class, MAJCOM size, construction year, weather effects, and economic conditions did not appear to have an appreciable influence on construction duration for the selected data. Many of these variables are traditionally thought to have a significant influence on the construction process and subsequent durations. For example, the design-build project delivery method is often viewed as a tool to produce accelerated construction times; however, this assertion was not validated by this research. Additionally, facility type and type work were also somewhat surprising exclusions from the prediction model. These results are important in that they suggest that the construction durations of Air Force MILCON facility projects are not highly correlated with these factors.

The resulting model also indicated that projects differ significantly based on several project characteristics. Projects completed in ACC, AETC, or AFSOC can be expected to differ significantly from those completed in the remaining MAJCOMs. No evidence was found to support the increased durations allowed for PACAF and USAFE projects under the current "Dirtkicker" criteria. Northwestern COE region projects can be expected to have significantly lower construction duration means from those projects completed in other COE regions, reinforcing the results of the ANOVA analysis. Finally, projects managed by in-house design/construction agents can be expected to differ significantly from those completed using COE or NAVFAC design agents. The cost term is the lone significant quantitative variable.

The resulting model may be interpreted as 16 regression lines through the data points with differing intercept values. While an MLR methodology was used to select factors, these models may be interpreted as separate BTC models which allow for multiple partitioning based on the selected significant factors. Each individual model represents a unique intercept value which accounts for differences between factors. Of the 16 possible combinations of regression coefficients, only 12 represent valid combinations. This is due to the fact that there are no AETC or AFSOC bases within the Northwestern COE Region. The possible models and associated regression coefficients are listed in Table 23.

Table 23. Possible MLR Project Models

MAJCOM	COE Region	Design/Construction Agent	Slope	Intercept	Applicable Model?	$5M Project Duration (days)
ACC	Northwestern	IH	0.198	3.042	Y	442
ACC	Northwestern	COE/NAVFAC	0.198	3.188	Y	511
ACC	All Others	IH	0.198	3.235	Y	536
ACC	All Others	COE/NAVFAC	0.198	3.381	Y	620
AETC	Northwestern	IH	0.198	3.031	N	N/A
AETC	Northwestern	COE/NAVFAC	0.198	3.177	N	N/A
AETC	All Others	IH	0.198	3.224	Y	530
AETC	All Others	COE/NAVFAC	0.198	3.370	Y	614
AFSOC	Northwestern	IH	0.198	2.879	N	N/A
AFSOC	Northwestern	COE/NAVFAC	0.198	3.025	N	N/A
AFSOC	All Others	IH	0.198	3.072	Y	455
AFSOC	All Others	COE/NAVFAC	0.198	3.219	Y	527
All Others	Northwestern	IH	0.198	3.101	Y	469
All Others	Northwestern	COE/NAVFAC	0.198	3.247	Y	543
All Others	All Others	IH	0.198	3.294	Y	569
All Others	All Others	COE/NAVFAC	0.198	3.441	Y	658

To provide an indication of the practical differences between models, the construction duration for a $5 million project was predicted with each of the 12 valid models in Table 23. These results showed that the majority of models produce significantly different construction durations based on the parameter values. For example, projects completed within the ACC MAJCOM, in the Northwestern COE region, by an in-house design agent (duration estimate = 442 days) produced significantly different duration predictions than the same project managed by COE/NAVFAC design agents (duration estimate = 511 days). However, some models produced nearly identical results when viewed in the context of a typical construction project. While these models contain statistically significant differences, practical differences may not always exist. For instance, duration estimates for AETC, all other COE regions, and in-house design agents (duration estimate = 530 days) differ only slightly from those for ACC, all other COE regions, and in-house design agents (duration estimate = 536 days). This 6-day difference in construction durations would not be considered a significant difference in a typical facility construction project.

Model Comparison and Final Model Selection

The completed models must now be compared in order to select the most appropriate one; this was accomplished by referring to goodness of fit. The coefficient of determination (R^2) has been previously discussed as one goodness of fit measure. Table 24 provides a comparison of R^2 values for both the partitioned BTC and MLR models. The MLR model had higher R^2 values than the majority of the partitioned BTC models; this indicated that the combination of factors in the MLR model was more successful in explaining the variability in Air Force MILCON project durations. Since both models exhibited significant relationships between construction time and a number of variables,

R^2 values were selected as the primary discriminator between models. Using these criteria, the MLR model was selected as the best model.

Table 24. Model R^2 Comparisons

Regression Model	R^2	R^2 (adj)
BTC Models		
All Facility Projects	**0.338**	**0.337**
MAJCOM Models		
AFMC	0.334	0.326
AFRC, USAFE, AETC, 11WG, PACAF, AFSOC, USAFA	0.334	0.331
AMC, ACC, AFSPC	0.324	0.322
COE Region Models		
Great Lakes, SW, NA, SA, SP	0.376	0.374
Overseas, Pacific Ocean, NW	0.279	0.276
Design/Construction Agent Models		
NAVFAC	0.338	0.328
COE	0.292	0.291
In House	0.459	0.448
Temperature Level Models		
High	0.353	0.349
Medium	0.347	0.344
Low	0.339	0.335
MLR Model	**0.374**	**0.368**

Step 5: Testing and Validation

This section focuses on testing and validation of the model through verification of model assumptions, sensitivity analysis, and various procedures used to investigate the usefulness of the regression models. This analysis was completed initially with data included in the formulation of the predictive model, and then with the validation data set aside before model development. Since none of the models were successful in predicting durations for non-facility Air Force MILCON projects, this analysis was limited to the comparison of the partitioned BTC and MLR models for facility projects developed.

Validation of Assumptions

As discussed previously, there are four assumptions that must be met for a regression model to be considered valid. These assumptions are discussed and verified individually below.

Assumption 1: The mean of the probability distribution of ε is 0. This assumption was evaluated by plotting the residuals against the predicted values of the dependent variable. If this assumption is valid, the plot should reveal a relatively equal number of data points on either side of a line through a residual of zero. As indicated from Figure 27, the mean of the residuals appeared to be zero.

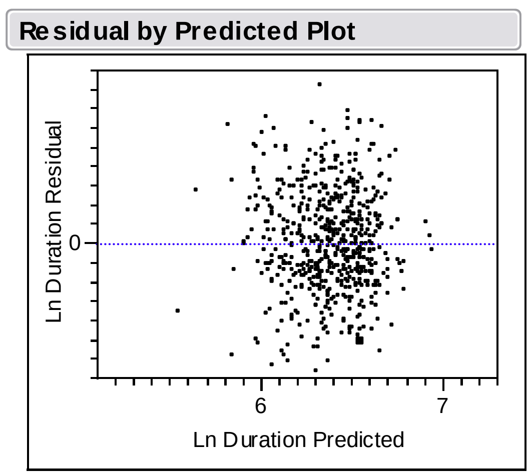


Figure 27. Residual vs. Predicted Plot

Assumption 2: The variance of the probability distribution of ε is constant. This assumption was verified by analyzing Figure 27. If the constant variance with respect to the predicted values is valid, the residuals should remain approximately constant as predicted values increase. Any patterns in this plot may suggest problems with this assumption. This plot revealed no significant patterns across predicted values of construction duration, so it is reasonable to assume that the variance is approximately constant.

Assumption 3: The probability distribution of ε is normal. This assumption may be verified by examining the distribution of residuals. If valid, these residuals should approximate a normal distribution. As shown in Figure 28, the distribution appears to be mound shaped and symmetric with a mean of zero. An additional verification of the normality assumption may be provided by the Shapiro-Wilks *W* test. This test evaluates the null hypothesis that the distribution is normally distributed. In this case, there was not sufficient evidence to conclude that the population was not normal at the 0.05 significance level (p = 0.113); therefore the normal assumption for this data appeared to be valid.

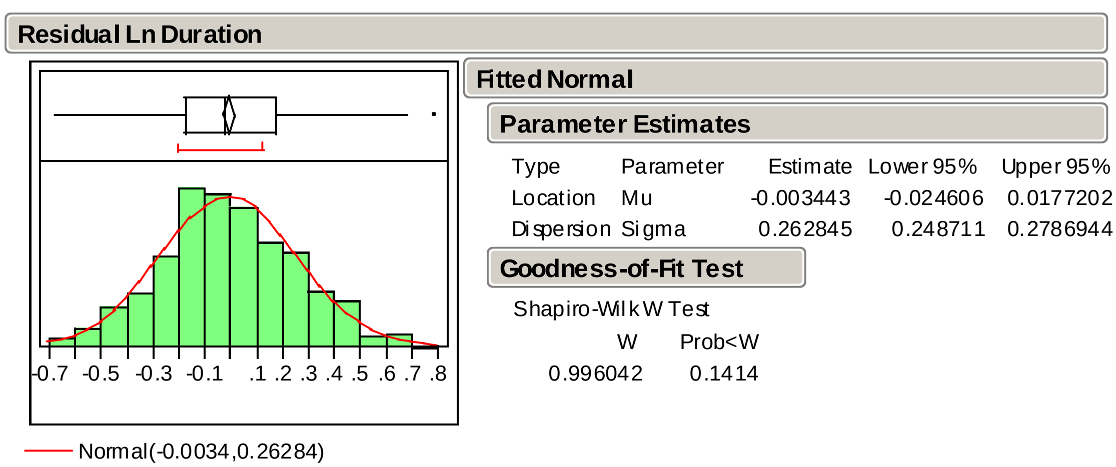


Figure 28. Residual Distribution

Assumption 4: The values of ε for differing values of *y* are independent. This assumption was verified by analyzing the nature of the data selected for inclusion in the model. Each selected data point represented a separate Air Force MILCON construction project completed at differing times and locations. The duration of an individual project should not have an impact on any other points within the data set. For this reason it was reasonable to assume that these data points are independent.

An additional potential problem with the selected prediction model may exist if independent variables are highly correlated with each other. One method of checking for correlation between independent variables is through the Variance Inflation Factor (VIF). High VIFs indicate a possible problem with correlation in the model (SAS Institute, 2003). VIFs were calculated for each independent variable selected for inclusion in the final model; the results of this analysis are shown in Figure 29. As shown in the figure, all VIF values are near 1; this indicated that no problems with correlation exist between the selected independent variables.

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	3.4406122	0.192648	17.86	<.0001	.
Ln Cost	0.1976649	0.012468	15.85	<.0001	1.0605971
ACC MAJCOM Dummy	-0.059409	0.0291	-2.04	0.0416	1.0648694
AETC MAJCOM Dummy	-0.070215	0.032457	-2.16	0.0309	1.0970396
AFSOC MAJCOM Dummy	-0.222033	0.069783	-3.18	0.0015	1.0278359
Northwestern COE Dummy	-0.193163	0.026872	-7.19	<.0001	1.0706636
IH DA/CA Dummy	-0.146322	0.039724	-3.68	0.0003	1.080955

Figure 29. Variance Inflation Factor Results

Sensitivity Analysis

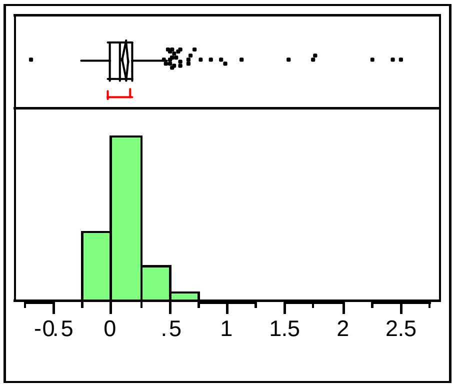
The various models developed to this point assume that the total contract cost is known or can be perfectly predicted prior to construction. In the current Air Force process, the total contract cost is estimated from information available during the programming or early planning phase of the project. Since the duration estimate is based on this estimated contract cost, it is necessary to examine the sensitivity of the models to deviations in this initial cost estimate.

To determine the approximate range of estimate accuracy for Air Force MILCON projects, actual contract costs were compared against the programmed amount (PA) specified during the planning phase and reported in the ACES-PM database. The PA accuracy was completed for each of the 616 projects previously selected using the following equation.

$$PA\ Accuracy(\%) = (PA\text{-}Actual\ Cost)/Actual\ Cost \qquad (28)$$

The results of this analysis are illustrated graphically in Figure 30. This plot revealed a wide variety of accuracy percentages, ranging from 67% under to 253% over actual contract cost. To capture the majority of likely deviations, 10% and 90% quantile limits were analyzed. The 10% quantile (-8.9%) and 90% qauntile (36.8%) by definition contain 80% of the PA accuracy percentages. Using these limits as a rough guideline, PA accuracy limits of -10% to +40% were selected as bounds for the sensitivity analysis.

PA Accuracy



Quantiles

100.0%	maximum	2.530
99.5%		2.243
97.5%		0.657
90.0%		0.368
75.0%	quartile	0.192
50.0%	median	0.082
25.0%	quartile	0.001
10.0%		-0.089
2.5%		-0.140
0.5%		-0.238
0.0%	minimum	-0.674

Moments

Mean	0.1279838
Std Dev	0.2690165
Std Err Mean	0.010839
upper 95% Mean	0.1492697
lower 95% Mean	0.1066979
N	616

Figure 30. PA Accuracy Distribution

Sensitivity analysis was conducted on the 12 valid regression models by varying the PA accuracy percentages. The results for model 1 (representing ACC projects completed in the Northwestern COE region using in-house design/construction agents) are illustrated graphically in Figure 31. A "perfect" PA estimate (one which exactly predicted the final contract cost) for a $5 million project would result in a duration estimate of 442 days. Similarly, a PA estimate which was 60% under actual cost would result in an estimate of 369 days, while an estimate 60% over would result in an estimate of 485 days. As discussed above, the majority (80%) of PA estimates are likely to fall between -10% and 40%. These limits, illustrated by the vertical lines in Figure 31, were calculated for each of the possible 12 regression models and analyzed to determine the worst case (largest deviation in predicted values) for each. The results of this analysis are shown in Table 25.

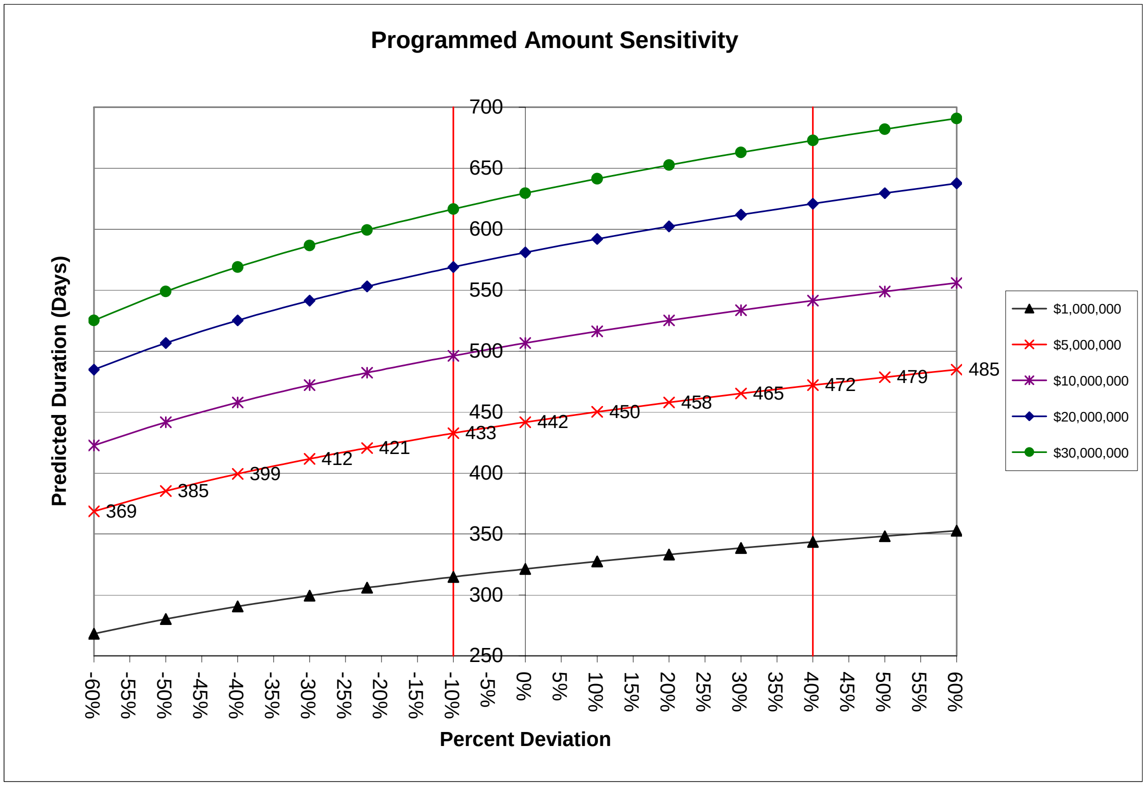


Figure 31. Sensitivity Analysis Graph

Table 25. Sensitivity Analysis Results

Actual Project Cost	Correct Duration	-10% Duration Estimate	Difference	+40% Duration Estimate	Difference
$ 1,000,000	479	469	-10	512	33
$ 5,000,000	658	645	-14	704	45
$ 10,000,000	755	739	-16	807	52
$ 20,000,000	866	848	-18	925	60
$ 30,000,000	938	919	-19	1,003	65

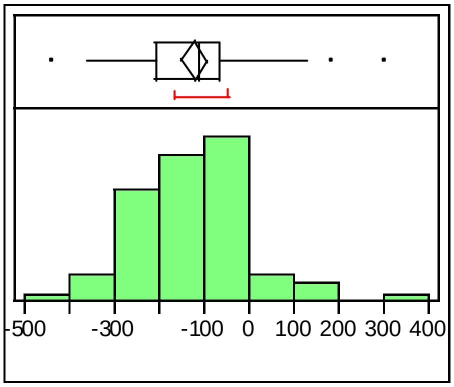
In Table 25, the difference columns provide a worst case scenario for differences in duration prediction caused by inaccurate PA estimates. For example, a \$1 million project with a PA which underestimated the actual project cost by 10% would result in a duration estimate 10 days under that which would have been predicted by a perfect PA estimate. For a \$30 million project, overestimating the PA by 40% results in a duration estimate 65 days over the correct PA duration estimate. The effect of underestimating the PA by 10% produced a 19 day deviation, which would not be significant in a typical construction project. However, the effect of overestimating the PA by 40% can produce larger differences in duration estimates, with a worst case of 65 days for a \$30 million project. When this worst case scenario is viewed in the context of a large \$30 million project, this amount of variation is typically considered tolerable. After all, this overestimation would result in a project being completed 65 days before the estimated completion date, which obviously produces none of the problems associated with underestimation. These results indicated that the model is somewhat sensitive to inaccurate initial PA estimates; however, the effects of this sensitivity are likely to be minimal, particularly if the initial estimate is within the +/- 10% range.

Measuring Model Validity

Model reliability is determined by the goodness of fit of the selected model to the available data. While goodness of fit was already measured using R^2, an additional measure of model validity may be obtained by comparing predicted and planned values, where planned values are those estimates specified prior to construction by the project management team (Chan and Kumaraswamy, 1999: 641). For Air Force MILCON projects, planned construction durations were selected as the number of days specified under the performance period on the contract form prior to award. Comparisons between planned and predicted values were conducted for a separate set of projects not included in the formulation of the predictive model. Of the 84 projects set aside, 77 of them had planned values.

The differences between planned and predicted values were calculated as a means of comparing the two estimation methods. Small differences between these values would indicate that the prediction model appeared to account for similar factors as those used in the planning estimate. The distribution for these calculations is shown in Figure 32. This distribution reveals several differences between the planner's and prediction estimates. First, it appears that the estimation methods are accounting for differing factors since there is a large range of differences between the two methods. Additionally, the distribution is skewed to the left. There are two possible explanations for this skewness: either the planner consistently underestimates the time for construction or the prediction model consistently overestimates it. To determine which model is more successful in predicting construction durations, a comparison of the actual construction durations with both the planner's and the prediction estimates was conducted. The distributions for these differences are shown in Figure 33.

Planned - Predicted



Quantiles

100.0%	maximum	306.7
99.5%		306.7
97.5%		193.4
90.0%		34.1
75.0%	quartile	-62.6
50.0%	median	-111.3
25.0%	quartile	-205.9
10.0%		-271.8
2.5%		-359.9
0.5%		-434.1
0.0%	minimum	-434.1

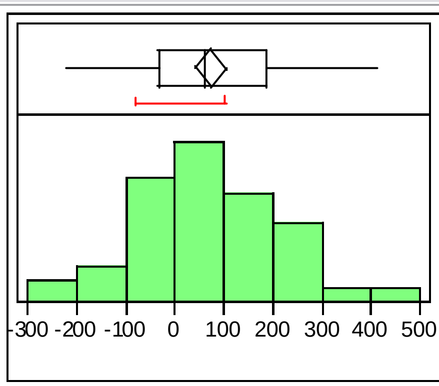
Moments

Mean	-119.7364
Std Dev	123.35502
Std Err Mean	14.057609
upper 95% Mean	-91.73821
lower 95% Mean	-147.7345
N	77

Figure 32. Planned-Predicted Distribution

Distributions

Predicted - Actual



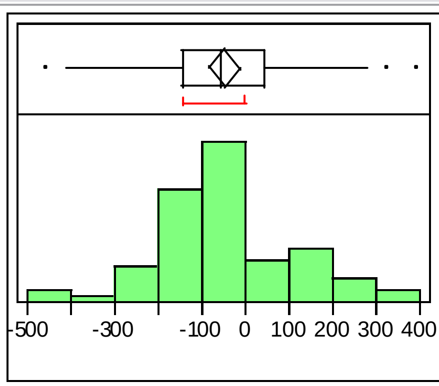
Quantiles

100.0%	maximum	412.0
99.5%		412.0
97.5%		404.4
90.0%		249.4
75.0%	quartile	189.5
50.0%	median	62.0
25.0%	quartile	-30.0
10.0%		-111.6
2.5%		-210.3
0.5%		-217.0
0.0%	minimum	-217.0

Moments

Mean	75.467532
Std Dev	142.42048
Std Err Mean	16.23032
upper 95% Mean	107.79302
lower 95% Mean	43.142048
N	77

Planned - Actual



Quantiles

100.0%	maximum	396.0
99.5%		396.0
97.5%		334.2
90.0%		159.4
75.0%	quartile	44.0
50.0%	median	-56.0
25.0%	quartile	-139.5
10.0%		-231.0
2.5%		-406.3
0.5%		-451.0
0.0%	minimum	-451.0

Moments

Mean	-44.2987
Std Dev	158.02074
Std Err Mean	18.008135
upper 95% Mean	-8.432393
lower 95% Mean	-80.16501
N	77

Figure 33. Predicted/Planned –Actual Duration Distributions

This analysis revealed several differences between planned and predicted durations. Planned durations consistently underestimated the time required for construction, with a mean value of 44 days below actual duration. The predictive model offered a more conservative estimate, with a mean of 75 days over actual duration. To provide an additional comparison, the average positive and negative residuals were calculated and are shown in Table 26. The prediction model and planner's estimates provide nearly identical positive error terms, with average values of 150 days and 149 days, respectively. The prediction model appeared to be more accurate when projects durations were underestimated, with an average negative error of 80 days as compared to 122 days for the planner's estimate. These results indicated that the prediction model is comparable to the planner's estimate in terms of estimation errors; additionally, it produces a more conservative estimate of construction duration for Air Force MILCON projects.

Table 26. Predicted vs. Planned Values Comparison

	Prediction Model	Planner's Estimate
Average Error (days)	75	-44
Average + Error (days)	150	149
Average - Error (days)	-80	-122

Another means of comparing the prediction model to the planner's estimate was conducted using the sum of squared errors (SSE) for each model. The SSE values for both planned and predicted models were calculated using the following equation for each project from the validation sample.

$$SSE = \sum(\text{Actual Duration} - \text{Predicted(or Planned) Duration})^2 \qquad (29)$$

The distribution with the smallest SSE term can be viewed as a more accurate predictor of the actual construction duration. The results of this analysis are shown in Figure 34. The prediction model has a lower SSE value when compared to the planner's estimate, although not by a significant margin. These results indicated that, in terms of estimation errors, the prediction model offers a slightly more reliable estimate for projects within the validation sample than that produced by the current method used by project planners.

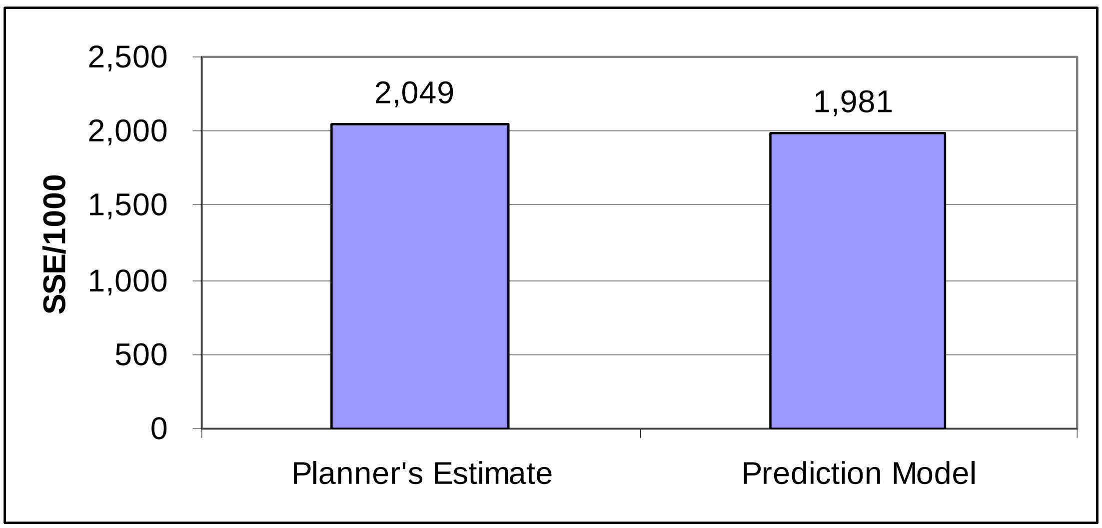


Figure 34. SSE Comparison

These results, in combination with those discussed above, indicated that the model provides a viable alternative to the methods currently used to estimate construction durations for Air Force MILCON projects. It appeared that the planner's estimate accounts for different project characteristics than those used to establish the construction duration using the prediction model. Since the prediction model offered a marginally better estimate than the planner's estimate, it was reasonable to assume that the planner's estimate was neglecting certain important factors thought to be influential to construction durations. Additionally, the prediction model offered the advantage of a more conservative duration estimate. A conservative estimate is preferable in construction projects as optimistic durations are likely to produce a number of problems associated with delayed occupancy dates. These results indicated that the prediction model offers a viable alternative capable of producing front-end duration estimates which are as accurate as, yet slightly more conservative than, the planner's estimates.

