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An Empirical Analysis of DoD Construction Task Order Performance

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AN EMPIRICAL ANALYSIS OF DOD CONSTRUCTION TASK ORDER PERFORMANCE

JOINT THESIS

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Abstract

Cost and schedule overrun plague over 50% of all construction projects, engendering diminished available funding that leads to deferred maintenance and impaired award ability for needed projects. Though existing research attempts to identify overrun's sources, the results are inconclusive and frequently differ. Accordingly, this research reviews DoD construction contract data from the past ten years to identify the contract attributes of 79,894 projects that correlate with superior performance for use in future project execution. This research starts with creating a database that houses the largest single source of construction contract information. The research then evaluates the data to determine if differences in project performance exist when comparing contracting agents, funding agents, and award months. Next, the research utilizes stepwise logistic regression to determine the significant contract attributes and predict future projects' overrun likelihoods. Model accuracy for predicting the likelihood of cost and schedule overrun is 65% and 75%, respectively. Finally, this research concludes by providing insights into efforts that could improve modeling accuracies, thereby informing better risk management practices. This research is expected to support public and private sector planners in their ongoing efforts to execute construction projects more cost-effectively and better utilize requested funds.

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AN EMPIRICAL ANALYSIS OF DOD CONSTRUCTION TASK ORDER PERFORMANCE

I. Introduction

Background

More than half of all construction projects exceed their target budget or schedule (Assaf et al. 1995; Habibi et al. 2018a; Ramanathan et al. 2012a). Department of Defense (DoD) construction projects are no exception (Dicks et al. 2017; Thal et al. 2010). The DoD was authorized $26.7 billion in fiscal year 2020 to construct, repair, alter, maintain, and modernize its 585,000 facilities and associated infrastructure (Office of the Under Secretary of Defense (Comptroller)/Chief Financial Officer 2019). Despite this considerable funding, there remains an estimated $116 billion maintenance project backlog (Cronk 2018). This backlog is made worse by a consistently underfunded yearly sustainment model and represents an increasing financial risk (Serbu 2015; USGAO United States Goverment Accountability Office 2019). Therefore, properly executing these projects and developing strategies for mitigating overruns and delays is crucial in reducing the project backlog.

The consequences of cost overruns and delays are manifest throughout the DoD. These issues lead to overtasked contracting and construction personnel, alter planned budgets affecting construction programs, and can even limit the ability to award future projects (Alleman et al. 2020). Deferring projects can result in delays in mission-essential readiness, missed requirements, lower morale, and reduced effectiveness (Mills et al. 2017; Roulo 2015). Furthermore, cost and schedule overrun can lead to a need to use

funds from the fixed operations and maintenance budget (Congressional Research Service 2019).

Identifying the sources of delays and cost overrun in the construction industry has been an ongoing effort for at least 40 years (Rowland 1981). However, according to most research, overrun sources vary from region-to-region, owner-to-owner, and project-to-project, with no single agreed-upon source. One previous study shows that the only underlying reason for cost overrun is design change (Chang 2002), while another identifies 73 different causes (Assaf and Al-Hejji 2006). Accordingly, this research investigates the primary causes of DoD construction project cost overrun and schedule delay.

Previous studies that analyzed construction performance using contract attributes have garnered considerable insights into the factors that significantly affect performance (Al-Momani 2000; Bordat et al. 2004; Lu et al. 2017; Rowland 1981). However, no studies have used DoD contract information at the scale to which this research attempts, to the authors' knowledge. Therefore, this review and analysis of the DoD's construction portfolio's past performance based on contract data could help determine future work's optimal execution strategy.

The U.S. government requires funding oversight and tracking for all contracts greater than $10 thousand. The DoD has used the Federal Procurement Database System – Next Generation (FPDS-NG) to track construction contracts meeting this requirement, making it the most relevant and complete contract data source ("Federal Procurement Data System - Next Generation" n.d.). Accordingly, the DoD could use information from

this database to analyze its entire project portfolio and potentially reduce the occurrences and magnitude of cost overrun and schedule delay.

Problem Statement

The United States Federal Government has enacted several policy changes regarding the execution of construction projects and the divestment practices of existing infrastructure to mitigate the project backlog. The realignment of the National Defense Strategy and implementation of base realignment and closure attempt to reduce the amount of infrastructure the DoD must maintain ("Base Realignment and Closure (BRAC)" n.d.; Serbu 2015). Newer project execution strategies, including enhanced use leases, public-private-partnerships, and use of condition assessments, have also been implemented to help curb ongoing maintenance costs (Aragon 2018; "Facilities Investment & Management" n.d.; Herrera 2019). While these efforts do much to reduce recurring expenses, funding shortfalls persist (Serbu 2019).

DoD facilities and infrastructure condition directly affect the military's capability and mission readiness, with service branches deliberately putting off mission-critical infrastructure projects because of the inability to fund them (Serbu 2015). Deferring maintenance to facilities and infrastructure because of budget shortfalls can quickly turn into a need to restore or modernize those same issues years later. Allowing further infrastructure degradation through maintenance deferment can ultimately lead to an increased cost for repairs (*Deferred Maintenance: The Cost of Doing Nothing* 2016). Therefore, a means to further mitigate this underfunding is needed.

This thesis seeks to identify construction contracting data attributes that significantly correlate to a project's ability to be completed within budget and delivered on-time. The DoD can avoid those attributes of contract data correlated with a greater cost overrun and schedule delay frequency or magnitude based on risk tolerance. Conversely, those correlated with better performance can be implemented on a greater number of projects to potentially mitigate cost and schedule overrun and further aid in diminishing the backlog of DoD construction projects and maintaining mission-readiness.

Research Objectives

The DoD can improve their management practices and possibly mitigate the need for unforeseen funding requests for future construction programming by identifying the contract attributes positively and negatively correlated with project performance. This research is expected to support military planners in their ongoing efforts to execute DoD construction projects more cost-effectively and responsibly utilize DoD funds, which contribute to maintaining the U.S. as the world's preeminent fighting force.

Due to the inconclusive nature and scope of current research, this study investigates sources of schedule and cost overrun within DoD construction project contract data. The specific research objectives within this project are determining:

1. the sources of cost and schedule overrun for construction contracts using the attributes contained within FPDS;
2. which execution agents and contract delivery methods are more effective at staying on budget and schedule;
3. if locally contracted projects perform better than centrally managed projects;

4. if the contract award date impacts the overall project performance in cost and schedule metrics; and
5. the likelihood and magnitude of a DoD construction project to experience an overrun.

This research's objectives align directly with the priorities outlined in the National Defense Strategy, specifically "Working with military engineering contracting communities to develop smarter contracts and executing contracts smartly" (Cronk 2018).

Thesis Organization

The following sections comprise this thesis:

- Chapter Two – A literature review of the current body of knowledge that focuses on cost and schedule overrun. This high-level overview provides information on common sources of overrun. This chapter also discusses how the categorization of literature follows techniques used to determine those overrun sources, including qualitative and quantitative methods. Each section of the chapter concludes by discussing the gaps within the current research.
- Chapter Three – Publication One – "United States Department of Defense (DoD) Real Property Repair, Alterations, Maintenance, and Construction Project Contract Data: 2009- 2020." This publication covers how the contract data were procured from the Federal Procurement Database System and transformed into a working DoD construction project database. The publication covers the compilation of 62 unique attributes for 132,665 projects into a single source, offering military planners the ability to perform analyses on the DoD's execution capability. These data also translate well for the private sector as they closely mirror work conducted in this area. To the authors' knowledge, this is the most extensive open-source data of its kind. This article was published in Elsevier's Data-In-Brief journal with a CiteScore of 1.5 (Stout et al. 2020).
- Chapter Four – Publication Two – International Journal of Project Management: "A Two-Stage Statistical Prediction Framework for Predicting Construction Cost and Schedule Overrun." This article analyzes the contract data of 79,894 projects from the past 11 years to determine those contract attributes significantly

correlated with a project's ability to remain within budget and be delivered on-time. The regression model developed for this analysis is then used in concert with testing and validation data sets to predict the likelihood of cost overrun and schedule delay. Additionally, a random forest algorithm is also applied to the data to categorize the expected magnitude of overrun a project will experience. Project programmers, planners, and managers alike can use this information to aid them in identifying projects that are likely to experience overrun. By identifying these at-risk projects, construction professionals can attempt to mitigate their effects. This paper has been submitted to the International Journal of Project Management (2021) for publication.

- Chapter Five – Publication Three – The Military Engineer: "Using Construction Contract Data to Improve Decision Making and Project Performance." This paper covers the investigation and outcome of a study conducted to identify the sources of cost and schedule overrun within DoD construction. Contract data are compared with performance indicators to determine which attributes increase the likelihood of overruns and how this information can be used to improve project planning. In addition, suggestions for the improvements of modeling efforts is also discussed. This article also serves as the summary and conclusion of the thesis. This paper has been submitted to The Military Engineer (2021) for publication in their May-June project delivery issue. Chapter five also includes those conclusions pertaining to the Air Force and recommendations for future research.

II. Literature Review

Chapter Introduction

The purpose of this chapter is to provide a summary of the body of knowledge surrounding cost overrun and schedule delay within construction. This chapter begins by defining cost overrun and its prevalence within this industry. It then discusses the findings of literature and those most commonly identified causal factors according to the methods utilized to include both qualitative and quantitative efforts. A similar format including predictive measures and mitigation sections are used in outlining the body of knowledge that currently exists for schedule delay. Finally, the chapter ends with a summary of the current literature limitations and research opportunities.

Cost Overrun

Cost overrun is a persistent and widespread issue plaguing the construction industry. Studies report that nearly 50% of all construction projects experience cost overrun (Ramanathan et al. 2012a) with an average growth of 8-12% (Love et al. 2013; Odeck 2004a; Turcotte 1996). The additional funds needed to cover construction overruns are frequently resolved with money earmarked to execute future construction projects. Planners use a host of other mitigation tactics to combat cost overrun, including the addition of contingency funds to account for the inherent uncertainty in cost estimation and unpredictable risks throughout the project (Yehiel 2013). Contingencies may be effective at securing money for unexpected circumstances; however, they do not identify or reduce the sources of cost overrun. Many researchers have attempted to

qualify and quantify sources of cost overrun in construction, though the studies' conclusions mostly do not concur.

Construction project characteristics and external factors frequently lead to cost overruns. Construction project characteristics include project size (Creedy et al. 2010; Islam et al. 2019a; Love 2002; Love et al. 2013; Odeck 2004a), project type (Creedy et al. 2010; Islam et al. 2019a; Love 2002; Love et al. 2013), design issues (Polat et al. 2014), and scope changes (Creedy et al. 2010; Kaliba et al. 2009; Kuprenas and Nasr 2003). External factors that lead to cost overrun include weather (Kaliba et al. 2009), unforeseen conditions (Alleman et al. 2020), and human influence such as management practices (Dada 2014; Turcotte 1996) and philosophy and politics (Cantarelli et al. 2010, 2012). The causal factors associated with cost growth not only differ based on project-specific attributes but can vary between studies based on the differences in focus areas and levels of analysis (e.g., statistical analysis of surveys vs. regression analysis of contract data). The literature investigating cost overrun can generally be categorized into two groups based on the methods employed to determine its cause: (1) qualitative research, including surveys and group decision making; and (2) quantitative research, including descriptive statistics and modeling.

Qualitative Research

The first step in most researchers' analysis of cost overruns is often defining the scope of the problem through extensive literature review. This review provides researchers with a foundation to proceed by identifying specific areas of interest. Even if researchers already have a particular purpose or scope of research regarding cost overrun, they all use literature to discover where the current body of knowledge stands. From this

point, researchers build theories and form hypotheses on what factors may contribute to cost overruns. At the lowest level, the analysis may end here, merely offering theories as justifications to cost overrun and calling for further research (Cantarelli et al. 2010).

These theories often provide the impetus for research, which seeks to identify causal factors for project cost overrun to apply mitigation tactics. One such approach involves eliciting expert opinions via surveys and interviews, as experts have firsthand field knowledge of construction projects and the varying factors that influence project cost performance. In a first-of-its-kind analysis, Rosenfeld (2014) evaluated 146 studies and surveyed 200 construction professionals to identify causal factors for cost overrun that universally applied to all construction projects. Rosenfeld tasked the engineers with ranking the five most influential factors to cost overrun based on their experiences. The aggregated opinions revealed premature bid documents, too many changes by the owner, and suicide bidding (i.e., bidding an unreasonable low amount for the sole purpose of being awarded the project) as top factors, while strikes, bad weather, regulation changes, and accidents receiving the fewest votes. While this study's results provide a thorough synthesis of information on the causes of cost overrun, the author indicates that it still requires local ranking for applicability and would rely on others' experience and expertise to implement.

Additional studies that focus on the causes of cost overruns that are region-, construction-, or even respondent-specific have also provided valuable, albeit conflicting, information. Polat et al. (2014) reported that design problems were the top factor contributing to cost overrun in Turkish micro-scaled construction. Unlike Rosenfeld's results, and when analyzing groups of factors, no one group was significantly more likely

to experience cost overrun than another. In another study on road projects in Zambia, 60 Zambian construction workers voted weather as the top factor in cost overrun. Though, like Rosenfeld, interviewees voted scope changes as the next highest-ranking factor (Kaliba et al. 2009).

Modified fuzzy group decision analysis (MFGDA), which is similar to surveys, is another qualitative technique one researcher used to identify and rank the influence of factors. Islam et al. (2019) used survey data and metadata of the interviewees to weigh the respective responses. The authors surveyed 60 experts on powerplant construction using a Likert scale to rank various cost overrun factors from the literature. The results were then transformed based on the respondents’ position and experience. Unlike previous studies, Islam et al. (2019) identified government bureaucracy as the most significant contributor to cost overrun in powerplant construction in Bangladesh. These varying results identify the issues related to the use of surveys in pinpointing the factors associated with overrun. It has also been shown that respondents' experiences can introduce bias and error into research (Kumaraswamy and Chan 1998), further undermining their results.

Quantitative Research

While qualitative analysis techniques often focus broadly on factors that relate to cost overrun by extracting summaries from literature reviews and opinions from field experts through surveys, quantitative analysis techniques review and analyze trends seeking to answer specific questions using construction project data such as initial and final cost and the number of modifications. At a fundamental level, researchers may use

quantitative analysis to purely describe their project data. They can extrapolate proportions and percentages as the means of comparison among various categories.

In a study on the relationship between cost overrun and scope creep of 90 projects, Kuprenas and Nasr (2003) determined that the magnitude of creep directly affected the amount of overrun experienced, especially in the design phase. Other research conducted by Woo et al. (2017), using the contract data from 513 projects, found that contractors' poor performance led to the most significant amount of cost escalation on projects. Turcotte (1996) concluded that design errors were the most significant source of avoidable cost growth in 102 Florida Department of Transportation projects.

These techniques provide analysts with a first glance and foundation to build their research efforts, though they fail to provide any statistical significance or confidence level on their findings. However, access to past and present projects' performance can provide planners with the attributes that are most frequently associated with overrun as well as the data necessary to analyze, mitigate, and possibly prevent cost overrun through discussion of changing management practices or quality control (Turcotte 1996).

When robust construction contract databases are not available, researchers must carefully use descriptive statistics to relate factors to cost overrun. Without the accompanying statistical significance, the findings may lack internal or external reliability and validity. Accordingly, hypothesis testing often includes the difference in means and one-way analysis of variance (ANOVA) to support their results. In one such use of these statistical techniques, Love et al. (2013) found that although 276 Australian construction projects experienced an average of 12% cost overrun; an in-depth statistical analysis revealed no significant differences in overrun concerning project size or type.

Hypothesis testing is also commonly paired with the qualitative component of surveys to obtain additional insights on those factors affecting cost overrun that may not be found in contract data, or that may not be readily available for comparison. For instance, Dada (2014) determined that cordiality among teams played a significant role in reducing overrun in 274 projects. Additional research by Love (2002) discovered that 51% of overrun could be attributed to rework based on data from 161 respondents, but that there were no significant differences between procurement method or project type on the magnitude of cost overrun experienced. Alleman et al. (2020) analyzed change orders by investigating 162 projects and interviewing 12 owners. The authors concluded that unforeseen conditions, owner-directed changes, and design errors most commonly led to cost overrun. However, there appeared to be no difference in mean cost overrun between several contracting methods (e.g., design-bid-build and design-build).

The conclusions drawn from hypothesis testing may also lead analysts to conduct subsequent modeling of their data to better understand the causes of, and possibly predict, overrun. Anastasopoulos et al. (2014) used binary probabilistic modeling to identify the likelihood of a project to experience overrun based on several factors, including planned duration and cost estimate for 601 Public-Private-Partnerships (PPP). Through the use of similar methods, Gkritza and Labi (2008) produced a statistically significant model that calculates the probability of highway projects to experience cost overrun using factors like project complexity, duration, and initial cost. Touran and Lopez (2006) used Monte Carlo simulations that predict the likelihood of certain thresholds of cost overrun a project may experience but require the input of an anticipated level of overrun that will occur, making it more useful to those with experience in the industry.

Project managers and owners can better manage the risks associated with cost overrun if they can determine the scale or magnitude of the overrun a project may experience. Researchers have accomplished this objective using different methods, including Multiple Linear Regression (MLR) and machine learning. MLR models have been utilized to predict the magnitude of cost overrun based on contract characteristics such as the period of performance and budgeted cost (Anastasopoulos et al. 2014; Gkritza and Labi 2008). However, comparisons between studies using MLR will often yield different results on the factors affecting cost overrun. In one case, Creedy et al. (2010) analyzed contract data from 231 highway projects and concluded that cost overrun was more due to uncertainty than risk. Jahren and Ashe (1991) used regression and determined that the difference between the owner's estimate and awarded contract price was the most significant cause of cost overrun among 1,561 Navy projects. Still, others have shown the significance of the contract award date using similar analysis techniques (Thal et al. 2010).

Processes like supervised machine learning classification techniques offer the ability to analyze the relationships between variables while allowing the use of data that may otherwise be unfit for use in MLR. Classification attempts to categorize construction projects into predetermined cost overrun categories based on some given input parameters rather than predicting the exact magnitude. These models use past construction project data to learn trends and to create a model that predicts the category of cost overrun, with some specified accuracy, on future construction projects. Williams and Gong (2014) used this process to test the hypothesis that analyzing a project description through data mining may better predict cost overrun. Their analysis of

highway construction projects revealed that when a project description contains words such as “binder” or “sand,” cost overrun is more likely due to the complexities associated with those projects. To further test this theory, they compared multiple classification techniques, which predicted cost overrun based on the project description, and determined that stacked ensembles provided the highest accuracy. Using a stacked ensemble, they accurately classified 43.27% of projects into the correct cost overrun category. They further concluded that classification models are better at categorizing projects with high cost overrun (Williams and Gong 2014).

