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Research Report

Leveraging Historical Bid Data to Improve Cost Estimating in Transportation Projects in Alabama: A Risk-Based Approach

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16. Abstract

The American Association of State Highway and Transportation Officials (AASHTO) provides basic guidance for state transportation agencies (STAs) on the preparation of construction cost estimates using bid data from previous construction projects. However, these guidelines are too general to effectively guide estimators on the effective implementation of bid-based cost estimating, which is the most common estimating approach used by STAs. Accurate and reliable estimates are required to effectively support STAs' planning and investment decisions. Thus, poor implementation of this cost estimating approach could potentially lead to an inefficient use of public resources. The research efforts presented in this report are intended to help the Alabama Department of Transportation (ALDOT) overcome this issue by proposing a bid-based cost estimating system that facilitates the leverage of available historical bid data to maximize estimating effectiveness. The proposed system integrates various statistical and data analytics techniques to model the cost impacts of four key factors on transportation construction costs in Alabama: 1) project scale, 2) time, 3) location, and 4) estimating uncertainty. The last factor refers to the modeling of unavoidable estimating uncertainty by converting a traditional deterministic estimate (produced after considering the first three factors) into a risk-based cost estimate. The effectiveness of the proposed system is demonstrated using an innovated moving-window cross-validation approach and via statistical testing to assess the level of significance of the observed improvements in estimating accuracy and reliability.

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EXECUTIVE SUMMARY

The American Association of State Highway and Transportation Officials (AASHTO) provides basic guidance for state transportation agencies (STAs) on the preparation of construction cost estimates using bid data from previous construction projects. However, these guidelines are too general to effectively guide estimators on the effective implementation of bid-based cost estimating, which is the most common estimating approach used by STAs. Accurate and reliable estimates are required to effectively support STAs' planning and investment decisions. Thus, poor implementation of this cost estimating approach could potentially lead to an inefficient use of public resources. The research efforts presented in this report are intended to help the Alabama Department of Transportation (ALDOT) overcome this issue by proposing a bid-based cost estimating system that facilitates the leverage of available historical bid data to maximize estimating effectiveness.

The proposed system integrates various statistical and data analytics techniques intended to model the cost impacts of four different factors on transportation projects in Alabama: 1) project scale, 2) time, 3) location, and 4) estimating uncertainty. The influence of *project scale* on construction costs is associated with the economies of scale principle. According to this principle, lower unit prices should be expected from larger quantities of work since applicable fixed costs can be distributed among a greater number of work units. This quantity-unit price relationship was modeled in this study using non-linear regression equations at the pay item level.

The *time* factor in this study is associated with two issues that arise when old data is used to estimate current prices. The first issue is the determination of an optimal number of years of historical data that should be used in bid-based estimating. This report includes a methodology to assist ALDOT in the effective determination of look-back periods. It consists of an innovative Moving-Window Cross-Validation (MWCV) approach designed to measure the estimating performance of the system under different look-back periods ranging from one to five years. This iterative process allows for the identification of the optimal amount of historical data that would maximize estimating effectiveness.

Defining an optimal look-back period is a critical aspect of bid-based cost estimating. However, it still does not address that fact that old data is being used to estimate current prices. Cost estimating systems based on historical data may be more effective at estimating prices for projects in the past and less effective for current projects. This is the second time-related issue identified and addressed in this study. This issue was tackled using construction cost indexes (CCIs) to adjust bid-based estimates according to observed fluctuations in construction prices. A total of 20 cost indexing alternatives were evaluated to find the one that offers the best estimating accuracy and reliability.

The *location* factor refers to the fact that different geographic conditions bring different types of challenges and project requirements. Therefore, different prices could be expected for the same type of work or construction activity in different geographic locations. A location cost index (LCI) has been developed in this study to compare construction prices across three different regions in

Alabama (north, central, and south) and to adjust cost estimates according to their respective geographic location.

The last cost-influencing factor considered in the proposed system, estimating uncertainty, refers to the quantification of the unavoidable uncertainty inherent in construction cost estimating. This factor was incorporated via probabilistic analysis to convert traditional deterministic estimates into risk-based cost estimates. A risk-based estimate, as defined in this study, is assumed to represent all possible cost scenarios, and their probability of occurrence, in the form of a probability distribution function. This type of estimate allows agencies to make estimating decisions under different levels of risk.

The study was conducted with historical bid data provided by ALDOT for all projects awarded between 2006 and 2016 (over 3,600 projects). The report illustrates the application of the proposed cost estimating system and validates its effectiveness using a pay item frequently included in ALDOT's construction contracts. The implementation and validation processes are presented in a detailed manner so that it can be repeated for other pay items. The selected case study item is the hot mixed asphalt pay item most commonly used by ALDOT (Item ID 424A360). This is considered by the authors as the most relevant pay item used by this agency in terms of frequency of use and dollar expenditure.

Finally, the results from the case study item were analyzed to determine the level of effectiveness of the cost estimating system. Effective cost estimating is defined in this study as the capacity of STAs to maximize estimating accuracy and reliability, with accuracy referring to a measure of central tendency among observed estimating errors, and reliability being the degree to which the system yields a sustained level of accuracy across all projects. The MWCV approach was not only used to define an optimal look-back period, but also to quantify the improvement in estimating effectiveness offered by each of the four cost-influencing factors. The validation process, via statistical testing, revealed that each factor, if appropriately incorporated into the estimating process, has the potential to significantly improve cost estimating effectiveness.