Measuring Predictive Accuracy

The MLR model was used to predict values for the dependent variable for the validation samples collected from ACES-PM. These values were then compared to the actual project durations as determined by the project completion date. The MLR model was applied to a total of 84 projects from the validation sample. As discussed earlier, the final regression equation may be viewed as 12 separate models. A summary of each of these models, along with the number of data points contained in the validation sample for each model is given in Table 27. Each model was plotted with the respective validation data points. While the results for each model are shown in Appendix G, the models with the most data points are discussed below.

Table 27. Validation Data Summary

MAJCOM	COE Region	DA/CA	Slope	Intercept	Data Points
ACC	Northwestern	IH	0.198	3.042	0
ACC	Northwestern	COE/NAVFAC	0.198	3.188	1
ACC	All Others	IH	0.198	3.235	8
ACC	All Others	COE/NAVFAC	0.198	3.381	13
AETC	All Others	IH	0.198	3.224	5
AETC	All Others	COE/NAVFAC	0.198	3.370	8
AFSOC	All Others	IH	0.198	3.072	3
AFSOC	All Others	COE/NAVFAC	0.198	3.219	0
All Others	Northwestern	IH	0.198	3.101	2
All Others	Northwestern	COE/NAVFAC	0.198	3.247	12
All Others	All Others	IH	0.198	3.294	11
All Others	All Others	COE/NAVFAC	0.198	3.441	21

Figure 35 overlays the model output with the project data points from the validation sample for the specified model. Also included are quartile limits, which may be seen as upper and lower bounds for expected project duration, similar to the original study by Bromilow (1969). The plot in Figure 35 reveals three projects below the 25% quartile limit; this indicates that these projects can be viewed as having faster than average construction durations. All other projects within this data set were within the bounds of expected project duration.

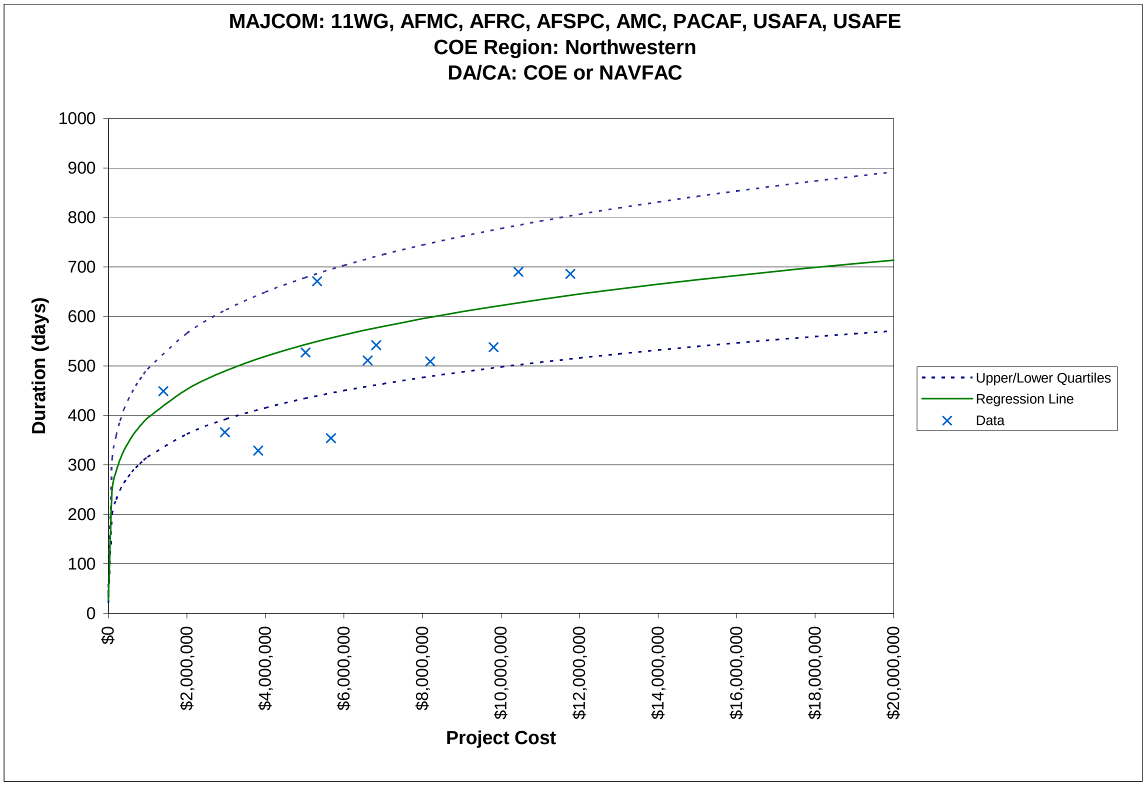


Figure 35. Model Regression Results

The projects in Figure 36 also illustrate similar results. In this case, two projects are identified above the 75% quartile limit; this indicates longer than average construction durations. There are also two projects below the 25% quartile. The model appears to be successful in providing a differentiation between projects with average, slower than average, and faster than average construction durations using these quartile limits.

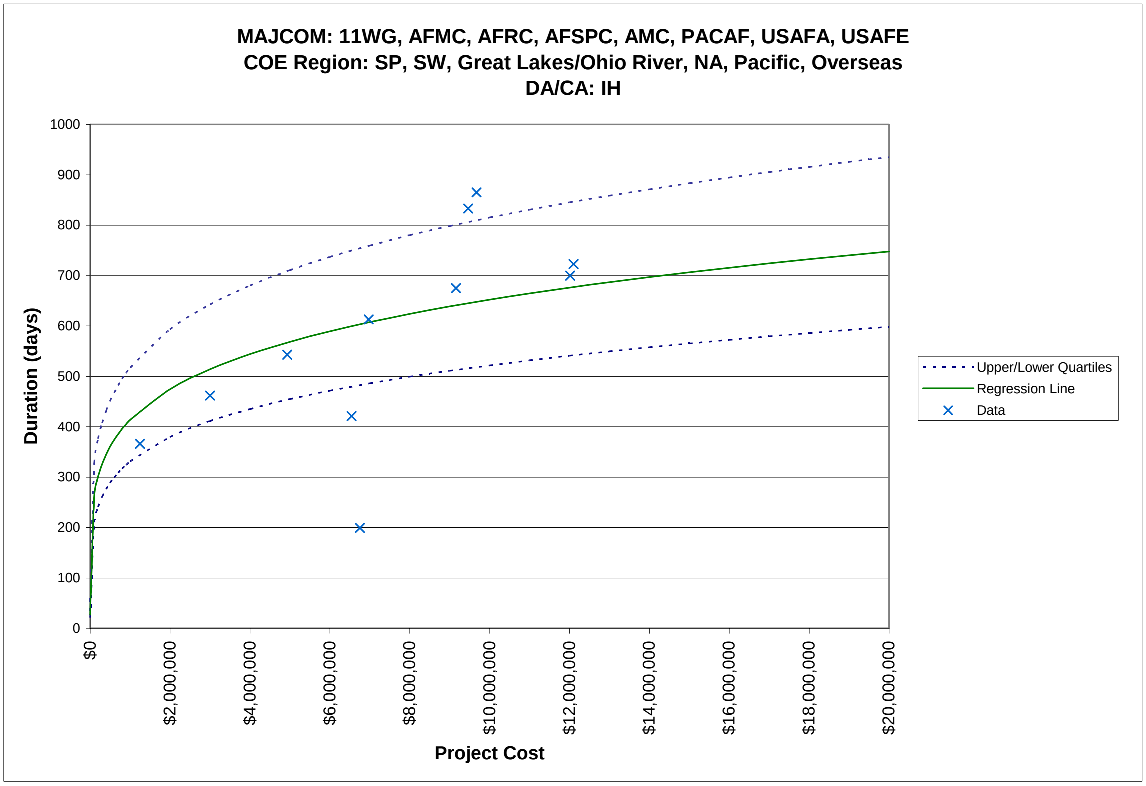


Figure 36. Model Regression Results

An indication of model validity can be found by comparing the number of projects falling within these quartile limits. By definition, these limits contain 50% of the projects used in the formulation of the model. Therefore, the total number of projects falling within, under, and over the specified quartile limits were calculated for the validation sample. The results of this analysis are shown in Table 28. These results showed that the quartile limits were successful in containing approximately 50% of the data points (54%). Although the above and below quartile limits are not near 25%, the quartile limits still appeared to be reasonable for the sample validation projects.

Table 28. Quartile Limits Analysis

	Total Projects	Percentage
Below 25% Quartile	34	40%
Within Quartile	45	54%
Above 75% Quartile	5	6%

The prediction model and the use of quartile limits as performance norms have several possible applications to Air Force MILCON project durations. The results above indicate that the model appeared to provide an objective method of estimating construction duration to supplement the current methods currently utilized by Air Force program managers. A main benefit of this model is that it can be utilized without a detailed analysis of the project design; for this reason it could be used to either produce or verify front-end duration estimates submitted by the A/E or contractor.

Since the model appears to offer reasonable limits by establishing these performance norms, a comparison between the regression model and the Air Force "Dirtkicker" benchmark limits is warranted. The "Dirtkicker" duration criteria were first compared with the prediction model. This analysis was conducted with the validation data to provide an indication of the percentage of projects either meeting or failing to meet the estimates specified by either the "Dirtkicker" criteria or the prediction model. All available projects (616 from the model formulation and 84 from the validation sample) were included in this analysis, for a total of 700 projects. The results of this comparison are shown in Table 29. Only 25% of the projects were below the "Dirtkicker" specified duration limit, as compared to 53% which were below the prediction model point estimates. The large percentage of projects falling outside of the

"Dirtkicker" criteria indicates that these benchmark limits are neither realistic nor achievable for a large number of Air Force MILCON projects. The prediction model, with 53% of projects within the estimate, appears to provide a more attainable duration benchmark limit, even without the use of quartile limits.

Table 29. Prediction Model vs. "Dirtkicker" Point Estimate Comparison

	Prediction Model	Dirtkicker
Below Point Estimate	53%	25%
Above Point Estimate	47%	75%

When a range of acceptable performance is desired, quartile limits may be used in conjunction with the prediction model to provide an additional discriminator between average, exceptional, and poor construction performance. These limits would allow the specification of a range of acceptable performance as a substitute for the pass/fail standards specified by the current "Dirtkicker" criteria. Figure 37 provides a comparison of the "Dirtkicker" criteria and the model limits for projects completed within a specific project type.

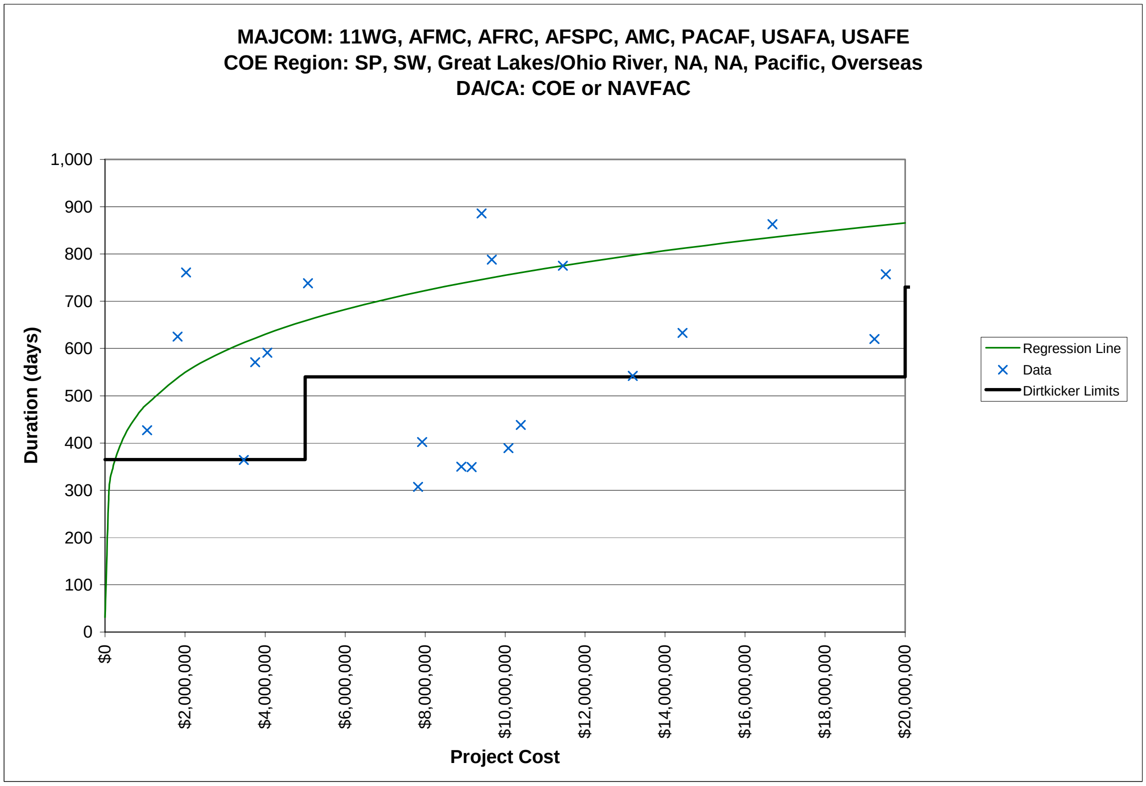


Figure 37. Model vs. "Dirtkicker" Comparison

The prediction model in the plot above appears to provide a better indication of the relative trend for the sample data. The prediction model also identifies a significant number (10) of projects which appear to be within the statistically average range contained by the quartile limits. In spite of this average performance, these same projects were identified as poor performers by the "Dirtkicker" limits. Used in this manner, this model appears to offer several advantages over the current "Dirtkicker" criteria. The model improves upon the stepwise nature of the "Dirtkicker" criteria by allowing for differentiation based on the project total cost. Additionally, the model offers a range of acceptable performance through the use of quartile limits, which may also be adjusted to achieve either a more strict or lenient policy. In comparison, the "Dirtkicker" criteria offer only pass/fail criteria for acceptable performance.

Step 6: Use for Prediction and Estimation

As previously discussed, the selected model appeared to provide a reasonable estimate of construction duration, both in terms of comparison to current estimation methods and through application to the validation data. These results suggested that the model should be useful for its intended purpose: to predict or provide reasonable estimates of construction duration for Air Force MILCON projects. This prediction step would involve the application of the model to projects still in the planning, programming, or early design phase. Since completion times are not available for these projects, this step was not conducted for this research effort.

Summary of Results

This research provided both an analysis of current Air Force duration estimation and benchmarking methods in addition to an investigation into several construction duration models for Air Force MILCON projects. Analysis of current Air Force methods revealed significant deviations between actual construction durations and those specified by current Air Force policy and planning estimates. A variety of independent variables were investigated for inclusion in potential predictive models. These models were developed for both facility and non-facility project types using both a partitioned linear regression and multiple linear regression methodology. The results for non-facility projects indicated that neither the linear nor multiple linear regression models were successful in providing a significant predictive model of construction duration. For facility projects, the MLR model containing the independent variables of cost, MAJCOM, COE Region, and design/construction agent variables was selected as the most significant predictive model of construction duration. This model appeared to offer a viable alternative for Air Force MILCON projects, both in terms of producing or verifying front-end estimates of project durations and when used as a policy setting tool. A summary of these results in relation to the research questions presented in Chapter I is presented in the following chapter, along with relevant conclusions and recommendations.

V. Conclusions and Recommendations

Introduction

This chapter provides a review of the research questions as well a short summary of the findings. The conclusions drawn from this research effort are also presented. Finally, the limitations of this research as well as recommendations for future research are discussed.

Summary of Findings

This section discusses the findings associated with the focus of this research as presented in Chapter I. This research sought to answer the question: What model, or combination of models, can be used to provide a statistically accurate prediction of project performance time for Air Force Military Construction (MILCON) facility projects? The investigative questions associated with this research question are shown below.

1) Does the current Air Force guidance used to benchmark project performance provide a statistically accurate estimate of actual construction durations?

2) What models have been identified by experts in the field that have been successful in predicting durations for construction projects?

3) Is there a model, or set of models, which can be used to predict construction durations across a range of Air Force MILCON projects?

4) What is the predictive accuracy of the proposed model?

The current methods and guidance for Air Force MILCON project duration estimation were analyzed, both in terms of "Dirtkicker" specified criteria and planning estimates. Both methods were found to differ significantly from the actual construction duration as determined at project completion. In fact, 72% of projects did not meet the current "Dirtkicker" criteria, and the mean value of the difference between the planned duration estimate and actual duration was found to be 167 days. These results indicate that a significant amount of variability within Air Force MILCON projects is not accounted for with either the "Dirtkicker" criteria or the planner's estimate.

An extensive literature review revealed two commonly accepted models of construction duration. The Bromilow Time-Cost (BTC) model was identified as the standard for estimating the performance time of construction projects (Bromilow, 1969). Refinements to the model as well as the inclusion of additional factors through multiple linear regression (MLR) were also found to be beneficial. A review of related literature was also conducted to identify those factors expected to influence project construction durations. A variety of factors were identified, with a specific focus on those factors which would be useful for providing front-end duration estimates. These factors were divided into categories of management attributes, project complexity, project environment, and project scope. These categories were then used to select possible factors influencing the duration of Air Force MILCON projects.

The BTC model, and subsequent MLR adaptations, were applied to a sample of Air Force MILCON projects. Through a comparison of the resulting models, the MLR version of the BTC model was found to provide the most useful prediction model for Air Force MILCON facility projects. The significant predictor variables for these projects were found to be total project cost, Major Command (MAJCOM), Corps of Engineers (COE) region, and Design/Construction agent. This model was considered statistically significant for a subset of Air Force MILCON facility projects, with all parameter values identified as significant at the $\alpha = 0.05$ significance level and an R^2 of 0.37. Neither form of the BTC model was found to be applicable to non-facility projects; results for this sample of projects yielded little statistical or practical significance. These projects appear to contain too much variability to gain any useful information from the application of a duration prediction model.

The selection of factors in the final model revealed several significant results. The factors shown in Table 30 were removed from the model due to insignificant differences between any of the categories in terms of construction duration means. Several of these excluded factors challenge commonly accepted notions. For example, the type work of a project (new construction versus addition/alteration) is typically thought to have a significant influence on construction characteristics. While this may be true, this research did not find any statistical significance between this factor and associated construction durations. Additionally, design build projects are often presented as a means to achieve accelerated project delivery. While this delivery may shorten design times, this research found no evidence that the design build delivery method produces significantly shorter construction durations. Several other factors such as facility type, weather, and economic conditions also did not appear to have any influence on construction durations for the sample Air Force MILCON projects.

Table 30. Insignificant Factors

Factor	Measure
Total Cost	Project Contract Total Cost
Project Delivery Method	Project Delivery Method
Type Work	Type Work
Design Method	Design Method
Facility Class	Air Force Category Code
MAJCOM Size	MAJCOM Size
Construction Year	Midpoint Construction Year
Weather: Temperature	Average Annual Minimum Temperature
Weather: Precipitation Level	Average Yearly Precipitation
Weather: Rain Days	Average Rain Days
Economic Conditions	Labor Elasticity Level

The model developed in this research revealed several factors which were considered significant influences on construction duration for Air Force MILCON facility projects. The final selected model was.

$$y = 3.44 + 0.198x_1 + -0.059x_2 + -0.070x_3 + -0.222x_4 + -0.193x_5 + -.0146x_6 \qquad (30)$$

where

y = Project construction duration (ln days),

x_1 = Project total cost (ln $),

x_2 = ACC MAJCOM dummy (1 if ACC, 0 if not),

x_3 = AETC MAJCOM dummy (1 if AETC, 0 if not),

x_4 = AFSOC MAJCOM dummy (1 if AFSOC, 0 if not),

x_5 = Northwestern COE Region (1 if Northwestern Region, 0 if not), and

x_6 = In-House Design/Construction Agent dummy (1 if In House, 0 if not).

The model revealed the dominating correlation between cost and duration, which is consistent with multiple previous research efforts reported in the literature. Several other factors were also identified. Projects completed within Air Combat Command (ACC), Air Education and Training Command (AETC), and Air Force Special Operations Command (AFSOC) were individually statistically different when compared to the combined group of all other MAJCOMs. Results indicated that projects completed within these three MAJCOMs can be expected to have lower than average construction durations. The same result was found for projects completed within the Northwestern COE region; construction durations in this region were significantly lower than all other regions. The reasons behind these observations are unknown; however, possible explanations include differences in either regional characteristics or the quality of management practices. Finally, projects completed using in-house design construction agents were found have significantly shorter durations than those managed by the COE or Naval Facilities Engineering Command (NAVFAC). Again, these results may or may not be indicative of the quality of management processes within these organizations. While management effectiveness may be an issue, another possible explanation is the nature of projects selected by each agent. For example, projects selected for in-house management may be less complex in nature, thereby explaining the lower construction durations associated with this project group.

The predictive accuracy of the model was analyzed using an additional set of projects not included in the formulation of the predictive model. The model was found to provide a reasonable means of predicting construction durations for this set of Air Force MILCON projects. Model predictions were compared both in terms of the planner's estimates specified prior to contract award, as well as in terms of the current Air Force "Dirtkicker" criteria. The model was found to offer a slightly more reliable and significantly more conservative estimate for projects than that produced by the current method used by project planners. When compared to the "Dirtkicker" criteria, the model was found to offer more realistic and achievable construction duration estimates for MILCON projects.

Limitations

This research is subject to several limitations. As with any prediction model, prediction is only valid within the range of characteristics of the selected sample data. For this reason, use of the model is limited to projects that meet the characteristics of the Air Force facility projects in the sample data. This limitation may require updates to parameter values if these conditions change.

The usefulness of this research is also limited by the accuracy and availability of project data. The assumption was made that the data taken from the Automated Civil Engineering-Project Management (ACES-PM) database is accurate. Any inaccuracies in this project information could result in distortions which influence the predictive accuracy of the model. The inclusion of significant factors was also limited by the availability of data. Some factors identified as having an important impact on construction duration by previous studies were not included due to a lack of information. Therefore, qualitative factors such as management effectiveness, project relationships, and communication, among others, were not explored as possible variables for inclusion in the final model. This model focuses on those variables which are possible to identify early in the planning process without the need to analyze specific construction tasks. For this reason, the resulting model is applicable for producing front-end predictions of construction duration; it is not intended as a replacement for estimates of project duration developed using detailed construction scheduling techniques.

While this research was successful in identifying several factors which have a statistically significant influence on construction durations, actual causal mechanisms cannot be determined. For instance, the findings of a significant difference between MAJCOMs and COE regions cannot be tied to a specific difference between these factors. Differences could be the result of regional variations, management policies, or any other number of causal influences. This research identified only correlations between the selected factors and the associated construction duration.

Recommendations

Usefulness of the Model

This research revealed several possible uses for the duration prediction model: as a front-end prediction tool as well as a policy setting and performance measurement tool. The validity of the model was verified through comparisons to the planner's estimate; therefore the model can be used as a substitute for currently unspecified estimation methods. Additionally, through the use of quartile limits, the model can be used to evaluate the construction duration estimates developed by an Architect/Engineer (A/E) or contractor without requiring a detailed analysis of the project design. In this way, the model can be used to either offer a valid front-end duration estimate or evaluate the validity of a duration estimate produced by other sources prior to contract award.

This research also identified possible uses of the model in terms of measuring contractor performance. Through the use of quartile limits, construction durations can be conveniently categorized into average, above average, and below average groupings based on the identified project characteristics. These limits provide an objective and defendable means by which to measure contractor performance and potentially serve as a basis for determining penalties or incentives.

Finally, the model offers a more realistic model of construction duration in terms of Air Force policy. This research revealed that the prediction model consistently provides a more realistic duration benchmark when compared to the "Dirtkicker" criteria. Through the use of quartile or other specified limits, the model appears to offer a valid tool for setting policy through the identification of acceptable performance standards. The current "Dirtkicker" limits appear to specify highly optimistic limits for construction duration. While these limits may be designed to set high performance standards, previous research has shown that specifying inadequate durations is not successful in motivating contractors to accelerate construction times (Bromilow, 1969: 77). The results of this research indicate that the prediction model, used either through point estimation or quartile limits, produces performance standards which are both more realistic and achievable than the current "Dirtkicker" construction duration limits. The selected factors also indicate that the increased durations allowed for PACAF and USAFE projects under the current "Dirtkicker" criteria may not be valid. This research found no statistical evidence that projects in these MAJCOMs took significantly more time to complete than those in other MAJCOMs.

Future Research

There are several areas for future research in the identification of significant duration-influencing factors. Little research has been completed to determine the perceptions of Air Force projects managers regarding which factors are likely to influence MILCON construction durations. A consolidated listing of these factors would provide valuable information for use in future research. Additionally, many qualitative management-related factors were excluded from this research due to problems of data collection with large sample sizes. Future research focusing on a smaller subset of projects divided by region or base may be able to include these more qualitative factors through direct interaction with individual project managers. Additional research could also be conducted into the possible causal influences behind factors identified during this research. While a variety of factors were identified as significant, future research could focus on the determination of possible causes; this might include an investigation into which project management characteristics appear to be responsible for shorter than average construction durations in selected COE regions and MAJCOMs.

Appendix A: ACES-PM Field Explanations

Each of the data entries below represent field selected from the ACES-PM database. The first column represents the coding used to identify the variable within the database, the second and third columns provide the actual field title and a description. These variables were investigated for either possible use as predictor variables or as a means to identify meaningful difference between projects.