Though modeling and quantitative analysis are increasingly popular in this research field, analysts need to give model quality a higher consideration and priority (van Wee 2007). One series of studies dismisses quantitative analysis as the proper way to determine factors for cost overrun. As data becomes more available and research progresses, cost overrun should trend downward. However, cost overrun trends appear to remain constant, thereby attributing economics, politics, and psychology to the potential dominant underlying factors (Cantarelli et al. 2010, 2012). As cost overrun continues to be an ever-present and unfavorable issue afflicting construction, research is still necessary to rule out those causal factors that significantly impact both the likelihood and magnitude of overrun. This research should focus on identifying those specific attributes associated with the cost overrun of DoD construction contract data and provide its probability and potential magnitude.

The Way Forward

Despite the significant contributions of the aforementioned research studies, there continues to be a lack of consensus on which factors consistently cause cost overrun.

Through the direct analysis of more than 79,000 Department of Defense construction projects, the factors associated with cost overrun, as found in contract data, can be ascertained. By identifying these factors, projects that are found to be at higher risk for cost overrun can also be identified. Additional mitigation techniques can be applied to future projects containing these factors to reduce or possibly prevent cost overrun. By reducing both the quantity and magnitude of cost overrun, this research adds to those programs already in place to reduce the nearly $16.8 billion backlog of sustainment projects currently maintained by the DoD.

Schedule Delay

Schedule delay is a pervasive issue in the construction industry, with as many as 50% of projects experiencing schedule delay (Al-Momani 2000; Assaf and Al-Hejji 2006). Additionally, schedule delays are frequently the source of increased and unforeseen costs associated with additional overhead incurred on a project (Assaf and Al-Hejji 2006; Rowland 1981; Semple et al. 1994a). Despite the prevalence of construction delays, it is difficult to identify the frequency and magnitude of root causes. Studies have sought to identify the causative factors associated with delays for more than 50 years. These research studies have utilized (1) qualitative methods, including surveys and literature reviews; and (2) quantitative methods, including case studies, regression, and computer modeling. The results of qualitative research provide importance factors or rank general causes of delay (Faridi and El-Sayegh 2006; Frimpong et al. 2003; Habibi et al. 2018; Kumaraswamy and Chan 1998; Prasad et al. 2018), while quantitative analysis offers insights into those attributes that result in, or predict the likelihood or magnitude

of, delay based on information collected from construction project data (Al-Momani 2000; Bhargava et al. 2010; Bordat et al. 2004; Maharjan and Shrestha 2018a; Rowland 1981; Zhang et al. 2019).

Qualitative Research

Questionnaires and surveys identify factors associated with construction delays (Habibi et al. 2018a). Surveys have contributed a great deal of information regarding the causes of delays by focusing their efforts on key stakeholders' expertise regarding specific project types and phases of construction. In doing so, parties involved in projects can use these results to predict, manage, or even mitigate the potential sources of schedule delay (Ahmed et al. 2003; Aibinu and Odeyinka 2006; Bhargava et al. 2010; Habibi et al. 2018a; Larsen et al. 2016a). In their study on the effects of project type on causes of schedule delay, Prasad et al. (2018) found that the respondents in India regarded financial issues as a relatively consistent and high-ranking cause of delay. This is likely due to the projects' locations and the developing nation status associated with the region. What this paper ultimately determines, however, is that each of the sectors of construction (transportation, power, building, and water) vary in their rankings of similar causes of delay.

When considering the different construction phases, few studies have focused on the engineering phase, which incorporates project planning and design (Yang, J.B. and Wei 2010). The author identified several engineering phase factors that presented themselves during the construction phase (Habibi et al. 2018b; Yang, J.B. and Wei 2010). Construction-related schedule delays were found to occur more frequently though and the ability to resolve them at this point is much more complicated and typically result in

disputes between parties (Assaf and Al-Hejji 2006; Prasad et al. 2018; Yang, J.B. and Wei 2010).

Conclusions from the perceptions of the stakeholders varied significantly, as well. For example, the lack of project funding was the most significant cause of schedule delays, according to project managers in Denmark (Larsen et al. 2016a). Based on contractors' opinion, code-related delays appeared to be the single most significant cause of delay (Ahmed et al. 2003). Conversely, engineers in Norway concluded that poor planning and scheduling was ranked highest (Zidane and Andersen 2018). Comparing the ranking of causes of delay between the different stakeholders of projects within the same region, Assaf et al. (1995) concluded that there were consistently different results regarding the causes of delay. This is confirmed in the work of Faridi et al. (2006). They found that the United Arab Emirates (UAE), Lebanon, and the Kingdom of Saudi Arabia (KSA) shared only 30% of the identified causes of delay. Conversely, in Nigeria, Aibinu (2006) notes no statistical difference in ranking between 88% of all identified factors, which cause 90% of delay.

The differing and sometimes conflicting results of surveys and questionnaires concerning the causes of delays further highlight the differences in perceptions between the parties and their ability to agree on matters affecting schedule delay, though. This could be the result of each parties' "preconditioned responses" (Kumaraswamy and Chan 1998). In other words, their opinions on the causes of delay are based on their experiences with the other parties and within their own. If, for instance, a respondent (contractor) has had consistently worse or more frequent unfavorable dealings with owners, they would be much more likely to respond that the owner is responsible for

delays or share those opinions within their organizations. It could also be the result of certain interdependencies between the causes of delay (Aibinu and Odeyinka 2006). These interdependencies within construction projects further intertwine and complicate the schedule and affect both concurrent and downstream activities (Aibinu and Odeyinka 2006; Bankvall et al. 2010). Surveys and questionnaires are also susceptible to attrition or volunteer bias, leading to the introduction of systematic errors and subsequently affect the ability to apply the conclusions made to the larger population (Patten 2016). The issues identified above, therefore, necessitate the use of contractual, unbiased quantitative data. The information on the causes of schedule delay derived from surveys and questionnaires has proven useful in developing a deeper and more robust body of knowledge.

Recent systematic literature reviews on schedule delay have guided researchers and planners alike by aggregating study findings. Ramanathan (2012) analyzed 41 individual schedule delay studies, each consisting of unique questionnaires for construction professionals that identified 113 causes. The five most frequently cited causes of delay were associated with (1) the owner; (2) contractor; (3) design, plant, or equipment issues; (4) labor; and (5) consultant contractual or relationships. It was noted in the research, though, that after comparing the rankings between studies that the vastly different methods of calculating the weighted rankings, as well as the differing scopes covered by the studies, resulted in a lack of correlation between their respective rankings (i.e., no significant difference in the causes from the studies). Consequently, the research uses the top five causes of schedule delay from each study and concludes that the causes of schedule delay appear to be based on location, country, and project.

Zidane (2018) and Durdyev (2018) presented similarly ambiguous conclusions. Zidane identified 33 causes of delay from 105 worldwide projects, whereas Durdyev found 149 unique causes from 97. Zidane identified a mixture of both design and construction phase-related causes of delays. Durdyev's findings were dominated by construction-related delays, illustrating the difference in causes and the timing that they can occur. Each of the papers offered unique insights on their findings regarding construction schedule delays. Lower GDP growth and per-capita earnings were correlated to the likelihood of the projects within a region to experience delays based on financial issues (e.g., lack of funding & delayed payments) (Zidane and Andersen 2018). Durdyev (2018) noted that most studies conducted in the USA focused on uncontrollable delays like weather, and those within developing nations focused on resource-related factors such as labor, materials, and finance. Despite these contributions, however, both papers noted that the literature shows that causes of delays differ from one country to another and that the causes were country- and project-specific (Durdyev and Hosseini 2018; Faridi and El-Sayegh 2006; Zidane and Andersen 2018). These studies have proven to be significant collections of research, and they can serve as the starting point for those seeking to identify the causes of schedule delay within their area of focus, possibly based on location or sector of construction using more definitive methods such as statistics, regression, and machine learning.

Quantitative Research

Quantitative studies that focus on the contractual outcomes, such as comparing contracted project duration and actual duration, can further narrow the possible causes of schedule delay. This can be accomplished using contract data and the results from

literature and surveys to identify potential investigation topics while avoiding some of the pitfalls associated with surveys (Ramanathan et al. 2012a), whose possibly biased results could be included in systematic reviews (Durdyev and Hosseini 2018; Habibi et al. 2018b; Ramanathan et al. 2012a). Rowland (1981) analyzed the pre-construction contract information of 19 Naval Facilities Engineering Command (NAVFAC) projects to provide information on the factors that most influenced project performance. The data they considered included award amount, differences between government estimate and winning bidder, differences between all bids, and project complexity. The authors determined that the larger a project was, both in terms of cost and duration, the greater the likelihood that a change order would occur. Additionally, the greater the number of change orders, the greater the frequency and length of delays that occurred. Shrestha et al. (2013) reached similar conclusions in their analysis of 363 public works projects. The authors found that the magnitude of schedule delay increased as both the projects' initial size and duration increased.

Al-Momani (2000) reviewed the sources of delays during the construction phase of 130 publicly funded projects in Jordan. Through the use of this contractual information and linear regression, he was able to determine that design-related issues, change orders, weather, site conditions, and late delivery were the leading causes of delays. In a study of 2,668 civil works projects conducted for the Indiana Department of Transportation (INDOT), Bordat et al. (2004) used ANOVA testing and discovered that the average delay per contract was 115 days. Through further regression analysis, it was also determined that the majority of the delays resulted from change orders that stemmed from issues within the purview of the owner (e.g., errors and omissions in design or quantities)

and are therefore within their capability to correct. Contract data used in these projects were able to identify the most frequent sources of delay in these cases. If, however, the use of contract information is not available, other data has proven useful in determining the delay sources. In a unique analysis using the judgments of 79 claims from previous construction projects, change orders, changes in scope, and delayed site handover were the three most prevalent causes of schedule delays (Yang et al. 2013). These findings continue to provide evidence that the causes of delays are specific not only to the location where they are being conducted but also to the type of construction and the parties involved.

Additional research analyzed the performance of contracting methods, including design-build, design-bid-build, or Public-Private-Partnerships (P3) and procurement methods, such as the number of bidders, funding types, and project locations (Anastasopoulos et al. 2014; Maharjan and Shrestha 2018b; Zhang et al. 2019). Zhang et al. (Zhang et al. 2019) evaluated the performance of 66 projects greater than $10 million. The authors discovered that P3 projects experienced significantly less schedule delay than traditional contracting methods. In fact, the P3 projects finished ahead of schedule, on average. In a similar study comparing the performance of 100 water infrastructure projects based on contracting methods, Bogus et al. (2010) determined that design-build projects experienced less schedule delay than those of design-bid-build. There is also evidence that the opposite is true, at least concerning large highway infrastructure projects, in so far as design-build projects had more schedule delay compared to design-bid-build (Shrestha et al. 2007).

Predicting Schedule Delay

Several studies focus on predicting the risk of schedule delays in construction projects. By identifying the risk potential of a project, mitigation measures such as refining project scope (Dicks et al. 2017) or adding higher contingencies (Thal et al. 2010) may reduce the severity of schedule delays. A recent study demonstrated that planners could use a project's current performance to predict the anticipated magnitude of schedule delay. Rudeli et al. (2018) processed existing schedule performance from 105 previous construction projects through a clustering analysis using the ongoing Earned Value Analysis (EVA). The authors used this method to predict final scheduling within 4% of the actual duration. However, in using the EVA as an attribute for analysis, predictions on schedule performance could only be made during the project's duration, not before it started.

Commonly identified sources associated with schedule delay found in literature, such as the owner, contractor, equipment, and external factors, were used in schedule performance research. By incorporating these factors, Yaseen et al. (2020) achieved a 91.67% accuracy rating to predict the percentage increase in schedule delay using a hybrid Artificial Neural Network (ANN). The Random Forest – Genetic Algorithm used the results of questionnaires and a 40 project database to determine whether a project would experience schedule delays of <50%, 50-100%, or >100%. Son and Lee (2019) demonstrated the value of text mining critical terms from previous lessons learned Statements of Work (SOW) in predicting the amount of schedule delay risk for contractors in the construction of 13 offshore drilling projects. Unlike previous studies, however, the expected delay was on a continuous scale instead of preset bins. The result

was an accuracy of 81%; yet, it was only tested on one project. The ability of machine learning to parse through large amounts of data with limited supervision while potentially providing novel insights about the relationships between attributes associated with schedule delay makes it an ideal way to analyze construction contract data.

Mitigating Schedule Delay

In addition to identifying and predicting delays, some studies provide management or mitigation methods to reduce their frequency and severity on projects. Kumaraswamy and Chan (1998) investigated the ability of increased productivity to counteract the delays that plagued projects in Hong Kong. While the authors determined that productivity was effective at decreasing the required duration of labor in a given activity, the overall project duration was not reduced due to the inability to increase the productivity in other areas of the projects. The project's complexity and scale likely affect the ability to enhance productivity across all trades and tasks. Other mitigation efforts include implementing the Project Definition Rating Index (PRDI), a method of measuring and scoring the scope's completeness before the design stage. One recent study of 263 Air Force military construction projects found projects that used PDRI experience 7.8% fewer schedule delay (Dicks et al. 2017). Still, more studies focus on the use of experienced personnel (Abdul-Rahman et al. 2006), more detailed contract language (Yates and Epstein 2006), and even the use of weather derivatives (Brusset and Bertrand 2018; Connors 2003) to either lessen or prevent the burdens of costs associated with schedule delay in construction.

The Way Forward

While previous studies have contributed much to identifying the many causes of schedule delay, none have used a larger or more diverse data set to the author's knowledge. Containing more than 79,000 projects and spanning 277 types of construction, the data set used in this research could provide valuable insight into variations based on location, size, contract type, execution agent, and award time frame that research using less robust data sets could miss. Still, fewer studies have used machine learning techniques on such data sets to identify those causes. And while DoD specific studies on schedule delay exist, none have focused their efforts on analyzing real property repair, alterations, maintenance, and construction project contract data – together forming a significant portion of the DoD’s yearly budget. In doing so, commonly identified causal factors from literature could be used more effectively to mitigate the chances of future occurrences of delay by identifying contract attributes most commonly associated with poor schedule performance. In conjunction with current congressionally mandated policies, this effort could help further reduce the funding deficits currently being experienced for facility sustainment throughout the DoD.

III. United States Department of Defense (DoD) Real Property Repair, Alterations, Maintenance, and Construction Project Contract Data: 2009-2020

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Abstract

Nearly one-half of all construction projects exceed planned costs and schedule, globally (Ramanathan et al. 2012a). Owners and construction managers can analyze historical project performance data to inform cost and schedule overrun risk-reduction strategies. Though, the majority of open-source project datasets are limited by the number of projects, data dimensionality, and location. A significant global customer of the construction industry, the Department of Defense (DoD) maintains a vast database of historical project data that can be used to determine the sources and magnitude of construction schedule and cost overruns for many continental and international locations. The selection of data provided by the authors is a subset of the U.S. Federal Procurement Data System-Next Generation (FPDS-NG), which stores contractual obligations made by the U.S. Federal Government ("Federal Procurement Data System - Next Generation" n.d.). The data comprises more than ten fiscal years (1 Oct 2009 – 04 June 2020) of construction contract attributes that will enable researchers to investigate spatiotemporal schedule and cost performance by, but not limited to: contract type, construction type, delivery method, award date, and award value. To the knowledge of the authors, this is the most extensive open-source dataset of its kind, as it provides access to the contract

data of 132,662 uniquely identified construction projects totaling $865 billion. Because the DoD's facilities and infrastructure construction requirements and use of private construction firms are congruent with the remainder of the public sector and the private sector, results obtained from analyses of this dataset may be appropriate for broader application.

Keywords

Construction, Cost, Schedule, Overrun, Delay, Growth, Data, Contract, Department of Defense

Table 3-1 Description of Data

Subject	Engineering (General)
Specific subject area	The data within are 10-plus (9 additional months of 2020 contract data) fiscal years' repair, alterations, maintenance, and construction project contract attributes, that represent an annual multi-billion-dollar effort by the U.S. Federal Government to ensure the continued use and functionality of DoD facilities (also known as 'real property'). These data may be used to better predict costs and durations in nearly all sectors of construction for the U.S. Federal Government. Furthermore, the data could be used to provide quantifiable performance metrics on the ability of the DoD to execute various project types.
Type of data	Table
How data were acquired	Data were acquired through the Federal Procurement Data System - Next Generation (FPDS-NG or FPDS). The FPDS-NG offers public users access to the spending patterns of the Federal government. The FPDS houses all contract actions of the Federal Government, beyond construction. Filters were applied to limit the results to just construction projects funded by the DoD.

Data format	Raw
Parameters for data collection	Access FPDS-NG website and create an ad hoc report filtering the contract data by: 1. Date Signed 2. Contracting Department Name 3. Product Service or Code
Description of data collection (600 max characters)	Government agencies are responsible for collecting and reporting data on federal procurements through the Federal Procurement Data System–Next Generation (FPDS-NG). Contracting Officers (COs) must submit complete reports on all contract actions, as required by the Federal Acquisition Regulation (FAR) ("Federal Procurement Data System | GSA" n.d.). Any contract with an estimated value greater than $10,000 must be reported using FPDS-NG ("FPDS-NG FAQ" n.d.). FPDS-NG is the sole location for all contractual and procurement obligations made by the U.S. Federal Government.
Data source location	Institution: Federal Procurement Data System - Next Generation (FPDS-NG)
Data accessibility	Repository name: Mendeley Data Data identification number: DOI: 10.17632/yk4s7pdsvk.1 http://dx.doi.org/10.17632/yk4s7pdsvk.1 Direct URL to data: https://data.mendeley.com/datasets/yk4s7pdsvk/1

Value of the Data

- These data contain 132,662 construction projects, spanning 10-plus years, and account for $856 billion in DoD spending. These data are categorically diverse; they contain many types of projects, including but not limited to, roads, runways,

administrative facilities, communications work, mechanical renovation, and demolition.

- Statistical analyses may be performed by researchers participating in construction auditing, cost estimating, planning, or programming.
- These data may identify trends and relationships in construction contract information at and between geographic locations, construction sectors, contract types, contracting agents, project costs, project durations, and modification frequency.
- Current literature focuses on a comparatively small sample size when empirically analyzing construction contract data. To the author's knowledge, this is the most extensive set of construction contract data from a single source.
- These data can also be used to track historical spending on construction projects within the U.S. DoD. These data could prove useful in creating forecasting models on construction cost fluctuations or even be used to calibrate project costs and schedules based on their type.