Additional research validation efforts were performed to compare the proposed system against ALDOT's current cost estimating practices, revealing an improvement in estimating reliability when using the system presented in this report to estimate unit prices for the case study item. However, this improvement in reliability was not found to be statistically significant. On the other hand, the proposed system was significantly superior in terms of accuracy, with an overall improvement in estimating accuracy of 15% with respect to ALDOT's current practices. These results are very promising when considering that observed improvements were obtained by processing only data extracted from ALDOT's bid tabulations. There is great potential for further improvement through the integration of the proposed system with the experience and knowledge of ALDOT's estimators. This integration could help to refine the system through a better understanding of major cost-influencing factors, as well as through the potential identification of additional factors that could be modeled and incorporated into the cost estimating process.

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LIST OF ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation
ALDOT	Alabama Department of Transportation
ANOVA	Analysis of Variance
APE	Absolute Percentage Error
BCI	Building Cost Index
CCIs	Construction Cost Indexes
CV	Cross Validation
EDA	Exploratory Data Analysis
ENR	Engineering News Record
FHWA	Federal Highway Administration
LAPV	Largest Average Price Validation
LCI	Location Cost Index
MAD	Median Absolute Deviation
MAPE	Mean Absolute Percentage Error
MCCI	Multilevel Construction Cost Index
MDT	Montana Department of Transportation
MnDOT	Minnesota Department of Transportation
MWCV	Moving-Window Cross-Validation
ROUT	Robust Regression and Outlier Removal Method
STAs	State Transportation Agencies
WSDOT	Washington State Department of Transportation

CHAPTER 1: INTRODUCTION AND BACKGROUND

1.1 Introduction

The U.S. transportation infrastructure network includes over four million miles of roads, from interstates to residential streets (ASCE, 2017). "In 2016 alone, U.S. roads carried people and goods over 3.2 trillion miles –or more than 300 round trips between Earth and Pluto" (ASCE, 2017), making it one of the most critical national infrastructure elements. State transportation agencies (STAs) play a key role in the planning, design, construction, operation, and maintenance of the highway network in the U.S. These duties and responsibilities are carried out with funding coming from various sources, including federal-aid programs and vehicle fuel taxes and registration fees collected at the state and federal level (Iowa DOT, 2017). The American Society of Civil Engineers (ASCE) estimates that in 2014, federal and state governments spent over $160 billion updating, operating, and maintaining the highway infrastructure system. Even though it may look like a massive investment in public infrastructure, the same study revealed that such levels of investment are not sufficient to satisfy the current needs of the national highway network. "The U.S. has been underfunding its highway system for years, resulting in an $836 billion backlog of highway and bridge capital needs" (ASCE, 2017).

This underfunding situation is one of the main causes of the rapidly deteriorating transportation infrastructure network and is affecting taxpayers in several ways, including increased vehicle operating costs, longer commute times, higher crash and traffic fatality rates, and increased pollution due to the longer commutes (Miller and Gransberg, 2014; ASCE, 2017). The increasing gap between available and needed funding is also affecting STAs ability to guarantee an optimal use of their limited available resources. The ability of STAs to offer the best value for taxpayers' money depends, in part, on the effectiveness of their cost estimating systems. Sound estimates of the expected costs of addressing current and foreseen infrastructure needs facilitate an effective allocation of resources through reliable cost-benefit analyses.

As a contingency measure to mitigate the impact of the unavoidable, increasing funding gap, STAs have been intensifying their efforts towards the improvement of cost estimating practices. This report is contributing to those efforts by proposing a methodology to improve what has become the estimating approach most commonly used by STAs: historical bid-based cost estimating (AASHTO 2013).

Bid-based estimating refers to the use of bid data from previously awarded projects to estimate unit prices for current or future projects (AASHTO 2013). Previous research has found that this estimating approach is used to some extent by all STAs (Anderson et al. 2009; Schexnayder et al. 2003). The Practical Guide to Cost Estimating, published by the American Association of State Highway and Transportation Officials (AASHTO) (2013), provides some guidance on the preparation of bid-based cost estimates. However, these guidelines are not presented at the level of detail required to effectively guide STAs on the implementation of bid-based cost estimating systems. This lack of guidance is preventing STAs from taking full advantage of their vast databases to improve their cost estimating practices. This report is aimed to guide the Alabama Department of Transportation (ALDOT) on the use of a cost estimating framework designed to exploit the unused potential of its historical bid data as a means to improve cost estimating accuracy and reliability.

The proposed bid-based cost estimating system integrates various statistical and data analytics techniques, including advanced data cleaning procedures, non-linear regression modeling, time series analysis, and various statistical significance tests. The system has been designed to account for the impact of four key cost-influencing factors in the estimation of construction costs of transportation projects in Alabama. These factors are: 1) project scale, 2) time, 3) location, and 4) estimating uncertainty. The proposed system produces a deterministic cost estimate after assessing scale, time, and location impacts (the first three factors). The fourth factor is then used to convert the deterministic estimate into a risk-based cost estimate using the distribution of percentage errors obtained during the validation of the deterministic process. A risk-based estimate, as defined in this study, consists of a range of possible construction cost values with their respective probability of occurrence. Risk-based estimates are represented by probability distribution functions that facilitate decision-making under different levels of risk.