Tab	Database Abbreviation	Actual Title	Field Description
General	PROJECTS.PJ_PROJECT_TITLE_TX	Project Title	The project title, normally a short description of the required work to be performed on the project.
	PROJECT.PJ_FISCAL_YEAR	Fiscal Year	The fiscal year in which obligation of funds has occurred or is programmed to occur.
	PROJECT.PJ_INSTALLATION	Installation	Installation at which project is constructed.
	PROJECTS.PJ_PROGRAM_TYPE_CD	Type	The type of program associated with the project, i.e. MCP, O&M.
Programming	PROJECTS.COMMAND_HOST	MAJCOM	The major command which hosts or operates the installation where the project is being accomplished. This field is defaulted from the ACES Real Property Installations table and is not updateable, except through the Air Staff Design Instruction process.
	KPY$PROJECT.FPM_GET_PA(SEQNBR)	Programmed Amount	The current programmed amount for the project. It should reflect the current cost estimate.
	PROJECTS.PJ_PROJECT_STATUS_CD	Status	The current status of the project. The value is automatically assigned as certain entries are made during the life cycle of the project. Valid values are DSG (Design), HIS (History), AWD (Contract Award), PRE (Preliminary Planning), ADV (Advertised), CNS (Construction), CNT (Continuous), BSE (Base Submitted to MAJCOM), PRG (MAJCOM Submitted to Air Staff), RTA (Ready to Advertise), MCV (MAJCOM Validated), INP (In Progress), CPD (Created from 1391), BID (Bid Opening), CNX (Cancelled), HLD (Project on Hold)
	PROJECTS.CAT_NBR	Category Code	The category code identified the function or usage of the primary project facility.
	NO CODE SPECIFIED	IRR Facility Class	IRR Facility Class identifying the function or usage of a facility bases on the category code.
	PROJECTS.PJ_SCOPE_OF_PROJECT_QY	Scope	The current scope or quantity of the project. The scope is tied to the unit of measure.
	PROJECTS.PJ_UNIT_OF_MEASURE	Unit of Measure	Unit of measure for scope term.
	PROJECTS.PJ_TYPE_WORK_CD	Type Work	The type of work being done on a project. This field is required prior to creating a DD Form 1391 for the project.
Supplemental	PROJECTS.COMMAND.DA	Design Agent	The major command serving as design agent for the project. This field is defaulted from the ACES Real Property Installations table. For MILCON projects, it may only be changed through the Air Staff Design instruction process.
	PROJECTS.COMMAND.CA	Construction Agent	The major command serving as construction agent for the project. This field is defaulted from the ACES Real Property Installations table. For MILCON projects, it may only be change through the Air Staff Design instruction process.
Design	PROJECTS.PD_PROJECT_DSG_METHOD_CD	Project Delivery Method	The type of design method used. Valid values are: DB (Design Build), T (Traditional Design Build), TK (Turn-key), O (Other Design/Build Methods).
	PROJECTS.PD_AE_OR_IN_HOUSE_NM	Designer/ A-E Firm	The name of the Architect-Engineer or in-house designer.
	PROJECTS.PD_DSG_STD_METHOD_CD	Method of Design	The design standard used for the project. Valid values are: AEC (A-E Contract, Closed-end), AEO (A-E Contract, Open-end), CAE (CADD A-E Contract), CIH (CADD In House), COE (Corps or Engineers), DBD (Design-Build Contract), I/H (In House), NAV (Navy), OTH (Other)

Tab	Database Abbreviation	Actual Title	Field Description
Contract Management	PROJECTS.PJ_METHOD_OF_CONTRACTING_CD	Method of Contract	The method of contracting used in the execution of the project. Valid values are: COE (Corps of Engineers), D/B (Design Build), 8A (Small Business Negotiated), I/H (In House), IDIQ (Indefinite Quantity / Indefinite Delivery), IFB (Invitation for Bid), NAV (Navy), R/H (Red Horse), RFP (Request for Proposal), SABER, SVC (Service Contract), T&M (Time and Materials)
	PROJECTS.PJ_METHOD_OF_CNS_CD	Construction Method	The method of construction or accomplishment. Valid values are: COE, DBD, EMP I/H, IDQ, NAV, OTH, PBF, RDH, SBR, SVC
	NO CODE SPECIFIED	Number of Modifications	The total number of modification executed against the contracts associated with this project.
	PROJECTS.CM_NOTICE_TO_PROCEED_DT	Notice to Proceed	The formal written authorization given to the design A-E, the contractor, or other outside agent to begin their contracted task.
	PROJECTS.PJ_PROJECT_TOTAL_COST	Total Contract Cost of Project	The final contract cost of the completed project.
	NO CODE SPECIFIED	Contract Days	The current estimated number of days required to complete the contract. This field is entered under "Performance Period" on the Contract form.
	NO CODE SPECIFIED	Modified Days	This represents any change to the original performance period on the contract. This field is updated from the modifications form.
	NO CODE SPECIFIED	Total Days	A total of the original performance period and any day changes entered via modification to the contract.
	NO CODE SPECIFIED	Cost of Contract Mods	This is the total cost of all executed modifications against a contract. The field is a total of all executed modifications and is entered on the modification form.
Milestones	PROJECT_MILESTONES.ACT_DT	Design Start Actual	The actual design start date of the project
	PROJECT_MILESTONES.ACT_DT	Design Complete Actual	The actual design completion date of the project
	PROJECT_MILESTONES.EST_DT	Construction Start Estimated	The estimated construction start date of the project.
	PROJECT_MILESTONES.EST_DT	Beneficial Occupancy Estimated	The estimated beneficial occupancy date of the project
	PROJECT_MILESTONES.ACT_DT	Beneficial Occupancy Actual	The actual beneficial occupancy date of the project.

Appendix B: ANOVA Results for Non-Facility Projects

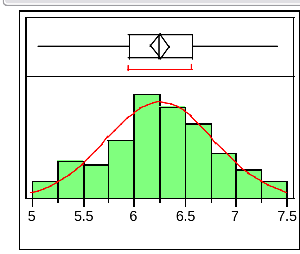
This appendix details the results of the ANOVA analysis for non-facility projects. The three basic ANOVA test assumptions are verified for factor as listed below.

1) The probability distribution of the populations sampled must all be normal

This assumption was first verified by analyzing the distribution of the dependent variable (ln duration) for the population of all non-facility projects. This distribution is shown below.

Distributions

Ln Duration



Quantiles

100.0%	maximum	7.3930
99.5%		7.3930
97.5%		7.3233
90.0%		6.9966
75.0%	quartile	6.5805
50.0%	median	6.2510
25.0%	quartile	5.9563
10.0%		5.4664
2.5%		5.1930
0.5%		5.0750
0.0%	minimum	5.0750

Moments

Mean	6.2622377
Std Dev	0.5289986
Std Err Mean	0.0478933
upper 95% Mean	6.3570551
lower 95% Mean	6.1674203
N	122

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	6.262238	6.167420	6.357055
Dispersion	Sigma	0.528999	0.469918	0.605205

Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.988044	0.3648

The normality assumption was verified through the Shapiro-Wilks W test. This test (W - 0.997, p = 0.3648) indicates a normal distribution by failing to reject the null hypothesis that the distribution is normal. Partitioned groupings can be assumed to be normal due to the sufficiently large sample size associated with each grouping.

2) The probability distributions of the populations of responses must have equal variances

This test will be verified for each factor below using Levene's test.

3) The samples selected must be random and independent.

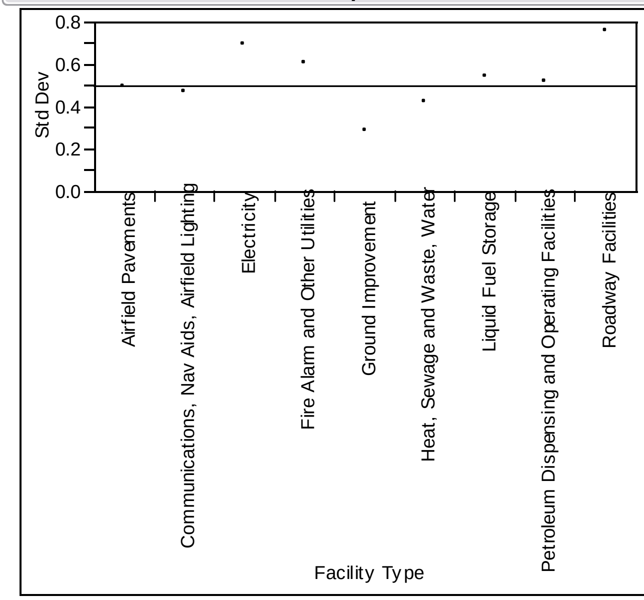
This assumption is valid due to the nature of the data selected. Separate construction projects from all Air Force bases can be assumed to be random and independent.

ANOVA results for Facility Class

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Facility Type	8	3.204242	0.400530	1.5993	0.1327
Error	113	28.300126	0.250444		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Airfield Pavements	38	0.4908665	0.3820853	0.3820853
Communications, Nav Aids, Airfield Lighting	3	0.4666243	0.3403946	0.4043266
Electricity	8	0.6883682	0.5231046	0.5231046
Fire Alarm and Other Utilities	3	0.6038073	0.4629365	0.4013759
Ground Improvement	9	0.2812957	0.2111001	0.1985759
Heat, Sewage and Waste, Water	40	0.4219542	0.3346298	0.3346298
Liquid Fuel Storage	5	0.5386641	0.4364061	0.4821694
Petroleum Dispensing and Operating Facilities	7	0.5144398	0.3647839	0.3700822
Roadway Facilities	9	0.7564777	0.6389415	0.6636146

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	2.0799	8	113	0.0434
Brown-Forsythe	1.9766	8	113	0.0556
Levene	1.7738	8	113	0.0895
Bartlett	1.3331	8	.	0.2214

Warning: Small sample sizes. Use Caution.

Welch Anova testing Means Equal, allowing Std Devs Not Equal

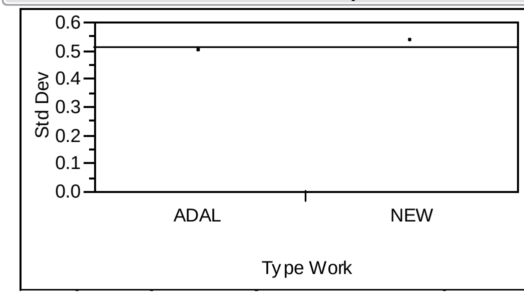
F Ratio	DFNum	DFDen	Prob > F
1.2843	8	15.587	0.3194

ANOVA Results for Type Work

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Type Work	1	0.116260	0.116260	0.4445	0.5063
Error	120	31.388108	0.261568		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
ADAL	72	0.4977779	0.3898145	0.3890696
NEW	50	0.5306047	0.4053086	0.4053086

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.2806	1	120	0.5973
Brown-Forsythe	0.0759	1	120	0.7834
Levene	0.0695	1	120	0.7925
Bartlett	0.2361	1	.	0.6270
F Test 2-sided	1.1362	49	71	0.6156

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
0.4343	1	101.13	0.5114

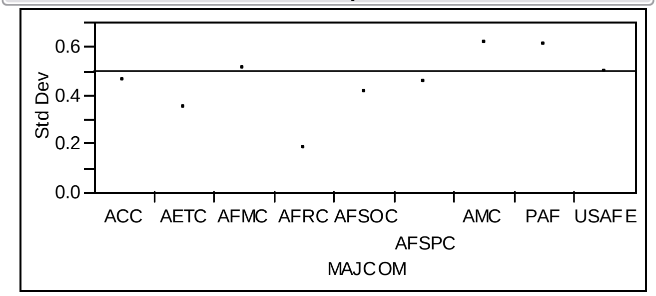
t Test
0.6590

ANOVA Results for MAJCOM

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
MAJCOM	8	2.926853	0.365857	1.4467	0.1849
Error	113	28.577515	0.252898		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
ACC	18	0.4573477	0.3430335	0.3369036
AETC	13	0.3477841	0.2731926	0.2771476
AFMC	25	0.5080179	0.3742598	0.3679586
AFRC	5	0.1792113	0.1533621	0.1535061
AFSOC	8	0.4077727	0.3373208	0.3373208
AFSPC	8	0.4521802	0.3704886	0.3704886
AMC	27	0.6094779	0.4972518	0.4902753
PAF	10	0.6033050	0.4551271	0.4292015
USAFE	8	0.4955135	0.3685849	0.3685849

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	1.1668	8	113	0.3254
Brown-Forsythe	0.9845	8	113	0.4519
Levene	1.2318	8	113	0.2870
Bartlett	1.3442	8	.	0.2160

Warning: Small sample sizes. Use Caution.

Welch Anova testing Means Equal, allowing Std Devs Not Equal

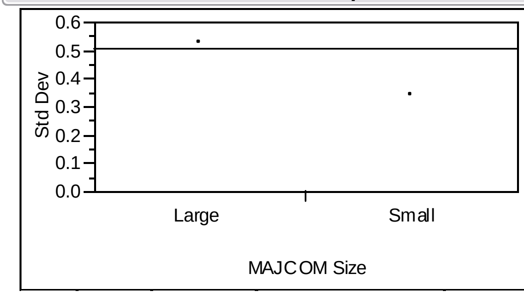
F Ratio	DFNum	DFDen	Prob > F
1.4521	8	33.677	0.2117

ANOVA Results for MAJCOM Size

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
MAJCOM Size	1	0.342239	0.342239	1.3179	0.2533
Error	120	31.162129	0.259684		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Large	109	0.5252487	0.4119660	0.4117691
Small	13	0.3374445	0.2739089	0.2680749

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	2.6755	1	120	0.1045
Brown-Forsythe	2.4006	1	120	0.1239
Levene	2.2729	1	120	0.1343
Bartlett	3.2651	1	.	0.0708
F Test 2-sided	2.4228	108	12	0.0884

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
2.6099	1	19.754	0.1221

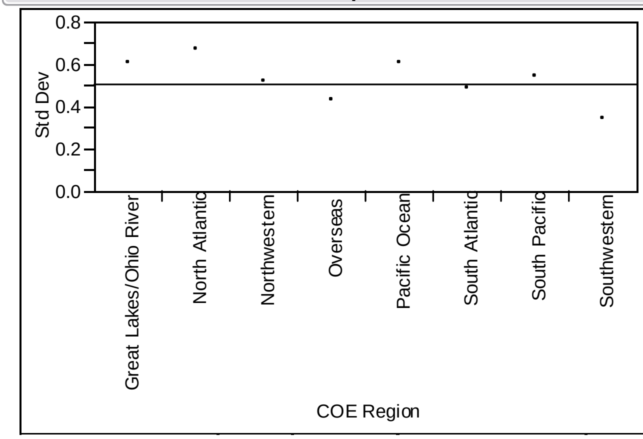
t Test
1.6155

<u>ANOVA Results for COE Region</u>

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
COE Region	7	2.340368	0.334338	1.3069	0.2534
Error	114	29.164000	0.255825		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Great Lakes/Ohio River	6	0.6026945	0.5268443	0.5268443
North Atlantic	7	0.6692900	0.5491065	0.5900329
Northwestern	23	0.5121964	0.4083538	0.4062342
Overseas	12	0.4247137	0.3096435	0.3031526
Pacific Ocean	10	0.6033050	0.4551271	0.4292015
South Atlantic	33	0.4865416	0.3820821	0.3824052
South Pacific	16	0.5426398	0.3883699	0.3857194
Southwestern	15	0.3418982	0.2608667	0.2605337

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	1.0334	7	114	0.4118
Brown-Forsythe	1.1508	7	114	0.3368
Levene	1.0813	7	114	0.3800
Bartlett	0.8737	7	.	0.5263

Welch Anova testing Means Equal, allowing Std Devs Not Equal

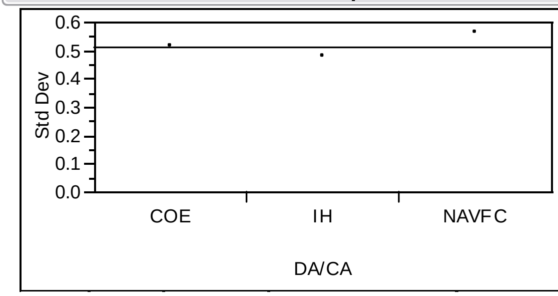
F Ratio	DFNum	DFDen	Prob > F
1.0725	7	31.879	0.4034

ANOVA Results for Design/Construction Agent

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
DA/CA	2	0.149389	0.074695	0.2835	0.7537
Error	119	31.354979	0.263487		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
COE	84	0.5129467	0.4101323	0.4098409
IH	21	0.4751344	0.3344474	0.3349206
NAVFC	17	0.5590973	0.4018901	0.3888674

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.2823	2	119	0.7546
Brown-Forsythe	0.4534	2	119	0.6366
Levene	0.4754	2	119	0.6228
Bartlett	0.2328	2	.	0.7923

Welch Anova testing Means Equal, allowing Std Devs Not Equal

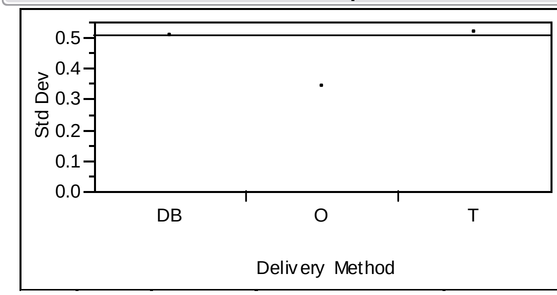
F Ratio	DFNum	DFDen	Prob > F
0.2981	2	32.506	0.7442

ANOVA Results for Project Delivery Method

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Delivery Method	2	0.914809	0.457404	1.7794	0.1732
Error	119	30.589559	0.257055		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
DB	27	0.5058678	0.3853092	0.3836298
O	4	0.3364051	0.2213807	0.2212282
T	91	0.5120395	0.3989294	0.3986424

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.3749	2	119	0.6882
Brown-Forsythe	0.6034	2	119	0.5486
Levene	0.6077	2	119	0.5463
Bartlett	0.3765	2	.	0.6863

Warning: Small sample sizes. Use Caution.

Welch Anova testing Means Equal, allowing Std Devs Not Equal

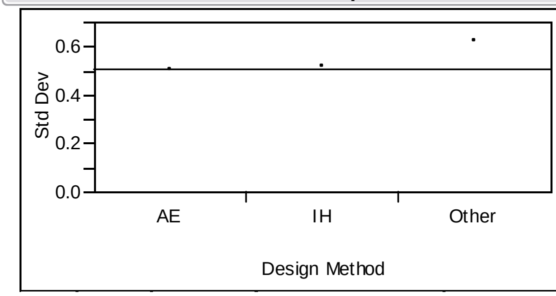
F Ratio	DFNum	DFDen	Prob > F
2.0230	2	8.5651	0.1907

ANOVA Results for Project Design Method

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Design Method	2	0.539675	0.269837	1.0370	0.3577
Error	119	30.964693	0.260208		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
AE	71	0.4973018	0.3838802	0.3837888
IH	44	0.5139931	0.3866822	0.3863757
Other	7	0.6181880	0.4867632	0.4809788

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.4854	2	119	0.6167
Brown-Forsythe	0.2950	2	119	0.7451
Levene	0.3329	2	119	0.7175
Bartlett	0.2904	2	.	0.7479

Welch Anova testing Means Equal, allowing Std Devs Not Equal

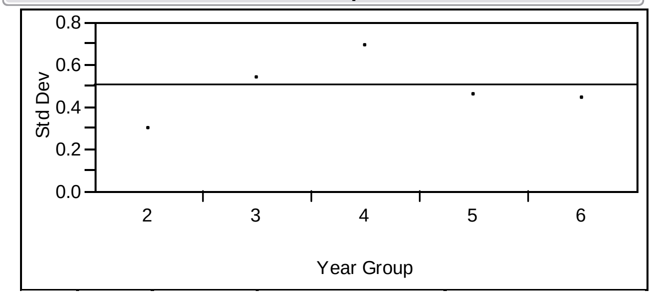
F Ratio	DFNum	DFDen	Prob > F
1.0009	2	16.073	0.3893

ANOVA Results for Project Year Group

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Year Group	4	1.507843	0.376961	1.4703	0.2156
Error	117	29.996525	0.256381		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
2	2	0.2929804	0.2071684	0.2071684
3	10	0.5343388	0.4320151	0.3812643
4	24	0.6846579	0.5738735	0.5669905
5	45	0.4530447	0.3459835	0.3410661
6	41	0.4338390	0.3403501	0.3384316

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	4.4604	3	116	0.0053
Brown-Forsythe	2.6213	4	117	0.0383
Levene	3.1650	4	117	0.0165
Bartlett	1.9093	4	.	0.1058

Warning: Small sample sizes. Use Caution.

Welch Anova testing Means Equal, allowing Std Devs Not Equal

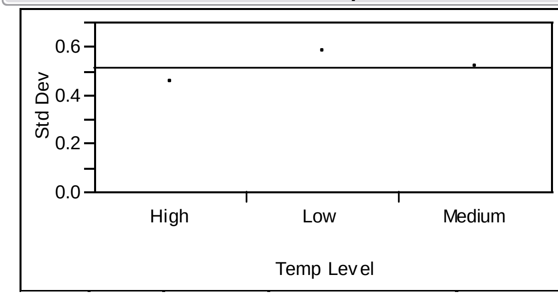
F Ratio	DFNum	DFDen	Prob > F
2.6558	4	7.499	0.1170

ANOVA Results for Temperature Level

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Temp Level	2	0.018262	0.009131	0.0345	0.9661
Error	119	31.486106	0.264589		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
High	36	0.4500249	0.3490341	0.3486804
Low	33	0.5808858	0.4564497	0.4472727
Medium	53	0.5114105	0.3915067	0.3906470

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	1.2700	2	119	0.2846
Brown-Forsythe	0.7896	2	119	0.4564
Levene	0.9884	2	119	0.3752
Bartlett	1.0761	2	.	0.3409

Welch Anova testing Means Equal, allowing Std Devs Not Equal

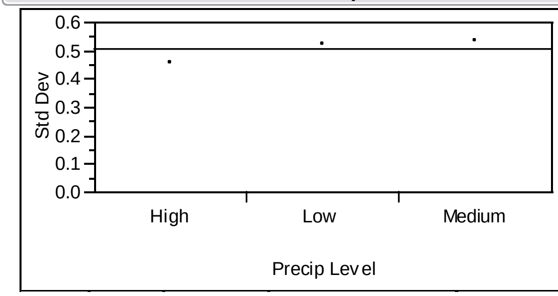
F Ratio	DFNum	DFDen	Prob > F
0.0381	2	71.228	0.9626

ANOVA Results for Precipitation Level

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Precip Level	2	0.748621	0.374310	1.4483	0.2391
Error	119	30.755747	0.258452		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
High	32	0.4509239	0.3460873	0.3430767
Low	18	0.5187920	0.3935456	0.3931814
Medium	72	0.5291100	0.4197886	0.4157369

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.6067	2	119	0.5468
Brown-Forsythe	0.5788	2	119	0.5622
Levene	0.6265	2	119	0.5362
Bartlett	0.5273	2	.	0.5902

Welch Anova testing Means Equal, allowing Std Devs Not Equal

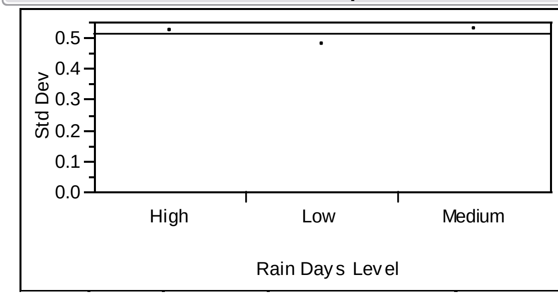
F Ratio	DFNum	DFDen	Prob > F
1.4653	2	43.511	0.2422

ANOVA Results for Rain Days Level

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Rain Days Level	2	0.208025	0.104012	0.3955	0.6742
Error	119	31.296343	0.262994		
C. Total	121	31.504368			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
High	30	0.5175781	0.3920223	0.3901852
Low	25	0.4759762	0.3482819	0.3464029
Medium	67	0.5235418	0.4134692	0.4133305

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.1709	2	119	0.8431
Brown-Forsythe	0.3959	2	119	0.6740
Levene	0.3789	2	119	0.6855
Bartlett	0.1560	2	.	0.8556

Welch Anova testing Means Equal, allowing Std Devs Not Equal

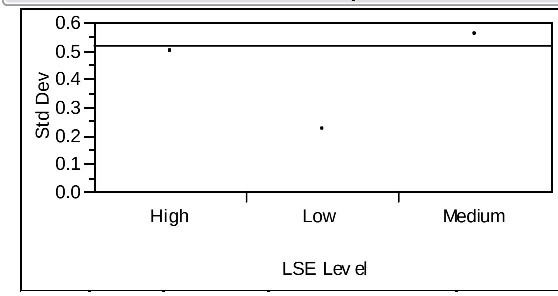
F Ratio	DFNum	DFDen	Prob > F
0.3906	2	55.959	0.6785

ANOVA Results for Labor Supply Elasticity Level

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
LSE Level	2	0.101069	0.050535	0.1896	0.8276
Error	97	25.851740	0.266513		
C. Total	99	25.952809			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
High	37	0.4932052	0.3909293	0.3894213
Low	8	0.2174109	0.1583033	0.1581556
Medium	55	0.5571724	0.4340014	0.4340510

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	2.0841	2	97	0.1300
Brown-Forsythe	2.6439	2	97	0.0762
Levene	2.6793	2	97	0.0737
Bartlett	3.4745	2	.	0.0310

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
0.2809	2	31.963	0.7569

The results for the outputs above can be interpreted in the following manner with respect to identifying significant differences between means and identifying violations of the constant variance assumption: A *p*-value less than the pre-selected significance level α (for purposes of this research 0.05) lead to the rejection of the null hypothesis that all means are equal. For *p*-values larger than 0.05, the null hypothesis is accepted, indicating that there are not significant differences between duration residuals in terms of facility type. The equal variance assumption was verified using Levene's test. This test evaluates the null hypothesis that variances are equal against the alternate that variances are not equal. A *p*-value less than the selected 0.05 indicates sufficient evidence to reject the null hypothesis and assume the variances are not equal. In this case (p=0.0737) the constant variance assumption cannot be disproved. If non-constant variance is detected, the Welch ANOVA results are used to identify differences between means. This test can be interpreted in the same manner as the ANOVA test. A summary of the results above is provided below.

	ANOVA			Levenes' test	Welch ANOVA	
Factor	F	df	p	p	F	p
Facility Class	1.60	8, 113	0.133	0.090	-	-
Type Work	0.44	1, 120	0.506	0.793	-	-
MAJCOM	1.45	8, 113	0.185	0.287	-	-
MAJCOM Size	1.32	1, 120	0.253	0.134	-	-
COE Region	1.31	7, 114	0.253	0.380	-	-
Design/Construction Agent	0.28	2, 119	0.754	0.623	-	-
Project Delivery Method	1.78	2, 119	0.173	0.546	-	-
Design Method	1.04	2, 119	0.358	0.718	-	-
Year Group	1.47	4, 117	0.216	0.017	2.66	0.117
Weather: Temperature	0.03	2, 119	0.966	0.375	-	-
Weather: Precipitation Level	1.45	2, 119	0.239	0.536	-	-
Weather: Rain Days	0.40	2, 119	0.674	0.686	-	-
Labor Elasticity Level	0.19	2, 97	0.828	0.074	-	-

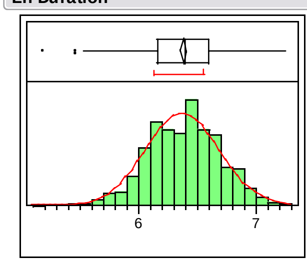
Appendix C: ANOVA Results for Facility Projects

This appendix details the results of the ANOVA analysis for facility projects. The three basic ANOVA test assumptions are verified for factors as listed below.