Data Description

The data were compiled from the FPDS-NG website using specific querying to obtain all real property repair, alterations, maintenance, and construction projects executed by the U.S. DoD from 2009 to 2020. These data represent 132,652 construction projects for which the U.S. DoD contracted outside entities to complete necessary maintenance, repairs, alterations, and modernization of U.S. DoD real property.

These U.S. DoD construction projects range from hangar and runway repairs to modernization projects for office space. Many of the projects completed on U.S. DoD installations can also be found in the public or private sectors of the construction industry.

Funding of U.S. DoD construction projects varies from year to year, much like other public and private entities. This variability in funding is based on factors outside of the control of the U.S. DoD and, therefore, requires these expenditures to be on-target with regard to planned cost and schedule. The effects of deviation from these planned attributes, for any project, can be far-reaching. Projects exceeding planned cost and schedule can result in deferred or cancelled facility maintenance, repair or construction initiatives elsewhere in the DoD's portfolio, both in the current and future years. To ensure the capability and mission readiness of the U.S. DoD (of which the U.S. military is a part), the facilities it operates must be maintained to meet the users' needs.

To mitigate these deferments, possible project cancellations, and in order to meet the needs of the facility occupants, these data can be used to identify key factors associated with cost and schedule deviations. Once isolated, these factors can be used to mitigate future cost or schedule overruns associated with public and private construction, as well as U.S. DoD construction projects.

Experimental Design, Material, and Methods

As mentioned previously, the data were pulled from FPDS-NG using several progressive filters. The filters used are listed below:

1. "Contracting Department Name" showing only "DEPT OF DEFENSE"

2. “Product Service Code” similar to “Y1” for “Construction of Structures and Facilities”
3. “Product Service Code” similar to “Z1” for “Maintenance of Real Property”
4. “Product Service Code” similar to “Z2” for “Repair of Alterations of Real Property”
5. “Date Signed only show values between” with dates “10/01/XXXX” and 09/31/XXXX” based on the fiscal year (e.g., 10/01/2017 and 09/31/2018 for fiscal year 2018)
6. “Treasury Account Symbol Main Account Code” showing only “3400”, “3300”, “3307”, “3404”, “1205”, “1206”, “1804”, “1805”, “1106”, “1107”, “2020”, “2022”, “2050”, “2051”, “3122”, “3123”,”3134”, “3135.”
7. Each Product Service Code was used for every fiscal year while keeping the Contracting Department Name consistently limited to the Department of Defense. In doing so, at least three spreadsheets were produced for each fiscal year from 2009 through the first 6 months 2020. The database output was limited to CSV files containing 30,000 or fewer lines that, in some cases, necessitated the production of additional files based on a given PCS and fiscal year.

A complete description of each of the elements contained in the data are listed below and unless otherwise noted found in the FPDS-NG User’s Manual (“GSA Federal Procurement Data System-Next Generation (FPDS-NG) Data Element Dictionary” 2019):

Table 3-2 Description of Attributes in the Dataset

Attribute Name	Attribute Description
Contracting Agency ID	The code for the agency of the contracting office that executed or is otherwise responsible for the transaction
Contracting Agency Name	Specific branch within the DoD requesting contract action**
Contracting Office ID	The agency-supplied code of the contracting office that executes the transaction
Contracting Office Name	The agency-supplied name of the contracting office that executes the transaction.
Country Where Award was Issued	Location of execution agent**
Major Command Name	Major Command of DoD requesting contracting action
Modification Number	An identifier issued by an agency that uniquely identifies one modification for one contract, agreement, order, etc.
Procurement Instrument Identifier (PIID)	The unique identifier for each contract, agreement, or order. In other words, the individual delivery or task orders (projects)
Referenced IDV PIID	When reporting orders under Indefinite Delivery Vehicles (IDV) such as a Governmentwide Acquisition Contract (GWAC), Indefinite Delivery Contract (IDC), Federal Supply Schedule (FSS), Basic Order Agreement (BOA), or Blanket Purchase Agreement (BPA), report the Procurement Instrument Identifier (Contract Number or Agreement Number) of the IDV. For the initial load of a BPA under an FSS, this is the FSS contract number. Note: BOAs and BPAs are with industry and not with other Federal Agencies. In other words, the parent contract ID of an IDV issued that can have multiple delivery or task orders (PIID) obligated against it.
Referenced IDV Mod Number	When reporting orders under Indefinite Delivery Vehicles (IDV) such as a GWAC, IDC, FSS, BOA, or BPA, report the Modification Number along with Procurement Instrument Identifier (Contract Number or Agreement Number) of the IDV. For the initial load of a BPA under an FSS, this is the FSS contract number. Note: BOAs and BPAs are with industry and not with other Federal Agencies
Transaction Number	Tie Breaker for legal, unique transactions that would otherwise have the same key
Date Signed	The date that a mutually binding agreement was reached. The date signed by the Contracting Officer or the Contractor, whichever is later.
Effective Date	The date that the parties agree will be the starting date for the contract's requirements. The Effective Date cannot be earlier than the Signed Date on the base document.

Completion Date	The [current] completion date of the base contract plus options that have been exercised
Est. Ultimate Completion Date	The estimated or scheduled completion date, including the base contract or order, and all options (if any), whether the options have been exercised or not
Fiscal Year	The fiscal year of action as determined by 'Date Signed'
Funding Agency ID	The agency ID that has provided the preponderance of funding
Funding Agency Name	The agency name that has provided the preponderance of funding (e.g, Dept of the Navy)
Funding Department ID	The Department or Independent Agency ID to which the 'Funding Agency' belongs
Funding Department Name	The Department or Independent Agency name to which the 'Funding Agency' belongs (e.g., DoD)
Funding Office ID	The code provided by the funding agency that identifies the office or other organizational entity that provided the funds for this transaction. If the Funding Agency is DoD, the code must be valid in the DoD Activity Address Code (DODAAC) table. This is a required field when DoD has funded the action.
Funding Office Name	The funding office is the office within the federal agency that is providing the funding for the contract
(Type of IDC)	Identifies whether the IDC or Multi-Agency Contract is Indefinite Delivery/Requirements, Indefinite Delivery/Indefinite Quantity, or Indefinite Delivery/Definite Quantity. A requirements contract provides for filling all actual purchase requirements of designated Government activities for supplies or services during a specified contract period, with deliveries or performance to be scheduled by placing orders with the contractor. A Requirements IDC or Multi-Agency Contract is a contract for all of the agency's requirement for the supplies or services specified, and effective for the period stated, in the IDC or Multi-Agency Contract.
Multiple or Single Award IDV	Indicates whether the contract is one of many that resulted from a single solicitation, all of the contracts are for the same or similar items, and contracting officers are required to compare their requirements with the offerings under more than one contract or are required to acquire the requirement competitively among the awardees

Multi-year Contract Code	A multi-year contract means a contract for the purchase of supplies or services for more than one, but not more than five, program years. Such contracts are issued under specific congressional authority for specific programs. A multi-year contract may provide that performance under the contract during the second and subsequent years of the contract is contingent upon the appropriation of funds, and (if it does so provide) may provide for a cancellation payment to be made to the contractor if appropriations are not made. The key distinguishing difference between multi-year contracts and multiple year contracts is that multi-year contracts buy more than one year of requirement (of a product or service) without establishing and having to exercise an option for each program year after the first
Type of Contract	The type of contract, as defined in FAR Part 16 that applies to this procurement. The following apply to all Awards and IDVs: A - Fixed Price Redetermination B - Fixed Price Level of Effort J - Firm Fixed Price K - Fixed Price with Economic Price Adjustment L - Fixed Price Incentive
	M - Fixed Price Award Fee R - Cost Plus Award Fee S - Cost No Fee T - Cost Sharing U - Cost Plus Fixed Fee V - Cost Plus Incentive Fee Y - Time and Materials Z - Labor Hours The following apply to IDVs only: 1 - Order Dependent (IDV allows pricing arrangement to be determined separately for each order) The following apply to Awards only: 2 - Combination (Applies to Awards where two or more of the above apply) 3 - Other (Applies to Awards where none of the above apply)
NAICS Code	The North American Industry Classification System (NAICS) codes designate major sectors of the economies of Mexico, Canada, and the United States
NAICS Description	Field providing further information on the description of work in reference to the 'NAICS Code'
Principal Place of Performance State Code	This is the location of the principal plant or place of business where the items will be produced, supplied from stock, or where the service will be performed.

Principal Place of Performance City Name	This is the location of the principal plant or place of business where the items will be produced, supplied from stock, or where the service will be performed.
Principal Place of Performance Country Name	This is the location of the principal plant or place of business where the items will be produced, supplied from stock, or where the service will be performed.
Place of Performance Zip Code	This is the location of the principal plant or place of business where the items will be produced, supplied from stock, or where the service will be performed.
Product or Service Description	A description of the product or service designated by the product code
Product or Service Code	These codes indicate “WHAT” was bought for each contract action reported
Description of Requirement	A brief description of the contract or award
Award or IDV Type	Types of awards: - Delivery /Task Order Against IDV - Purchase Order - Definitive Contract - BPA Call - Other Transaction Order* - Other Transaction Agreement*
	Types of IDVs(Indefinite Delivery Vehicles): - Federal Supply Schedule (FSS) - Governmentwide Acquisition Contract (GWAC) - Basic Ordering Agreement (BOA) - Blanket Purchase Agreement (BPA) - Indefinite Delivery Contracts (IDC) - Other Transaction IDV* * Can only be used by DoD, DHS, and HHS
Reason For Modification Description	Reason for modification (change order) which may or may not be applicable: A - Additional Work (new agreement, FAR part 6 applies) B - Supplemental Agreement for work within scope C - Funding Only Action D - Change Order E - Terminate for Default (complete or partial) F - Terminate for Convenience (complete or partial) G - Exercise an Option H - Definitize Letter Contract J - Novation Agreement

	K - Close Out
	L - Definitize Change Order M - Other Administrative Action
IDV Type	The type of Indefinite Delivery Vehicle being (IDV) loaded by this transaction. IDV Types include Government-Wide Acquisition Contract (GWAC), Multi-Agency Contract, Other Indefinite Delivery Contract (IDC), Federal Supply Schedule (FSS), Basic Ordering Agreement (BOA), and Blanket Purchase Agreements (BPA)
Extent Competed	A code that represents the competitive nature of the contract: A - Full and Open Competition B - Not Available for Competition C - Not Competed D - Full and Open Competition after exclusion of sources E - Follow On to Competed Action F - Competed under Simplified Acquisitions Program (SAP) G - Not Competed under SAP CDO - Competitive Delivery Order NDO - Non-Competitive Delivery Order
Number of Offers Received	The number of actual offers/bids received in response to the solicitation
Treasury Account Symbol Agency Identifier	Agency Identifier represents the department, agency, or establishment of the U.S. Government that is responsible for the Treasury Account Symbol.
Treasury Account Symbol Main Account Code	The U.S. Federal Agency account code for the agency supplying the preponderance of funding as assigned by the U.S. Treasury **
Treasury Account Symbol Sub Account Code	Identifies a Treasury-defined sub-division of the main account**
IDV NAICS Code	The NAICS Code of the parent IDV contract**
IDV NAICS Description	The NAICS Description of the parent IDV contract**
IDV Contracting Agency ID	The code for the agency of the contracting office that executed the parent IDV contract**
IDV Contracting Agency Name	The name of the entity responsible for the initial parent IDV contract action**
IDV Department ID	The department ID of the entity responsible for the initial parent IDV contract action**
IDV Department Name	The department name of the entity responsible for the initial parent IDV contract action. Typically the U.S. DoD or GSA**

IDV Major Program Code	This field is not required, but you may enter it on all IDVs except for an FSS. This is the agency-determined code for a major program within the agency. For an Indefinite Delivery Vehicle, this may be the name of a GWAC (such as ITOPS or COMMITS).
IDV Referenced IDV Agency Code	The agency code that initially input the parent IDV contract**
IDV Referenced IDV PIID	The Contract Number of the IDV against which the order is placed
IDV Subcontract Plan	This data element is required for a DCA, Purchase Order, Delivery Order against a BOA, and Part 13 BPA Call. A Delivery Order against FSS, GWAC, and IDC will be propagated. Part 8 BPA Call is Not Applicable. This field indicates whether the contract award required a Subcontracting Plan. This field is also used to provide information to the Electronic Subcontracting Reporting System (eSRS) on awards that have subcontracting plans. Failure to complete this field accurately impacts vendors' ability to report subcontracting achievement to the eSRS. Select the appropriate value from the drop-down menu. See Data Dictionary Element 11B Use Case for appropriate data entry requirements. A - Plan Not Included - No Subcontracting Possibilities B - Plan Not Required C - Plan Required - Incentive Not Included D - Plan Required - Incentive Included E - Plan Required (Pre 2004) F - Individual Subcontract Plan G - Commercial Subcontract Plan H - DoD Comprehensive Subcontract Plan
IDV Subcontract Plan Description	A description of the subcontract plan work performed under the parent IDV contract**
IDV Type of IDC	This data element is required on an IDC and Populates to the Modification. It is Not Applicable for all other IDVs. This field identifies whether the IDC or Multi-Agency Contract is Indefinite Delivery/Requirements, Indefinite Delivery/Indefinite Quantity, or Indefinite Delivery/Definite Quantity (FAR 16.5). An entry is required for civilian agency and DoD IDCs. Values are listed below: A - Indefinite Delivery / Requirements B - Indefinite Delivery / Indefinite Quantity C - Indefinite Delivery / Definite Quantity
IDV Type of IDC Description	The type of Indefinite Delivery Contract Descriptions of the parent IDV contract**

IDV Who Can Use	This data element is required on all IDVs and is Not Applicable for Modifications. This field designates agencies that may place orders against this indefinite delivery vehicle. For the initial award of an IDV, select one of the following: − Only My Agency – Only the agency awarding the contract may place orders. − All Agencies – All Federal Government agencies may place orders against the contract. − Defense – Only Department of Defense agencies may place orders against the contract. − Civilian – Only civilian agencies may place orders against the contract. − Other – Provide a text statement of which agencies may place orders against the contract.
IDV Who Can Use Description	The description of the Who Can Use field: – Only the agency awarding the contract may place orders. – All Federal Government agencies may place orders against the contract. – Only Department of Defense agencies may place orders against the contract. – Only civilian agencies may place orders against the contract. – Provide a text statement of which agencies may place orders against the contract.
Base and Exercised Options Value	The contract value for the base contract and any options that have been exercised
Action Obligation	The amount that is obligated or de-obligated by this transaction
Base and All Options Value (Total Contract Value)	Required for all Awards and Modifications except for a BPA Call. It is not required for a Change or Delete/Void. It is the mutually agreed upon total contract or order value including all options (if any). For modifications, this is the change (positive or negative, if any) in the mutually agreed upon total contract value.
** Indicates that the attribute definition was not provided by the FPDS-NG user's manual or wiki, but was provided based on the insight of contracting officers.	

IV. A Two-Stage Statistical Prediction Framework for Predicting Construction Cost and Schedule Overrun

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Abstract

Cost and schedule overrun impact over 50% of all construction projects and create various cascading effects. Overrun diminish funding for concurrent projects, deplete operational budgets, causing deferred infrastructure maintenance, and impair future project award ability. Though existing research identifies sources of overrun, models are overfitting or too narrowly focused for broad application. This research analyzes 79,894 US Department of Defense (DoD) projects and uses stepwise logistic regression to determine which of 62 contract attributes are most skillful in determining, categorically, whether a project will experience cost or schedule overrun. A second, random forest categorization framework is used to determine the magnitude of project overruns. The most skillful models explain 65% of cost and 75% of schedule overrun. This research is expected to support public and private sector planners in the cost-efficient execution of construction projects and aid in reducing the DoD's $116 billion project backlog.

Keywords

Cost overrun, Schedule Delay, Construction, Contract Data, Department of Defense

Introduction

More than half of all construction projects exceed their target budget or schedule (Assaf and Al-Hejji 2006; Habibi and Kermanshachi 2018; Ramanathan et al. 2012b) Publicly funded projects are no exception (Bordat et al. 2004; Shane et al. 2009). Among their many consequences, cost and schedule overrun's impact on funding for future construction is especially severe. Public organizations like the United States Federal Government, state, and local municipalities must adhere to their approved budgets to remain fiscally accountable and financially solvent. However, the need for infrastructure construction, repair, and modernization often exceeds those budgets. In these cases, prioritization and, often, deferment are the only available solutions (ASCE 2016). Consequently, overruns can further postpone much-needed work.

Despite significant spending on infrastructure and facilities by local, state, and federal governments, the backlog of projects continues to rise. Currently, it represents an unfunded gap of $2.1 trillion within the US alone (Deloitte 2009). This backlog of transportation, utility, environment, and facilities projects (Deloitte 2017; Oberhelman 2015) comes at the cost of continuously deteriorating infrastructure with a high risk of failure (ASCE 2016). Research indicates that infrastructure's health is directly related to the economy's performance and quality of life for citizens (Clarke 2014; Fischer and Amekudzi 2011). Given the rigidity of the budget and the urgency of the need for infrastructure improvements, mitigation of cost and schedule overrun is essential. Though construction technology and management practices continue to be revised and improved based on past experiences, cost and schedule overrun persist (Flyvbjerg et al. 2003;

Katseff et al. 2020). Therefore, avoiding those common sources of cost and schedule overrun is a critical yet tangible means to execute projects more effectively.

The US Department of Defense (DoD) provides an excellent case study, as it executes a large construction budget and holds a $116B backlog in construction requirements (Cronk 2018). This backlog results in a lack of mission-essential readiness, missed requirements, lower morale, and reduced effectiveness (Knopman et al. 2017; Roulo 2015). DoD projects are not immune from overrun, with more than 48% of projects sampled experiencing it, exacerbating the backlog. Furthermore, cost and schedule overrun on construction projects can drive borrowing from fixed operations and maintenance budgets (Congressional Research Service 2019), which is already underfunded (Serbu 2019; USGAO United States Goverment Accountability Office 2019).

The sources of overrun in the construction industry have been studied for at least 35 years (Durdyev and Hosseini 2018). However, overrun sources vary from region-to-region, owner-to-owner, and project-to-project. One previous study shows that the only underlying reason for overruns is design change (Chang 2002), while another found 73 different causes identifying incorrect award duration as the most significant contributor to overrun (Assaf et al. 1995). Literature surrounding overruns is discussed more fully in the next section. Previous studies that analyzed construction performance using contract attributes have garnered significant insights into the factors that greatly affect performance (Al-Momani 2000; Bordat et al. 2004; Rowland 1981; Zhang et al. 2019), but are limited in terms of scope, projects evaluated, or spatiotemporal variety.