The study was conducted with historical data extracted from ALDOT's bid tabulations for all projects awarded between 2006 and 2016 (over 3,600 projects in eleven years). The report illustrates the application of the proposed cost estimating system and validates its effectiveness using a pay item frequently found in ALDOT's construction contracts. The application of the system on the selected case study item is presented in a step-by-step fashion and with a sufficient level of detail to facilitate its eventual application on other pay items. The case study item (Item ID 424A360) is considered by the authors as the most relevant pay item used in ALDOT's construction projects in terms of frequency of use and dollars expenditure. This is a hot mixed asphalt pay item defined in ALDOT's contracts as a superpave bituminous concrete wearing surface layer with a maximum aggregate size of 1/2". The system is used to estimate unit prices for this item on a tonnage basis, including the cost for "all materials, procurement, handling, hauling, and processing cost, […] all equipment, tools, labor, and incidentals required to complete the work" (ALDOT 2018).

Finally, a three-part research validation process was implemented to assess the performance of the proposed cost estimating system when applied to the case study item. The following is a brief description of each of the three parts of the validation process:

- <u>*Research Validation Part 1*</u> is aimed to assess the estimating improvement offered by each of the first three cost-influencing factors in the generation of *deterministic* cost estimates. This assessment is performed using an innovative Moving-Window Cross Validation (MWCV) algorithm. Part 1 also allows estimators to determine the optimal amount of years of historical bid data that should be used to maximize estimating effectiveness. Results from

Part 1 are used in the other two parts of the validation process to compare the performance of the proposed methodology against ALDOT's current cost estimating system.

- Research Validation Part 2 is conducted to compare the overall *deterministic* performance of the proposed cost estimating system, with the first three factors and the look-back period identified in Part 1, against ALDOT's current cost estimating practices.
- Research Validation Part 3 is intended to compare the overall *stochastic* performance of the proposed cost estimating system against ALDOT's current cost estimating practices. In other words, Part 3 is intended to test the performance of the risk-based cost estimates obtained with the system against ALDOT's cost estimate ranges.

When applied to the case study item, all three parts of the validation process yielded positive results in favor of the proposed bid-based cost estimating system, demonstrating that ALDOT's current cost estimating practices could still be significantly improved through an appropriate utilization of its historical bid data. The fact that these positive results were obtained by processing only data provided in ALDOT's bid tabulations suggests that there is still considerable room for improvement if other sources of project-specific information are considered and if the experience and empirical knowledge of ALDOT's estimators are used to refine the system.

The following sections in this chapter present some relevant background information intended to facilitate the understanding of this report and summarize the research objectives that motivated this study.

1.2 Alabama Department of Transportation – Facts and Funding

Alabama has over 102,000 miles of public roads. This number includes all types of roads; freeways, arterials, collectors, local roads, and neighborhood streets (ASCE, 2017). The ASCE estimates that about 60% of all travel miles in Alabama occur on the 11,000 miles of federal and state highways operated and maintained by ALDOT (ASCE 2017; ASCE 2015). A study conducted by ALDOT in 2014 revealed that only 51% of these 11,000 miles can be considered to be in good condition, while 40% were rated as fair, and the remaining 9% as poor or very poor (ASCE, 2015). A report published in 2016 by TRIP, a nonprofit national transportation research group, shows that the percentage of roads in poor and very poor condition increased from 9% to 11% during a two-year period of time (TRIP, 2016). The TRIP's study also estimates that deficient roads are costing Alabama motorists about $1.5 billion a year in extra vehicle operating costs and repairs. This number does not include the additional almost $2 billion a year due to motor vehicle crashes and congestion costs (ASCE, 2015).

ALDOT's current funding situation, and the condition of its infrastructure assets, is not very different from the current situation of the other STAs nationwide. STAs across the country are currently looking for strategies that allow them to maintain the expanding highway network with a shrinking funding stream (Taylor and Maloney 2013). In view of the lack of sufficient funding, ALDOT has been modifying its resource allocation strategies to spend less to make needed improvements, and more to maintain existing roads and bridges open and in acceptable condition (ASCE, 2015). “Without an increase in funding, Alabama will no longer be able to make needed improvements and is facing significant impacts to highway conditions and safety and risks losing economic development opportunities in the future” (ASCE, 2015). Unfortunately, there is little ALDOT can do to increase its funding stream. ALDOT’s budget is built with funding from multiple federal, state, local sources (ALDOT, 2015). Federal and state gasoline and diesel taxes are the main sources of transportation funding. These taxes are collected as a fixed-rate for every gallon of fuel purchased. The federal gas tax rate has not increased since 1993 (ASCE, 2015). On the other hand, in March 2019, the Alabama State Legislature approved the Rebuild Alabama Act, which included an increase of 10 cents in the state gas tax. This is the first increase in the Alabama gas tax since 1992 (ASCE, 2015). This means that the government has collected exactly the same amount of cents on every gallon of fuel purchased for more than 25 years, a situation recognized in the literature as one of the main causes of the increasing funding gap (Miller, 2015). Although the recent increase in the state gas tax will definitely contribute to reducing the funding gap, it is not expected to fully address the backlog of existing transportation infrastructure needs in Alabama.

Recognizing their funding constraints, and their limited ability to increase their funding capacity, STAs have been investing efforts in the optimization of their resource management systems to ensure that their shrinking budgets are effectively invested to maintain the transportation infrastructure system in the best possible condition with the available resources. Effective resource management systems count with reliable procedures to prioritize infrastructure needs based on cost-benefit analyses, which rely on the effectiveness of STAs’ cost estimating practices. This is how the methodology proposed in this report will contribute to improving ALDOT’s budget control and management capabilities –by facilitating a more effective use of ALDOT’s historical bid data to produce better construction cost estimates.