1) The probability distribution of the populations sampled must all be normal

This assumption was first verified by analyzing the distribution of the dependent variable (ln duration) for the population of all non-facility projects. This distribution is shown below. The normality assumption was verified through the Shapiro-Wilks W test. This test ($W = 0.997$, $p = 0.463$) indicates a normal distribution by failing to reject the null hypothesis that the distribution is normal. This normality assumption can also be assumed valid for the partition groups selected below due to the sufficiently large sample size of each group.

Ln Duration



Normal(6.38422,0.31204)

Quantiles

100.0%	maximum	7.2490
99.5%		7.1675
97.5%		6.9795
90.0%		6.7835
75.0%	quartile	6.5990
50.0%	median	6.4010
25.0%	quartile	6.1643
10.0%		6.0115
2.5%		5.7500
0.5%		5.4756
0.0%	minimum	5.1930

Moments

Mean	6.3842172
Std Dev	0.312036
Std Err Mean	0.0129566
upper 95% Mean	6.4096649
lower 95% Mean	6.3587696
N	580

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	6.384217	6.358770	6.409665
Dispersion	Sigma	0.312036	0.295053	0.331109

Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.997297	0.4627

2) The probability distributions of the populations of responses must have equal variances

This test will be verified for each factor below using Levene's test.

3) The samples selected must be random and independent.

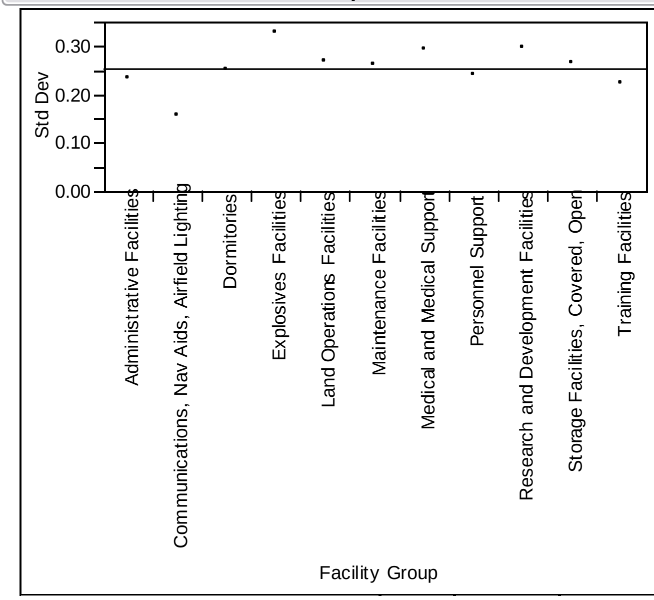
This assumption is valid due to the nature of the data selected. Separate construction projects from all Air Force bases can be assumed to be random and independent.

ANOVA results for Facility Class.

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Facility Group	10	0.694652	0.069465	1.0791	0.3761
Error	569	36.628979	0.064374		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Administrative Facilities	38	0.2315059	0.1722942	0.1702917
Communications, Nav Aids, Airfield Lighting	7	0.1564721	0.1329514	0.1393729
Dormitories	112	0.2504188	0.1993212	0.1992642
Explosives Facilities	9	0.3285847	0.2297952	0.2255884
Land Operations Facilities	91	0.2680870	0.2176538	0.2166143
Maintenance Facilities	122	0.2609901	0.2115533	0.2099689
Medical and Medical Support	13	0.2924130	0.2412631	0.2447904
Personnel Support	85	0.2396028	0.1951251	0.1948337
Research and Development Facilities	21	0.2959942	0.2596334	0.2604666
Storage Facilities, Covered, Open	21	0.2653464	0.2047046	0.1957095
Training Facilities	61	0.2219344	0.1736005	0.1713445

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	1.0572	10	569	0.3938
Brown-Forsythe	1.1048	10	569	0.3560
Levene	1.1376	10	569	0.3314
Bartlett	0.8758	10	.	0.5552

Welch Anova testing Means Equal, allowing Std Devs Not Equal

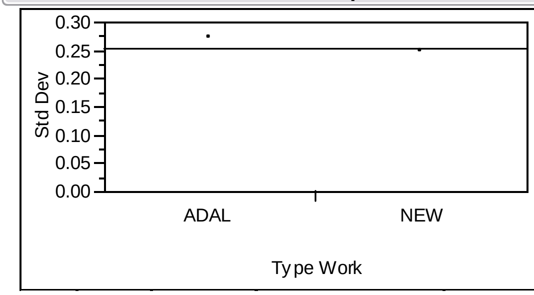
F Ratio	DFNum	DFDen	Prob > F
1.6578	10	77.225	0.1063

ANOVA Results for Type Work

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Type Work	1	0.045445	0.045445	0.7046	0.4016
Error	578	37.278186	0.064495		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
ADAL	154	0.2717036	0.2262268	0.2249665
NEW	426	0.2472593	0.1979556	0.1969416

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	2.7844	1	578	0.0957
Brown-Forsythe	3.8531	1	578	0.0501
Levene	4.1134	1	578	0.0430
Bartlett	2.0528	1	.	0.1519
F Test 2-sided	1.2075	153	425	0.1459

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
0.6450	1	250.25	0.4227

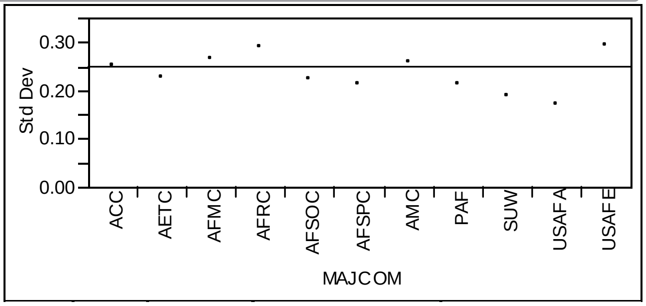
t Test
0.8031

ANOVA Results for MAJCOM

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
MAJCOM	10	1.405858	0.140586	2.2271	0.0151
Error	569	35.917772	0.063124		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
ACC	103	0.2512541	0.2018168	0.1987450
AETC	83	0.2246207	0.1754448	0.1754080
AFMC	93	0.2659754	0.2273296	0.2263031
AFRC	29	0.2879036	0.2444655	0.2325281
AFSOC	13	0.2208636	0.1493105	0.1502752
AFSPC	48	0.2105775	0.1678149	0.1676442
AMC	112	0.2575428	0.1992182	0.1992182
PAF	29	0.2121847	0.1662406	0.1661183
SUW	4	0.1866322	0.1502802	0.1502802
USAFA	7	0.1688963	0.1221873	0.1225675
USAFE	59	0.2919601	0.2511453	0.2498523

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	1.6153	10	569	0.0985
Brown-Forsythe	2.0004	10	569	0.0312
Levene	2.3982	10	569	0.0086
Bartlett	1.2730	10	.	0.2392

Warning: Small sample sizes. Use Caution.

Welch Anova testing Means Equal, allowing Std Devs Not Equal

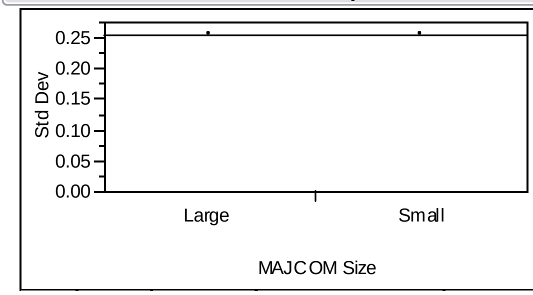
F Ratio	DFNum	DFDen	Prob > F
2.0124	10	58.143	0.0483

ANOVA Results for MAJCOM Size

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
MAJCOM Size	1	0.008542	0.008542	0.1323	0.7162
Error	578	37.315089	0.064559		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Large	527	0.2540579	0.2061181	0.2055310
Small	53	0.2543540	0.2022532	0.1916689

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.0002	1	578	0.9897
Brown-Forsythe	0.3965	1	578	0.5291
Levene	0.0326	1	578	0.8568
Bartlett	0.0001	1	.	0.9910
F Test 2-sided	1.0023	52	526	0.9461

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
0.1321	1	62.896	0.7175

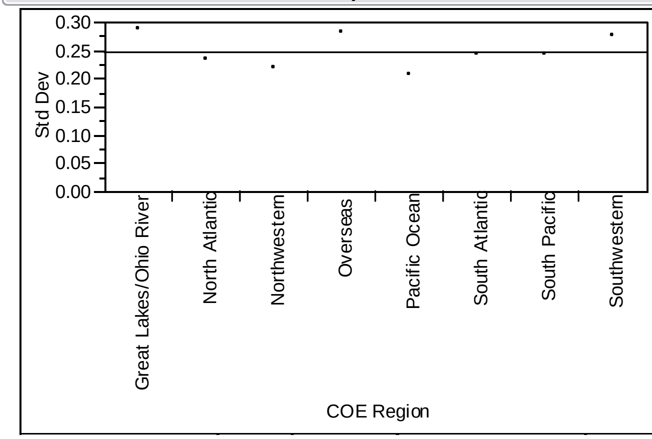
t Test
0.3634

ANOVA Results for COE Region

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
COE Region	7	2.483556	0.354794	5.8250	<.0001
Error	572	34.840075	0.060909		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
Great Lakes/Ohio River	28	0.2853467	0.2374147	0.2349408
North Atlantic	46	0.2328303	0.1818314	0.1818069
Northwestern	128	0.2185959	0.1751977	0.1751742
Overseas	67	0.2801253	0.2371463	0.2339882
Pacific Ocean	31	0.2066325	0.1600861	0.1601206
South Atlantic	125	0.2422403	0.1946631	0.1905048
South Pacific	70	0.2413880	0.2026670	0.2004995
Southwestern	85	0.2755259	0.2271961	0.2264793

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	2.2303	7	572	0.0304
Brown-Forsythe	2.1369	7	572	0.0382
Levene	2.4830	7	572	0.0162
Bartlett	1.6098	7	.	0.1273

Welch Anova testing Means Equal, allowing Std Devs Not Equal

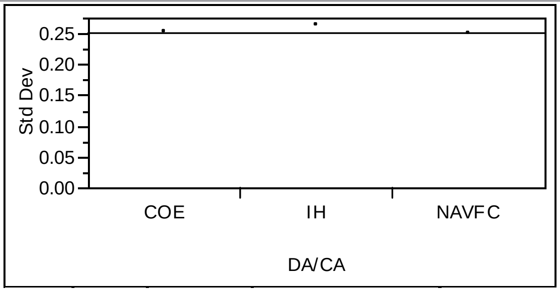
F Ratio	DFNum	DFDen	Prob > F
6.4323	7	169.25	<.0001

ANOVA Results for Design/Construction Agent

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
DA/CA	2	0.631993	0.315997	4.9693	0.0072
Error	577	36.691638	0.063590		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
COE	454	0.2517927	0.2027217	0.2016432
IH	51	0.2616561	0.2096499	0.2031700
NAVFC	75	0.2479222	0.2000105	0.1999986

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.1198	2	577	0.8872
Brown-Forsythe	0.0067	2	577	0.9933
Levene	0.0668	2	577	0.9354
Bartlett	0.0915	2	.	0.9126

Welch Anova testing Means Equal, allowing Std Devs Not Equal

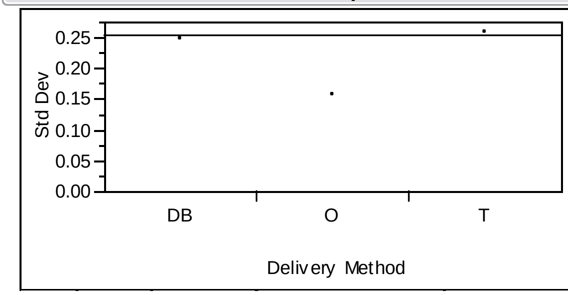
F Ratio	DFNum	DFDen	Prob > F
4.8687	2	98.357	0.0096

ANOVA Results for Project Delivery Method

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Delivery Method	2	0.128289	0.064144	0.9951	0.3703
Error	577	37.195342	0.064463		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
DB	162	0.2466975	0.1995961	0.1970363
O	5	0.1549597	0.1087588	0.1144311
T	413	0.2574185	0.2091392	0.2082448

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.8888	2	577	0.4117
Brown-Forsythe	1.1899	2	577	0.3050
Levene	1.3239	2	577	0.2669
Bartlett	0.8915	2	.	0.4101

Warning: Small sample sizes. Use Caution.

Welch Anova testing Means Equal, allowing Std Devs Not Equal

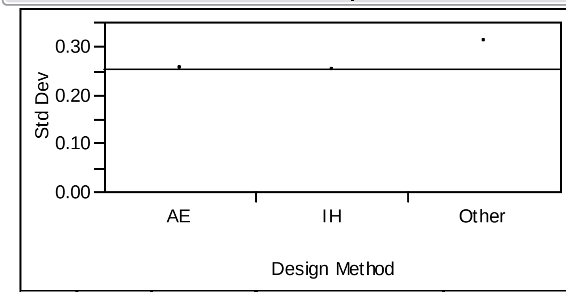
F Ratio	DFNum	DFDen	Prob > F
1.7466	2	11.017	0.2194

<u>ANOVA Results for Project Design Method</u>

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Design Method	2	0.108790	0.054395	0.8434	0.4308
Error	577	37.214841	0.064497		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
AE	383	0.2528918	0.2067393	0.2046638
IH	176	0.2492145	0.1962206	0.1962206
Other	21	0.3094701	0.2708104	0.2730275

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	1.6525	2	577	0.1925
Brown-Forsythe	2.3754	2	577	0.0939
Levene	2.4234	2	577	0.0895
Bartlett	0.9549	2	.	0.3849

Welch Anova testing Means Equal, allowing Std Devs Not Equal

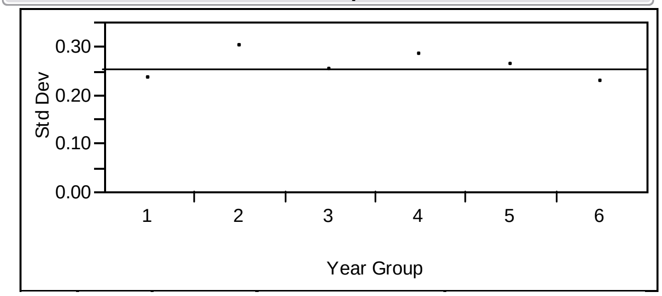
F Ratio	DFNum	DFDen	Prob > F
0.7918	2	52.705	0.4584

ANOVA Results for Project Year Group

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Year Group	5	0.296530	0.059306	0.9194	0.4679
Error	574	37.027101	0.064507		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
1	5	0.2327670	0.1704241	0.1824603
2	20	0.2979158	0.2606936	0.2606936
3	21	0.2498673	0.2025141	0.2010984
4	71	0.2806331	0.2295300	0.2282763
5	292	0.2602906	0.2095112	0.2073216
6	171	0.2255313	0.1825128	0.1786948

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	1.8883	5	574	0.0945
Brown-Forsythe	1.8278	5	574	0.1055
Levene	1.8807	5	574	0.0958
Bartlett	1.4508	5	.	0.2024

Warning: Small sample sizes. Use Caution.

Welch Anova testing Means Equal, allowing Std Devs Not Equal

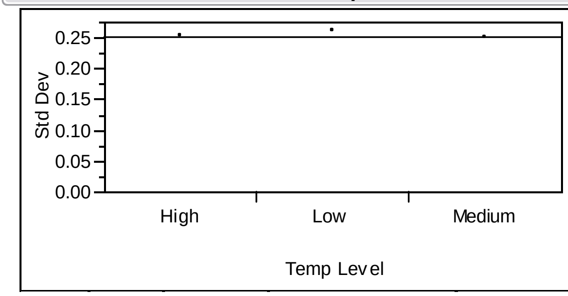
F Ratio	DFNum	DFDen	Prob > F
0.9148	5	32.724	0.4837

ANOVA Results for Temperature Level

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Temp Level	2	0.753140	0.376570	5.9414	0.0028
Error	577	36.570491	0.063380		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
High	157	0.2505331	0.2017254	0.1990690
Low	160	0.2590223	0.2065502	0.2060045
Medium	263	0.2479777	0.2045296	0.2039865

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.2512	2	577	0.7780
Brown-Forsythe	0.0895	2	577	0.9144
Levene	0.0435	2	577	0.9574
Bartlett	0.1937	2	.	0.8239

Welch Anova testing Means Equal, allowing Std Devs Not Equal

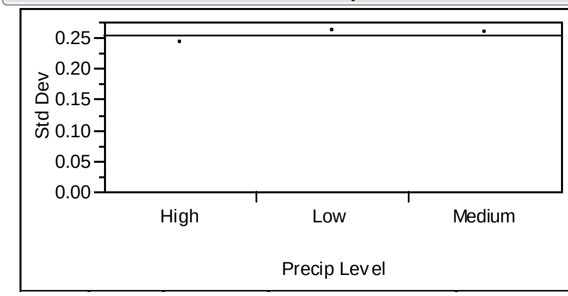
F Ratio	DFNum	DFDen	Prob > F
5.7605	2	336.91	0.0035

<u>ANOVA Results for Precipitation Level</u>

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Precip Level	2	0.182899	0.091450	1.4207	0.2424
Error	577	37.140732	0.064369		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
High	146	0.2417651	0.1924862	0.1891979
Low	88	0.2587621	0.2093933	0.2082606
Medium	346	0.2572998	0.2098649	0.2095738

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.5283	2	577	0.5899
Brown-Forsythe	0.9585	2	577	0.3841
Levene	0.7455	2	577	0.4749
Bartlett	0.4283	2	.	0.6516

Welch Anova testing Means Equal, allowing Std Devs Not Equal

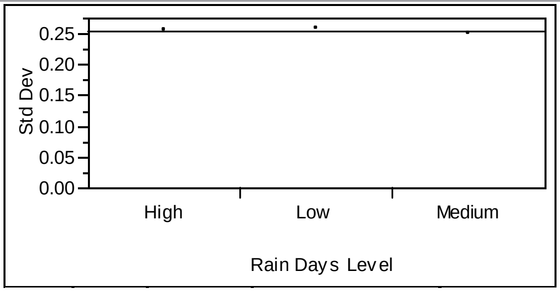
F Ratio	DFNum	DFDen	Prob > F
1.4789	2	212.97	0.2302

ANOVA Results for Rain Days Level

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Rain Days Level	2	0.261658	0.130829	2.0368	0.1314
Error	577	37.061973	0.064232		
C. Total	579	37.323631			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
High	147	0.2554883	0.2063326	0.2048357
Low	131	0.2584701	0.2116459	0.2116336
Medium	302	0.2502294	0.2006147	0.1996468

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	0.1366	2	577	0.8723
Brown-Forsythe	0.2882	2	577	0.7498
Levene	0.2650	2	577	0.7673
Bartlett	0.1086	2	.	0.8971

Welch Anova testing Means Equal, allowing Std Devs Not Equal

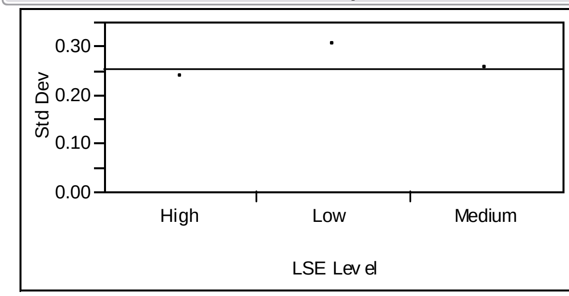
F Ratio	DFNum	DFDen	Prob > F
2.0325	2	286.77	0.1329

ANOVA Results for Labor Supply Elasticity Level

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
LSE Level	2	0.312925	0.156462	2.4566	0.0868
Error	479	30.507735	0.063690		
C. Total	481	30.820660			

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
High	156	0.2372472	0.1922621	0.1909769
Low	38	0.3016756	0.2641695	0.2620523
Medium	288	0.2533130	0.2013980	0.2007862

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	2.8493	2	479	0.0589
Brown-Forsythe	3.4049	2	479	0.0340
Levene	3.7011	2	479	0.0254
Bartlett	1.8932	2	.	0.1506

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
2.0096	2	97.314	0.1396

The results for the outputs above can be interpreted in the following manner with respect to identifying significant differences between means and identifying violations of the constant variance assumption: A *p*-value less than the pre-selected significance level α (for purposes of this research 0.05) lead to the rejection of the null hypothesis that all means are equal. For *p*-values larger than 0.05, the null hypothesis is accepted, indicating that there are not significant differences between duration residuals in terms of facility type. The equal variance assumption was verified using Levene's test. This test evaluates the null hypothesis that variances are equal against the alternate that variances are not equal. A *p*-value less than the selected 0.05 indicates sufficient evidence to reject the null hypothesis and assume the variances are not equal. In this case (*p*=0.0254) the constant variance assumption cannot be disproved. If non-constant variance is detected, the Welch ANOVA results are used to identify differences between means. This test can be interpreted in the same manner as the ANOVA test. A summary of the results is provided below.

	ANOVA			Levenes' test	Welch ANOVA	
Factor	F	df	p	p	F	p
Facility Class	1.08	10, 569	0.3761	0.3314	-	-
Type Work	0.70	1, 578	0.4016	0.0430	0.65	0.4227
MAJCOM	2.23	10, 569	0.0151	0.0086	2.01	0.0483
MAJCOM Size	0.13	1, 578	0.7162	0.8658		
COE Region	5.83	7, 572	<.0001	0.0162	6.43	<.0001
Design/Construction Agent	4.97	2, 577	0.0072	0.9354		
Project Delivery Method	1.00	2, 577	0.3703	0.2699		
Design Method	0.84	2, 577	0.4308	0.0895		
Year Group	0.92	5, 574	0.4679	0.0958		
Weather: Temperature	5.94	2, 577	0.0028	0.9574		
Weather: Precipitation Level	1.42	2, 577	0.2424	0.4749		
Weather: Rain Days	2.04	2, 577	0.1314	0.7673		
Labor Elasticity Level	2.46	2, 479	0.0868	0.0254	2.01	0.1396

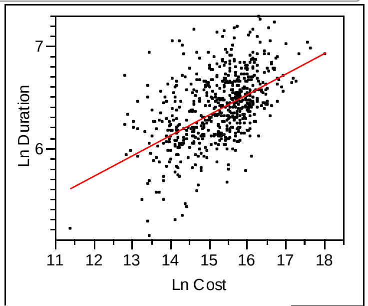
Appendix D: Linear Regression Results for Facility Projects

The linear regression results for the various combinations of partitioned models are shown below. The summary of fit, global *F* test, parameter *t* tests are provided for each model. The residual distribution is also provided for each model in order to test the validity of the normality assumption.

All Facility Projects

Whole Model

Regression Plot



Summary of Fit

RSquare	0.337942
RSquare Adj	0.336797
Root Mean Square Error	0.254114
Mean of Response	6.384217
Observations (or Sum Wgts)	580

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	19.051554	19.0516	295.0356
Error	578	37.323631	0.0646	Prob > F
C. Total	579	56.375185		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	273	20.315434	0.074416	1.3345
Pure Error	305	17.008197	0.055765	Prob > F
Total Error	578	37.323631		0.0071
				Max RSq
				0.6983

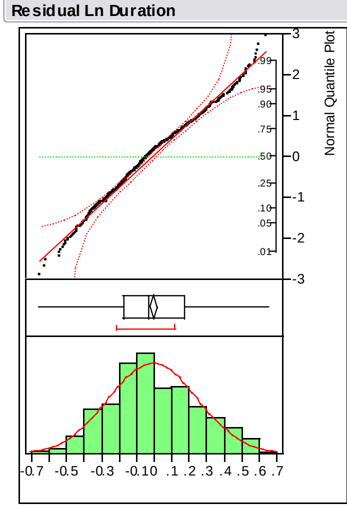
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.2893727	0.180487	18.23	<.0001
Ln Cost	0.2020136	0.011761	17.18	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Ln Cost	1	1	19.051554	295.0356	<.0001

Residual Ln Duration



Normal(-4e-15,0.25389)

Quantiles

100.0%	maximum	0.6486
99.5%		0.5991
97.5%		0.5255
90.0%		0.3418
75.0%	quartile	0.1789
50.0%	median	-0.0279
25.0%	quartile	-0.1727
10.0%		-0.3281
2.5%		-0.4583
0.5%		-0.6120
0.0%	minimum	-0.6491

Moments

Mean	-4.5e-15
Std Dev	0.2538941
Std Err Mean	0.0105424
upper 95% Mean	0.020706
lower 95% Mean	-0.020706
N	580

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	-4.5e-15	-0.020706	0.0207060
Dispersion	Sigma	0.253894	0.240076	0.2694129

Goodness-of-Fit Test

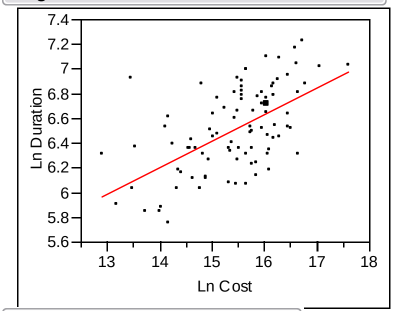
Shapiro-Wilk W Test

W	Prob<W
0.990985	0.0013

AFMC MAJCOM Model

Whole Model

Regression Plot



Summary of Fit

RSquare	0.333616
RSquare Adj	0.326294
Root Mean Square Error	0.279514
Mean of Response	6.511968
Observations (or Sum Wgts)	93

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	3.559360	3.55936	45.5580
Error	91	7.109659	0.07813	Prob > F
C. Total	92	10.669019		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	79	6.9049330	0.087404	5.1232
Pure Error	12	0.2047262	0.017061	Prob > F
Total Error	91	7.1096591		0.0017
				Max RSq
				0.9808

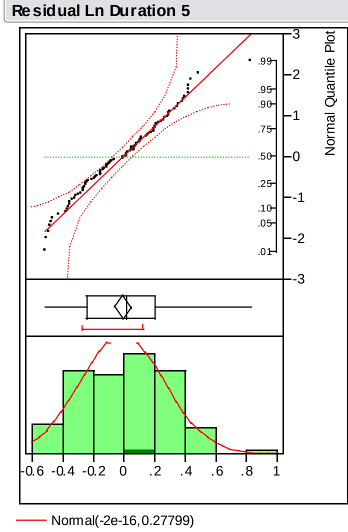
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.1947897	0.492312	6.49	<.0001
Ln Cost	0.2145473	0.031786	6.75	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Ln Cost	1	1	3.5593598	45.5580	<.0001

Residual Ln Duration 5



Quantiles

100.0%	maximum	0.8330
99.5%		0.8330
97.5%		0.4804
90.0%		0.3784
75.0%	quartile	0.2074
50.0%	median	0.0244
25.0%	quartile	-0.2358
10.0%		-0.3600
2.5%		-0.4908
0.5%		-0.5070
0.0%	minimum	-0.5070