This research presents the most extensive investigation of construction contract data on record, to the authors' knowledge. 79,894 DoD construction projects spanning ten years are analyzed to determine the primary causes of project cost and schedule overrun. The size of this data set also increases the meaningfulness of the statistical relationships found. Additionally, a two-stage statistical approach for determining both the likelihood and magnitude of cost and schedule overruns are explored. First, a stepwise logistic regression model is employed to predict the likelihood that a project will experience overrun. Then, a Random Forest Classification (RFC) algorithm is applied to determine the extent to which a project will experience overrun. These efforts will enable project managers and planners to implement mitigation techniques and methods to curb overrun's effects based on their own risk tolerance. While this analysis uses DoD's construction portfolio's past performance based on contract data, which could directly help the DoD mitigate overruns (Darren et al. 2009; Dicks et al. 2017; Rosner et al. 2009), the similarities between public and private projects suggest that the results are likely more-broadly applicable.

Background/Literature Review

The causal factors associated with cost and schedule overrun varied significantly between previous studies based on the size and composition of projects contained in their datasets. Consequently, there exists a myriad of different causes correlated with overrun, which, according to the same research, tended to be project-, location-, or owner-specific. The literature investigating overruns can generally be categorized into two groups based on the methods employed to determine its cause: (1) qualitative research, including

surveys and group decision making; and (2) quantitative research, including descriptive statistics and modeling.

Qualitative Research - Cost Overrun

Surveys of experts with firsthand knowledge of construction projects have proven useful in identifying causes of overrun such as construction project characteristics, including project size and type (Islam et al. 2019b), design issues (Polat et al. 2014), and scope changes (Kaliba et al. 2009). This method has also been used to identify exogenous factors leading to cost overrun, including weather (Kaliba et al. 2009) and optimism bias and political deceit, e.g., pressing for projects for personal gain (Cantarelli et al. 2010, 2012). Research studies using surveys tend to have a project-, region-, or respondent-specific focus on overruns, limiting how they can generalize to all projects. Furthermore, this method can introduce unintended biases in the results, such as party-specific perceptions (Kumaraswamy and Chan 1995) or volunteerism (Patten 2016). However, surveys have been used to identify generic root causes for overrun, which are applicable to all projects (Rosenfeld 2014).

Quantitative Research - Cost Overrun

While qualitative analysis techniques are broadly focused and can identify factors related to cost overrun, quantitative analysis techniques identify specific relationships and their strengths using construction project data. Construction contract data has been used to show how team cordiality (Dada 2014), the use of lowest bid price (Woo et al. 2017), and contract type (Anastasopoulos et al. 2014) affect project performance. Similar to research using surveys, these types of studies also tend to use contract data from projects that are of a specific kind (Alleman et al. 2020; Anastasopoulos et al. 2014; Kuprenas and

Nasr 2003; Turcotte 1996), location (Kuprenas and Nasr 2003; Turcotte 1996) or similar execution method (Kuprenas and Nasr 2003). In a broader study of project types, Love et al. (2013) reviewed 276 different projects spanning all of Australia, ultimately concluding that neither project size nor type had any significant impact on cost overrun. In previous research, Love et al. (2002) found that the procurement method did not affect overrun either. The findings from these types of work have proven invaluable in expanding the body of knowledge from which more in-depth analysis is performed.

The use of contract data has also enabled researchers to identify the degree to which project attributes explain variability in project performance and measure the expected magnitude of cost overrun. Statistical regression-based models are most commonly used to establish the aforementioned relationships and create forecast models (Creedy et al. 2010; Gkritza and Labi 2008; Odeck 2004b; Thal et al. 2010). In research conducted by Thal et al. (2010), there is an apparent implication that cost overruns are an inevitable part of construction and, as such, focused their efforts on the ability to accurately account for contingencies as a means to prevent unforeseen spending. Again, noting the uncertainty associated with construction projects, Touran and Lopez (2006), asserted that escalation, including inflation, taxes, market conditions, and interest rate, should be accounted for as it is a significant overrun source in projects with multi-year durations. However, other research attempts to identify the causes of overrun to help mitigate cost overruns on future projects instead of merely accounting for them. Odeck (2004), found that of 620 Norwegian roadway projects, lower cost projects experienced 10.62% more cost overrun than larger projects, which, on average, ended up coming in below budget.

Further confirming these results, Creedy et al. (2010) found that for 231 Queensland, Australia highway projects, the amount of overrun incurred reduced as the project cost increased. They also noted that the work's geographic location did not impact overrun costs. The differential in cost between the owner's estimate and bid price has also proved useful in modeling cost overruns. In a study of 1,576 navy projects, Jahren and Ashe (1991) found that as the difference between the estimate and bid increased, so did overruns. Contract schedule information has also proved useful, as demonstrated by Gkritza and Labi (2008). As the programmed duration increased, so did the likelihood and magnitude of cost overruns within 1,957 Indiana highway projects. They also found that a project's complexity and initial cost were positively correlated with increased overrun. In general, modeling efforts have revealed that significant insights into cost overruns can be gained by analyzing contract attributes. By using these results to modify future project execution strategies, overruns can be mitigated. There is, however, an apparent lack of agreement in research as to which attributes of a project are indicators of overrun, which could be attributed to a lack of scale or diversity in datasets used.

Qualitative Research - Schedule Overrun

Schedule overruns are frequently the source of increased and unforeseen costs associated with additional overhead incurred on a project (Assaf and Al-Hejji 2006; Rowland 1981; Semple et al. 1994b). Accordingly, researchers have utilized surveys to identify the causes of schedule overruns. Causes include unforeseen site conditions (Kumaraswamy and Chan 1998), code issues (Ahmed et al. 2003), owner changes (Assaf and Al-Hejji 2006; Marzouk et al. 2008; Yang, J.B. and Wei 2010), and financial difficulties (Aibinu and Odeyinka 2006; Assaf et al. 1995; Frimpong et al. 2003; Larsen

et al. 2016b; Prasad et al. 2018). Much like that of cost overrun, these studies are frequently project-, region-, or respondent-specific, limiting their capability for broader application across the industry. However, literature reviews of schedule overruns have synthesized hundreds of papers in attempts to provide universally applicable overruns, which provide valuable information and ideas on where industry can start their mitigation efforts (Durdyev and Hosseini 2018; Habibi et al. 2018b; Zidane and Andersen 2018).

Quantitative Research - Schedule Overrun

Quantitative studies that focus on the contractual outcomes, such as comparing contracted project duration and actual duration, can further narrow the possible causes of schedule overrun. Research using these methods has identified several factors, including delivery method (Bogus et al. 2010; Cheng 2014; Zhang et al. 2019), initial cost (Rowland 1981), initial duration (Maharjan and Shrestha 2018a), and contract type (Cheng 2014). A study on 100 different water infrastructure projects determined that the magnitude of schedule overrun was affected by choice of delivery methods and payment structures (Bogus et al. 2010). Similarly, Zhang (2019) found that the Public-Private-Partnership delivery method reduced overruns by four months on average in Western Canada. In research conducted by Rowland (1981), schedule overrun increased as the difference between the programmed cost and awarded cost increased and when the difference between high and low bidders increased. However, Rowland also determined that projects would experience a more significant overrun if the bids were very close together, which is likely due to a small sample of only 20 projects. A larger initial or programmed duration is also shown to increase schedule overrun (Maharjan and Shrestha 2018a). In a study that uses both public and private projects, Chen et al. (2016) concluded

that contract type and owner were affected by the amount of overrun. The statistical methods used here equips owners with additional information that may be used to mitigate schedule overrun further or be analyzed further to estimate the likelihood or magnitude of overrun.

Statistical regression is commonly used to estimate the expected amount of project schedule overrun. Al-Momani was able to estimate the duration of various projects using linear regression, explaining more than 60% of the variation in time using only the programmed duration, but noted that additional factors like contractor performance could influence the number of overruns experienced. Bordat et al. (2004) found that schedule overrun among 2,668 INDOT projects was significantly correlated with project type (e.g., bridge, resurfacing, maintenance), the proportion of inclement weather days, programmed duration, and project cost. The importance of the information contained within the database was also evidenced by the ability to assign responsibility for most overruns to the owner (Bordat et al. 2004). Using multiple linear regression, Maharjan (2018) found that among 129 Texas Department of Transportation projects, the number of bidders and difference between the award and estimated costs were statistically significant. As the number of bidders and difference increased, so did the estimated schedule overrun (Maharjan and Shrestha 2018a). In a study on the interdependencies of cost and schedule overrun, Bhargava et al. (Bhargava et al. 2010) found that, for all but one type of project, as programmed duration increased, the estimate for schedule overrun decreased. The study concludes that the number of attributes accounts for only 40% of the variation and is thus not comprehensive. It can be summarized that the insight provided by contract data through regression has been

significant, albeit primarily focused on a specific type of project within a relatively small geographic area.

Despite these studies' significant contributions, few have focused on predicting a project's likelihood to experience cost or schedule overrun using attributes from contract data. Even fewer studies have used DoD projects as the basis for analysis despite the similarities between them and the industry as a whole. The scale and diversity of data used in this study also solve another of the limitations highlighted above by providing an unprecedented look at contract information and performance from a construction portfolio that spans hundreds of project types, more than ten years, and a large geographic area. Therefore, this study should produce more definitive and broadly applicable results.

Data Characterization

The data used in this study was obtained from Stout et al. (2020) that spans 132,662 DoD construction projects with 62 contract attributes per-project, covering over 10 fiscal years, and accounting for over $856 billion in funding. A subset of this data was used to study factors associated with cost and schedule overrun. For this research, cost and schedule overrun are defined as any positive deviation, as a percentage, from the original programmed or award amount. These overruns are calculated using Equations **(1)** and **(2)**:

$$Percent\ Cost\ Overrun\ = \left(\frac{Final\ Cost - Award\ Cost}{Award\ Cost}\right) \times 100\% \quad \textbf{(1)}$$

$$Percent\ Schedule\ Overrun = \left(\frac{Final\ Duration - Award\ Duration}{Award\ Duration}\right) \times 100\% \quad \textbf{(2)}$$

As overruns are calculated by the percent change from the award value, projects with an award cost of $0 or duration of 0 days were removed, as a percent change in cost/schedule cannot be executed with a zero value. Moreover, according to Federal Acquisition Regulations (FAR), which police government procurement, projects cannot be awarded with either of these conditions and are therefore considered erroneous. The remaining dataset, which was the subset used for analysis, contains 79,894 projects. Additionally, attributes that uniquely identified a project or any of its characteristics were removed as these would not add value to the analysis given the methods used. Finally, where redundancy among attributes existed (e.g., contracting agent name v. contracting agent office), all but a single instance was removed. This work resulted in the retention of 36 attributes.

The final dataset contains construction, maintenance, restoration, and modernization projects across the DoD to include the military branches: Air Force (AF), Army, and Navy, which also includes the Marine Corps. Each branch has unique policies, regulations, structures, and missions, and to investigate whether overruns are subject to institutional differences, each branch was subset. Table 4-1 below provides a breakdown of data in each of these subsets, including the historical cost and schedule overrun occurrences (i.e., the percentage of projects that experienced overrun).

Table 4-1 *Data breakdown by military branch subset: Number of projects, historical cost overrun occurrence, and historical schedule overrun occurrence.*

	Total	**Air Force**	**Army**	**Navy**
Projects	79,894	21,554	29,541	23,966
Cost Overrun	43.49%	50.00%	47.40%	29.27%
Schedule Overrun	35.13%	43.40%	36.99%	24.31%

There are many ways to visualize and characterize this dataset due to its breadth and depth. Accordingly, this section explores various breakdowns of the data to enrich the understanding of patterns and trends. A project may be awarded any month within the fiscal year, though as Figure 4-1 visualizes, over 38% of projects are awarded in September, the last month of the fiscal year. Furthermore, this figure shows that as the fiscal year progresses, more projects are awarded each month. This spending pattern likely comes as a direct result of DoD financial policy (i.e., use or lose), in which the funds set for the fiscal year must be spent prior to its end or risk losing the remaining funds next year.

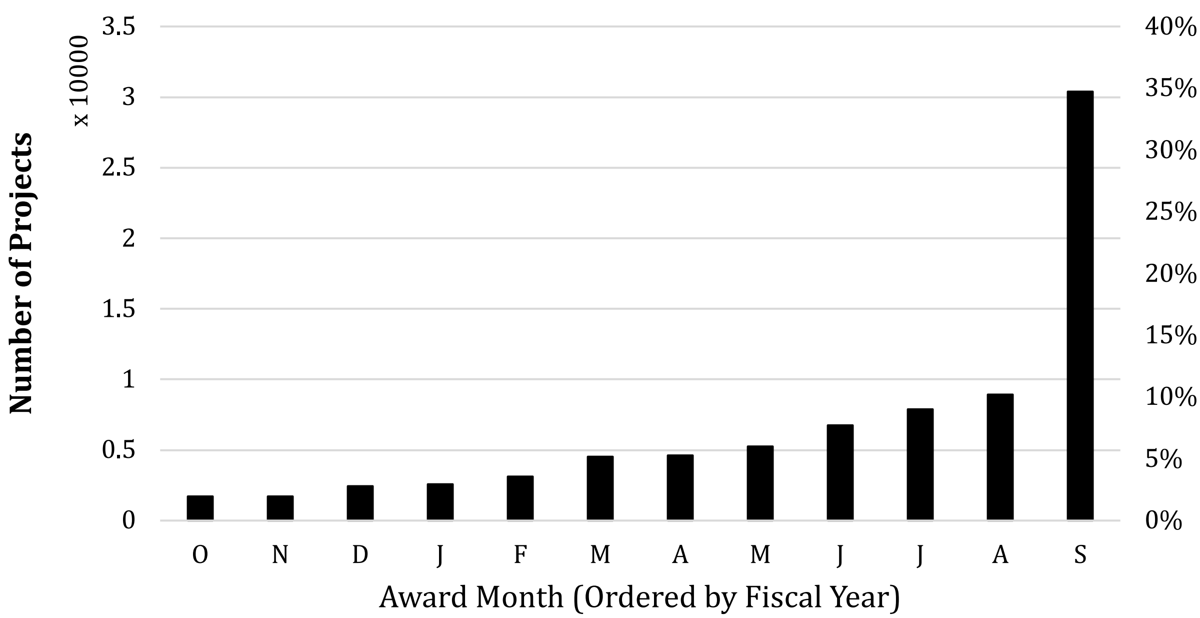


Figure 4-1 *Number of DoD construction projects awarded by month from fiscal year 2010 through fiscal year 2020.*

Building on the breakdown by award month, Figure 4-2 visualizes the trends of cost and schedule overrun occurrence by the month of award, with September

experiencing the highest rates. Though, it is worth noting cost overrun always exceeds schedule overrun.

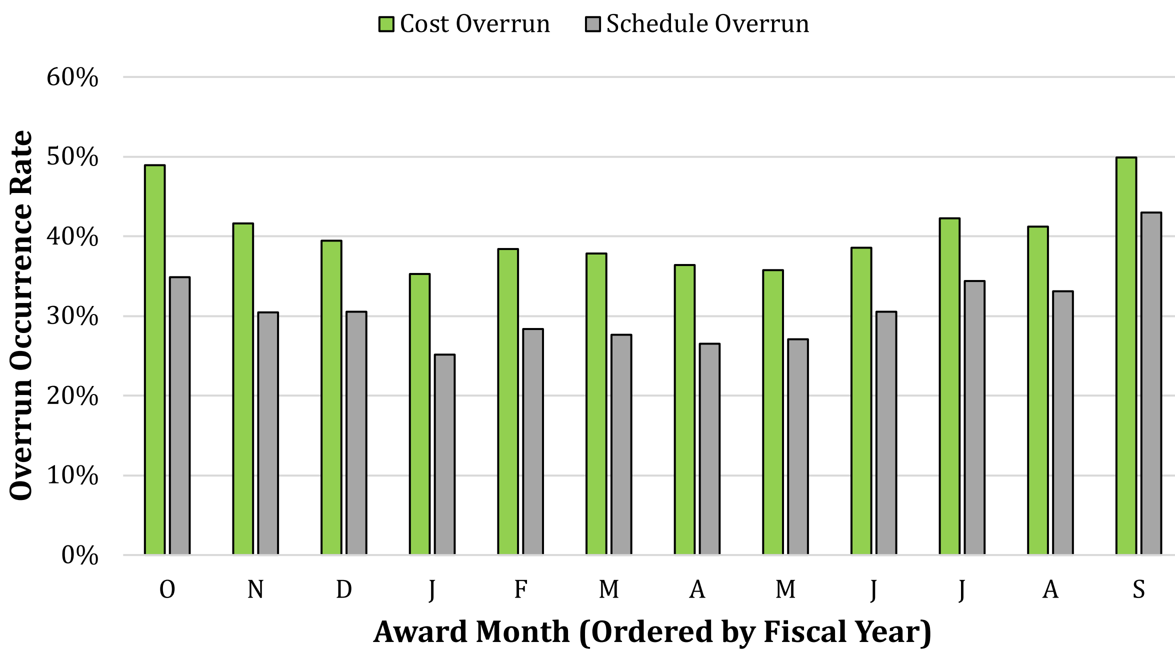


Figure 4-2 *Historical trend of cost and schedule overrun occurrence by project award month.*

Cost overrun rate by award duration (i.e., project length) is another way to inspect data trends. Figure 4-3 visually summarizes the cost overrun rate for projects with an award duration of less than one month through projects programmed as longer than a year. Historically, as the duration increases, the percent of projects that experience cost overrun also increases. This result is expected because longer projects are typically more complex, and those exposed to environmental factors (e.g., precipitation and temperature) are more likely to experience a greater number of weather-related delay events.