1.3 Challenges in Construction Cost Estimating

In project management, a project is defined as a “temporary endeavor undertaken to create a unique product, service, or result” (PMI 2013), and these endeavors usually demand the consumption of different types of resources (i.e., money, time, materials, and labor/equipment hours). Under this definition, cost estimating is the process used to predict the required amount of a specific type of resource: money. The required amount of money is associated with the required quantities for other resources. Higher costs are expected from larger projects that require a significant consumption of materials and labor/equipment hours.

Cost estimating processes are used in all industries and businesses, not only on construction projects. However, unlike other industries, a single construction owner or contractor might need to manage a highly diversified project portfolio in terms of project-specific scopes, designs, and requirements. Each construction project is characterized by a unique combination of several factors, including project objectives, deliverables, location, environmental requirements, technical complexity, etc. This uniqueness, and the fact that it is virtually impossible to accurately quantify the impacts of all these factors on a project, makes construction cost estimating a particularly challenging process.

From a construction owner's perspective, cost estimates are commonly used to define the project scope, to determine whether or not a project should proceed, and to allocate the required funds for its completion (AASHTO 2013). On the other hand, a construction contractor may use cost estimates to assess its financial capacity to undertake a given project and to prepare a bid for an owner. In both cases, cost estimates are basically used for risk assessment purposes, to support business decisions, and to maximize returns from project portfolios. Thus, effective cost estimating could be translated into effective decision-making and greater returns for owners or contractors (Fakültesi and Zeynep 2004; Arafa and Alqedra 2011; Byrnes 2002).

The selection of projects for funding is becoming more challenging for STAs due to the increasing gap between available resources and those actually required to maintain the national transportation infrastructure in optimal conditions. This situation is demanding more effective resource allocation and cost estimating practices by transportation public owners. The 2013 Report Card for America's Infrastructure (ASCE 2013), published by the U.S. Society of Civil Engineers (ASCE), estimates that "32 percent of America's major roads are in poor or mediocre condition, costing U.S. motorists more than $67 billion a year […] in additional repairs and operating costs." The same study has found that about $170 billion should be invested annually to improve the current conditions and performance of all roads and bridges across the country by 2028. However, only $91 billion is currently being assigned for this purpose (ASCE 2013). The evident growth in this gap during the last two decades led to the enactment of the Moving Ahead for Progress in the 21st Century Act (MAP-21), through which the federal government allocated over $105 billion to surface transportation programs (U.S. Congress 2012). To ensure the best value for taxpayers' money, and recognizing the limitations of traditional deterministic cost estimating practices, MAP-21 also requires STAs to develop and implement better cost estimating and risk control strategies (U.S. Congress 2012) such as the bid-based cost estimating system presented in this report.

1.4 Factors Influencing Construction Cost Estimating

The main challenges faced by STAs in their efforts to produce effective cost estimates are associated with their capacity to identify, understand, and model the impacts of cost-influencing factors. Thus, one of the first steps in this study was to conduct a literature search to identify key factors impacting the effectiveness of cost estimating practices in the transportation construction industry. Project scale, time, geographic location, and estimating uncertainty are identified in the literature as major cost-influencing factors. Those are also the factors considered in this report. Those four factors, and the approaches used to include them in the proposed methodology, are described in the following subsections.

1.4.1 Project Scale

Project scale refers to the size of the project, which is usually reflected in the project budget, schedule, physical dimensions, and overall consumption of resources (Odeck 2004). It is usually assumed that larger projects have higher costs. Although this is a valid assumption, the relationship between these two parameters is not linear. The relationship between project scale and unit prices is defined by the concept of economies of scale (Akintoye 2000). "Economies of scale refers to a reduction in total cost per unit as output increases" (Betts 2007). The higher the quantities of work, the lower the unit price (Zhang and Sun 2007; Akintoye 2000).

Figure 1.1 illustrates the concept of economies of scale using unit prices for the case study item in bids received by ALDOT between 2012 and 2016. As shown in this figure, the quantity-unit price relationship for this item can be modeled using a non-linear regression equation. This type of model is actually how this study incorporated the project scale into the proposed cost estimating system. A detailed description of the non-linear regression models developed in this study is presented in Chapter 3 of this report.

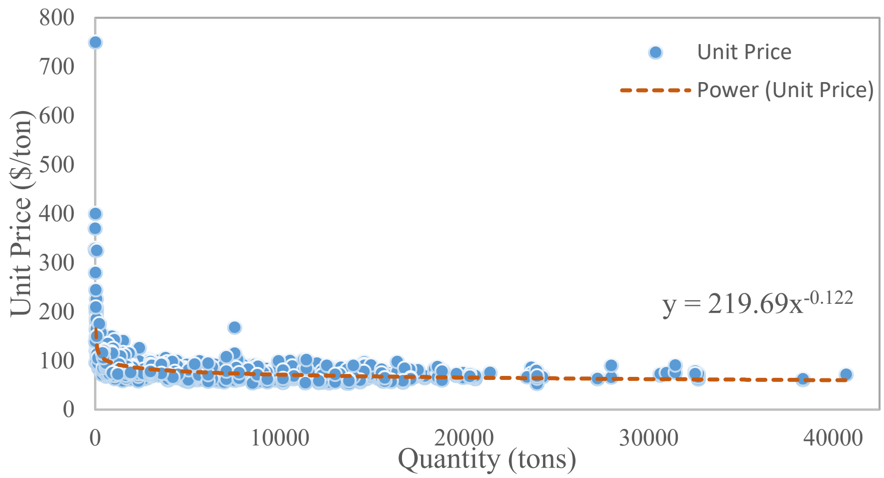


Figure 1.1 Quantity and unit price relationship for case study item (Item ID 424A360).