Moments

Mean	-1.91e-16
Std Dev	0.2779908
Std Err Mean	0.0288263
upper 95% Mean	0.0572515
lower 95% Mean	-0.057252
N	93

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	-1.91e-16	-0.057252	0.0572515
Dispersion	Sigma	0.277991	0.242975	0.3248910

Goodness-of-Fit Test

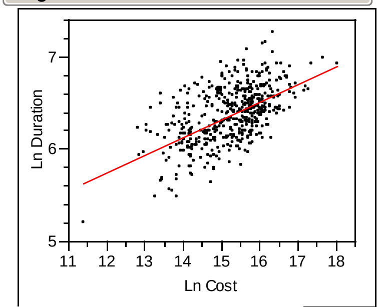
Shapiro-Wilk W Test

W	Prob<W
0.979985	0.1644

AFRC, USAFE, AETC, 11WG, PACAF, AFSOC, USAFA, AMC, ACC, AFSPC Model

Whole Model

Regression Plot



Summary of Fit

RSquare	0.324322
RSquare Adj	0.322929
Root Mean Square Error	0.247955
Mean of Response	6.360384
Observations (or Sum Wgts)	487

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	14.312768	14.3128	232.7972
Error	485	29.818621	0.0615	Prob > F
C. Total	486	44.131389		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	245	17.773860	0.072546	1.4455
Pure Error	240	12.044762	0.050187	Prob > F
Total Error	485	29.818621		0.0021
				Max RSq
				0.7271

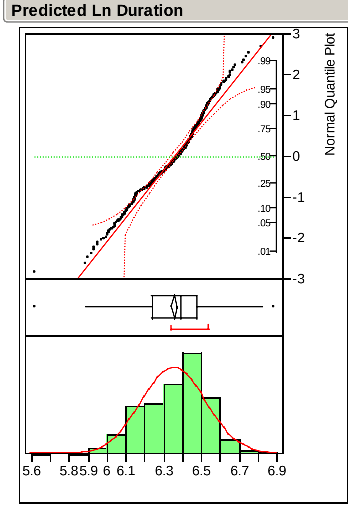
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.4332444	0.192176	17.87	<.0001
Ln Cost	0.1914453	0.012547	15.26	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Ln Cost	1	1	14.312768	232.7972	<.0001

Predicted Ln Duration



Normal(6.36038,0.17161)

Quantiles

100.0%	maximum	6.8927
99.5%		6.7949
97.5%		6.6568
90.0%		6.5473
75.0%	quartile	6.4772
50.0%	median	6.3930
25.0%	quartile	6.2437
10.0%		6.1242
2.5%		6.0105
0.5%		5.8984
0.0%	minimum	5.6234

Moments

Mean	6.360384
Std Dev	0.1716104
Std Err Mean	0.0077764
upper 95% Mean	6.3756635
lower 95% Mean	6.3451044
N	487

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	6.360384	6.345104	6.375664
Dispersion	Sigma	0.171610	0.161467	0.183124

Goodness-of-Fit Test

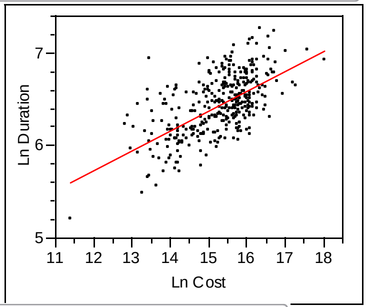
Shapiro-Wilk W Test

W	Prob<W
0.980559	<.0001

Great Lakes, SW, NA, SA, SP COE Region Model

Whole Model

Regression Plot



Summary of Fit

RSquare	0.375877
RSquare Adj	0.374104
Root Mean Square Error	0.255928
Mean of Response	6.428562
Observations (or Sum Wgts)	354

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	13.885210	13.8852	211.9914
Error	352	23.055625	0.0655	Prob > F
C. Total	353	36.940835		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	217	15.888869	0.073221	1.3793
Pure Error	135	7.166756	0.053087	Prob > F
Total Error	352	23.055625		0.0212
				Max RSq
				0.8060

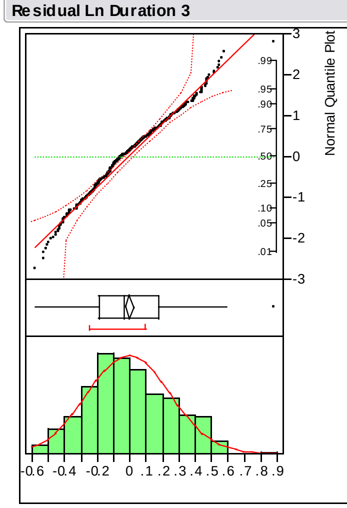
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.1150775	0.227982	13.66	<.0001
Ln Cost	0.216409	0.014863	14.56	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Ln Cost	1	1	13.885210	211.9914	<.0001

Residual Ln Duration 3



Normal(-3e-17,0.25556)

Quantiles

100.0%	maximum	0.8876
99.5%		0.6546
97.5%		0.4999
90.0%		0.3588
75.0%	quartile	0.1810
50.0%	median	-0.0345
25.0%	quartile	-0.1834
10.0%		-0.3179
2.5%		-0.4454
0.5%		-0.5337
0.0%	minimum	-0.5719

Moments

Mean	-2.76e-17
Std Dev	0.2555648
Std Err Mean	0.0135831
upper 95% Mean	0.026714
lower 95% Mean	-0.026714
N	354

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	-2.76e-17	-0.026714	0.0267140
Dispersion	Sigma	0.255565	0.238024	0.2759183

Goodness-of-Fit Test

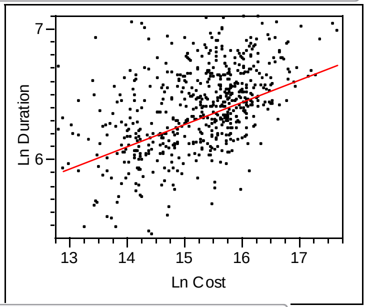
Shapiro-Wilk W Test

W	Prob<W
0.987441	0.0037

Overseas, Pacific Ocean, NW COE Region Model

Whole Model

Regression Plot



Summary of Fit

RSquare	0.279179
RSquare Adj	0.275961
Root Mean Square Error	0.240037
Mean of Response	6.315969
Observations (or Sum Wgts)	226

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	4.998753	4.99875	86.7568
Error	224	12.906428	0.05762	Prob > F
C. Total	225	17.905181		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	159	9.569188	0.060184	1.1722
Pure Error	65	3.337240	0.051342	Prob > F
Total Error	224	12.906428		0.2347
				Max RSq
				0.8136

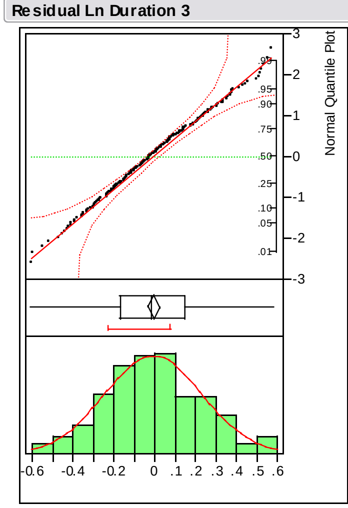
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.7153529	0.279662	13.29	<.0001
Ln Cost	0.16968	0.018217	9.31	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Ln Cost	1	1	4.9987531	86.7568	<.0001

Residual Ln Duration 3



Normal(-2e-15,0.2395)

Quantiles

100.0%	maximum	0.5791
99.5%		0.5769
97.5%		0.5218
90.0%		0.3359
75.0%	quartile	0.1520
50.0%	median	-0.0123
25.0%	quartile	-0.1642
10.0%		-0.2966
2.5%		-0.4509
0.5%		-0.5964
0.0%	minimum	-0.5975

Moments

Mean	-2.02e-15
Std Dev	0.2395034
Std Err Mean	0.0159315
upper 95% Mean	0.0313941
lower 95% Mean	-0.031394
N	226

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	-2.02e-15	-0.031394	0.0313941
Dispersion	Sigma	0.239503	0.219271	0.2638813

Goodness-of-Fit Test

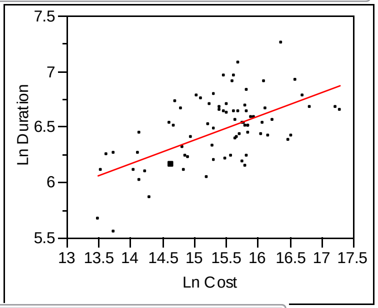
Shapiro-Wilk W Test

W	Prob<W
0.994630	0.6050

NAVFAC Design/Construction Agent Model

Whole Model

Regression Plot



Summary of Fit

RSquare	0.337523
RSquare Adj	0.328448
Root Mean Square Error	0.249453
Mean of Response	6.471933
Observations (or Sum Wgts)	75

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	2.3143724	2.31437	37.1925
Error	73	4.5425582	0.06223	Prob > F
C. Total	74	6.8569307		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	64	3.9959427	0.062437	1.0280
Pure Error	9	0.5466155	0.060735	Prob > F
Total Error	73	4.5425582		0.5292
				Max RSq
				0.9203

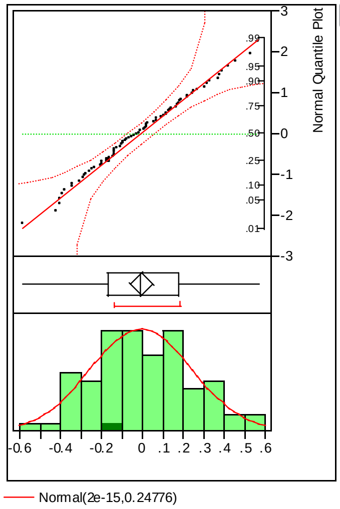
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.1918322	0.538619	5.93	<.0001
Ln Cost	0.2127376	0.034883	6.10	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Ln Cost	1	1	2.3143724	37.1925	<.0001

Residual Ln Duration 4



Quantiles

100.0%	maximum	0.5704
99.5%		0.5704
97.5%		0.5386
90.0%		0.3538
75.0%	quartile	0.1789
50.0%	median	-0.0066
25.0%	quartile	-0.1626
10.0%		-0.3350
2.5%		-0.4317
0.5%		-0.5781
0.0%	minimum	-0.5781

Moments

Mean	1.966e-15
Std Dev	0.2477618
Std Err Mean	0.0286091
upper 95% Mean	0.0570048
lower 95% Mean	-0.057005
N	75

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	1.966e-15	-0.057005	0.0570048
Dispersion	Sigma	0.2477618	0.213476	0.2952702

Goodness-of-Fit Test

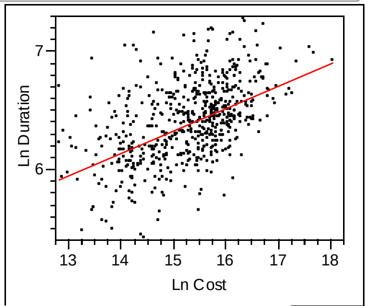
Shapiro-Wilk W Test

W	Prob<W
0.991148	0.8855

<u>COE Design/Construction Agent Model</u>

Whole Model

Regression Plot



Summary of Fit

RSquare	0.292275
RSquare Adj	0.290709
Root Mean Square Error	0.251866
Mean of Response	6.392385
Observations (or Sum Wgts)	454

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	11.841451	11.8415	186.6664
Error	452	28.673276	0.0634	Prob > F
C. Total	453	40.514728		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	236	16.081321	0.068141	1.1689
Pure Error	216	12.591956	0.058296	Prob > F
Total Error	452	28.673276		0.1217
				Max RSq
				0.6892

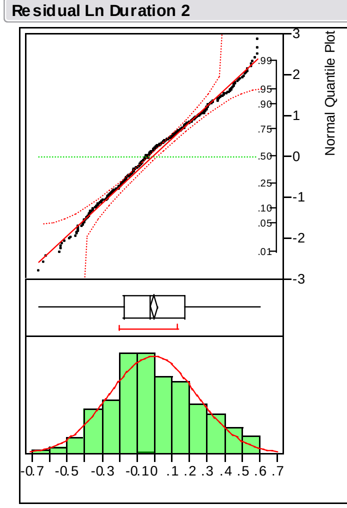
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.4701157	0.214215	16.20	<.0001
Ln Cost	0.1900737	0.013912	13.66	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Ln Cost	1	1	11.841451	186.6664	<.0001

Residual Ln Duration 2



Normal(-2e-15,0.25159)

Quantiles

100.0%	maximum	0.5985
99.5%		0.5965
97.5%		0.5252
90.0%		0.3370
75.0%	quartile	0.1776
50.0%	median	-0.0211
25.0%	quartile	-0.1679
10.0%		-0.3230
2.5%		-0.4407
0.5%		-0.6231
0.0%	minimum	-0.6535

Moments

Mean	-2.35e-15
Std Dev	0.2515878
Std Err Mean	0.0118076
upper 95% Mean	0.0232045
lower 95% Mean	-0.023204
N	454

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	-2.35e-15	-0.023204	0.0232045
Dispersion	Sigma	0.251588	0.236219	0.2691125

Goodness-of-Fit Test

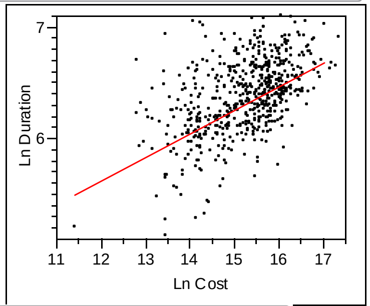
Shapiro-Wilk W Test

W	Prob<W
0.991696	0.0122

<u>In House Design/Construction Agent Model</u>

Whole Model

Regression Plot



Summary of Fit

RSquare	0.459161
RSquare Adj	0.448124
Root Mean Square Error	0.264141
Mean of Response	6.18251
Observations (or Sum Wgts)	51

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	2.9024475	2.90245	41.6000
Error	49	3.4187493	0.06977	Prob > F
C. Total	50	6.3211967		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	41	3.1746508	0.077431	2.5377
Pure Error	8	0.2440985	0.030512	Prob > F
Total Error	49	3.4187493		0.0826
				Max RSq
				0.9614

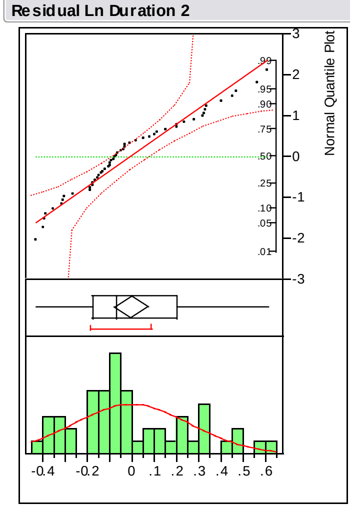
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.0939211	0.480292	6.44	<.0001
Ln Cost	0.2102427	0.032597	6.45	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Ln Cost	1	1	2.9024475	41.6000	<.0001

Residual Ln Duration 2



Normal(-2e-15,0.26149)

Quantiles

100.0%	maximum	0.6128
99.5%		0.6128
97.5%		0.6003
90.0%		0.3957
75.0%	quartile	0.2080
50.0%	median	-0.0661
25.0%	quartile	-0.1709
10.0%		-0.3388
2.5%		-0.4157
0.5%		-0.4248
0.0%	minimum	-0.4248

Moments

Mean	-2.35e-15
Std Dev	0.2614861
Std Err Mean	0.0366154
upper 95% Mean	0.0735442
lower 95% Mean	-0.073544
N	51

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	-2.35e-15	-0.073544	0.0735442
Dispersion	Sigma	0.261486	0.218788	0.3250477

Goodness-of-Fit Test

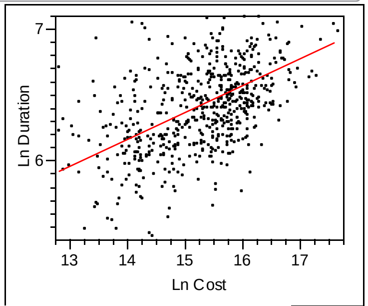
Shapiro-Wilk W Test

W	Prob<W
0.953833	0.0456

<u>High Temperature Level Model</u>

Whole Model

Regression Plot



Summary of Fit

RSquare	0.353473
RSquare Adj	0.349301
Root Mean Square Error	0.251336
Mean of Response	6.404242
Observations (or Sum Wgts)	157

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	5.353133	5.35313	84.7423
Error	155	9.791278	0.06317	Prob > F
C. Total	156	15.144411		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	114	7.9780140	0.069983	1.5824
Pure Error	41	1.8132639	0.044226	Prob > F
Total Error	155	9.7912779		0.0476
				Max RSq
				0.8803

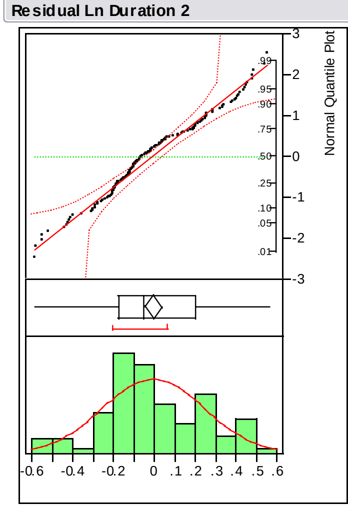
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.3087011	0.336866	9.82	<.0001
Ln Cost	0.20366	0.022124	9.21	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Ln Cost	1	1	5.3531329	84.7423	<.0001

Residual Ln Duration 2



Normal(2.4e-15,0.25053)

Quantiles

100.0%	maximum	0.5608
99.5%		0.5608
97.5%		0.4881
90.0%		0.3870
75.0%	quartile	0.2047
50.0%	median	-0.0513
25.0%	quartile	-0.1714
10.0%		-0.2859
2.5%		-0.5418
0.5%		-0.5761
0.0%	minimum	-0.5761

Moments

Mean	2.427e-15
Std Dev	0.2505286
Std Err Mean	0.0199944
upper 95% Mean	0.0394946
lower 95% Mean	-0.039495
N	157

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	2.427e-15	-0.039495	0.0394946
Dispersion	Sigma	0.2505286	0.225545	0.2817850

Goodness-of-Fit Test

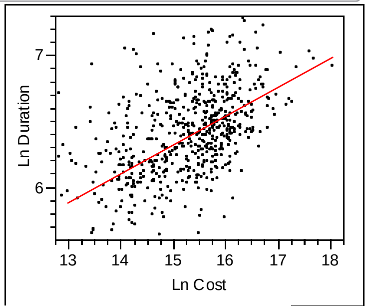
Shapiro-Wilk W Test

W	Prob<W
0.979212	0.0180

Medium Temperature Level Model

Whole Model

Regression Plot



Summary of Fit

RSquare	0.346844
RSquare Adj	0.344342
Root Mean Square Error	0.248071
Mean of Response	6.40243
Observations (or Sum Wgts)	263

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	8.529224	8.52922	138.5985
Error	261	16.061702	0.06154	Prob > F
C. Total	262	24.590926		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	171	10.398555	0.060810	0.9664
Pure Error	90	5.663147	0.062924	Prob > F
Total Error	261	16.061702		0.5810
				Max RSq
				0.7697

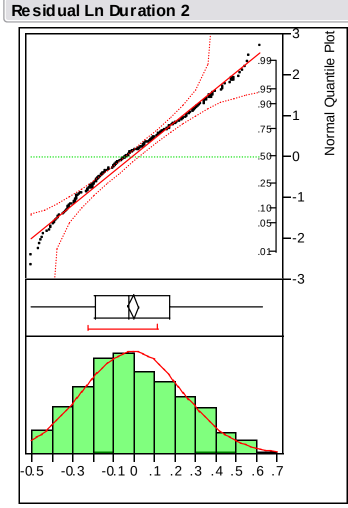
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.0385584	0.286142	10.62	<.0001
Ln Cost	0.2186626	0.018574	11.77	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Ln Cost	1	1	8.5292244	138.5985	<.0001

Residual Ln Duration 2



Normal(1.2e-15,0.2476)

Quantiles

100.0%	maximum	0.6266
99.5%		0.6077
97.5%		0.5218
90.0%		0.3494
75.0%	quartile	0.1805
50.0%	median	-0.0199
25.0%	quartile	-0.1861
10.0%		-0.3153
2.5%		-0.4389
0.5%		-0.4955
0.0%	minimum	-0.4960

Moments

Mean	1.216e-15
Std Dev	0.2475969
Std Err Mean	0.0152675
upper 95% Mean	0.0300626
lower 95% Mean	-0.030063
N	263

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	1.216e-15	-0.030063	0.0300626
Dispersion	Sigma	0.2475969	0.228090	0.2707800

Goodness-of-Fit Test

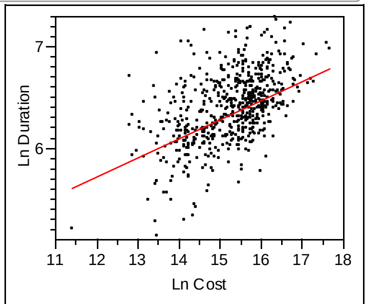
Shapiro-Wilk W Test

W	Prob<W
0.984824	0.0068

Low Temperature Level Model

Whole Model

Regression Plot



Summary of Fit

RSquare	0.339403
RSquare Adj	0.335222
Root Mean Square Error	0.259419
Mean of Response	6.334631
Observations (or Sum Wgts)	160

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	5.463117	5.46312	81.1776
Error	158	10.633136	0.06730	Prob > F
C. Total	159	16.096253		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	129	9.151546	0.070942	1.3886
Pure Error	29	1.481590	0.051089	Prob > F
Total Error	158	10.633136		0.1528
				Max RSq
				0.9080

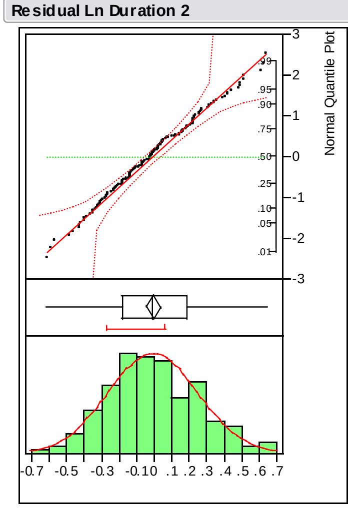
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.4653891	0.319115	10.86	<.0001
Ln Cost	0.1871263	0.020769	9.01	<.0001

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Ln Cost	1	1	5.4631174	81.1776	<.0001

Residual Ln Duration 2



Normal(-5e-16,0.2586)

Quantiles

100.0%	maximum	0.6461
99.5%		0.6461
97.5%		0.5182
90.0%		0.3496
75.0%	quartile	0.1920
50.0%	median	-0.0100
25.0%	quartile	-0.1747
10.0%		-0.3191
2.5%		-0.4794
0.5%		-0.6052
0.0%	minimum	-0.6052

Moments

Mean	-4.88e-16
Std Dev	0.2586021
Std Err Mean	0.0204443
upper 95% Mean	0.0403774
lower 95% Mean	-0.040377
N	160

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	Mu	-4.88e-16	-0.040377	0.0403774
Dispersion	Sigma	0.258602	0.233034	0.2905227

Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.991683	0.4795

A summary of the model outputs is provided in the table below.

Regression Model	n	Model F Ratio	Prob >F	Slope	t Ratio	P>t	Intercept	t Ratio	P>t	r2	r2 (adj)	Shapiro Wilks W	P<W
All Facility Projects	580	295.0	<.0001	0.202	17.2	<.0001	3.29	18.2	<.0001	0.3379	0.337	0.991	0.001
MAJCOM Models													
AFMC	93	45.6	<.0001	0.2145	6.8	<.0001	3.19	6.5	<.0001	0.3336	0.326	0.980	0.164
AMC, ACC, AFSPC	263	125.2	<.0001	0.205	11.2	<.0001	3.20	11.3	<.0001	0.324	0.322	0.993	0.210
AFRC, USAFE, AETC, 11WG, PACAF, AFSOC, USAFA	224	111.6	<.0001	0.184	10.6	<.0001	3.56	13.4	<.0001	0.334	0.331	0.990	0.104
COE Region Models													
Great Lakes, SW, NA, SA, SP	354	212.0	<.0001	0.216	14.6	<.0001	3.12	13.7	<.0001	0.376	0.374	0.987	0.004
Overseas, Pacific Ocean, NW	226	86.8	<.0001	0.170	9.3	<.0001	3.72	13.3	<.0001	0.279	0.276	0.995	0.605
Design/Construction Agent Models													
NAVFAC	75	37.2	<.0001	0.213	6.1	<.0001	3.19	5.9	<.0001	0.338	0.328	0.991	0.886
COE	454	186.7	<.0001	0.190	13.7	<.0001	3.47	16.2	<.0001	0.292	0.291	0.992	0.012
In House	51	41.6	<.0001	0.210	6.5	<.0001	3.09	6.4	<.0001	0.459	0.448	0.954	0.046
Temperature Level Models													
High	157	84.7	<.0001	0.204	9.2	<.0001	3.31	9.8	<.0001	0.353	0.349	0.979	0.018
Medium	263	138.6	<.0001	0.219	11.8	<.0001	3.04	10.6	<.0001	0.347	0.344	0.985	0.007
Low	160	81.2	<.0001	0.187	9.0	<.0001	3.47	10.9	<.0001	0.339	0.335	0.992	0.480

Several of the models do not pass the Shapiro-Wilks test for normality. These model are shown in the table above as those with a P<W of less than 0.05. The departures from normality were assumed to be small for these models for the purpose of the analysis. Further investigation into this assumption was not conducted as these models were not selected as the final duration prediction model.

Appendix E: MLR Model Results for Non-Facility Projects

The results of the initial stepwise regression analysis from JMP are shown below.