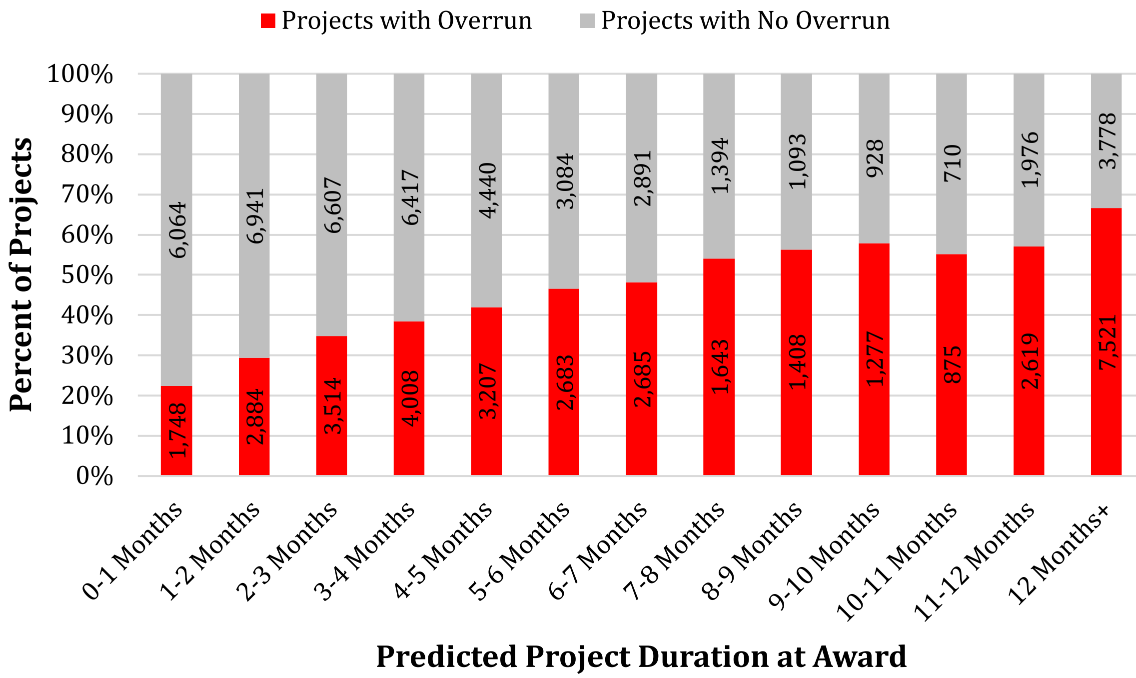


Figure 4-3 *Historical trend of cost overrun occurrence by project award duration. The number of projects awarded by month and overrun category is also annotated by the number within each column.*

Methodology

While many studies use surveys (Assaf and Al-Hejji 2006; Ramanathan et al. 2012a; Yehiel 2013) and statistical analysis such as ANOVA (Love et al. 2013; Senouci et al. 2016; Thal et al. 2010) and multiple linear regression (El-Maaty et al. 2017; Jahren 1991; Maharjan and Shrestha 2018a) to identify contract/project attributes correlated with overrun, this research uses logistic regression and RFC to help predict the likelihood and magnitude of overruns, respectively, while also identifying significant attributes. While the intended application is running both processes in series, feeding projects classified as experiencing overrun from the likelihood model into the RFC to obtain a magnitude prediction, these processes are run independently to calibrate the models most accurately

without introducing additional noise. This two-fold ideological approach to analysis explores a novel application of both methods.

Figure 4-4 depicts the process of data entering each model and outputting results. It is to note, a 70:30 split is used to train the models on a random 70% of data and to test the models on the remaining 30%. This is a common practice in data analytics (Coleman et al. 2020; Liu and Cocea 2017; Yang 2020). The resulting methodology is intended to be applicable for any construction entity; however, this research and resulting models have been tailored to the DoD and each military branch.

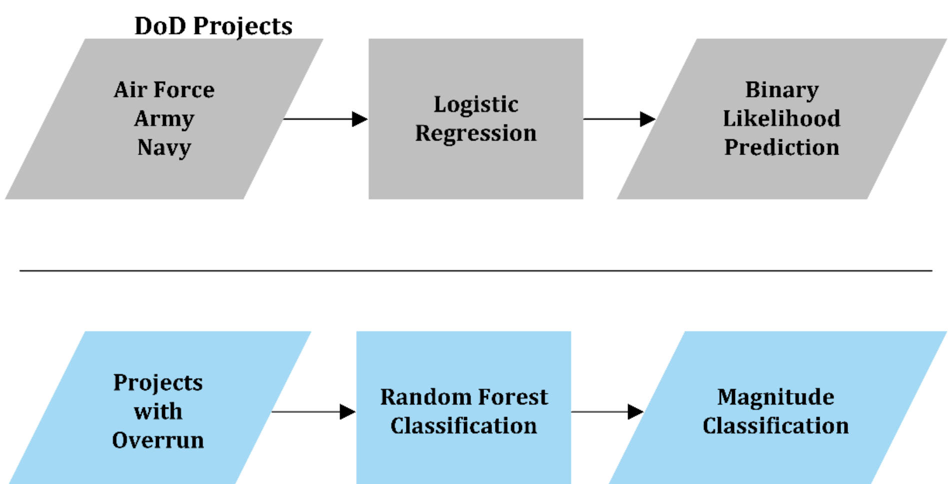


Figure 4-4 *Ideological methodical approach. Two main methods were utilized: 1) Logistic Regression to determine cost and/or schedule overrun likelihood and 2) Random Forest Classification to determine magnitude of overrun.*

Logistic Regression

Logistic regression is like multiple linear regression in that multiple variables are combined to predict some dependent outcome; however, in logistic regression, the dependent outcome is binary. Logistic regression has been extensively used in medical research for more than 20 years because of the dichotomous nature of the outcome (i.e.,

Yes/No) and its robustness regarding deviation from normality, with prediction applications varying from diagnosis to reaction susceptibility (Bender and Grouven 1997). More recently, it has also been successfully applied within construction research to determine influential factors in project cost (Lu et al. 2017), project management factors affecting delay (Nguyen 2020), and critical success factors of contractors (Alzahrani and Emsley 2013). Accordingly, this model is used to predict the binary outcome of overrun experienced by a project (1 = overrun predicted; 0 = no overrun predicted). Logistic regression can be simplified in Equation **(3)**:

$$\text{Log}\left[\frac{Y}{1-Y}\right] = b_0 + b_1X_1 + \ldots\ b_nX_n \tag{3}$$

The left-hand side of the equation, or logit, is the log of the ratio of success probability to failure probability, where Y is the probability of success. The right-hand side is a combination of variables (X_n) with their associated beta weights (b_n) and addition of the intercept b_0. The independent variables (X_n) on the equation's right-hand side are combinations of seven categories (Contracting Offices, Funding Offices, Procurement data, Climate Zones, Award Type, Project Type, and Award Type). The combinations of contract attributes create a model that outputs probabilities between 0 and 1, and a set threshold determines if the model predicts a project as experiencing overrun or not. The following eight models were created using various combinations of variables: Cost overrun (DoD, Air Force, Army, and Navy) and Schedule overrun (DoD, Air Force, Army, and Navy). Before analysis, the attribute categories were converted to flag variables, and the numeric attributes were normalized using min-max normalization.

See Table 4-2 for all the tested attributes and their associated type, category, and explanation.

Table 4-2 *Contract attributes used for analysis with their associated type, category, and a brief explanation of what the attribute represents within the data.*

Attribute	Type	Category	Explanation
C_AFCEC	Factor	Contracting Office	Contract executed by the Air Force Civil Engineer Center
C_USACE	Factor	Contracting Office	Contract executed by the U.S. Army Corps of Engineers
C_NAVFAC	Factor	Contracting Office	Contract executed by the Naval Facilities Engineering Systems Command
C_Base	Factor	Contracting Office	Contract executed by a squadron/unit on the installation (not outsourced)
C_Other	Factor	Contracting Office	Contract executed by an entity not represented above
F_AFCEC	Factor	Funding Office	Funding provided by the Air Force Civil Engineer Center
F_USACE	Factor	Funding Office	Funding provided by the U.S. Army Corps of Engineers
F_NAVFAC	Factor	Funding Office	Funding provided by the Naval Facilities Engineering Systems Command
F_Base	Factor	Funding Office	Funding provided by a squadron/unit on the installation (not outsourced)
F_Other	Factor	Funding Office	Funding provided by an entity not represented above
September	Factor	Procurement Data	Contract awarded in the month of September, the end of the fiscal year
mmInitialCost	Numeric	Procurement Data	The programmed cost of the project, normalized
mmInitialDuration	Numeric	Procurement Data	The programmed duration of the project, normalized
mmNumberofOffers	Numeric	Procurement Data	The number of offers/bids a project receives from contractors, normalized
CZone1	Factor	Climate Zone	Climate Zone 1 from the International Energy Conservation Code (IECC)
CZone2	Factor	Climate Zone	Climate Zone 2 from the IECC
CZone3	Factor	Climate Zone	Climate Zone 3 from the IECC
CZone4	Factor	Climate Zone	Climate Zone 4 from the IECC
CZone5	Factor	Climate Zone	Climate Zone 5 from the IECC
CZone6	Factor	Climate Zone	Climate Zone 6 from the IECC
CZone7	Factor	Climate Zone	Climate Zone 7 from the IECC
CZone8	Factor	Climate Zone	Climate Zone 8 from the IECC
Competed	Factor	Procurement Data	There was competitive solicitation of contractors for the project
Y1	Factor	Project Type	Y1 Product or Service Code--Construction of Structures and Facilities
Z1	Factor	Project Type	Z1 Product or Service Code--Maintenance of Structures and Facilities
Z2	Factor	Project Type	Z2 Product or Service Code--Repair or Alteration of Structures and Facilities
MILCON	Factor	Contract Type	The final approval authority is Congress
FirmFixed	Factor	Contract Type	Contract is any variation of a Firm Fixed contract
Cost	Factor	Contract Type	Contract is any variation of a Cost-Plus contract
DefinitiveContract	Factor	Award Type	Project awarded as a definitive contract
DeliveryOrder	Factor	Award Type	Contract for property that does not procure/specify a firm quantity of property
PurchaseOrder	Factor	Award Type	Purchase orders represent single business transactions
Construction	Factor	Project Type	Project is classified as Construction under North American Industry Classification (NAICS)
Manufacturing	Factor	Project Type	Project is classified as Manufacturing under NAICS
Admin Services	Factor	Project Type	Project is classified as Admin and Services under NAICS
Vertical	Factor	Project Type	Project consists of Vertical Construction, based on NAICS classification

Since there are many variable combinations, forward stepwise regression was used to determine which factors were significant and which combination of factors produced optimal model performance. This process is depicted in Figure 4-5.

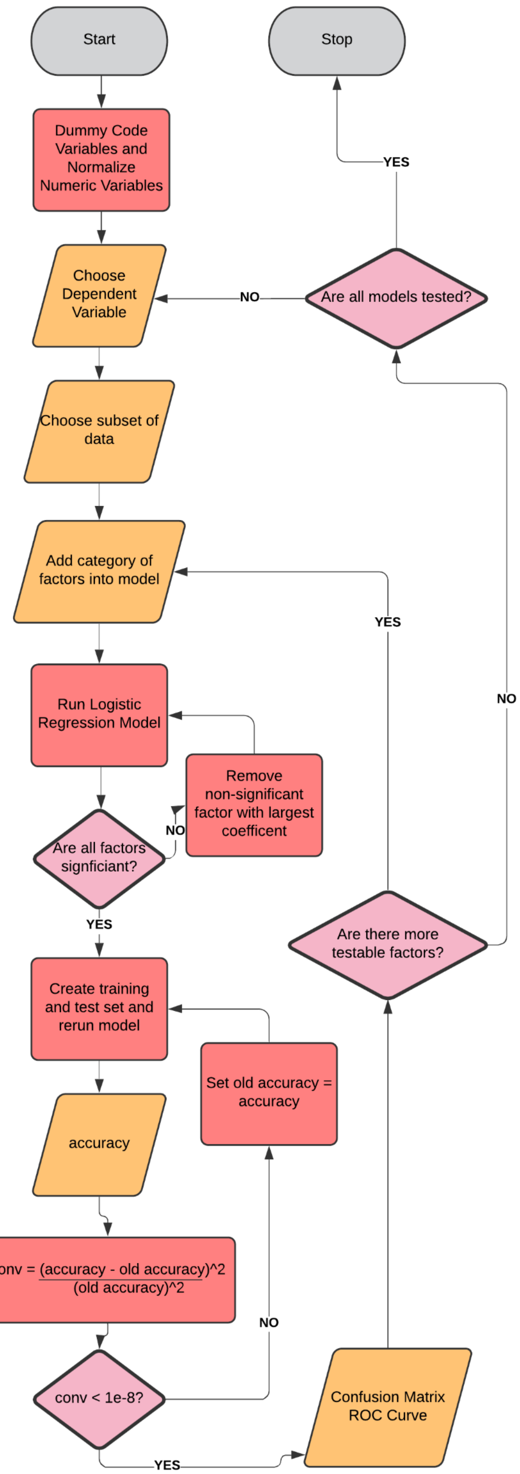


Figure 4-5 *Stepwise logistic regression process: Variable selection and accuracy determination.*

Since the logistic regression output is a number between 0 and 1, the threshold value was set to 0.5, which aligns with current literature that nearly half of projects experience cost and schedule overrun. If a project received a probability of 0.5 or greater, it received a predicted classification or experience overrun; otherwise, it was classified as not experiencing overrun. The whole process was iterated until the solution converged.

Logistic Regression: Model and Results Validation

A visual inspection of the receiver operating characteristic (ROC) curves is the first step in validating model effectiveness for predicting cost and schedule overrun likelihood. These curves output a true positive and false positive value for every possible classification threshold. The shape of the curves indicates performance ability; if the model curve lies above the no information rate (NIR) curve, the model performs better than the NIR. Likewise, if the model curve mimics or lies below the NIR, the model performs as good or worse than the NIR. The NIR is calculated using Equation **(4)**.

$$NIR = \frac{\#\ of\ Projects\ in\ Category\ with\ Largest\ Sample\ Size}{Total\ \#\ of\ Projects\ in\ Sample} \tag{4}$$

The next step in model validation is a numeric assessment of model performance. In this analysis, performance is measured in three ways: classification accuracy, sensitivity, and specificity. Equations **(5)**, **(6)**, and **(7)** below describe these measures.

$$Classification\ Accuracy = \frac{\#\ of\ Projects\ Classified\ Correctly}{Total\ \#\ of\ Projects\ in\ Sample} \tag{5}$$

$$Sensitivity = \frac{\#\ of\ Projects\ with\ No\ Overrun\ Classified\ Correctly}{Total\ \#\ of\ Projects\ in\ Sample} \qquad \textbf{(6)}$$

$$Specificity = \frac{\#\ of\ Projects\ with\ Overrun\ Classified\ Correctly}{Total\ \#\ of\ Projects\ in\ Sample} \qquad \textbf{(7)}$$

The accuracy indicates if the model performs better or worse in overall classification than the NIR. If the accuracy is greater than the NIR, the model has better performance. While accuracy is a good summary statistic, the sensitivity and specificity reveal the skew in the model to classify one category better than another.

Random Forest Classification

Random forest classification is used to predict the magnitude of overrun on the projects that experience cost or schedule overrun. Of the 79,894 projects, 34,664 projects experience cost overrun, and 28,067 projects experience schedule overrun. RFC is a supervised machine learning algorithm that introduces randomness to the normal decision tree classification process. It randomly combines multiple variables at tree splits and compares various iterations to determine an overall accuracy. This method was chosen for its ability to classify or categorize data based on the use of various input variable types, including ordinal, continuous, and interval. RFC has been successfully applied in construction research regarding the strength of materials (Han et al. 2019), construction site safety risks (Poh et al. 2018), and predicting the level of delay from common sources of delay as seen on-site (Yaseen et al. 2020). Accordingly, this research employs RFC to predict the magnitude of overruns using contract data.

For this analysis, 2 to 7 variables were combined at each split, comparing 100-500 trees. The combination with the highest accuracy was considered the best model. Many variations of RFC models were tested to determine the best classification method and the ability for the models to predict within different subsets of data. Table 4-3 describes the classification method used for every model on the various data subsets.

Table 4-3 *Models used in random forest classification to classify magnitude of cost and schedule overruns.*

Data Subset Description	Model #	Classification Method
C: All Projects with Cost Overrun	1C & 1S	3 K-Means Clusters
S: All Projects with Schedule Overrun	2C & 2S	3 Equally Proportioned (EP) Categories
	3C & 3S	3 K-Means Clusters with Grouping Clusters
	4C & 4S	3 EP Categories with Grouping Clusters
	5C & 5S	2 Categories (<100% & >100%)
C: Projects with <= 100% Cost Overrun	6C & 6S	3 K-Means Clusters
S: Projects with < 64% Schedule Overrun	7C & 7S	4 K-Means Clusters
	8C & 8S	3 EP Categories
	9C & 9S	4 EP Categories
C: Projects with > 100% Cost Overrun	10C & 10S	3 K-Means Clusters
S: Projects with > 64% Schedule Overrun	11C & 11S	4 K-Means Clusters
	12C & 12S	3 EP Categories
	13C & 13S	3 EP Categories

Note: Each model has a "C" or "S" next to the number to indicate if the model was tailored to cost or schedule overrun, respectively.

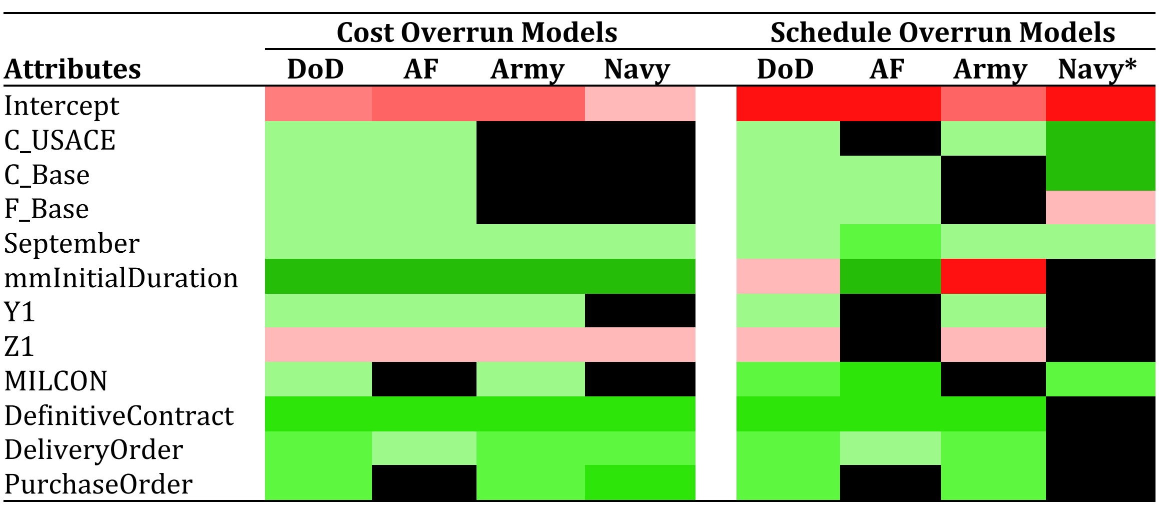
Four model variations were used: (1) K-Means clustering to determine the overrun clusters ranges for classification; (2) K-Means to cluster the data, excluding the overrun amount, into multiple categories and used those category values as attributes in the classification process; (3) equally proportioned (EP) categories (i.e., all three of four categories had an even number of projects); and (4) a combination of each of these.