1.4.2 Time

The ability to track changes in the construction market over time is a major challenge faced by STA estimators (Shane et al. 2009). Fluctuations of construction prices may occur due to inflationary trends at industry or commodity-levels, changes in demand conditions of labor and materials, changes in interest rates, or seasonal effects (Xu and Moon 2011; Zou, Zhang, and Wang 2007). In the context of this study, the time factor is associated with the constant fluctuations of construction prices over time. The total cost of a given project today is not expected to be equal to the cost of the same project a year ago or next year. More specifically, the time factor is considered in this study to answer two questions that arise when data from old projects are used to produce cost estimates for current projects:

1. How much historical data should be used?

2. How can old prices be adjusted to reflect current construction market conditions?

The first question refers to the determination of the optimal number of years of historical data that should be used in bid-based estimating. When defining a look-back period for data retrieval in bid-based estimating, STAs usually face two conflicting requirements: 1) the amount of historical bid data must be large enough to allow for a valid and reliable statistical analysis; and 2) the historical bid data must be recent enough to effectively reflect current market conditions in the construction industry. The conflict between these two requirements lies in the fact that larger datasets can be obtained with longer look-back periods, but it implies the use of older data that could not effectively reflect current pricing trends. Thus, the look-back period should be long enough to include sufficient data to model price fluctuation trends, but not too long that older (and now irrelevant) trends do not affect estimating accuracy. This report includes a methodology to assist ALDOT in the effective determination of look-back periods. This methodology consists of an innovative MWCV approach designed to evaluate different possible look-back periods ranging from one to five years in order to identify the optimal amount of historical data that would offer the optimal cost estimating effectiveness.

The optimal look-back period must be identified before the actual implementation of the proposed cost estimating methodology on a given pay item. It indicates the amount of data that should be used to create the non-linear regression model used during system implementation. Knowing the optimal number of years of historical data that should be used in the regression models is a fundamental part of the proposed system. However, it still does not address that fact that old data is being used to estimate current prices. This fact refers to the second question stated above.

Cost estimating systems based on past data might be more effective at estimating prices for projects in the past and less effective for current projects. Ideally, bid-based estimates should be adjusted to represent current market conditions. This type of price adjustment over time is commonly done using construction cost indexes (CCIs) (Rueda 2016), which is the approach adopted in this study. A total of 20 CCIs are evaluated in this report in order to find the one that offers the best estimating accuracy and reliability for the case study item. The selected CCI is then used to bring unit prices from the non-linear regression models into current dollars. The 20 indexing alternatives evaluated by the authors include twelve different CCIs developed in this study using ALDOT's historical data and eight existing CCIs currently used in the construction industry.

It should be noted that in the context of this study the time factor does not refer to the duration of construction projects. Even though the research team recognizes that the duration of a project has some impact on its cost, the study assumes that project duration is directly proportional to the project scale. Therefore, it can be said that this factor (project duration) has already been accounted for by the project scale factor. However, future research should evaluate the impact of project duration on ALDOT's construction costs since this impact might not be fully accounted for through the assessment of the project scale factor.

1.4.3 Location

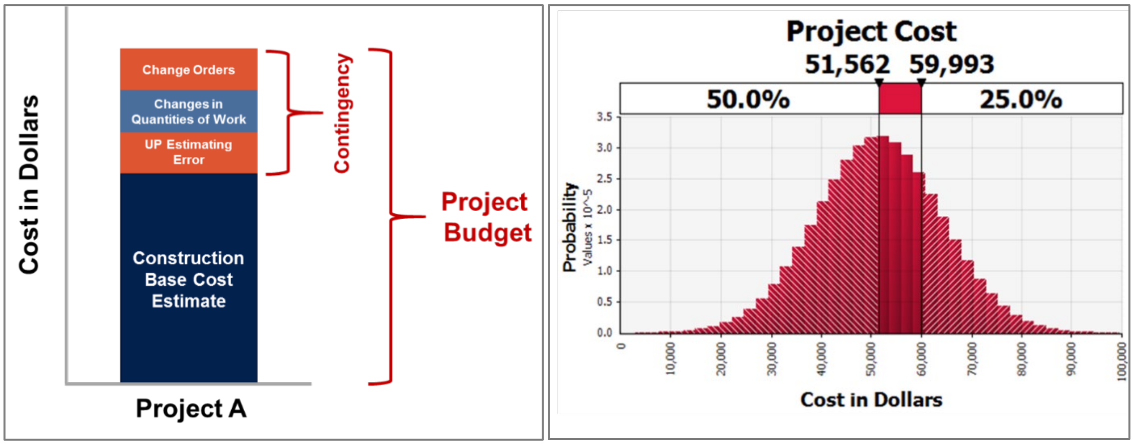
Different geographic locations bring different challenges and project requirements. Therefore, different prices could be expected for the same type of work or commodity in different locations. Price variability across the country and at the state level depends on multiple factors including local climate and geological conditions, availability of qualified local labor, suppliers, and subcontractors, and local applicable regulations (Akanni, Oke, and Akpomiemie 2015; Cuervo and Sui 2003; Kaming et al. 1997). Traffic characteristics at the jobsite also affect costs in transportation construction projects since those dictate the strictness or laxity of traffic control requirements, increasing or reducing construction costs.