Current Estimates

SSE	DFE	MSE	RSquare	RSquare Adj	Cp	AIC
33.473747	116	0.2885668	0.2552	0.1846	-1.849461	-147.682

Lock	Entered	Parameter	Estimate	nDF	SS	F Ratio	Prob>F
☑	☑	Intercept	6.22778859	1	0	0.000	1.0000
☐	☐	Ln Cost	0	1	0.035021	0.120	0.7292
☐	☐	Airfield Pavements Dummy	0	1	0.217166	0.751	0.3880
☐	☑	Comm Navaids Dummy	0.45465419	1	0.442693	1.534	0.2180
☐	☑	Electricity Dummy	0.42642821	1	1.220974	4.231	0.0419
☐	☐	Fire Alarm Dummy	0	1	0.089692	0.309	0.5794
☐	☐	Ground Improvement Dummy	0	1	0.154411	0.533	0.4669
☐	☑	Heat Sewage Dummy	0.14567221	1	0.547632	1.898	0.1710
☐	☐	Liquid Fuel Storage Dummy	0	1	0.105457	0.363	0.5478
☐	☐	Petro Dispensing Dummy	0	1	0.145704	0.503	0.4797
☐	☐	ADAL Dummy	0	1	0.10063	0.347	0.5571
☐	☑	ACC Dummy	-0.2411832	1	0.869504	3.013	0.0852
☐	☐	AETC Dummy	0	1	0.00097	0.003	0.9541
☐	☐	AFMC Dummy	0	1	0.109291	0.377	0.5406
☐	☐	AFRC Dummy	0	1	0.000343	0.001	0.9727
☐	☑	AFSOC Dummy	0.48172091	1	1.631163	5.653	0.0191
☐	☑	AFSPC Dummy	0.257118	1	0.51375	1.780	0.1847
☐	☐	AMC Dummy	0	1	0.040523	0.139	0.7096
☐	☐	PAF Dummy	0	1	0.072221	0.249	0.6190
☐	☐	Large MAJCOM Dummy	0	1	0.23228	0.804	0.3719
☐	☐	Great Lakes COE Dummy	0	1	0.364649	1.267	0.2628
☐	☐	North Atlantic COE Dummy	0	1	0.003287	0.011	0.9155
☐	☑	Northwestern COE Dummy	-0.2952388	1	1.51541	5.252	0.0237
☐	☑	Overseas COE Dummy	0.26576867	1	0.788432	2.732	0.1010
☐	☐	Pacific Ocean COE Dummy	0	1	0.098694	0.340	0.5609
☐	☐	South Atlantic COE Dummy	0	1	0.345193	1.198	0.2760
☐	☐	South Pacific COE Dummy	0	1	0.082598	0.284	0.5948
☐	☐	COE DA/CA Dummy	0	1	0.058397	0.201	0.6548
☐	☐	IH DA/CA Dummy	0	1	0.044372	0.153	0.6967
☐	☑	DB Delivery Method Dummy	0.20957013	1	0.873096	3.026	0.0846
☐	☐	O Delivery Method Dummy	0	1	0.37941	1.318	0.2533
☐	☐	AE Design Method Dummy	0	1	0.215955	0.747	0.3893
☐	☑	IH Design Method Dummy	-0.1728667	1	0.823901	2.855	0.0938
☐	☑	Year Group Dummy 1	-0.9431219	1	1.448659	5.020	0.0270
☐	☐	Year Group Dummy 2	0	1	0.11697	0.403	0.5267
☐	☐	Year Group Dummy 3	0	1	0.023131	0.080	0.7785
☐	☐	Year Group Dummy 4	0	1	0.150139	0.518	0.4731
☐	☐	Avg Min Daily Temp (C)	0	1	0.190179	0.657	0.4193
☐	☐	Avg Yearly Precip (mm)	0	1	0.007685	0.026	0.8712
☐	☐	Mean Rain Days	0	1	0.06013	0.207	0.6500

The variables selected through the stepwise regression above were used to fit a multiple linear regression model to the data. The results for this model are shown below.

Summary of Fit

RSquare	0.262458
RSquare Adj	0.193116
Root Mean Square Error	0.539757
Mean of Response	6.269047
Observations (or Sum Wgts)	129

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.2306543	0.085966	72.48	<.0001
Comm Navaids Dummy	0.4693683	0.368692	1.27	0.2055
Electricity Dummy	0.4236902	0.208292	2.03	0.0442
Heat Sew age Dummy	0.1648427	0.105425	1.56	0.1206
ACC Dummy	-0.254712	0.139296	-1.83	0.0700
AFSOC Dummy	0.4753669	0.203537	2.34	0.0212
AFSPC Dummy	0.2533841	0.193605	1.31	0.1932
Northw estern COE Dummy	-0.29941	0.129419	-2.31	0.0224
Overseas COE Dummy	0.2545811	0.16137	1.58	0.1174
DB Delivery Method Dummy	0.2410353	0.119099	2.02	0.0453
IH Design Method Dummy	-0.185848	0.102405	-1.81	0.0721
Year Group Dummy 1	-0.942902	0.422944	-2.23	0.0277

Next, all parameter estimates with a *p*-value greater than 0.05 are removed one at a time, removing the highest *p*-value first and re-fitting a multiple linear regression model fit to the remaining data points. The Communications/Navigation Aids facility class dummy was removed first. The results of the new model are shown below.

Summary of Fit

RSquare	0.252241
RSquare Adj	0.188872
Root Mean Square Error	0.541174
Mean of Response	6.269047
Observations (or Sum Wgts)	129

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.2279613	0.086166	72.28	<.0001
Electricity Dummy	0.4040093	0.208263	1.94	0.0548
Heat Sew age Dummy	0.1564679	0.105496	1.48	0.1407
ACC Dummy	-0.258874	0.139623	-1.85	0.0662
AFSOC Dummy	0.473461	0.204066	2.32	0.0221
AFSPC Dummy	0.3148837	0.187973	1.68	0.0966
Northw estern COE Dummy	-0.28344	0.129148	-2.19	0.0301
Overseas COE Dummy	0.2955424	0.158546	1.86	0.0648
DB Delivery Method Dummy	0.2338285	0.119276	1.96	0.0523
IH Design Method Dummy	-0.175398	0.102343	-1.71	0.0892
Year Group Dummy 1	-0.749484	0.39575	-1.89	0.0607

The Heat and Sewage facility class dummy was removed next. The results of the new model are shown below.

Summary of Fit

RSquare	0.238301
RSquare Adj	0.180694
Root Mean Square Error	0.543896
Mean of Response	6.269047
Observations (or Sum Wgts)	129

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.2826523	0.078269	80.27	<.0001
Electricity Dummy	0.3538097	0.206528	1.71	0.0893
ACC Dummy	-0.241505	0.139831	-1.73	0.0867
AFSOC Dummy	0.4442094	0.204133	2.18	0.0315
AFSPC Dummy	0.3018644	0.188713	1.60	0.1123
Northwestern COE Dummy	-0.292943	0.129638	-2.26	0.0257
Overseas COE Dummy	0.2832389	0.159125	1.78	0.0776
DB Delivery Method Dummy	0.2394874	0.119815	2.00	0.0479
IH Design Method Dummy	-0.168616	0.102755	-1.64	0.1034
Year Group Dummy 1	-0.796305	0.396473	-2.01	0.0469

The AFSPC MAJCOM dummy was removed next. The results of the new model are shown below.

Summary of Fit

RSquare	0.221924
RSquare Adj	0.170052
Root Mean Square Error	0.547417
Mean of Response	6.269047
Observations (or Sum Wgts)	129

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.2893835	0.078662	79.95	<.0001
Electricity Dummy	0.419559	0.203707	2.06	0.0416
ACC Dummy	-0.264884	0.139965	-1.89	0.0608
AFSOC Dummy	0.3988951	0.203466	1.96	0.0523
Northwestern COE Dummy	-0.238593	0.125916	-1.89	0.0605
Overseas COE Dummy	0.2725738	0.160014	1.70	0.0911
DB Delivery Method Dummy	0.2432176	0.120568	2.02	0.0459
IH Design Method Dummy	-0.144482	0.102299	-1.41	0.1604
Year Group Dummy 1	-0.691346	0.393537	-1.76	0.0815

The In House Design Method dummy was removed next. The results of the new model are shown below.

Summary of Fit

RSquare	0.20899
RSquare Adj	0.163229
Root Mean Square Error	0.549662
Mean of Response	6.269047
Observations (or Sum Wgts)	129

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.2410126	0.071105	87.77	<.0001
Electricity Dummy	0.4121726	0.204475	2.02	0.0460
ACC Dummy	-0.284703	0.139831	-2.04	0.0439
AFSOC Dummy	0.4030291	0.20428	1.97	0.0508
Northwestern COE Dummy	-0.253678	0.125977	-2.01	0.0463
Overseas COE Dummy	0.307962	0.158688	1.94	0.0546
DB Delivery Method Dummy	0.2297637	0.120684	1.90	0.0593
Year Group Dummy 1	-0.707674	0.394981	-1.79	0.0757

The Year Group 1 dummy was removed next. The results of the new model are shown below.

Summary of Fit

RSquare	0.188005
RSquare Adj	0.148071
Root Mean Square Error	0.554619
Mean of Response	6.269047
Observations (or Sum Wgts)	129

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.2273278	0.071331	87.30	<.0001
Electricity Dummy	0.4200978	0.20627	2.04	0.0439
ACC Dummy	-0.273823	0.140959	-1.94	0.0544
AFSOC Dummy	0.4196738	0.205908	2.04	0.0437
Northwestern COE Dummy	-0.271174	0.12673	-2.14	0.0344
Overseas COE Dummy	0.3165121	0.160047	1.98	0.0502
DB Delivery Method Dummy	0.2402049	0.12163	1.97	0.0505

The ACC MAJCOM dummy was removed next. The results of the new model are shown below.

Summary of Fit

RSquare	0.162889
RSquare Adj	0.12886
Root Mean Square Error	0.560837
Mean of Response	6.269047
Observations (or Sum Wgts)	129

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.1844638	0.068593	90.16	<.0001
Electricity Dummy	0.4664432	0.207183	2.25	0.0261
AFSOC Dummy	0.4552357	0.207392	2.20	0.0300
Northwestern COE Dummy	-0.250614	0.127703	-1.96	0.0520
Overseas COE Dummy	0.3027041	0.161682	1.87	0.0636
DB Delivery Method Dummy	0.2154018	0.122314	1.76	0.0807

The DB Delivery Method dummy was removed next. The results of the new model are shown below.

Summary of Fit

RSquare	0.141782
RSquare Adj	0.114098
Root Mean Square Error	0.565569
Mean of Response	6.269047
Observations (or Sum Wgts)	129

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.2343041	0.063009	98.94	<.0001
Electricity Dummy	0.4692362	0.208925	2.25	0.0265
AFSOC Dummy	0.4688559	0.208997	2.24	0.0266
Northwestern COE Dummy	-0.277172	0.12788	-2.17	0.0321
Overseas COE Dummy	0.2988219	0.163031	1.83	0.0692

The Overseas COE Region dummy was removed next. The results of the new model are shown below.

Summary of Fit

RSquare	0.11853
RSquare Adj	0.097375
Root Mean Square Error	0.570882
Mean of Response	6.269047
Observations (or Sum Wgts)	129

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.2763449	0.059238	105.95	<.0001
Electricity Dummy	0.4679603	0.210887	2.22	0.0283
AFSOC Dummy	0.4415588	0.210424	2.10	0.0379
Northwestern COE Dummy	-0.316063	0.127292	-2.48	0.0144

All parameter estimates are now less than the specified 0.05 *p*-value.

Appendix F: MLR Model Results for Facility Projects

The results of the initial stepwise regression analysis from JMP are shown below.

Current Estimates

SSE	DFE	MSE	RSquare	RSquare Adj	Cp	AIC
54.99774	594	0.0925888	0.3767	0.3547	12.351704	-1444.23

Lock	Entered	Parameter	Estimate	nDF	SS	F Ratio	Prob>F
☑	☑	Intercept	3.42669837	1	0	0.000	1.0000
☐	☑	Ln Cost	0.20097974	1	15.88887	171.607	0.0000
☐	☑	Admin Facility Class Dummy	-0.0815069	1	0.240213	2.594	0.1078
☐	☑	Comm, Navaids Facility Class Dummy	0.22601149	1	0.334949	3.618	0.0577
☐	☑	Dorms Facility Class Dummy	-0.0607821	1	0.297882	3.217	0.0734
☐	☑	Explosives Facility Class Dummy	0.12895107	1	0.141815	1.532	0.2164
☐	☐	Land Operations Facility Class Dummy	0	1	0.040103	0.433	0.5109
☐	☐	Maint Facility Class Dummy	0	1	0.021157	0.228	0.6330
☐	☑	Medical Facility Class Dummy	0.25564054	1	0.851205	9.193	0.0025
☐	☐	Personnel Facility Class Dummy	0	1	0.032296	0.348	0.5552
☐	☐	RDTE Facility Class Dummy	0	1	0.050069	0.540	0.4626
☐	☐	Storage Facility Class Dummy	0	1	0.007239	0.078	0.7800
☐	☐	ADAL Type Work Dummy	0	1	0.072606	0.784	0.3763
☐	☑	ACC MAJCOM Dummy	-0.1348867	1	1.225304	13.234	0.0003
☐	☑	AETC MAJCOM Dummy	-0.0979915	1	0.519751	5.614	0.0181
☐	☐	AFMC MAJCOM Dummy	0	1	0.00948	0.102	0.7493
☐	☐	AFRC MAJCOM Dummy	0	1	0.008245	0.089	0.7657
☐	☑	AFSOC MAJCOM Dummy	-0.2560303	1	0.863112	9.322	0.0024
☐	☐	AFSPC MAJCOM Dummy	0	1	0.031168	0.336	0.5622
☐	☑	AMC MAJCOM Dummy	-0.0996117	1	0.602518	6.507	0.0110
☐	☐	PACAF MAJCOM Dummy	0	1	0.099275	1.072	0.3008
☐	☐	SUW MAJCOM Dummy	0	1	0.018474	0.199	0.6555
☐	☑	USAFA MAJCOM Dummy	-0.2085425	1	0.342637	3.701	0.0549
☐	☐	Large MAJCOM Size Dummy	0	1	0.001192	0.013	0.9098
☐	☐	Great Lakes COE Dummy	0	1	0.027866	0.301	0.5837
☐	☑	North Atlantic COE Dummy	0.13889925	1	0.771565	8.333	0.0040
☐	☑	Northwestern COE Dummy	-0.1095414	1	0.648409	7.003	0.0084
☐	☐	Overseas COE Dummy	0	1	0.016311	0.176	0.6751
☐	☐	Pacific Ocean COE Dummy	0	1	0.089495	0.967	0.3259
☐	☐	South Atlantic COE Dummy	0	1	2.19e-7	0.000	0.9988
☐	☐	South Pacific COE Dummy	0	1	0.056002	0.604	0.4372
☐	☑	COE DA/CA Dummy	-0.0490036	1	0.133256	1.439	0.2307
☐	☑	IH DA/CA Dummy	-0.2314146	1	1.465583	15.829	0.0001
☐	☑	DB Delivery Method Dummy	0.05241957	1	0.257913	2.786	0.0956
☐	☐	T Delivery Method Dummy	0	1	0.093237	1.007	0.3160
☐	☐	AE Design Method Dummy	0	1	0.001688	0.018	0.8927
☐	☑	IH Design Method Dummy	-0.0373431	1	0.158533	1.712	0.1912
☐	☐	Year Group Dummy 1	0	1	0.082453	0.890	0.3458
☐	☑	Year Group Dummy 2	-0.222696	1	0.930143	10.046	0.0016
☐	☑	Year Group Dummy 3	-0.0845692	1	0.15619	1.687	0.1945
☐	☑	Year Group Dummy 4	-0.0811244	1	0.379824	4.102	0.0433
☐	☐	Year Group Dummy 5	0	1	0.000068	0.001	0.9784
☐	☑	Avg Min Daily Temp C	0.0054455	1	0.260697	2.816	0.0939
☐	☐	Total Avg Yearly Precip mm	0	1	0.049014	0.529	0.4673
☐	☐	Mean Rain Days	0	1	0.000177	0.002	0.9651

The remaining variables selected using the stepwise procedure above were used to fit a multiple linear regression model to the data. The results for this model are shown below.

Summary of Fit

RSquare	0.376696
RSquare Adj	0.35466
Root Mean Square Error	0.304284
Mean of Response	6.386284
Observations (or Sum Wgts)	616

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.4266984	0.244514	14.01	<.0001
Ln Cost	0.2009797	0.015342	13.10	<.0001
Admin Facility Class Dummy	-0.081507	0.050603	-1.61	0.1078
Comm, Navaids Facility Class Dummy	0.2260115	0.118829	1.90	0.0577
Dorms Facility Class Dummy	-0.060782	0.033887	-1.79	0.0734
Explosives Facility Class Dummy	0.1289511	0.104194	1.24	0.2164
Medical Facility Class Dummy	0.2556405	0.084312	3.03	0.0025
ACC MAJCOM Dummy	-0.134887	0.037079	-3.64	0.0003
AETC MAJCOM Dummy	-0.097992	0.041359	-2.37	0.0181
AFSOC MAJCOM Dummy	-0.25603	0.083857	-3.05	0.0024
AMC MAJCOM Dummy	-0.099612	0.039049	-2.55	0.0110
USAFA MAJCOM Dummy	-0.208542	0.108407	-1.92	0.0549
North Atlantic COE Dummy	0.1388992	0.048116	2.89	0.0040
Northw estern COE Dummy	-0.109541	0.041394	-2.65	0.0084
COE DA/CA Dummy	-0.049004	0.040847	-1.20	0.2307
IH DA/CA Dummy	-0.231415	0.058165	-3.98	<.0001
DB Delivery Method Dummy	0.0524196	0.031408	1.67	0.0956
IH Design Method Dummy	-0.037343	0.028538	-1.31	0.1912
Year Group Dummy 2	-0.222696	0.070261	-3.17	0.0016
Year Group Dummy 3	-0.084569	0.065112	-1.30	0.1945
Year Group Dummy 4	-0.081124	0.040053	-2.03	0.0433
Avg Min Daily Temp C	0.0054455	0.003245	1.68	0.0939

Next, all parameter estimates with a *p*-value greater than 0.05 are removed one at a time, removing the highest *p*-value first and re-fitting a multiple linear regression model fit to the remaining data points. The COE DA/CA dummy was removed first. The results of the new model are shown below.

Summary of Fit

RSquare	0.375186
RSquare Adj	0.354183
Root Mean Square Error	0.304396
Mean of Response	6.386284
Observations (or Sum Wgts)	616

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.3670982	0.239503	14.06	<.0001
Ln Cost	0.2018618	0.01533	13.17	<.0001
Admin Facility Class Dummy	-0.081831	0.050621	-1.62	0.1065
Comm, Navaids Facility Class Dummy	0.2404833	0.118258	2.03	0.0424
Dorms Facility Class Dummy	-0.057269	0.033773	-1.70	0.0905
Explosives Facility Class Dummy	0.1319142	0.104203	1.27	0.2060
Medical Facility Class Dummy	0.2555033	0.084343	3.03	0.0026
ACC MAJCOM Dummy	-0.132629	0.037045	-3.58	0.0004
AETC MAJCOM Dummy	-0.09873	0.04137	-2.39	0.0173
AFSOC MAJCOM Dummy	-0.26219	0.08373	-3.13	0.0018
AMC MAJCOM Dummy	-0.091025	0.038401	-2.37	0.0181
USAFA MAJCOM Dummy	-0.204117	0.108384	-1.88	0.0602
North Atlantic COE Dummy	0.14275	0.048027	2.97	0.0031
Northwestern COE Dummy	-0.117004	0.040939	-2.86	0.0044
IH DA/CA Dummy	-0.188682	0.046	-4.10	<.0001
DB Delivery Method Dummy	0.0525828	0.031419	1.67	0.0947
IH Design Method Dummy	-0.041896	0.028295	-1.48	0.1392
Year Group Dummy 2	-0.222638	0.070287	-3.17	0.0016
Year Group Dummy 3	-0.078149	0.064916	-1.20	0.2291
Year Group Dummy 4	-0.07429	0.039661	-1.87	0.0615
Avg Min Daily Temp C	0.0057536	0.003236	1.78	0.0759

The Year Group dummy 3 was removed next. The results are shown below.

Summary of Fit

RSquare	0.373664
RSquare Adj	0.353697
Root Mean Square Error	0.304511
Mean of Response	6.386284
Observations (or Sum Wgts)	616

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.369255	0.239586	14.06	<.0001
Ln Cost	0.2016024	0.015334	13.15	<.0001
Admin Facility Class Dummy	-0.084492	0.050592	-1.67	0.0954
Comm, Navaids Facility Class Dummy	0.2437633	0.118271	2.06	0.0397
Dorms Facility Class Dummy	-0.055435	0.033751	-1.64	0.1010
Explosives Facility Class Dummy	0.1329027	0.104239	1.27	0.2028
Medical Facility Class Dummy	0.2515483	0.084311	2.98	0.0030
ACC MAJCOM Dummy	-0.133618	0.03705	-3.61	0.0003
AETC MAJCOM Dummy	-0.097728	0.041377	-2.36	0.0185
AFSOC MAJCOM Dummy	-0.259502	0.083732	-3.10	0.0020
AMC MAJCOM Dummy	-0.093267	0.03837	-2.43	0.0154
USAFA MAJCOM Dummy	-0.208388	0.108367	-1.92	0.0550
North Atlantic COE Dummy	0.1395854	0.047973	2.91	0.0038
Northwestern COE Dummy	-0.120214	0.040867	-2.94	0.0034
IH DA/CA Dummy	-0.19275	0.045893	-4.20	<.0001
DB Delivery Method Dummy	0.0545556	0.031388	1.74	0.0827
IH Design Method Dummy	-0.039952	0.02826	-1.41	0.1580
Year Group Dummy 2	-0.216281	0.070115	-3.08	0.0021
Year Group Dummy 4	-0.069617	0.039485	-1.76	0.0784
Avg Min Daily Temp C	0.0055852	0.003234	1.73	0.0847

The Explosives Facility class dummy variable was removed next, with results below.

Summary of Fit

RSquare	0.371955
RSquare Adj	0.353019
Root Mean Square Error	0.304671
Mean of Response	6.386284
Observations (or Sum Wgts)	616

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.3983813	0.23862	14.24	<.0001
Ln Cost	0.1998945	0.015284	13.08	<.0001
Admin Facility Class Dummy	-0.086514	0.050593	-1.71	0.0878
Comm, Navaids Facility Class Dummy	0.240166	0.1183	2.03	0.0428
Dorms Facility Class Dummy	-0.056991	0.033747	-1.69	0.0918
Medical Facility Class Dummy	0.2493442	0.084338	2.96	0.0032
ACC MAJCOM Dummy	-0.131502	0.037032	-3.55	0.0004
AETC MAJCOM Dummy	-0.09854	0.041394	-2.38	0.0176
AFSOC MAJCOM Dummy	-0.259852	0.083775	-3.10	0.0020
AMC MAJCOM Dummy	-0.093022	0.03839	-2.42	0.0157
USAFA MAJCOM Dummy	-0.211054	0.108403	-1.95	0.0520
North Atlantic COE Dummy	0.1374798	0.04797	2.87	0.0043
Northw estern COE Dummy	-0.121308	0.040879	-2.97	0.0031
IH DA/CA Dummy	-0.193603	0.045912	-4.22	<.0001
DB Delivery Method Dummy	0.0574829	0.03132	1.84	0.0670
IH Design Method Dummy	-0.038146	0.028239	-1.35	0.1773
Year Group Dummy 2	-0.217562	0.070145	-3.10	0.0020
Year Group Dummy 4	-0.065762	0.03939	-1.67	0.0955
Avg Min Daily Temp C	0.0053457	0.003231	1.65	0.0985

The In House Design Method dummy was removed next. The results of the new model are shown below.

Summary of Fit	
RSquare	0.370036
RSquare Adj	0.352127
Root Mean Square Error	0.304881
Mean of Response	6.386284
Observations (or Sum Wgts)	616

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.3667626	0.237632	14.17	<.0001
Ln Cost	0.2013006	0.015259	13.19	<.0001
Admin Facility Class Dummy	-0.081253	0.050478	-1.61	0.1080
Comm, Navaids Facility Class Dummy	0.2418063	0.118375	2.04	0.0415
Dorms Facility Class Dummy	-0.060839	0.033649	-1.81	0.0711
Medical Facility Class Dummy	0.2563968	0.084234	3.04	0.0024
ACC MAJCOM Dummy	-0.134852	0.036974	-3.65	0.0003
AETC MAJCOM Dummy	-0.103886	0.041232	-2.52	0.0120
AFSOC MAJCOM Dummy	-0.267054	0.083663	-3.19	0.0015
AMC MAJCOM Dummy	-0.093183	0.038416	-2.43	0.0156
USAFA MAJCOM Dummy	-0.212313	0.108474	-1.96	0.0508
North Atlantic COE Dummy	0.1398371	0.047971	2.92	0.0037
Northw estern COE Dummy	-0.12442	0.040843	-3.05	0.0024
IH DA/CA Dummy	-0.187435	0.045716	-4.10	<.0001
DB Delivery Method Dummy	0.0500105	0.030849	1.62	0.1055
Year Group Dummy 2	-0.218395	0.07019	-3.11	0.0020
Year Group Dummy 4	-0.063992	0.039395	-1.62	0.1048
Avg Min Daily Temp C	0.0056151	0.003227	1.74	0.0823

The Administrative facility class dummy was removed next. The results of the new model are shown below.

Summary of Fit	
RSquare	0.367306
RSquare Adj	0.350406
Root Mean Square Error	0.305285
Mean of Response	6.386284
Observations (or Sum Wgts)	616

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.3821939	0.237754	14.23	<.0001
Ln Cost	0.2000157	0.015258	13.11	<.0001
Comm, Navaids Facility Class Dummy	0.2481265	0.118467	2.09	0.0366
Dorms Facility Class Dummy	-0.052967	0.033336	-1.59	0.1126
Medical Facility Class Dummy	0.2634695	0.084231	3.13	0.0018
ACC MAJCOM Dummy	-0.130561	0.036927	-3.54	0.0004
AETC MAJCOM Dummy	-0.108722	0.041177	-2.64	0.0085
AFSOC MAJCOM Dummy	-0.261587	0.083705	-3.13	0.0019
AMC MAJCOM Dummy	-0.089601	0.038403	-2.33	0.0200
USAFA MAJCOM Dummy	-0.201826	0.108422	-1.86	0.0632
North Atlantic COE Dummy	0.1388614	0.048031	2.89	0.0040
Northw estern COE Dummy	-0.129528	0.040773	-3.18	0.0016
IH DA/CA Dummy	-0.188043	0.045775	-4.11	<.0001
DB Delivery Method Dummy	0.0488201	0.030881	1.58	0.1144
Year Group Dummy 2	-0.2232	0.07022	-3.18	0.0016
Year Group Dummy 4	-0.064566	0.039446	-1.64	0.1022
Avg Min Daily Temp C	0.0053694	0.003227	1.66	0.0967

The Design Build Delivery Method class dummy was removed next. The results of the new model are shown below.