Results

The results are organized to reflect the order of the methodology. First, the variable selection outcomes of all eight cost and schedule overrun logistic regression models are addressed. Next, the accuracies and performance of each model are presented and compared. Lastly, the performance of the random forest classification models is summarized.

Logistic Regression: Significant Variables

The forward stepwise logistic regression process served multiple purposes for this analysis. It was used to identify significant attributes, optimize model performance through various attribute combinations, output attribute influence (positive/negative) and magnitude, and evaluate the overall effectiveness of contract attributes prediction capability in cost and schedule overrun likelihood. Figure 4-6 provides a summary of the most influential attributes, which were significant in at least five of the eight models. Each column in this table represents each model.



Note: * indicates model was not significant at the 95% confidence level

Figure 4-6 *Summary of the direction and magnitude of the most influential attributes for all eight likelihood models, based on the attribute logistic regression coefficient values.*

Each column represents the top attributes of the respective models. This color chart uses green to represent an increase in overrun probability, red to represent a decrease in overrun probability, and black to indicate an insignificant attribute. Lighter colors represent attributes with lower influence, whereas darker colors represent those attributes with higher influence.

The most influential attribute categories in increasing the probability of a project experiencing overrun are Procurement Data (mmInitialDuration and September) and Award Type (DefinitiveContract, DeliveryOrder, and PurchaseOrder).

The initial duration (mmInitialDuration) has the largest positive influence for cost overrun models. As the initial duration of a project increases, the probability of cost overrun also increases. Initial duration is also the most influential factor for schedule overrun models, though it varies between positive and negative influence. The other procurement data attribute, September, also positively influences overrun in every model, though its influence is smaller. Notably, initial cost (mmInitialCost) was not a significant attribute, regardless of the variable combinations. Within the award type category, DefinitiveContract has the largest positive influence on overrun for all models but navy schedule overrun. Delivery Order also has a positive influence on overrun for all models but one, though its magnitude is smaller. Many factors were significant at the DoD (global) level, but the significance and influence varied across subsets; the opposite is also true.

Logistic Regression: Performance

This section displays the variable combinations with the highest accuracies. The first step of performance evaluation is an inspection of ROC curves. Upon visual inspection, most models perform better than the NIR. The navy schedule overrun model appears to perform similarly to the NIR. More variability exists within cost overrun

models than schedule overrun models, though these differences in performance are difficult to qualify. Accordingly, the quantitative measures of performance provide useful insights into the various deviations in model results. Table 4-4 summarizes these performance metrics for each of the eight models.

Table 4-4 *Measures of performance for cost and schedule overrun logistic regression models.*

	Cost Overrun Models				Schedule Overrun Models			
	DoD	AF	Army	Navy	DoD	AF	Army	Navy*
Sample Size	79,894	21,554	29,941	23,966	79,894	21,554	29,941	23,966
Accuracy	64-66%	61-63%	61-63%	72-74%	67-68%	60-62%	65-67%	75-77%
NIR	57%	50%	52%	71%	65%	57%	63%	75%
Sensitivity	82%	67%	79%	95%	92%	78%	90%	99%
Specificity	43%	57%	43%	19%	22%	39%	24%	5%

Note: * indicates model was not significant at the 95% confidence level

A 95% confidence interval is used to define model accuracy. Additionally, the solution remained stable regardless of testing threshold values between 0.4 and 0.6. All models are statistically significant except for the navy schedule overrun model, indicating they more accurately classify projects than the NIR. Additionally, every model does a better job of classifying projects that do not experience overrun than projects that experience overrun. Projects that did not experience overrun were correctly classified by the DoD cost and schedule models, nearly 82% and 92%, respectively. Conversely, these models only correctly classified 43% and 22% of the projects that experienced overrun, respectively. The AF cost overrun model performs with 11% greater accuracy than the NIR. While the Navy cost overrun model appears to have much higher accuracy than the other models, this is expected as the subset of navy contracts have a higher rate of experiencing no overrun. When the Navy model accuracy is compared with the NIR, its performance, while statistically significant, performs only marginally better.

Random Forest Classification Performance

The final phase of analysis was predicting the magnitude of overrun for the projects that experienced overrun. The median cost and schedule overrun are 149% and 36%, respectively. Since models for the likelihood of overrun were created using contract attributes, the next step in the process is determining if these same attributes are beneficial in predicting how much overrun a project will experience. RFC was used to accomplish this step. Table 4-5 provides a summary of the classification accuracy compared to the NIR for each model variation.

Table 4-5 *Random forest classification model accuracy compared with the no information rate for all cost and schedule overrun models.*

Model	Accuracy (%)	NIR (%)	Difference	Splits	# of Trees
1C	52.35	51.26	1.09*	4	300
1S	57.26	55.70	1.56*	4	300
2C	43.28	34.00	9.28***	4	200
2S	44.09	33.61	10.48***	5	300
3C	51.83	51.27	0.57*	4	200
3S	47.51	54.93	-7.42	2	100
4C	42.74	34.00	8.74***	5	300
4S	44.97	33.61	11.36***	4	200
5C	62.10	58.98	3.12**	5	300
5S	68.26	66.39	1.87*	5	300
6C	47.61	47.40	0.21*	4	200
6S	40.62	37.40	3.22**	3	100
7C	38.70	39.79	-1.09	4	200
7S	30.75	26.92	3.83**	3	300
8C	39.66	34.01	5.65***	4	200
8S	70.93	63.95	1.58*	3	200
9C	32.61	25.01	7.60***	7	200
9S	30.63	25.01	5.62***	4	200
10C	43.38	43.01	0.37*	2	300
10S	56.73	53.01	3.72**	3	300
11C	36.01	33.82	2.19*	2	300
11S	43.97	43.06	0.91*	3	300
12C	59.23	60.76	-1.53	7	100
12S	61.10	53.79	7.31***	5	100
13C	27.85	25.00	2.85*	5	300
13S	29.38	25.00	4.38**	5	100

Note: * = difference of 0-3%; ** = difference of 3-5%; *** = difference of greater than 5%

There are varying results amongst the models. Less than half of the models performed only 2-3% greater than the NIR. Three models performed worse, indicating these models are not useful for classification purposes, at least given the current data and attributes used. The best model, model 4S, performed 11.36% better than the NIR. This model classified schedule overrun into three equally proportioned categories using grouping clusters as an attribute. Splitting the data into lower and upper subsets and creating individual models was somewhat successful as well. Additionally, in most cases, classifying the projects into balanced/even proportioned categories proved more accurate than using K-Means clustering to determine the classification categories.

Results Summary

The likelihood modeling is currently more successful with prediction than the random forest classification modeling efforts in this analysis. The likelihood modeling revealed a strong relationship between the programmed duration (mmInitialDuration) of the project and overrun. Additionally, the type of award also highly influenced overrun on a project. Though RFC was less successful than likelihood modeling, it further revealed the ability to classify projects into categories of overrun. The use of equally proportioned categories for RFC modeling proved more successful than using clustering techniques to form categories.

Discussion

The structure of this section is broken down into three main areas, which highlight the contributions of the research. Individual attributes and their significance are reviewed

first. Then the model accuracy and classification impact are discussed. Finally, discussions on the limitations and broader applicability of this research are provided.

Significant Attributes

Some of the more significant attributes are the initial (i.e., estimated) duration, the month of award, and award type. These results align with previous literature and provide additional evidence of the similarities between public and private construction industry projects. This alignment with the literature also suggests that the use of logistic regression in the identification of contract attributes correlated with overrun is validated. Accordingly, based on their importance to the modeling efforts and applicability to the industry as a whole, these attributes are discussed further.

Procurement Data - Initial Duration

Initial duration is one aspect of project size that has been shown to affect project performance. Previous research regarding the correlation between initial duration and overrun indicates that it can have a negative effect (Jahren 1991), a positive effect (Odeck 2004b), or not be of significance (Love et al. 2013). However, this research has found that initial duration, or the estimated duration at the award, is the attribute with the single greatest effect on overrun probability. Unlike the previous studies, though, the scale and diversity of the data set used in the analysis present a unique result that implicates longer initial durations with an increased probability of cost overruns. This result is likely due to project length being associated with project complexity. Projects of a month or less may be more routine and less complicated projects, such as maintenance or repair requests, reducing variability and the chance of unforeseen errors/conditions. This assertion is further confirmed by a decreased probability of overruns for those projects classified as

maintenance. It should be noted that as the initial duration increased, it served to reduce the probability of schedule overrun within the DoD model. This could be the result of increased float days or over-estimation of the duration in longer projects, but as it is not consistent across all models and even serves to increase the probability in others, further investigation would be required.

Procurement Data - Month of Award

For US federal spending, including DoD construction, September is the last month to award projects within the fiscal year due to funds being constrained to each fiscal year. This process is similar in private industry only that the funds available to them are not "use or lose" but instead crucial for tax and accounting purposes. Thal et al. (2010) discuss how project award month positively correlates to increased contingency. Our findings further validate that projects awarded in the last quarter of the fiscal year, specifically September, increase the probability a project will experience cost/schedule overrun. However, September is more influential in schedule overrun models, which implies that a project awarded in the final month of the fiscal year has a greater probability of experiencing schedule overrun than cost overrun. Nearly 40% of the projects contained in the data set were issued in September, which provides a much larger sample from which overruns could occur. This information does not discredit the finding, though, because it is very well known that unallocated funds that could not be spent by installations are typically shared among others. This last-minute notification of funds can lead to ill-defined requirements and scopes for projects, which leads to additional cost and schedule overrun.

Award Type

Multiple studies have analyzed the performance of different contract compositions and found procurement (Dicks et al. 2017), delivery (Zhang et al. 2019), and payment methods (Bogus et al. 2010; Chen et al. 2016) influenced outcomes. Conversely, other research indicated execution methods had no significant effect (Hashem Mehany et al. 2018). This study finds that a relationship between the award type and cost and schedule overrun does exist. Of the different award types, definitive contracts were the most influential in increasing the probability of overrun. According to the FAR, definitive contracts are all contract actions except those executed under an Indefinite-Delivery Vehicle (IDV). The results indicate that projects requiring a stand-alone contract action with a definite time frame and quantity are more likely to have overrun than those IDV actions with specific clauses altering the time or quantity of the order to an indefinite nature. While the reasons for this are currently unknown, creating data subsets based on this contract type and performing additional analyses could prove useful in future research.

Model Accuracy

Overall, model accuracy is very similar between cost and schedule overrun classifications. The DoD model outperforms branch-specific models except for the cost overrun model for the Navy. At first glance, this may suggest that a larger, more diverse dataset equates to better results. However, the DoD model accuracy is being augmented by the Navy model accuracy as it is higher. Regardless, the model accuracy is higher than the no-information rate for all models except the schedule overrun Navy model. Therefore, every model still performs better than chance. The performance could be the

result of the number of design/procurement phase attributes compared to construction. The more likely cause for lower accuracy is the variation between the projects and results in considerable noise within the data set. However, this variability in the size, type, and location of projects allows the model to be broadly applied to the entire DoD construction portfolio.

As shown in Table 4-4, sensitivity is higher than specificity, meaning the models more accurately classified projects with no cost or schedule overrun. Considering 56% of the projects in the data experience no cost or schedule overrun, this model can classify the majority of the data. This information is valuable and could be used to prevent additional resources from being spent scrutinizing a project which may not be warranted.

Limitations

Based on previous research, it is likely that the model accuracy could be improved with the addition of several attributes not currently available in the system where these data were procured. Attributes like the delta between cost estimate and award price (Jahren 1991), risk assessment values for pre-bid documents (Lee and Yi 2017; Son and Lee 2019), team performance history (Dada 2014), contractor performance history, and improved project type classifications (Bhargava et al. 2010) have benefited previous analyses. Model accuracy would likely also improve with the implementation of a more objective and standardized method for data entry. Values of zero initial cost or estimated duration were not uncommon. Additionally, issues such as inconsistencies between the classification of project types and reasons for modifications (i.e., change orders) could likely have contributed to the lack of significance for attributes that proved significant in previous research. It should also be noted that overrun is strictly an objective term and

does not take into consideration the constructive nature or value-added of some modifications. Therefore, additional information regarding the modification is required to make better-informed decisions.

Further analysis of these data was conducted to classify the magnitude of cost and schedule overruns a project would experience. The work focused on the use of a random forest classification algorithm to model the magnitude of overrun for those projects that did experience it into predetermined bins (e.g., 0-25%, 25-50%, 50-75%, etc.). Overall, the model accuracies were low though some were successful at classifying magnitude better than the NIR, as shown in Table 4-5. Given the data's breadth and variety, there currently may not be enough similarity for the RFC algorithm to learn and classify projects correctly. Had the projects been more homogeneous, the algorithm could have likely produced more accurate results and should improve as more projects are added to the dataset. Therefore, given these results, it is logical to conclude that the use of RF algorithms is a viable option for classifying the magnitude of overrun despite the limited granularity in category sizes (e.g., 0-50% overrun).

Conclusions

The prevalence and detrimental impacts of cost and schedule overruns on construction projects have made the search for their causes vital to improving failing infrastructure and the continued success of construction programs. Previous research has shown that modifying project procurement and contracting methods have served to mitigate the occurrence of overruns. Not having been the focus of much research, this work analyzes the DoD construction portfolio, 48% of which experience overrun.

Accordingly, a means to identify the contract attributes that correlate to poorer project performance was investigated.

Logistic regression has proven an invaluable method in medical and social sciences research. Similarly, RFC models are used for classification and multiple prediction efforts within these same fields. To the author's knowledge, however, neither of these methods have been used to predict the likelihood and magnitude of construction overruns. The result was an efficient way to predict cost and schedule overrun that could be applied to future projects identifying those at risk with probabilistic modeling in lieu of deterministic (e.g., linear regression). Eight models were created using logistic regression to predict the likelihood of overruns (i.e., binary output), with accuracies varying between 66% and 75% for cost and schedule, respectively.

Additionally, this study identified several attributes that significantly impacted the likelihood of overrun, including initial duration, award month, and award type (i.e., definitive or IDV). The likelihood of overrun was seen to increase as a project's awarded duration increased. A similar increase in overrun was found to occur for projects as their award month approached the end of the fiscal year. Furthermore, those projects with definitive award contract types were found to have a greater likelihood to experience overrun than those of indefinite such as indefinite delivery indefinite quantity. These results will aid owners, project managers, and planners by providing insights into the risks associated with their projects and allowing for the implementation of mitigation techniques.

These results also demonstrate the use of project procurement data, through cost and schedule overrun likelihood predictions at the DoD-level, could help project

managers make better data-informed decisions, resulting in improved proactive construction planning and better cost management. This could take the form of revised guidance and more strict project award controls for projects containing high-risk factors as identified previously. These findings could also be used to identify the level of maturation and vetting that must occur for a project's scope, definition, requirements, and subsequent documentation.

Ultimately, this exploration of DoD-level cost and schedule overrun prediction modeling is one of the first of its kind in terms of size and diversity of data analyzed. Containing 79,894 projects, the quantity of data used in this study is an order of magnitude greater than the next largest sample from previous studies. Moreover, the data used here covers 281 different types of construction. These hallmark features provide a more holistic view of the contract factors that play a significant role in the project performance of entire construction portfolios in lieu of the project-centric conclusions of previous studies.

Future research should focus on better predicting the magnitude of overrun a project will experience. Knowing how much a project may increase in cost and schedule can facilitate more accurate planning and contingency. Improving the accuracy of both likelihood and magnitude predictions may be accomplished through including additional contract attributes (i.e., government estimate, planning time, etc.), and the addition of the human factors of construction such as contractor quality, team cordiality, political climate, and expert opinions.

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V. Conclusions and Recommendations - Using Construction Contract Data to Improve Decision Making and Project Performance

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Article Summary

This article covers the investigation and outcome of a study conducted to identify the sources of cost and schedule overrun within DoD construction. Contract data are compared with performance indicators to determine which attributes increase the likelihood of overruns and how this information can be used to improve project planning.

The Problem

48% of DoD projects completed in the last decade have experienced some form of overrun. Additional metrics outlining the severity of overrun issues in DoD construction are shown in Figure 5-1. Despite technological and organizational advances in construction planning and execution, these issues persist. These issues occur at the expense of overtasked contracting and construction personnel, altered budgets, and ultimately, the ability to award future projects. Deferring projects can result in delays in mission-essential readiness, missed requirements, lower morale, and reduced effectiveness. Furthermore, cost and schedule overrun can lead to a need to use fixed operations and maintenance funds. With more than 585,000 facilities to maintain and an existing $116 billion backlog of projects, the causes of these overruns must be identified

and mitigated through every available means (Cronk 2018; Office of the Under Secretary of Defense (Comptroller)/Chief Financial Officer 2019).