The location factor has been addressed in this study by developing a location cost index (LCI) for the case study item. This index was developed by dividing the state of Alabama into three different regions: north, central, and south. The process to develop the LCI is described in Chapters 3 of this report.

1.4.4 Estimating Uncertainty

Traditional deterministic cost estimating practices have shown to have a limited capacity to cope with the current needs of the transportation construction industry since they fail to objectively account for the unavoidable and increasing uncertainty associated with the development of cost estimates. In an attempt to quantify this uncertainty, some STAs have already developed and implemented data-driven systems that produce risk-based estimates on a per project basis. These agencies include the STAs in Florida, Colorado, Washington State, Nevada, New Jersey, and Texas. A risk-based cost estimate is a range of possible construction costs with their respective probabilities of occurrence (ASCE 2013). These estimates are usually represented by probability distribution functions that allow STAs to make better estimating decisions under different confidence levels. In this study, deterministic estimates are converted into probability distributions by multiplying the deterministic value by a distribution of percentage errors obtained during Part 1 of the validation process. A detailed description of the development of risk-based estimates is presented in Chapter 3.

Figure 1.2 shows an example of a risk-based estimate for a given project. Using the probability distribution from Figure 1.2 (b), an agency could decide to set a base cost estimate of $51,600 for this project plus a contingency of $8,400 ($59,993 - $51,562 ≈ $8,400) if a 75% confidence level is desired. It means that the agency would be 75% confident of having enough funds to complete the project. The base cost estimate in this example corresponds to the 50% confidence level. Risk-based estimates provide STAs with great flexibility to establish risk tolerance levels based on the specifics of each project. The budget contingency is intended to account for the uncertainty associated with unit price estimating errors, changes in quantities of work, and other variations in project costs due to potential change orders issued by the agency. Given that this study was conducted using historical bid data, the risk-based estimates presented later in this report only represent possible bid prices to be submitted by the winning contractor. These estimates do not correspond to expected costs at project completion. However, future research efforts to refine the proposed system should analyze the impact of change orders issued by ALDOT during the construction of previous projects, as well as historical discrepancies between planned and actual quantities of work in order to produce risk-based estimates for total construction costs at project completion.



(a) (b)

Figure 1.2 Risk-based cost estimate – Example.

1.5 Bid-Based Cost Estimating

"There is a growing data torrent such that managers and potential users are 'drowning in data while thirsting for knowledge'" (Woldesenbet, 2014). With this sentence, Woldesenbet is referring to the fact that public agencies have been spending a considerable amount of resources to collect, clean, and store large amounts of different types of data, but they lack the tools and skills to process this data into meaningful knowledge that could be exploited to improve various types of procedures undertaken by these agencies. The unused potential of existing STAs' data could help to optimize procedures in virtually all management areas, including construction cost estimating.

The use of historical bid data to estimate costs for current and future projects is not a new practice in the transportation construction industry. It has been used for decades and has become the most commonly used estimating approach among STAs (Anderson et al. 2009; Schexnayder et al. 2003). However, it does not mean this is a mature approach that has been successfully refined over the years. Unfortunately, there is not much guidance for STAs on how to develop, implement, and update bid-based cost estimating systems, which often leads to an inefficient use of public resources due to a "trial and error" approach. Likewise, most STAs have not taken full advantage of the advanced data processing technologies and procedures available today (Woldesenbet, 2014).

1.6 Effective Construction Cost Estimating

This study has evaluated and modeled the impact of four key cost-influencing factors. Although these four factors account for most of the variability in construction cost estimating, there are still several other internal and external factors that are virtually impossible to identify and/or model.

Nonetheless, it would be unreasonable to condition effective cost estimating to perfect accuracy. Effective cost estimating is defined in this study as the capacity of STAs to maximize estimating accuracy and reliability. The validation process in this report was focused on the assessment of these two effectiveness parameters by applying the proposed system to a group of projects (hereinafter referred to as testing projects) for which actual bid prices are known. This allowed for a comparison between actual and estimated values.

Accuracy is usually a measure of central tendency such as mean, median, and mode values. This parameter is defined in this report as the degree to which the system truly measures what it is intended to measure. The level of accuracy in a unit price estimated with the proposed system is given by the absolute percentage error (APE) calculated as shown in Equation 1.1. Equation 1.2 is then used to determine the overall accuracy of the system by averaging the APEs of all testing projects. This is called the mean absolute percentage error (MAPE). MAPE values are commonly used in the cost estimating literature to measure and compare accuracy levels between cost estimating models (Gardner 2015).

$$APE = \frac{|A_i - E_i|}{A_i} \times 100\% \qquad \textbf{Eq. 1.1}$$

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|A_i - E_i|}{A_i}}{n} \times 100\% \qquad \textbf{Eq. 1.2}$$

Where: APE = Absolute Percentage Error

MAPE = Mean Absolute Percentage Error

A_i = Actual unit price for intended item in testing project i

E_i = Estimated unit price for intended item in testing project i

n = Number of testing projects

In quantitative modeling, reliability refers to the degree of consistency in the model's outputs (Golafshani 2003). In the context of this study, reliability is the degree to which the proposed cost estimating system consistently yields similar APEs every time it is used. Reliability represents the amount of variability in APE values and is measured in this study as the standard deviation of APEs across testing projects.