Summary of Fit

RSquare	0.364666
RSquare Adj	0.348783
Root Mean Square Error	0.305666
Mean of Response	6.386284
Observations (or Sum Wgts)	616

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.3418896	0.236678	14.12	<.0001
Ln Cost	0.2042181	0.015044	13.58	<.0001
Comm, Navaids Facility Class Dummy	0.2384095	0.118455	2.01	0.0446
Dorms Facility Class Dummy	-0.053262	0.033377	-1.60	0.1111
Medical Facility Class Dummy	0.2546623	0.084151	3.03	0.0026
ACC MAJCOM Dummy	-0.13615	0.036803	-3.70	0.0002
AETC MAJCOM Dummy	-0.121227	0.040461	-3.00	0.0028
AFSOC MAJCOM Dummy	-0.275692	0.083332	-3.31	0.0010
AMC MAJCOM Dummy	-0.100933	0.037775	-2.67	0.0077
USAFA MAJCOM Dummy	-0.221875	0.107812	-2.06	0.0400
North Atlantic COE Dummy	0.1343916	0.048007	2.80	0.0053
Northwestern COE Dummy	-0.128291	0.040817	-3.14	0.0018
IH DA/CA Dummy	-0.178019	0.045391	-3.92	<.0001
Year Group Dummy 2	-0.235078	0.069904	-3.36	0.0008
Year Group Dummy 4	-0.07324	0.039111	-1.87	0.0616
Avg Min Daily Temp C	0.0049071	0.003218	1.52	0.1278

The average min daily temperature variable was removed next. The results of the new model are shown below.

Summary of Fit

RSquare	0.362204
RSquare Adj	0.347347
Root Mean Square Error	0.306003
Mean of Response	6.386284
Observations (or Sum Wgts)	616

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.4204211	0.231261	14.79	<.0001
Ln Cost	0.2019231	0.014985	13.48	<.0001
Comm, Navaids Facility Class Dummy	0.2360896	0.118576	1.99	0.0469
Dorms Facility Class Dummy	-0.051925	0.033403	-1.55	0.1206
Medical Facility Class Dummy	0.2534878	0.084241	3.01	0.0027
ACC MAJCOM Dummy	-0.123962	0.035964	-3.45	0.0006
AETC MAJCOM Dummy	-0.103781	0.038852	-2.67	0.0078
AFSOC MAJCOM Dummy	-0.252875	0.082068	-3.08	0.0022
AMC MAJCOM Dummy	-0.08582	0.036492	-2.35	0.0190
USAFA MAJCOM Dummy	-0.219652	0.107921	-2.04	0.0423
North Atlantic COE Dummy	0.1148847	0.046322	2.48	0.0134
Northwestern COE Dummy	-0.162448	0.034158	-4.76	<.0001
IH DA/CA Dummy	-0.185402	0.045181	-4.10	<.0001
Year Group Dummy 2	-0.234241	0.069979	-3.35	0.0009
Year Group Dummy 4	-0.071232	0.039132	-1.82	0.0692

The Dorms facility class dummy was removed next. The results of the new model are shown below.

Summary of Fit

RSquare	0.35964
RSquare Adj	0.345812
Root Mean Square Error	0.306363
Mean of Response	6.386284
Observations (or Sum Wgts)	616

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.4962582	0.226323	15.45	<.0001
Ln Cost	0.1962161	0.014545	13.49	<.0001
Comm, Navaids Facility Class Dummy	0.2404963	0.118681	2.03	0.0432
Medical Facility Class Dummy	0.2616293	0.084176	3.11	0.0020
ACC MAJCOM Dummy	-0.119972	0.035915	-3.34	0.0009
AETC MAJCOM Dummy	-0.104066	0.038898	-2.68	0.0077
AFSOC MAJCOM Dummy	-0.255604	0.082146	-3.11	0.0019
AMC MAJCOM Dummy	-0.083099	0.036493	-2.28	0.0231
USAFA MAJCOM Dummy	-0.209053	0.107832	-1.94	0.0530
North Atlantic COE Dummy	0.1099588	0.046268	2.38	0.0178
Northwestern COE Dummy	-0.16129	0.03419	-4.72	<.0001
IH DA/CA Dummy	-0.185075	0.045234	-4.09	<.0001
Year Group Dummy 2	-0.233465	0.070059	-3.33	0.0009
Year Group Dummy 4	-0.067503	0.039104	-1.73	0.0848

The Year Group 4 dummy was removed next. The results of the new model are shown below.

Summary of Fit

RSquare	0.35647
RSquare Adj	0.343664
Root Mean Square Error	0.306865
Mean of Response	6.386284
Observations (or Sum Wgts)	616

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.4081834	0.220858	15.43	<.0001
Ln Cost	0.2012616	0.014272	14.10	<.0001
Comm, Navaids Facility Class Dummy	0.2223065	0.118406	1.88	0.0609
Medical Facility Class Dummy	0.2380827	0.0832	2.86	0.0044
ACC MAJCOM Dummy	-0.117674	0.035949	-3.27	0.0011
AETC MAJCOM Dummy	-0.099277	0.038862	-2.55	0.0109
AFSOC MAJCOM Dummy	-0.244406	0.082023	-2.98	0.0030
AMC MAJCOM Dummy	-0.082611	0.036551	-2.26	0.0242
USAFA MAJCOM Dummy	-0.218471	0.10787	-2.03	0.0433
North Atlantic COE Dummy	0.1104976	0.046343	2.38	0.0174
Northwestern COE Dummy	-0.158519	0.034208	-4.63	<.0001
IH DA/CA Dummy	-0.178406	0.045143	-3.95	<.0001
Year Group Dummy 2	-0.215592	0.069404	-3.11	0.0020

The Comm/ Navaids facility class dummy was removed next. The results of the new model are shown below.

Summary of Fit

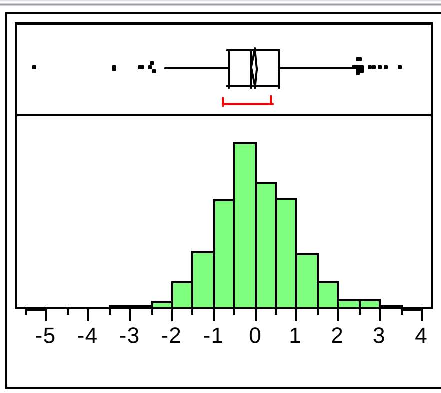
RSquare	0.352708
RSquare Adj	0.34092
Root Mean Square Error	0.307506
Mean of Response	6.386284
Observations (or Sum Wgts)	616

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.4451588	0.220438	15.63	<.0001
Ln Cost	0.1989428	0.014248	13.96	<.0001
Medical Facility Class Dummy	0.235049	0.083358	2.82	0.0050
ACC MAJCOM Dummy	-0.11607	0.036014	-3.22	0.0013
AETC MAJCOM Dummy	-0.096543	0.038916	-2.48	0.0134
AFSOC MAJCOM Dummy	-0.24605	0.08219	-2.99	0.0029
AMC MAJCOM Dummy	-0.0814	0.036622	-2.22	0.0266
USAFA MAJCOM Dummy	-0.218978	0.108095	-2.03	0.0432
North Atlantic COE Dummy	0.1122164	0.046431	2.42	0.0160
Northwestern COE Dummy	-0.161093	0.034252	-4.70	<.0001
IH DA/CA Dummy	-0.169121	0.044965	-3.76	0.0002
Year Group Dummy 2	-0.22124	0.069483	-3.18	0.0015

All *p*-values are now less than the specified 0.05 value. The model was now investigated for possible influential cases (outliers). Studentized residuals were first used to identify possible outliers. The studentized residual distribution for the model above is shown below.

Studentized Resid Ln Duration 4



Quantiles

100.0%	maximum	3.536
99.5%		3.067
97.5%		2.140
90.0%		1.266
75.0%	quartile	0.607
50.0%	median	-0.071
25.0%	quartile	-0.584
10.0%		-1.197
2.5%		-1.865
0.5%		-3.255
0.0%	minimum	-5.228

Moments

Mean	0.0001206
Std Dev	1.0042114
Std Err Mean	0.0404608
upper 95% Mean	0.0795788
lower 95% Mean	-0.079338
N	616

Possible outliers were investigated individually for possible removal from the model. Outliers were removed identifying studentized residuals falling outside of the outlier box plot as specified by the JMP software and removing them from the data set. This analysis resulted in 21 projects being removed from the data. The model was then re-ran to determine any changes to the significance level of the selected variables. The output from this model is shown below.

Summary of Fit

RSquare	0.385561
RSquare Adj	0.373968
Root Mean Square Error	0.261956
Mean of Response	6.387387
Observations (or Sum Wgts)	595

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.5181605	0.195105	18.03	<.0001
Ln Cost	0.1928092	0.012587	15.32	<.0001
Medical Facility Class Dummy	0.1235385	0.080636	1.53	0.1261
ACC MAJCOM Dummy	-0.076966	0.031038	-2.48	0.0134
AETC MAJCOM Dummy	-0.075744	0.033628	-2.25	0.0247
AFSOC MAJCOM Dummy	-0.225596	0.070118	-3.22	0.0014
AMC MAJCOM Dummy	-0.044633	0.03163	-1.41	0.1587
USAFA MAJCOM Dummy	0.0174438	0.103524	0.17	0.8662
North Atlantic COE Dummy	0.089034	0.041306	2.16	0.0315
Northwestern COE Dummy	-0.173726	0.029376	-5.91	<.0001
IH DA/CA Dummy	-0.148284	0.040076	-3.70	0.0002
Year Group Dummy 2	-0.144134	0.064476	-2.24	0.0258

After the removal of outliers, several of the previously selected variables are no longer significant. Removed data points must be analyzed to see if removing these variables from the model is appropriate. A listing of projects removed through outlier analysis is provided below.

Project Title	Normalized Total Cost	Duration (days)	*Facility Class*	*MAJCOM*	*COE Region*	*Command DA/CA*	*Year Group*
CONSTR IAAFA MAINT TNG COMPLEX	$ 1,252,780	135	Training Facilities	ACC	South Atlantic	COE	2
RESISTANCE TRAINING LABORATORY	$ 908,652	137	Training Facilities	USAFA	Northwestern	IH	3
FIELD ENGRG AND READINESS LAB	$ 1,402,593	152	Training Facilities	USAFA	Northwestern	IH	4
C-5 MOBILITY/AERIAL PORT CNTR	$ 7,534,510	154	Land Operations Facilities	AMC	North Atlantic	COE	4
BC-ADAL QLA SECURE WAREHOUSE	$ 725,703	167	Administrative Facilities	AFMC	South Pacific	COE	5
BASE CIVIL ENGINEER FACILITY	$ 1,423,247	195	Administrative Facilities	AMC	North Atlantic	COE	2
ALTER FAC FOR C-141 SIMULATOR	$ 1,742,095	204	Training Facilities	AFMC	Great Lakes/Ohio	IH	5
BC-IAAFA FLIGHTLINE MAINT TRNG	$ 1,907,486	224	Training Facilities	AETC	Southwestern	COE	3
2ND ECH MED LOG STOR FAC	$ 729,788	289	Medical and Medical Support	USAFE	Overseas	NAVFC	1
ADD TO SECURITY POLICE FAC	$ 381,747	810	Personnel Support	AFSPC	Northwestern	COE	5
BC-ADAL ANECHOIC CHAMBER	$ 720,970	1014	Research and Development Facilities	AFMC	South Pacific	COE	5
CHEM WARFARE PROTECT-AVION SHP	$ 1,696,469	1095	Maintenance Facilities	USAFE	Overseas	COE	2
AIR CONDITION PORT MORTUARY	$ 1,593,830	1135	Personnel Support	AMC	North Atlantic	COE	6
BC-ADAL FUEL/AIR FACILITY	$ 1,345,091	1141	Maintenance Facilities	AFMC	Southwestern	COE	6
CONTROL TOWER	$ 4,211,089	1240	Land Operations Facilities	AETC	Southwestern	COE	5
RENOVATE ACQUISITION MGT FAC	$ 10,861,003	1583	Research and Development Facilities	AFMC	North Atlantic	IH	6
RENOVATE DEPOT PLATING SHOP	$ 8,538,602	1632	Maintenance Facilities	AFMC	South Pacific	COE	4
ADD CHILD DEVELOPMENT CENTER	$ 3,076,410	1674	Personnel Support	SUW	North Atlantic	NAVFC	5
CMF LIFE SAFETY UPGRADE	$ 3,912,649	1757	Medical and Medical Support	AMC	North Atlantic	COE	5
FIRE TRAINING FACILITY	$ 3,105,493	1815	Training Facilities	PAF	Pacific Ocean	NAVFC	4
COMPOSITE MED FAC ADD/ALT	$ 21,173,007	2453	Medical and Medical Support	USAFE	Overseas	IH	4

The project data above does not appear to contain patterns in terms of facility class, MAJCOM, COE Region, Design/Construction agent, or year group. Patterns (i.e. all one facility class) in the data would indicate that these data may not represent outliers, but instead some unique project type which can be expected to have abnormally long or short construction durations. It is reasonable to assume that these projects may differ from other projects within the population sample for reasons that are not included in the model (i.e. accelerated construction schedules). Because no patterns are identified, the assumption is made that removing model variables is appropriate. Variables were removed one at a time, with the corresponding changes in the model noted. The final selected model is shown below.

Summary of Fit

RSquare	0.374385
RSquare Adj	0.368002
Root Mean Square Error	0.263201
Mean of Response	6.387387
Observations (or Sum Wgts)	595

Parameter Estimates

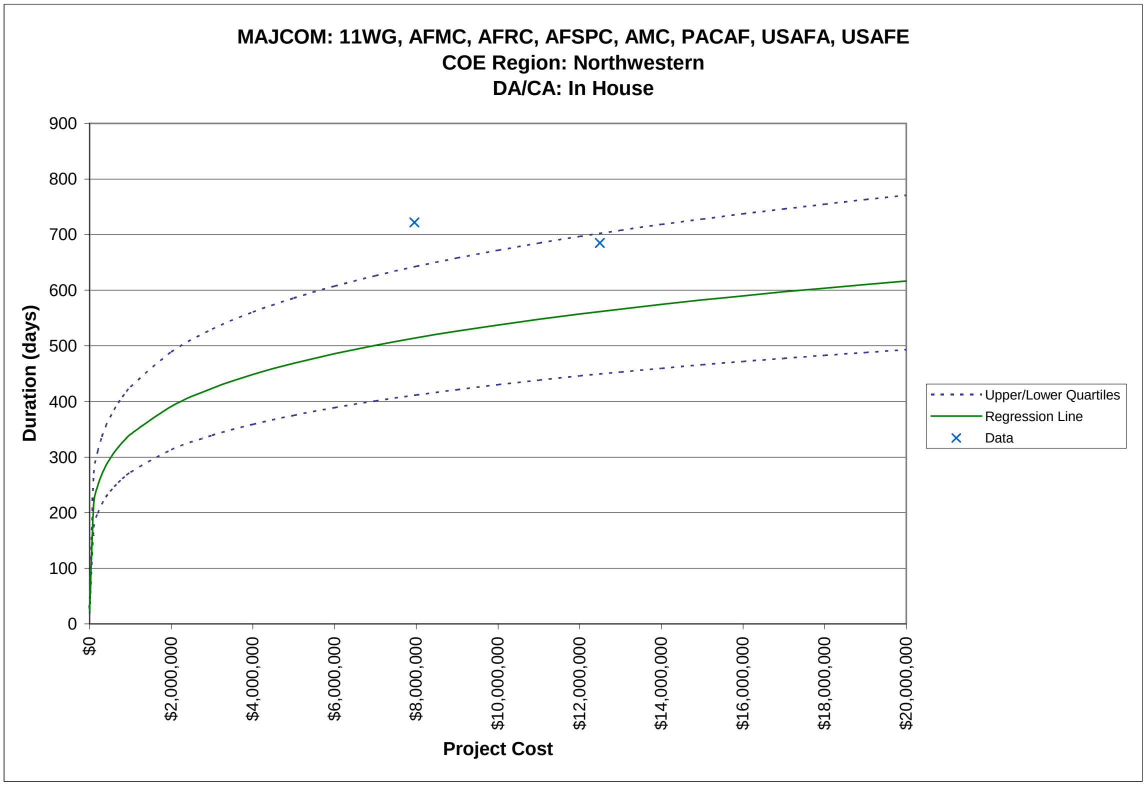
Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	3.4406122	0.192648	17.86	<.0001
Ln Cost	0.1976649	0.012468	15.85	<.0001
ACC MAJCOM Dummy	-0.059409	0.0291	-2.04	0.0416
AETC MAJCOM Dummy	-0.070215	0.032457	-2.16	0.0309
AFSOC MAJCOM Dummy	-0.222033	0.069783	-3.18	0.0015
Northwestern COE Dummy	-0.193163	0.026872	-7.19	<.0001
IH DA/CA Dummy	-0.146322	0.039724	-3.68	0.0003

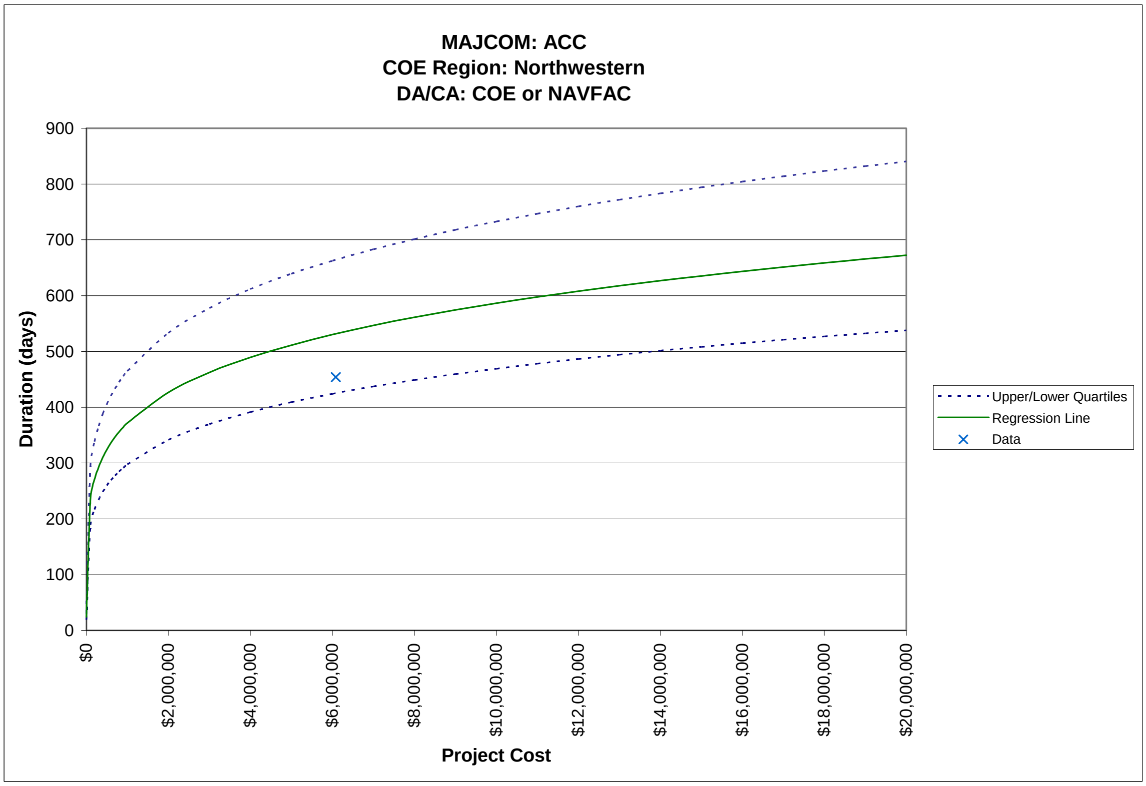
Appendix G: Validation Model Results

Validation data was available for the projects types shown in the table below.

MAJCOM	COE Region	DA/CA	Slope	Intercept	Data Points
ACC	Northwestern	IH	0.198	3.042	0
ACC	Northwestern	COE/NAVFAC	0.198	3.188	1
ACC	All Others	IH	0.198	3.235	8
ACC	All Others	COE/NAVFAC	0.198	3.381	13
AETC	All Others	IH	0.198	3.224	5
AETC	All Others	COE/NAVFAC	0.198	3.370	8
AFSOC	All Others	IH	0.198	3.072	3
AFSOC	All Others	COE/NAVFAC	0.198	3.219	0
All Others	Northwestern	IH	0.198	3.101	2
All Others	Northwestern	COE/NAVFAC	0.198	3.247	12
All Others	All Others	IH	0.198	3.294	11
All Others	All Others	COE/NAVFAC	0.198	3.441	21

The selected final models were overlayed on the available validation data for each model containing data points in the above table. Results for each model are shown below.


MAJCOM: 11WG, AFMC, AFRC, AFSPC, AMC, PACAF, USAFA, USAFE
COE Region: Northwestern
DA/CA: In House
Duration (days)
900
800
700
600
500
400
300
200
100
0
$0
$2,000,000
$4,000,000
$6,000,000
$8,000,000
$10,000,000
$12,000,000
$14,000,000
$16,000,000
$18,000,000
$20,000,000
Project Cost
Upper/Lower Quartiles
Regression Line
Data


MAJCOM: ACC
COE Region: Northwestern
DA/CA: COE or NAVFAC
Duration (days)
900
800
700
600
500
400
300
200
100
0
$0
$2,000,000
$4,000,000
$6,000,000
$8,000,000
$10,000,000
$12,000,000
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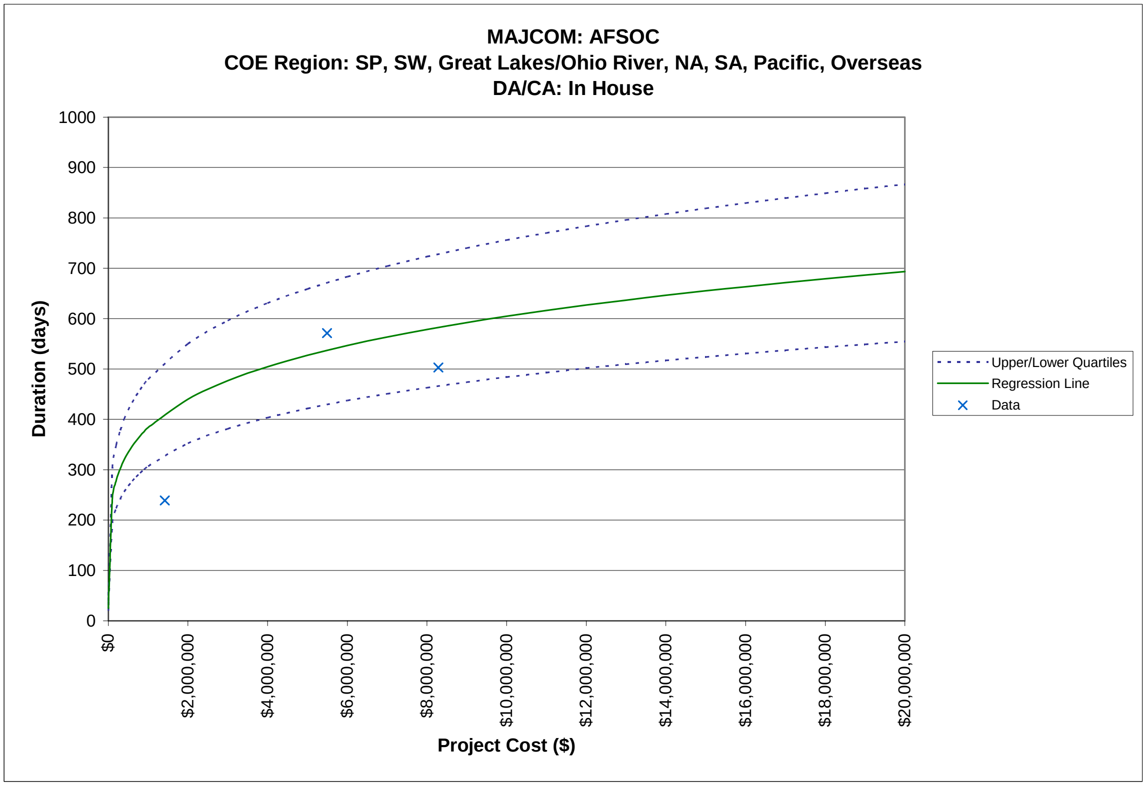
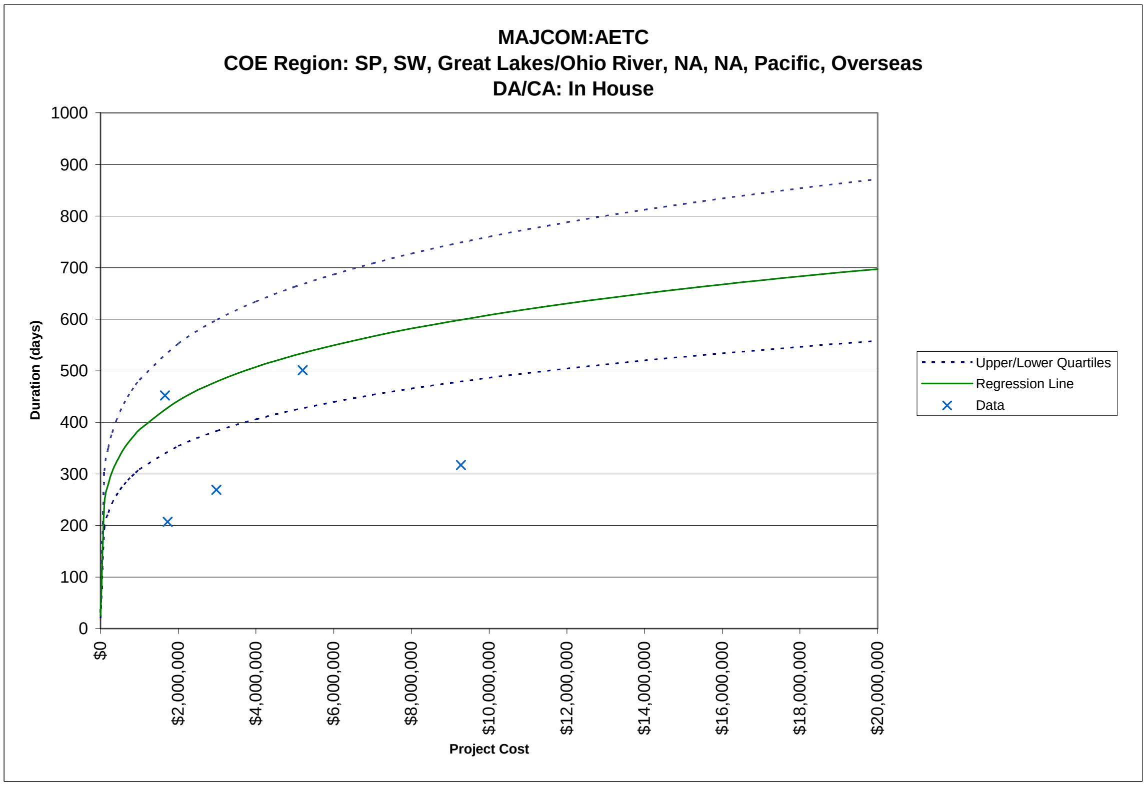
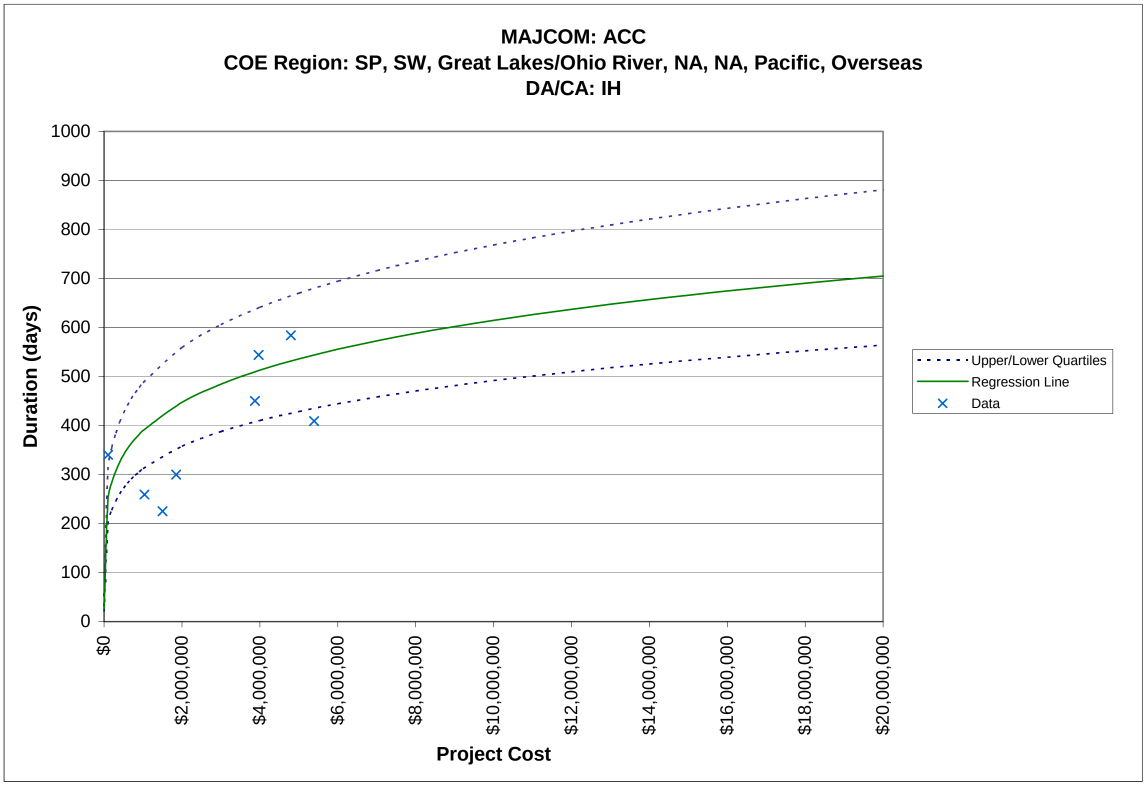
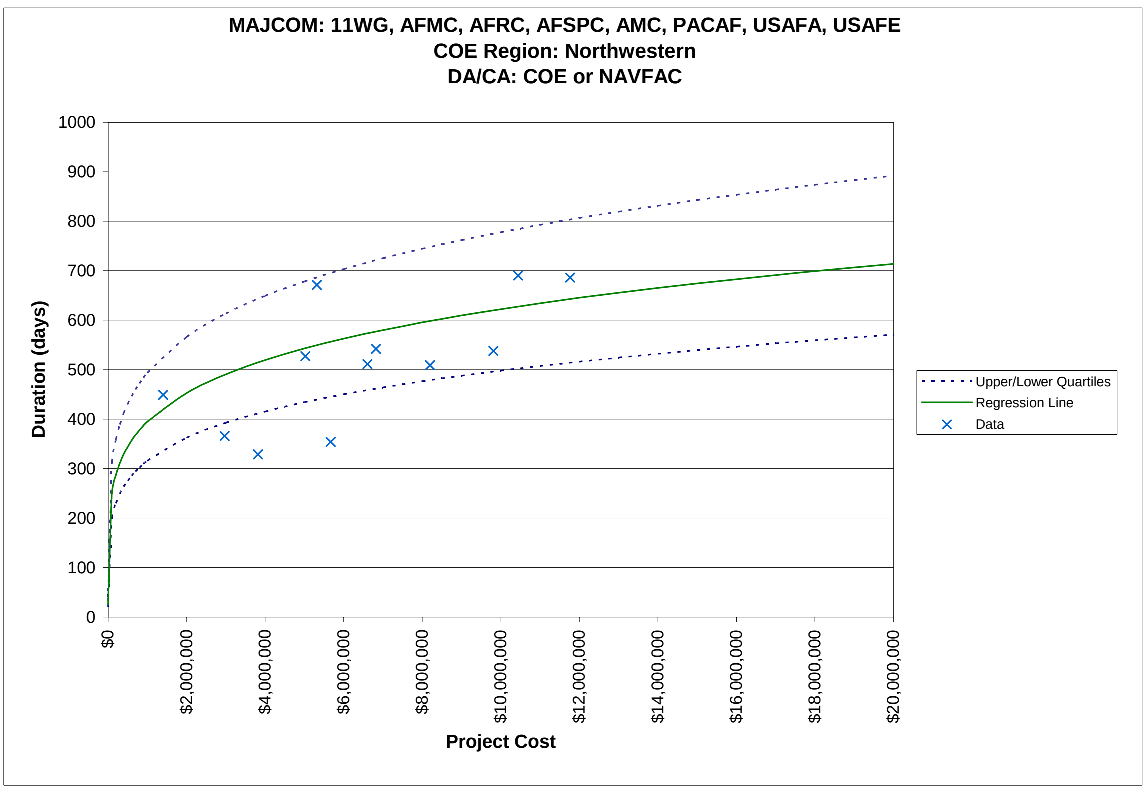
$16,000,000
$18,000,000
$20,000,000
Project Cost
Upper/Lower Quartiles
Regression Line
Data