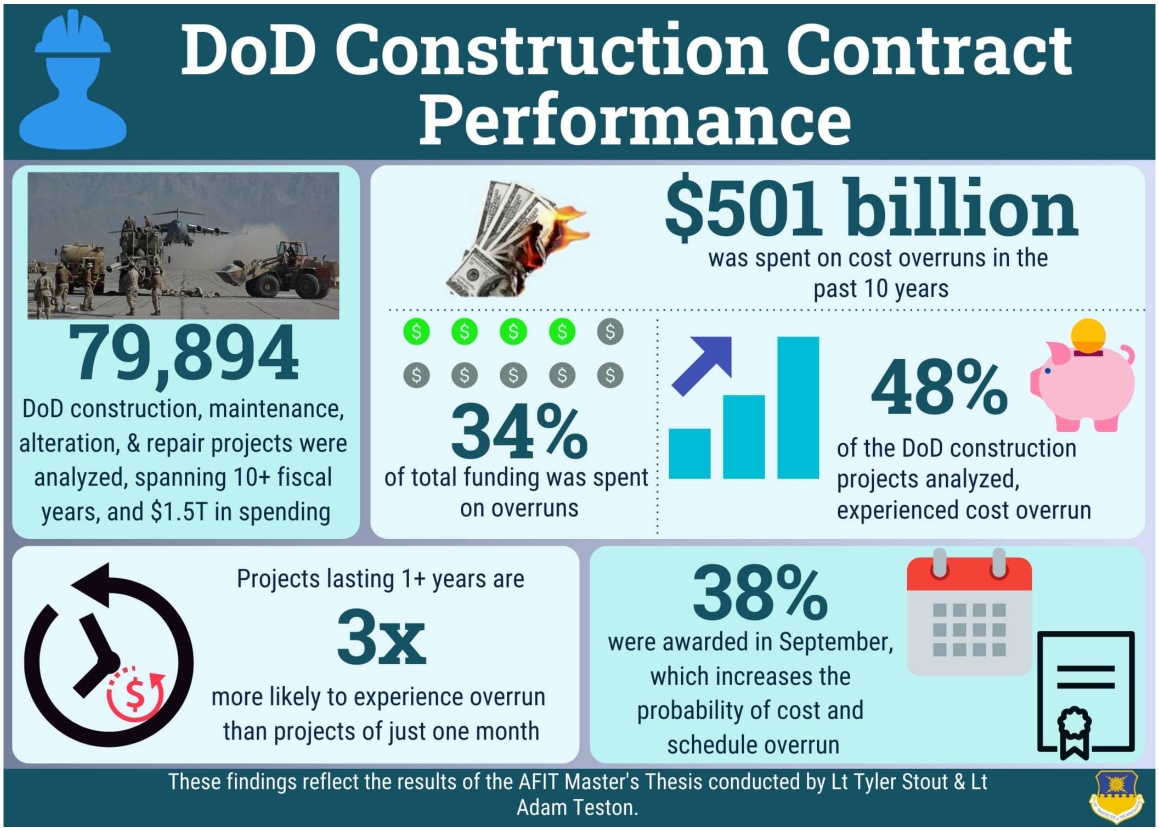


Figure 5-1 *Summary of DoD Construction Contract Performance*

For at least the past four decades, researchers performed hundreds of analyses on overrun using various methods, including surveys, questionnaires, statistical regression, and even machine learning (Durdyev and Hosseini 2018; Zidane and Andersen 2018). The first two methods ranked respondent responses while the latter two primarily focused on the attributes (e.g., contract type, delivery method, sector of construction) of contract data or bid documents to identify and mitigate the causes of overrun. However, even as a considerable consumer of construction, the DoD has not found itself at the center of

much of this research. Furthermore, the development of smarter, more effectively executed contracts is a current priority of the National Defense Strategy .

Through a partnership between the Air Force Civil Engineer Center (AFCEC) and the Air Force Institute of Technology (AFIT), a research project was funded to review and analyze the contract data for all military projects designated as maintenance, alteration, repair, or construction. Ultimately, the research focused on determining which contract attribute(s) significantly affected project performance.

Analyzing the Data

Using the Federal Procurement Database System-Next Generation (FPDS-NG) (now beta.SAM.gov), construction contract data from the past ten years was obtained and transformed into a construction repository housing 79,894 DoD projects (Stout et al. 2020). These data contained attributes like the location, duration, cost, and modifications associated with the maintenance, alteration, repair, and construction of real property. Initial statistical analysis of this data revealed that there were, in fact, differences between the performance of projects based on attributes like contracting agents, funding agents, and award months. These results proved informative and would serve as the foundation for future, more in-depth analysis.

Further investigation using logistic regression produced models that accounted for the complex interactions between contract attributes to help predict the likelihood of overruns and to grasp a holistic view of the attribute's roles in overrun occurrence. The dependent variable (overrun) was converted from a percentage to a simple 'yes' or 'no' for all projects. Eight models were created to determine the significance of each attribute

concerning this outcome. The results were twofold: 1) Models that could predict whether a project experienced overrun and 2) an understanding of how each significant attribute changes a project's probability of overrun.

Accuracies ranging between 66% and 75% were achieved. Additionally, all models exceeded the no information rate, a key performance indicator for logistic regression modeling. The no information rate is, essentially, an educated guess given no other information beyond the distributions of the attributes contained within the data. In other words, if we know that 50% of all DoD projects experienced overrun, then we have a 50% chance of guessing that a given project experiences overrun. The drawback of this model was that the accuracy lay in predicting the likelihood of a project that would not experience overrun. However, this information is still of use to planners and programmers because it identifies projects that represent less risk and likely require no additional vetting or mitigation methods to prevent cost or schedule overruns.

The contract attributes that greatly increased the probability of overrun across the DoD were the project duration at award, award type (i.e., purchase order, delivery order, bid-purchase agreement, definitive contracts), and award month. For the length of duration at award, the probability that a project will experience an overrun increases as the project's length increases. Definitive contracts increased the likelihood of overrun compared to other award types, including delivery orders. Additionally, projects awarded in September were found to have a higher probability of overrun than any other month. A closer look at each month revealed that nearly 50% of all projects awarded at the end of the fiscal year experienced overrun while, on average, the other months experienced only 39%. However, 38% of DoD projects were issued in September, larger than any other

month. Additional data, not currently available in FPDS, and further analysis would be required to better understand each attribute's significance in the probability of overrun.

Moving Forward

While the goal of this investigation was to aid planners and programmers in analyzing the risk of overruns using contract attributes currently available in FPDS-NG, its impact stretches beyond post-hoc analysis. This research could serve as the starting point for data-informed decisions regarding planning within DoD construction. Decisions currently made based on personal experience, expertise, and opinion could incorporate more objective lessons learned from the success and failure of past projects (DoD-wide). Additionally, this data can be used to assess construction project execution efficacy at the base-level to fine-tune local procurement methods and as a means of performance reporting and accountability should it be required. Ultimately, these analyses and decisions rely on the veracity and relevancy of their source. Therefore, improving existing attributes, adding supplemental information, and maintaining an up-to-date repository of projects is vital to ensuring success.

Accordingly, this research concluded by providing a list of changes that could be implemented in contract data tracking to increase the DoD's capability to curb overruns through more effective risk management in the procurement process. It was noted that, throughout this research effort, several of the contract attributes recorded in FPDS-NG were input inconsistently. Moreover, a review of previous overrun studies revealed additional attributes of construction projects that could be used to increase the modeling

accuracy (i.e., predicting project performance) and create a better understanding of the causes of overrun when they do occur.

Improvements to existing attributes:

- Prevent zero values for awarded cost and duration - an additional 52,768 projects were excluded because of this issue
- Provide objective guidance for product service code (PSC) entry (e.g., what is construction v. repair)
- Provide specific reasons for modifications (e.g., "design error - voltage for chiller incorrectly specified")

Additional attributes:

- Government estimate to compare to award price
- Contractor evaluation (e.g., CPARS)
- Type(s) of work (by percentage) of man-hours/cost (e.g., HVAC, electrical, civil, etc.) involved in the project
- Controllable v. Uncontrollable modification reasons (e.g., scope creep = controllable cost increase, rain = uncontrollable delay)
- Value-added v. not added indication for modifications (e.g., value-added = an omission that is required to make the facility complete and usable)
- Information from engineering databases like TRIRIGA, BUILDER, and TRACES
    - Pay apps and project progress
    - Building and component conditions
    - Project metrics (e.g., sq. ft. of renovation or length of road)

For the Future - Create an ad-hoc system, rather than post-hoc reports

- ○ A system designed to give real-time metrics of projects. Used for planning future projects and reflecting on lessons learned from past projects
  - ■ Actual working days versus available working days
  - ■ Percentage of equipment downtime
  - ■ Percentage of labor downtime
  - ■ Time to rectify defects
  - ■ Number of accidents
  - ■ Problems discovered in construction documentation
  - ■ Logging requests for information and responses
- ○ Include live-time Top Factors of "Non-Value Added, Controllable Cost Overrun," "Value Added, Controllable Cost Overrun," etc.
- ○ Enable real-time access to average cost/schedule overrun of current projects, past projects, specific project types, etc.

The vast majority of these attributes already exist in some form or fashion within project documentation or even within other databases used by the DoD. Researchers, planners, and programmers would benefit from a centralized system that maintains this information, if for no other reason than to provide a project-specific source of lessons learned. By arming DoD personnel with this knowledge, it is hoped that future construction projects will be delivered with fewer overruns enabling the DoD to fund more projects and reduce its current backlog.

Conclusion – Mitigating Overruns in DoD Construction

This research illustrates both the prevalence and impact of cost and schedule overruns within DoD construction by creating a repository that houses all construction, repair, alteration, and maintenance task orders from the past decade. From this repository, it was determined that 48% of projects had experienced some form of overrun, totaling over $500 billion in unplanned expenditures. These overruns diminish funding for concurrent projects, deplete operational budgets that cause deferred infrastructure maintenance, and impair future project award ability. To aid in the reduction of an existing $116 billion backlog in projects, the DoD must address these overruns in new and innovative ways.

Accordingly, this research demonstrates the application of and efficacy in using historical DoD construction contract data in objectively identifying projects that will experience cost and schedule overrun. This same data was also shown to be useful in predicting the magnitude of project overruns. Consequently, projects that are at risk for experiencing overruns can be identified before their award. Additional measures and resources can then be selectively applied to help mitigate overrun occurrence based on both the risk assessment of the project and risk tolerance of the organization.

Research Significance

Studies focusing on identifying the sources of cost and schedule overrun have been ongoing for at least the past 40 years. In that time, existing research has found that the sources vary between projects, locations, and parties. However, these same studies have used methods that may be overfit, introduce biases, or are based on limited data sets.

Moreover, the DoD has garnered little attention from previous research in this field. The data used in this analysis is the single largest source of construction contract information to the authors' knowledge, containing 79,894 projects. Furthermore, as the database spans 281 types of construction and contains 62 contract attributes, the conclusions drawn from this work offer more robust results that can be more broadly applied to the DoD's diverse portfolio of facilities and infrastructure in an attempt to mitigate overrun.

While additional factors contribute to overruns within DoD construction projects, including inclement weather, contractor performance, and poor requirement definition, this research demonstrates that skillful models can be created to inform planners and programmers of the risks posed by specific attributes of contract data. The DoD must consider historical construction contract data when planning future projects.

Research Contributions

This research offered the first large-scale review at DoD construction. It reinforced the need to track historical construction spending for which a repository was created using key attributes of contract data from FPDS-NG (Chapter 3). Furthermore, this thesis reviewed the capability of predicting the likelihood and magnitude of overruns within DoD construction. The applicability of logistic regression was demonstrated by creating a binary output with regard to whether a project was going to experience overrun (i.e., overrun?, 'yes' or 'no'). RFC was also identified as a means to predict the magnitude of overrun a project is likely to experience (Chapter 4).

In using the database and methods established in this thesis, DoD planners and programmers are empowered with the ability to analyze future projects, providing an

objective assessment of risk which could inform execution strategies like the need for further scope development, alternative contracting methods, or deferment of projects to create a more risk-neutral portfolio based on current priorities. By reviewing, analyzing, and modifying planning and procurement methods based on performance metrics (i.e., data-driven decisions), the DoD can better align itself with the National Defense Strategy's directive to develop smarter contracts and execute contracts more effectively. As part of this work, a poster presentation was created and culminated in the development of two journal articles, which created a construction task order database (Chapter 3) and determined contract attributes most significantly correlated with project performance (Chapter 4).

Recommendations for Future Research

This research explored the relevance and impact of cost and schedule overruns in DoD construction by creating a historical database. Additionally, methods to identify those contract attributes significantly correlated with project performance using logistic regression and RFC were determined. Accordingly, there are several areas where this research could be expanded:

1. Sub-setting data: Analyzing the data in smaller quantities based on specific award months, contracting agents, or project types could result in alternate attributes significantly correlated with project performance. Identifying those attributes that apply to only a smaller sample of projects could lead to amended execution strategies, thereby expanding the DoD's capabilities in mitigating overruns.

2. Inclusion of additional data: It was noted in literature that several attributes not present in FPDS-NG served to enhance the skillfulness of modeling efforts used to predict the likelihood and magnitude of cost and schedule overrun. These attributes include, but are not limited to, the programmed estimate, project metrics (e.g., sq. ft. of flooring), and contractor performance. It is expected that if these and other similar attributes were incorporated into the task order database from sources such as TRACES or TRIRIGA, the skillfulness of the methods used here could be enhanced.
3. Alternative Machine Learning Techniques: Several techniques outside of logistic regression and RFC have shown proficiency in quantifying the probability and magnitude of risk associated with overruns. Research could focus on comparing these techniques' capabilities, which include text mining, principal component analysis, ensemble learning, and fuzzy logic to determine the optimal method, or methods, which further mitigate overrun in future awards.

Among others, these avenues provide further research and development opportunities for mitigating cost and schedule overrun in DoD construction projects.

Appendix

This section includes the statistical comparison between the factors of the contracting agent, funding agent, and award month that were not published. This effort was undertaken at the behest of AFCEC to investigate whether project performance could be improved by selecting any one factor comprising these attributes. Subsequent sections of this appendix offer further insights into each of these attributes to include descriptive statistics.

The research uses statistical analysis software, SPSS, to conduct the comparison between the various factors of each attribute. This software is well known and commonly used for this type of work. Additionally, a comparison of means between these factors is a readily accepted method within mathematical and social sciences to determine if significant differences exist. As the residuals' distribution is not assumed to be normal, the non-parametric Kruskal-Wallis test was used to compare each of the attributes' overrun rates. This test compares the variance of each factor's ranked overrun percentages and, as it is a form of ANOVA, tests the difference between only two each time.

Consequently, each factor is compared to every other factor in a single test (i.e., pairwise comparisons). We can also not assume that each of the factors' distributions is similar and must use the mean or average ranked overrun in lieu of comparing the medians. The average ranked overrun is computed by ranking all of the overrun percentages from 1 to N without their groupings (i.e., the factor within each attribute is disregarded when projects are ranked). Once the rankings have been assigned, an average of the ranks within each factor is calculated.

All pairwise comparisons with an adjusted significance of 0.05 or lower provide the test's confidence level, ensuring a true difference between the factors. That is not to say that greater significance levels (e.g., $p > 0.05$) indicate a lack of true difference between the average ranked overrun. Significance levels of 0.10 are not uncommon in statistical analyses. A higher level of confidence was utilized in testing to ensure future research focuses solely on those factors which have a high probability of affecting project performance.

An additional step is required to determine which of the factors within each attribute experienced greater overrun among the significant pairwise comparisons. The average rankings can then be compared using the ranking distance relationship figures. The larger the average ranked overrun value, the greater the amount of overrun experienced by each factor.

Contracting Agent

Descriptive Statistics

The contracting agent attribute is composed of six individual agents, including AFCEC, USACE, NAVFAC, ARNG, Base, and Other. When the contracting agent is listed as base, it implies that the contract execution was handled at the base level instead of being contracted out to AFCEC, USACE, or NAVFAC. Additionally, when the contracting agent is listed as other, it implies that a higher-level agent like a MAJCOM or HQ executed the project.

Table A-1 *The number and percentage of projects awarded by each contracting agent.*

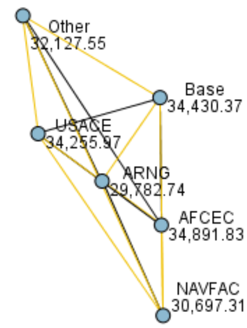
Agent	Frequency	Percent
AFCEC	152	.2
ARNG	321	.5
Base	24827	37.7
NAVFAC	19691	29.9
Other	10520	16.0
USACE	10280	15.6
Total	65791	100.0

Table A-**1** above shows the number of projects executed by each contracting agent over the past ten years. Base and NAVFAC agencies executed the majority of projects.

Statistical Comparison

A comparison between the contracting agents' effect on both cost and schedule overrun was conducted to determine if any single agent significantly impacts project performance. Regarding cost overrun, the significant differences in performance between agents are noted in the rows where the adjusted significance is less than 0.05. These values are also highlighted in yellow.

Pairwise Comparisons of COffCat



Each node shows the sample average rank of COffCat.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
ARNG-NAVFAC	-914.575	847.058	-1.080	.280	1.000
ARNG-Other	-2,344.820	852.959	-2.749	.006	.090
ARNG-USACE	-4,473.238	853.254	-5.243	.000	.000
ARNG-Base	-4,647.640	845.651	-5.496	.000	.000
ARNG-AFCEC	5,109.097	1,482.212	3.447	.001	.009
NAVFAC-Other	-1,430.245	181.800	-7.867	.000	.000
NAVFAC-USACE	-3,558.663	183.178	-19.427	.000	.000
NAVFAC-Base	3,733.065	143.657	25.986	.000	.000
NAVFAC-AFCEC	4,194.522	1,225.750	3.422	.001	.009
Other-USACE	-2,128.418	208.776	-10.195	.000	.000
Other-Base	2,302.820	175.130	13.149	.000	.000
Other-AFCEC	2,764.277	1,229.836	2.248	.025	.369
USACE-Base	174.402	176.560	.988	.323	1.000
USACE-AFCEC	635.860	1,230.041	.517	.605	1.000
Base-AFCEC	461.458	1,224.779	.377	.706	1.000

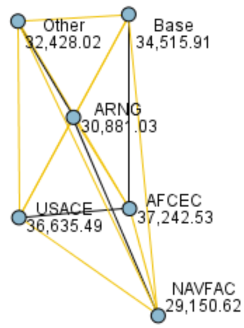
Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

Figure A-1 *Average ranked cost overrun comparisons by contract agent.*

AFCEC, as a sponsor of this research, was interested in understanding how they compared with other agents. An output of this analysis is found in Figure A-1. There were only two statistically significant pairwise comparisons that included AFCEC. Accordingly, when compared to NAVFAC and ARNG agents, AFCEC experienced a greater average ranked cost overrun. AFCEC also wanted to understand how they fared when compared to USACE. The adjusted significance of that comparison reveals that neither agent outperformed the other. Their average ranked cost overrun values found in the distance/relationship figure were very similar.

It should also be noted that projects executed at the base level were no more likely to experience cost overrun than those executed by USACE or AFCEC. This overrun could result from the difference in size between the types of projects executed between these agents. If, however, larger Air Force projects are traditionally executed by AFCEC and USACE, then based on these results, a smaller amount of cost overrun is incurred at the base level.