The concepts of accuracy and reliability are relative to the type of estimate and project phase during which they are produced. While conceptual estimates performed early in the planning phase are expected to have an accuracy between -50% and +200%, detailed construction cost estimates at design completion tend to be significantly more accurate with errors ranging between -5% and +10% (AASHTO 2013). It should be noted that the cost estimating approach presented in this report is intended to be applied at the pay item level and at design completion, or as soon as the bid quantity for the intended item is known.

1.7 Development of Proposed Bid-Based Cost Estimating System – Overview

Figure 1.3 is a simplified representation of the process that ALDOT should follow to get the bid-based cost estimating system ready for implementation.

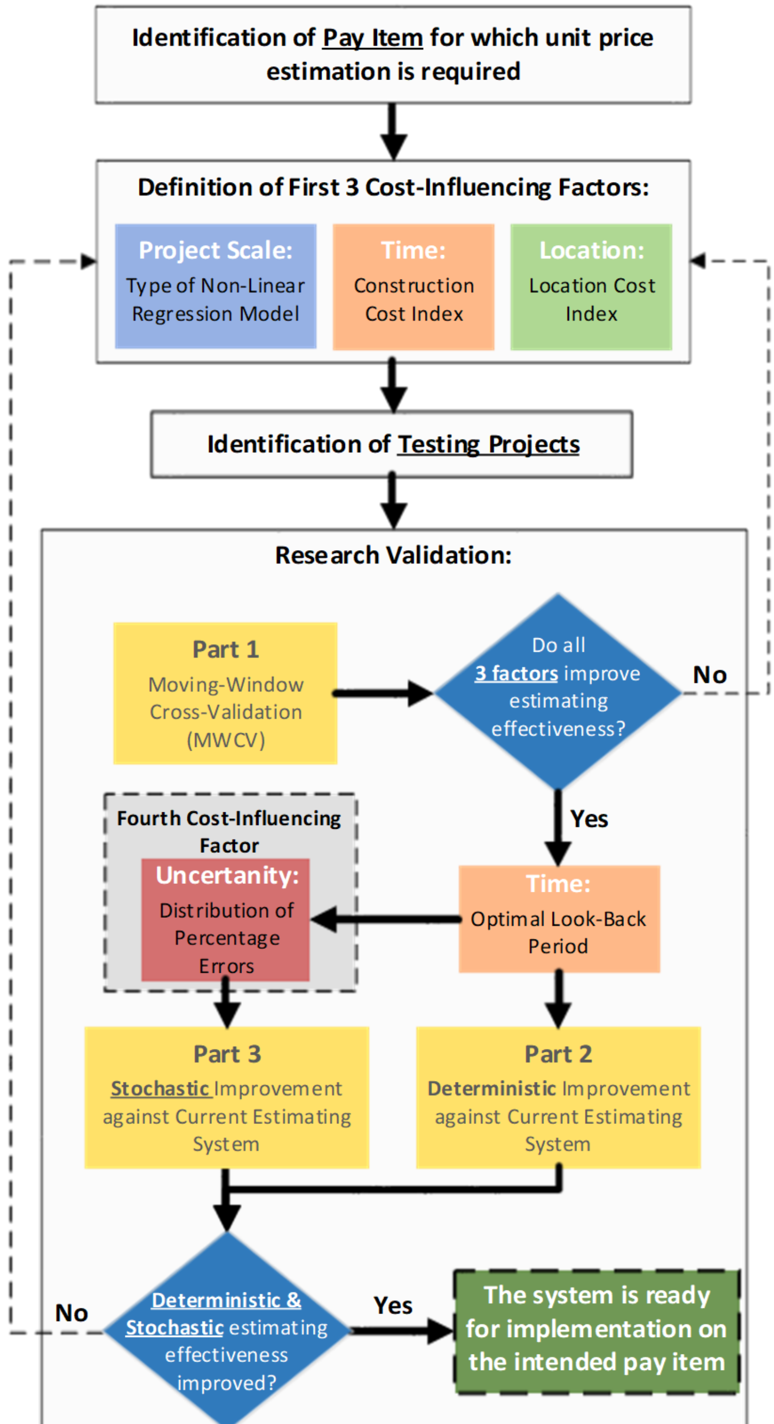


Figure 1.3 Development of proposed bid-based cost estimating system.

The process illustrated in this figure must be repeated for every pay item to be incorporated into the system. This section briefly summarizes the steps of this process, but they are explained in more detail throughout this report as they are applied to the case study item.After identifying a pay item to be added to the system, the next step in the process shown in Figure 1.3 is to define the elements required to account for the impact of the first three cost-influencing factors. To model the project scale impact, it is necessary to identify the type of non-linear regression model that reasonably explains the quantity-unit price relationship for the item under consideration. On the other hand, suitable construction and location cost indexes (CCI and LCI) must be selected/developed to incorporate the time and location factors into the system. As explained earlier in this chapter (Section 1.4.2), there are two elements associated with the time factor; however, only one, the CCI, is required at this early stage. The second time-related element, the optimal look-back period, is actually a byproduct of the MWCV in the first part of the research validation process. Once the elements for each factor are defined, their performance is assessed through the three-part research validation, but it is first necessary to identify the testing projects to be used to quantify the estimating effectiveness of the system. Guidelines on the selection of testing projects are provided in Chapter 3 of this report.