MAJCOM: AFSOC
COE Region: SP, SW, Great Lakes/Ohio River, NA, SA, Pacific, Overseas
DA/CA: In House
Duration (days)
Project Cost ($)
Upper/Lower Quartiles
Regression Line
Data
0
100
200
300
400
500
600
700
800
900
1000
$0
$2,000,000
$4,000,000
$6,000,000
$8,000,000
$10,000,000
$12,000,000
$14,000,000
$16,000,000
$18,000,000
$20,000,000


MAJCOM:AETC
COE Region: SP, SW, Great Lakes/Ohio River, NA, NA, Pacific, Overseas
DA/CA: In House
Duration (days)
Project Cost
Upper/Lower Quartiles
Regression Line
Data
0
100
200
300
400
500
600
700
800
900
1000
$0
$2,000,000
$4,000,000
$6,000,000
$8,000,000
$10,000,000
$12,000,000
$14,000,000
$16,000,000
$18,000,000
$20,000,000


MAJCOM: ACC
COE Region: SP, SW, Great Lakes/Ohio River, NA, NA, Pacific, Overseas
DA/CA: IH
Duration (days)
1000
900
800
700
600
500
400
300
200
100
0
$0
$2,000,000
$4,000,000
$6,000,000
$8,000,000
$10,000,000
$12,000,000
$14,000,000
$16,000,000
$18,000,000
$20,000,000
Project Cost
Upper/Lower Quartiles
Regression Line
Data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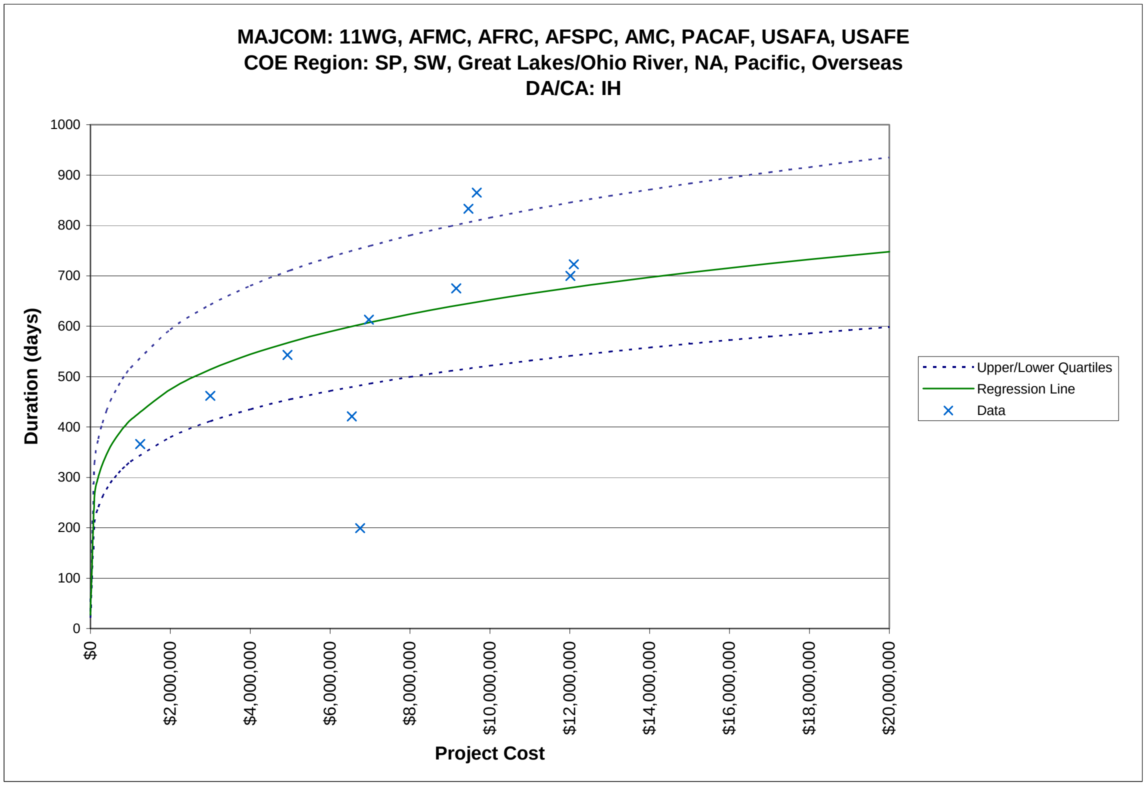
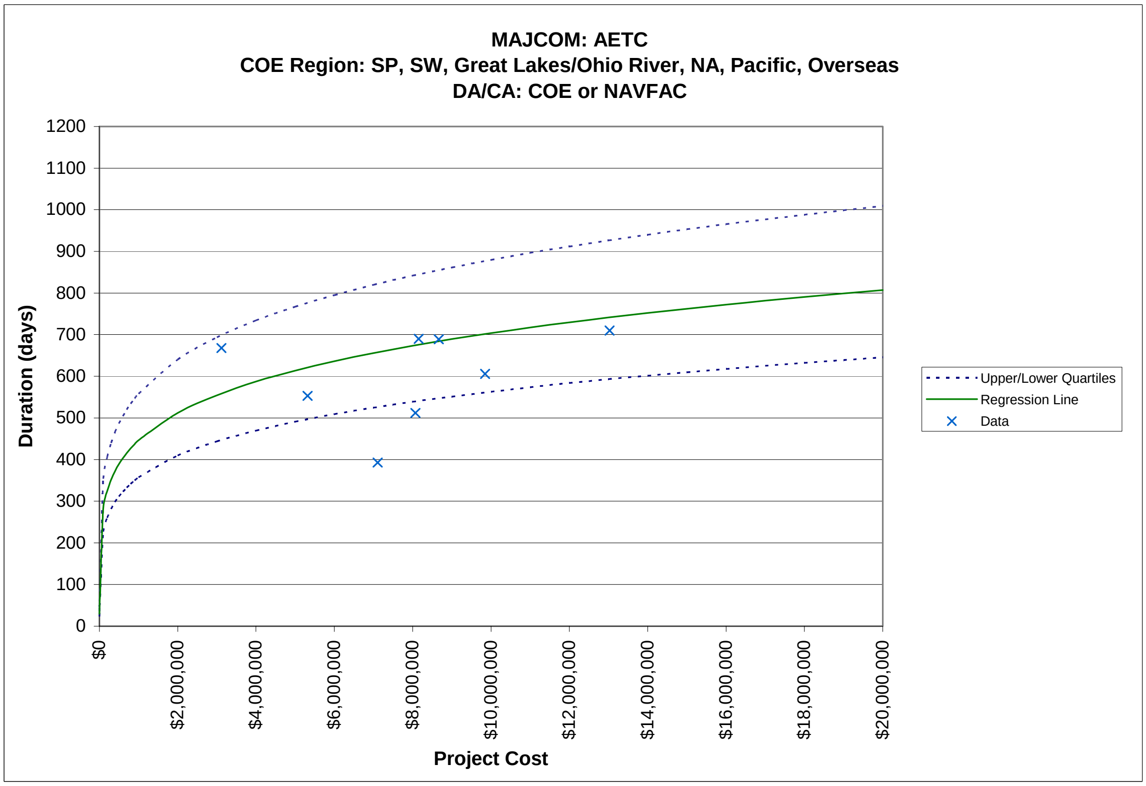
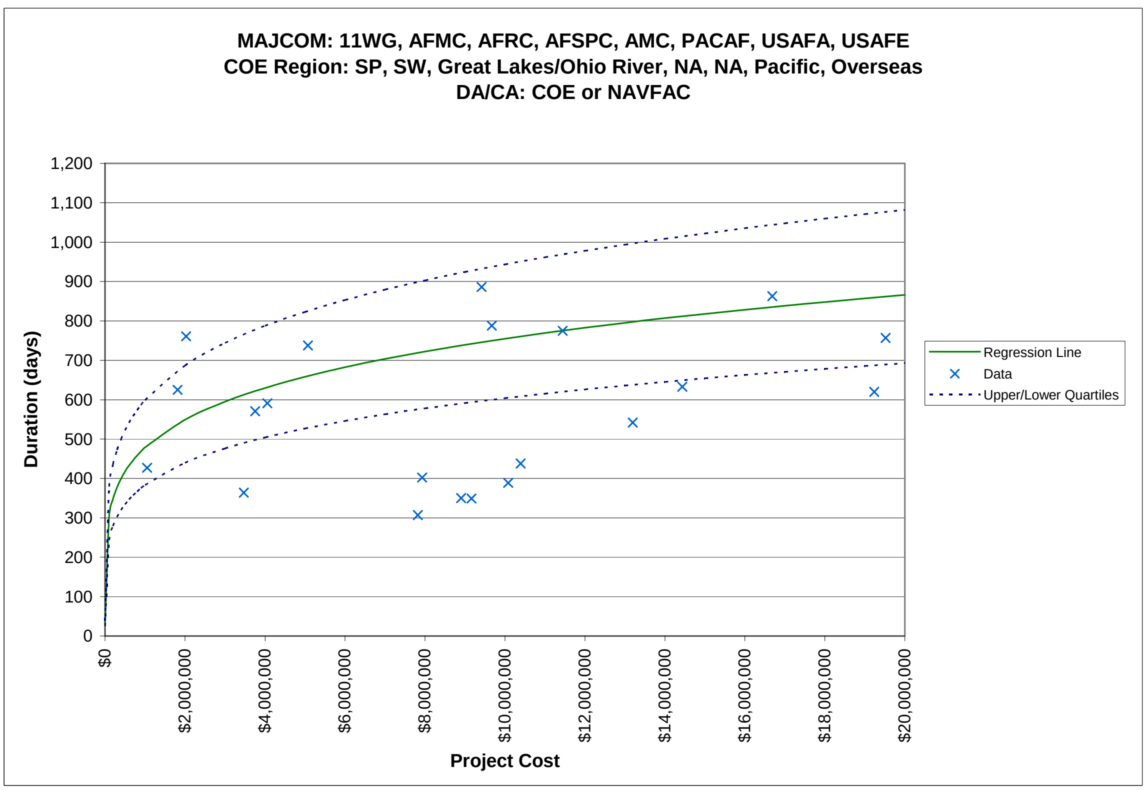
COE Region: Northwestern
DA/CA: COE or NAVFAC
Duration (days)
1000
900
800
700
600
500
400
300
200
100
0
$0
$2,000,000
$4,000,000
$6,000,000
$8,000,000
$10,000,000
$12,000,000
$14,000,000
$16,000,000
$18,000,000
$20,000,000
Project Cost
Upper/Lower Quartiles
Regression Line
Data


MAJCOM: 11WG, AFMC, AFRC, AFSPC, AMC, PACAF, USAFA, USAFE
COE Region: SP, SW, Great Lakes/Ohio River, NA, Pacific, Overseas
DA/CA: IH
Duration (days)
0
100
200
300
400
500
600
700
800
900
1000
$0
$2,000,000
$4,000,000
$6,000,000
$8,000,000
$10,000,000
$12,000,000
$14,000,000
$16,000,000
$18,000,000
$20,000,000
Project Cost
Upper/Lower Quartiles
Regression Line
Data


MAJCOM: AETC
COE Region: SP, SW, Great Lakes/Ohio River, NA, Pacific, Overseas
DA/CA: COE or NAVFAC
Duration (days)
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
$0
$2,000,000
$4,000,000
$6,000,000
$8,000,000
$10,000,000
$12,000,000
$14,000,000
$16,000,000
$18,000,000
$20,000,000
Project Cost
Upper/Lower Quartiles
Regression Line
Data


MAJCOM: ACC
COE Region: SP, SW, Great Lakes/Ohio River, NA, NA, Pacific, Overseas
DA/CA: COE or NAVFAC
Duration (days)
0
100
200
300
400
500
600
700
800
900
1000
1100
1200
$0
$2,000,000
$4,000,000
$6,000,000
$8,000,000
$10,000,000
$12,000,000
$14,000,000
$16,000,000
$18,000,000
$20,000,000
Project Cost
Upper/Lower Quartiles
Regression Line
Data


MAJCOM: 11WG, AFMC, AFRC, AFSPC, AMC, PACAF, USAFA, USAFE
COE Region: SP, SW, Great Lakes/Ohio River, NA, NA, Pacific, Overseas
DA/CA: COE or NAVFAC
Duration (days)
0
100
200
300
400
500
600
700
800
900
1,000
1,100
1,200
$0
$2,000,000
$4,000,000
$6,000,000
$8,000,000
$10,000,000
$12,000,000
$14,000,000
$16,000,000
$18,000,000
$20,000,000
Project Cost
Regression Line
Data
Upper/Lower Quartiles

Bibliography

Arditi,D., G.T. Akan, and S. Gurdamer. "Reasons for delays in public projects in Turkey," *Construction Management and Economics*, 3: 171-181 (1985).

Assaf, Sadi A., Mohammed Al-Khalil, and Muhammad Al-Hazmi. "Causes of delay in large building construction projects," *Journal of Management in Engineering*, 11: 45-50 (1995).

Baldwin, J. R., J. M. Manthei, H. Rothbart, and R. B. Harris. "Causes of Delay in the Construction Industry," *Journal of Construction Division, ASCE*, 97: 177-187 (1971).

Baumol, William J. and Alan S. Blinder. *Economics: Principles and Policy* (3rd Edition). New York: Harcourt Brace Jovanovich, 1985.

Bromilow, F. J. "Contract Time Performance Expectations and the Reality," *Building Forum*, 1: 70-80 (1969).

Bromilow, F. J., M.F. Hinds, and N. F. Moody. "AIQS survey of building contract time performance," *The Building Economist*: 79-82 (1980).

Bromilow, F.J., M.F. Hinds, and N.F Moody. *The time and cost performance of building contracts 1976-1986.* Barton, Australia: Australian Institute of Quantity Surveyors, September 1988.

Bureau of Economic Analyis, Regional Economic Accounts. *Total full-time and part time employment by industry.* 2004. Electronic Version. http://www.bea.gov/regional/reis.

Chalabi, F.A., and D. Camp. "Causes of delays and overruns of construction projects in developing countries," *Proceedings of the Fourth International Symposium on Organization and Management of Construction: Developing Countries*. 723-734. Waterloo, Canada: 1984.

Chan, Albert P. C. "Modeling building durations in Hong Kong," *Construction Management and Economics*, 17: 189-196 (1999).

Chan, Daniel W.M., and Mohan M. Kumaraswamy. "A study of the factors affecting construction durations in Hong Kong," *Construction Management and Economics*, 13: 319-333 (1995).

Chan, Daniel W.M., and Mohan M. Kumaraswamy. "Forecasting construction durations for public housing projects: a Hong Kong perspective," *Building and Environment*, 34: 633-646 (1999).

Chan, Daniel W.M., and Mohan M. Kumaraswamy. "Compressing construction durations: lessons learned from Hong Kong building projects," *International Journal of Project Management*, 20: 23-35 (2002).

Chan, Daniel W.M. and Mohan M. Kumaraswamy. "Comparative study of causes of time overruns in Hong Kong construction projects," *International Journal of Project Management*, 15: 55-63 (1997).

Cole, Ronald C. *Analysis of the Air Force Methods for Facility Sustainment and Restoration.* MS Thesis, AFIT/GEE/ENV/03-04. School of Engineering and Management, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, March 2003.

Department of the Air Force. *Design and Construction Standards and Execution of Facility Construction Projects.* AFI 32-1023. Washington: HQ USAF, July 1994.

Department of the Air Force. *Facility Requirements.* AFH 32-1084. Washington: HQ USAF, September 1996.

Department of the Air Force. *FY04 MILCON Dirtkicker Award Criteria Memorandum.* Washington: HQ USAF, October 2003.

Department of the Air Force. *Planning and Programming Military Construction (MILCON) Projects.* AFI 32-1021. Washington: HQ USAF, October 2003.

Department of the Air Force. *The United States Air Force Project Manager's Guide for Design and Construction.* Washington: HQ AFCEE, June 2000.

Ireland, V.B.E. "The role of managerial actions in the cost, time and quality performance of high rise commercial building projects," *Construction Management and Economics*, 3: 59-87 (1985).

Kaka, Ammar, and A.D.F. Price. "Relationship between value and duration of construction projects," *Construction Management and Economics*, 9: 383 (1991).

Khosrowshahi, F., and Ammar P. Kaka. "Estimation of project total cost and duration for housing projects in the U.K." *Building and Environment*, 31: 373-383 (1996).

Kumaraswamy, Mohan M., and Daniel W.M. Chan. "Determinants of construction duration," *Construction Management and Economics*, 13: 209-217 (1995).

Mansfield, N. R., O.O. Ugwu, and T. Doran. "Causes of delay and cost overruns in Nigerian construction projects," *International Journal of Project Management,* 11: 45-50 (1994).

McClave, James T. and others. *Statistics for Business and Economics* (8th Edition). New Jersey: Prentice Hall, 2000.

McGraw Hill Construction. "Most Recent Cost Indexes," *Engineering News Record.* 4 October 2004. Electronic version. http://enrconstruction.com/features/coneco/mostRecentIndexes.asp.

National Economic Development Office (NEDO). *Faster building for commerce*. Millbank, London (UK), 1988.

National Economic Development Office (NEDO). *Faster building for industry*. Millbank, London (UK), 1983.

Naoum, S.G. *Procurement and Project Performance - a Comparison of Management Contracting and Traditional Contracting*. Ascot, UK: The Chartered Institute of Building, 1991.

Ng, S. Thomas, Micheal M.Y. Mak, R.M. Skitmore, Ka C. Lam, and Mark Varnam. "The predictive ability of Bromilow's time-cost model," *Construction Management and Economics*, 19: 165-173 (2001).

Nkado, Raymond N. "Construction time-influencing factors. the contractor's perspective," *Construction Management and Economics*, 13: 81-89 (1995).

The Royal Australian Institute of Architects (RIRA). *Pre-assessing using contract/time related formula*. Australia, 1989.

SAS Institute. *JMP User's Guide.* Cary, NC, 2003.

Skitmore, R.M., and S.T. Ng. "Forecast models for actual construction time and cost," *Building and Environment,* 38: 1075-1083 (2003).

U.S. Army Corps of Engineers. *Air Force Military Construction Program Program Management Plan.* May 2003.

U.S. Army Corps of Engineers. *Map of USACE Engineer Divisions and Districts.* 17 January 2002. Electronic version: http://www.usace.army.mil/militarymap.html.

Walker, Derek H.T. "An investigation into construction time performance," *Construction Management and Economics,* 13: 263-274 (1995).

World Meteorological Organization. *World Weather Information Service Climatological Information.* 2004. Electronic version: http://www.worldweather.org/wmo.html.

Yeong, C.M. *Time and cost performance of building contracts in Australia and Malaysia.* MS Thesis, University of Southern Australia, Australia, 1994.

Vita

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REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 074-0188*

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
21-03-2005	**Master's Thesis**	Aug 2003 – Mar 2005

4. TITLE AND SUBTITLE

Estimating Performance Time for Air Force Military Construction Projects

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

Hoffman, Greg, J., Captain, USAF

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)

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2950 Hobson Way
WPAFB OH 45433-7765

8. PERFORMING ORGANIZATION REPORT NUMBER

AFIT/GEM/ENV/05M-05

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

AETC/CECT
Attn: Major Frank Simas
266 F Street West
Randolph AFB, TX 78150-4319 DSN: 487-2786

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

The prediction of construction time performance is a problem of interest to both researchers and construction industry practitioners. This research seeks to identify significant factors which may influence construction durations for Air Force Military Construction (MILCON) projects to establish a time prediction model. Data were collected for 856 MILCON projects completed between 1988 and 2004; this included both traditional facility and non-facility (e.g. airfield pavements, utilities) projects. These data were analyzed using Bromilow's time-cost (BTC) model (1969) as well as multiple linear regression. Neither model produced acceptable results for non-facility projects; however, the multiple linear regression model was found to provide the most acceptable time prediction model for facility projects.

As with the BTC model and previous research reported in the literature, there was a significant correlation between cost and duration. However, several other factors were also identified that resulted in significantly lower than average construction durations. These include projects completed within certain management groupings (referred to as Major Commands in the Air Force), projects where the Northwestern Army Corps of Engineers served as the construction agent, and projects completed using in-house design services. Several possible reasons may exist for these differences; therefore, it cannot be inferred that the results are indicative of the organizations' management processes.

The forecasting ability of the model was then evaluated using a set of 129 projects not used in the formulation of the model. The resulting model appears to provide a valid alternative for predicting construction durations for Air Force MILCON facility projects. Therefore, it may be used as a prediction tool or as a policy setting tool.

15. SUBJECT TERMS

Construction Project Duration, Time-Cost Models, Multiple Linear Regression, Air Force Military Construction, Bromilow's Time-Cost Model, Forecasting, Building Projects, Construction Performance, Construction Scheduling

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
REPORT	**ABSTRACT**	**c. THIS PAGE**			Alfred E. Thal, Jr. (ENV)
U	**U**	**U**	UU	230	**19b. TELEPHONE NUMBER** *(Include area code)* (937) 255-3636, ext 4798; e-mail: Alfred.Thal@afit.edu