Pairwise Comparisons of COffCat



Each node shows the sample average rank of COffCat.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
NAVFAC-ARNG	1,730.414	896.769	1.930	.054	.805
NAVFAC-Other	-3,277.404	192.470	-17.028	.000	.000
NAVFAC-Base	5,365.293	152.088	35.278	.000	.000
NAVFAC-USACE	-7,484.869	193.929	-38.596	.000	.000
NAVFAC-AFCEC	8,091.906	1,297.687	6.236	.000	.000
ARNG-Other	-1,546.990	903.018	-1.713	.087	1.000
ARNG-Base	-3,634.879	895.280	-4.060	.000	.001
ARNG-USACE	-5,754.454	903.330	-6.370	.000	.000
ARNG-AFCEC	6,361.492	1,569.200	4.054	.000	.001
Other-Base	2,087.889	185.408	11.261	.000	.000
Other-USACE	-4,207.465	221.029	-19.036	.000	.000
Other-AFCEC	4,814.502	1,302.013	3.698	.000	.003
Base-USACE	-2,119.576	186.922	-11.339	.000	.000
Base-AFCEC	2,726.613	1,296.658	2.103	.035	.532
USACE-AFCEC	607.038	1,302.229	.466	.641	1.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

Figure A-2 *Average ranked schedule overrun comparisons by contract agent.*

Similar to cost, schedule overrun was similarly affected by each of the factors within the contracting agent. That is to say, a similar number of statistically significant comparisons exists. As shown in Figure A-2, AFCEC construction projects experienced the largest average ranked schedule overrun of all the contracting agents. NAVFAC projects experienced the least overrun, followed by ARNG, Other, Base, and USACE. Like cost, the amount of schedule overrun experienced by projects could likely increase with its size based on these results.

Funding Agent

Descriptive Statistics

The funding agent attribute is composed of six individual agents, including AFCEC, USACE, NAVFAC, ARNG, Base, and Other. When the contracting agent is listed as base, it implies that the contract funding was provided from the base level. Additionally, when the contracting agent is listed as other, it means that a higher-level agent like a MAJCOM or HQ funded the project.

Table A-2 *The number and percentage of projects awarded by each funding agent.*

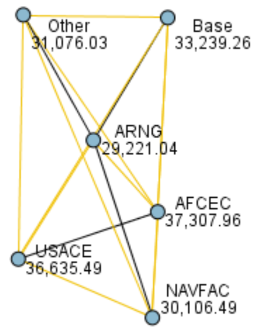
Agent	Frequency	Percent
AFCEC	158	.2
ARNG	52	.1
Base	40459	61.5
NAVFAC	3802	5.8
Other	15022	22.8
USACE	6298	9.6
Total	65791	100.0

Table A-2 shows the number of projects funded by each of the agents. Note that a majority of projects were funded at the base level. The next most frequent source of funding was other, implying that MAJCOM or their equivalents were used.

Statistical Comparison

It was assumed that, like the contracting agent, the funding agent also played a role in a project's likelihood to experience cost and schedule overrun. At least in terms of FPDS data, the funding agent is the party responsible for the preponderance of the funds for the requirement (i.e., project). Traditionally this also means that that same party establishes the initial requirements. As the initial requirements can dictate how a project performs throughout its duration, this attribute may give insight into each of these agents' ability to communicate a project's overall scope consistently and effectively.

Pairwise Comparisons of FOffCat



Each node shows the sample average rank of FOffCat.

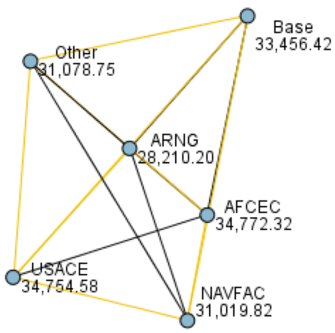
Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
ARNG-NAVFAC	-885.449	2,225.205	-.398	.691	1.000
ARNG-Other	-1,854.992	2,213.964	-.838	.402	1.000
ARNG-Base	-4,018.223	2,211.562	-1.817	.069	1.000
ARNG-USACE	-7,414.448	2,219.248	-3.341	.001	.013
ARNG-AFCEC	8,086.917	2,548.011	3.174	.002	.023
NAVFAC-Other	-969.543	289.340	-3.351	.001	.012
NAVFAC-Base	3,132.774	270.345	11.588	.000	.000
NAVFAC-USACE	-6,528.999	327.322	-19.947	.000	.000
NAVFAC-AFCEC	7,201.468	1,294.002	5.565	.000	.000
Other-Base	2,163.232	152.273	14.206	.000	.000
Other-USACE	-5,559.457	239.249	-23.237	.000	.000
Other-AFCEC	6,231.926	1,274.575	4.889	.000	.000
Base-USACE	-3,396.225	215.892	-15.731	.000	.000
Base-AFCEC	4,068.694	1,270.398	3.203	.001	.020
USACE-AFCEC	672.469	1,283.730	.524	.600	1.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

Figure A-3 *Average ranked cost overrun comparisons by funding agent.*

As shown above in Figure A-3, a majority of funding agents have a significant statistical difference between one another regarding project cost overrun. Again, AFCEC has the largest average ranked cost overrun of any of the funding agencies. ARNG was the agency with the least average ranked overrun, followed by NAVFAC, Other, Base, and USACE. Similar to the contracting agent attribute, when USACE or AFCEC was the funding agent, no significant difference exists in the average ranked cost overrun of their projects.

Pairwise Comparisons of FOffCat



Each node shows the sample average rank of FOffCat.

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
ARNG-NAVFAC	-2,809.615	2,101.852	-1.337	.181	1.000
ARNG-Other	-2,868.545	2,091.235	-1.372	.170	1.000
ARNG-Base	-5,246.214	2,088.966	-2.511	.012	.180
ARNG-USACE	-6,544.381	2,096.225	-3.122	.002	.027
ARNG-AFCEC	6,562.121	2,406.764	2.727	.006	.096
NAVFAC-Other	-58.930	273.300	-.216	.829	1.000
NAVFAC-Base	2,436.599	255.359	9.542	.000	.000
NAVFAC-USACE	-3,734.766	309.177	-12.080	.000	.000
NAVFAC-AFCEC	3,752.505	1,222.270	3.070	.002	.032
Other-Base	2,377.669	143.832	16.531	.000	.000
Other-USACE	-3,675.836	225.986	-16.266	.000	.000
Other-AFCEC	3,693.576	1,203.920	3.068	.002	.032
Base-USACE	-1,298.167	203.924	-6.366	.000	.000
Base-AFCEC	1,315.907	1,199.974	1.097	.273	1.000
USACE-AFCEC	17.740	1,212.568	.015	.988	1.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

Figure A-4 *Average ranked schedule overrun comparisons by funding agent.*

The order of performance for the funding agents' average ranked schedule overrun is the same for cost. The only difference here is that three fewer comparisons were statistically different, as shown above in Figure A-4.

Award Month

Descriptive Statistics

The award month of the project was assumed, at least anecdotally, to influence the amount of overrun a project would experience. The assumption being that those projects issued close to the end of the fiscal year would experience more overrun based on their perceived lack of scoping or definition.

Table A-3 *The number and percentage of projects awarded in each month.*

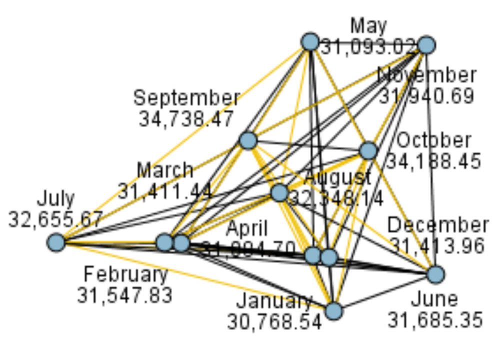
Month	Frequency	Percent
April	3958	6.0
August	7452	11.3
December	2011	3.1
February	2618	4.0
January	2210	3.4
July	6554	10.0
June	5683	8.6
March	3849	5.9
May	4561	6.9
November	1416	2.2
October	1337	2.0
September	24142	36.7
Total	65791	100.0

As indicated in Table A-3 that the DoD executed a large portion of projects in September. Additionally, the results presented earlier showed that a greater percentage of

projects awarded in September experienced overruns than other months. However, these statistics alone cannot be used to determine whether or not the month of September is the cause of increased overruns within projects. As this month contains a large percentage of projects, greater variability in performance is expected. Therefore, projects awarded in September would need to be investigated further to identify the factors correlated with overruns.

Statistical Comparison

The statistical comparison results revealed additional information about the end of the fiscal year concerning cost and schedule overrun. These comparisons are visualized in Figure A-5, Figure A-6, Figure A-7, and Figure A-8. The months of July, August, and September were higher in average ranked overrun than other months in most cases. These results indicate that, generally, projects awarded in the final quarter of the fiscal year experience more overrun than those in other quarters.



Each node shows the sample average rank of AwardMonth.

Figure A-5 *Average ranked cost overrun distance/relationship by month.*

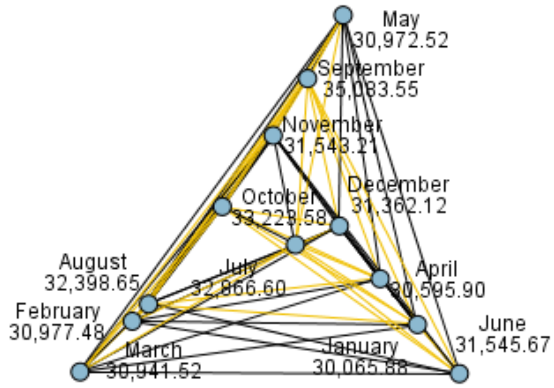


Figure A-6 *Average ranked schedule overrun distance/relationship by month.*

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
January-April	316.160	423.214	.747	.455	1.000
January-May	-324.486	413.069	-.786	.432	1.000
January-March	-642.905	425.356	-1.511	.131	1.000
January-December	645.419	491.165	1.314	.189	1.000
January-February	779.294	460.389	1.693	.091	1.000
January-June	-916.811	399.538	-2.295	.022	1.000
January-November	-1,172.151	542.510	-2.161	.031	1.000
January-August	1,579.600	386.032	4.092	.000	.003
January-July	-1,887.133	392.034	-4.814	.000	.000
January-October	-3,419.918	552.193	-6.193	.000	.000
January-September	-3,969.932	354.198	-11.208	.000	.000
April-May	-8.325	346.217	-.024	.981	1.000
April-March	-326.744	360.788	-.906	.365	1.000
April-December	-329.259	436.444	-.754	.451	1.000
April-February	-463.134	401.495	-1.154	.249	1.000
April-June	-600.651	329.956	-1.820	.069	1.000
April-November	-855.991	493.516	-1.734	.083	1.000
April-August	-1,263.439	313.466	-4.031	.000	.004
April-July	-1,570.973	320.829	-4.897	.000	.000
April-October	-3,103.757	504.140	-6.157	.000	.000
April-September	-3,653.772	273.307	-13.369	.000	.000
May-March	318.419	348.832	.913	.361	1.000
May-December	320.934	426.614	.752	.452	1.000
May-February	454.809	390.786	1.164	.244	1.000
May-June	592.325	316.838	1.869	.062	1.000
May-November	-847.665	484.844	-1.748	.080	1.000
May-August	1,255.114	299.627	4.189	.000	.002
May-July	1,562.648	307.322	5.085	.000	.000
May-October	-3,095.432	495.654	-6.245	.000	.000
May-September	-3,645.447	257.317	-14.167	.000	.000
March-December	2.515	438.521	.006	.995	1.000
March-February	136.390	403.752	.338	.736	1.000
March-June	273.906	332.699	.823	.410	1.000
March-November	-529.246	495.354	-1.068	.285	1.000
March-August	936.695	316.352	2.961	.003	.202
March-July	1,244.229	323.649	3.844	.000	.008
March-October	-2,777.013	505.939	-5.489	.000	.000
March-September	-3,327.028	276.612	-12.028	.000	.000
December-February	-133.875	472.579	-.283	.777	1.000
December-June	-271.391	413.526	-.656	.512	1.000
December-November	-526.732	552.893	-.953	.341	1.000
December-August	934.180	400.492	2.333	.020	1.000
December-July	-1,241.714	406.281	-3.056	.002	.148
December-October	-2,774.498	562.397	-4.933	.000	.000
December-September	-3,324.513	369.905	-8.987	.000	.000
February-June	-137.517	376.455	-.365	.715	1.000
February-November	-392.857	525.743	-.747	.455	1.000
February-August	800.305	362.089	2.210	.027	1.000
February-July	-1,107.839	368.482	-3.006	.003	.174
February-October	-2,640.624	535.728	-4.929	.000	.000
February-September	-3,190.638	327.939	-9.729	.000	.000
June-November	-255.340	473.369	-.539	.590	1.000
June-August	662.789	280.680	2.361	.018	1.000
June-July	970.322	288.880	3.359	.001	.052
June-October	-2,503.107	484.435	-5.167	.000	.000
June-September	-3,053.121	234.983	-12.993	.000	.000
November-August	407.449	462.026	.882	.378	1.000
November-July	714.982	467.053	1.531	.126	1.000
November-October	-2,247.767	607.754	-3.698	.000	.014
November-September	-2,797.781	435.780	-6.420	.000	.000
August-July	-307.534	269.892	-1.139	.255	1.000
August-October	-1,840.318	473.358	-3.888	.000	.007
August-September	-2,390.333	211.204	-11.318	.000	.000
July-October	-1,532.784	478.265	-3.205	.001	.089
July-September	-2,082.799	221.985	-9.383	.000	.000
October-September	-550.014	447.776	-1.228	.219	1.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

Figure A-7 *Average ranked cost overrun comparisons by month.*

Sample1-Sample2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj.Sig.
January-April	530.020	399.753	1.326	.185	1.000
January-March	-875.642	401.776	-2.179	.029	1.000
January-May	-906.638	390.170	-2.324	.020	1.000
January-February	911.599	434.867	2.096	.036	1.000
January-December	1,296.244	463.938	2.794	.005	.344
January-November	-1,477.333	512.437	-2.883	.004	.260
January-June	-1,479.797	377.390	-3.921	.000	.006
January-August	2,332.774	364.632	6.398	.000	.000
January-July	-2,800.725	370.302	-7.563	.000	.000
January-October	-3,157.703	521.582	-6.054	.000	.000
January-September	-5,017.675	334.563	-14.998	.000	.000
April-March	-345.622	340.788	-1.014	.310	1.000
April-May	-376.618	327.025	-1.152	.249	1.000
April-February	-381.579	379.238	-1.006	.314	1.000
April-December	-766.224	412.250	-1.859	.063	1.000
April-November	-947.313	466.158	-2.032	.042	1.000
April-June	-949.777	311.665	-3.047	.002	.152
April-August	-1,802.754	296.089	-6.089	.000	.000
April-July	-2,270.705	303.044	-7.493	.000	.000
April-October	-2,627.683	476.193	-5.518	.000	.000
April-September	-4,487.655	258.156	-17.383	.000	.000
March-May	-30.996	329.494	-.094	.925	1.000
March-February	35.957	381.370	.094	.925	1.000
March-December	420.602	414.212	1.015	.310	1.000
March-November	-601.691	467.894	-1.286	.198	1.000
March-June	604.155	314.256	1.922	.055	1.000
March-August	1,457.132	298.815	4.876	.000	.000
March-July	1,925.083	305.708	6.297	.000	.000
March-October	-2,282.061	477.893	-4.775	.000	.000
March-September	-4,142.033	261.278	-15.853	.000	.000
May-February	4.962	369.123	.013	.989	1.000
May-December	389.607	402.964	.967	.334	1.000
May-November	-570.696	457.967	-1.246	.213	1.000
May-June	573.159	299.275	1.915	.055	1.000
May-August	1,426.136	283.018	5.039	.000	.000
May-July	1,894.087	290.286	6.525	.000	.000
May-October	-2,251.065	468.178	-4.808	.000	.000
May-September	-4,111.037	243.053	-16.914	.000	.000
February-December	384.645	446.382	.862	.389	1.000
February-November	-565.734	496.599	-1.139	.255	1.000
February-June	-568.197	355.587	-1.598	.110	1.000
February-August	1,421.174	342.017	4.155	.000	.002
February-July	-1,889.126	348.055	-5.428	.000	.000
February-October	-2,246.103	506.031	-4.439	.000	.001
February-September	-4,106.075	309.760	-13.256	.000	.000
December-November	-181.089	522.244	-.347	.729	1.000
December-June	-183.552	390.603	-.470	.638	1.000
December-August	1,036.529	378.291	2.740	.006	.405
December-July	-1,504.481	383.759	-3.920	.000	.006
December-October	-1,861.458	531.221	-3.504	.000	.030
December-September	-3,721.430	349.399	-10.651	.000	.000
November-June	2.463	447.128	.006	.996	1.000
November-August	855.440	436.414	1.960	.050	1.000
November-July	1,323.391	441.162	3.000	.003	.178
November-October	-1,680.369	574.063	-2.927	.003	.226
November-September	-3,540.341	411.623	-8.601	.000	.000
June-August	852.977	265.121	3.217	.001	.085
June-July	1,320.928	272.866	4.841	.000	.000
June-October	-1,677.906	457.581	-3.667	.000	.016
June-September	-3,537.878	221.957	-15.939	.000	.000
August-July	-467.951	254.930	-1.836	.066	1.000
August-October	-824.929	447.118	-1.845	.065	1.000
August-September	-2,684.901	199.496	-13.458	.000	.000
July-October	-356.978	451.753	-.790	.429	1.000
July-September	-2,216.950	209.679	-10.573	.000	.000
October-September	-1,859.972	422.954	-4.398	.000	.001

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is .05.

Figure A-8 *Average ranked schedule overrun comparisons by month.*

In all cases except one, the comparisons revealed that projects awarded in September experienced more average ranked cost overrun than in any other month. The only other month to experience a similar amount of overrun was October. It's not clear from this statistical analysis why that is. As October is the beginning of the fiscal year, an increased average ranked cost overrun could result from a premature project award. In a rush to obligate the initial disbursement of funds, projects could be prone to the same lack of scoping and definition that likely occurs in September. With fewer projects issued in October than in any other month, the overrun amount is comparatively worse than in September and should be investigated further.

In every comparison made, projects awarded in September experienced a significantly greater average ranked overrun than any other month. This result reveals the increased likelihood of projects to experience schedule overrun when awarded in September and indicates the seriousness of schedule overrun and its correlation with cost overrun.

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14. ABSTRACT
Cost and schedule overrun plague over 50% of all construction projects, engendering diminished available funding that leads to deferred maintenance and impaired award ability for needed projects. Though existing research attempts to identify overrun's sources, the results are inconclusive and frequently differ. Accordingly, this research reviews DoD construction contract data from the past ten years to identify the contract attributes of 79,894 projects that correlate with superior performance for use in future project execution. This research starts with creating a database that houses the largest single source of construction contract information. The research then evaluates the data to determine if differences in project performance exist when comparing contracting agents, funding agents, and award months. Next, the research utilizes stepwise logistic regression to determine the significant contract attributes and predict future projects' overrun likelihoods. Model accuracy for predicting the likelihood of cost and schedule overrun is 65% and 75%, respectively. Finally, this research concludes by providing insights into efforts that could improve modeling accuracies, thereby informing better risk management practices. This research is expected to support public and private sector planners in their ongoing efforts to execute construction projects more cost-effectively and better utilize requested funds.

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