Part 1 of the validation process corresponds to the proposed MWCV algorithm. It is intended to determine if each of the three input elements is actually contributing to the overall improvement in estimating accuracy and reliability at the deterministic level. After the contribution to estimating effectiveness offered by each input is demonstrated, Parts 2 and 3 of validation are used to compare the performance of the proposed methodology against ALDOT's current cost estimating system, at the deterministic and stochastic level, respectively. A detailed description of the three-part validation process is provided in Chapter 4 of this report.

If the deterministic and risk-based estimates produced with the proposed system show higher accuracy and reliability than those developed by ALDOT for the same item, it can be concluded that the system offers an effective performance for the intended pay item. Therefore, the system is ready for implementation on that specific pay item.

1.8 Research Objectives

The main objective of this study is to determine if an appropriate processing and analysis of historical bid data would improve the effectiveness of ALDOT's construction cost estimating practices while allowing for the development of reliable risk-based cost estimates. The following sub-objectives have been identified as necessary steps to accomplish the main research objective:

- Identify major cost-influencing factors in the transportation construction industry, and assess and model the relationship between each factor and construction prices paid by ALDOT.

- Design and develop a system that integrates the impacts of all cost-influencing factors in an attempt to maximize cost estimating accuracy and reliability in ALDOT's construction projects.
- Develop and implement a reliable research validation approach to demonstrate the effectiveness of the proposed cost estimating methodology.

1.9 Organization of the Report

This report has been organized intofive chapters, as follows:

Chapter 1: Introduction and Background, describes the research problem that motivated this study, summarizes the fundamentals of bid-based cost estimating, and presents the main research objectives.

Chapter 2: Literature Review, summarizes the existing literature on cost estimating, including previous studies and research reports. This chapter explains the cost estimating process across project development phases. It describes the different cost estimating approaches currently used by STAs, paying particular attention to bid-based and risk-based cost estimating, which are the primary concern of this study.

Chapter 3: Research Approach, describes the research plan that led to the development of the cost estimating methodology proposed in this study. The research plan is presented in detail, describing all research procedures and tools used to develop and validate the proposed methodology. Chapter 3 also describes the data analytics and statistical techniques used to model the impacts of the four cost-influencing factors on prices paid by ALDOT for the case study item. This chapter ends with the framework designed to integrate all identified factors to produce both deterministic and risk-based cost estimates.

Chapter 4: Development and Validation of Stochastic Bid-based Cost Estimating System, discusses the process to develop the proposed bid-based cost estimating and presents and analyzes the results from the three-part research validation approach designed to demonstrate the effectiveness of the proposed methodology at the deterministic and stochastic level.

Chapter 5: Conclusions and Recommendations, summarizes the main conclusions, findings, and contributions to the body of knowledge made by this study and discusses the limitations. Finally, this chapter outlines some limitations associated with the research findings presented in this report and recommends some research topics that should be considered to further explore and develop this study's findings and contributions.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

Cost estimating is critical at any project phase, from conceptual design and planning to the operation and maintenance of infrastructure assets. The estimation of construction costs may be a complex process involving a number of challenges. It seems that it was not until the mid-1960s that these challenges started to be addressed through formal research. From 1965 onwards, there has been an exponential increase in research conducted on how to develop better and more effective cost estimating systems at all project phases (Trost and Oberlender 2003).

Even though there is a great variety in the configuration and definition of project life cycle phases among STAs, in general, a construction project can be represented as a sequence of three phases: conceptual, engineering/design, and execution (Phaobunjong 2002). Each phase poses different estimating challenges and requirements. With the amount of project-specific information constantly increasing while a project moves from conception to project completion, the estimator's understanding of the project also increases allowing for better cost estimating effectiveness (Manfredonia 2016). Figure 2.1 shows the classification of construction cost estimates based on the three generic project phases.

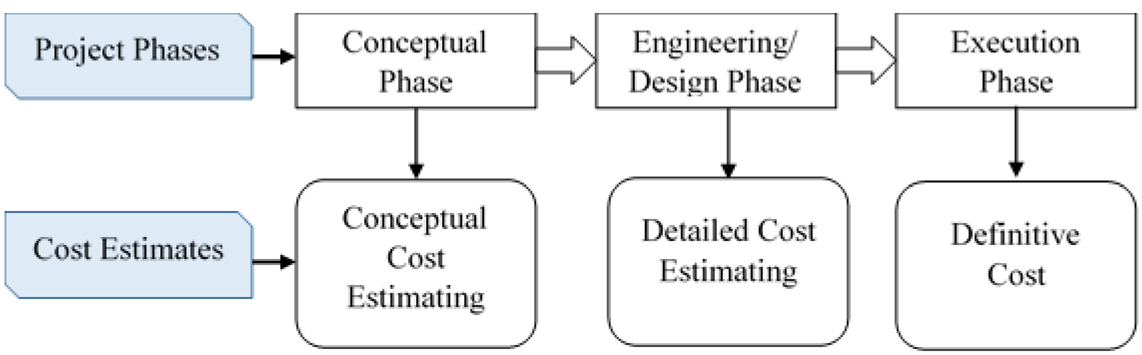


Figure 2.1 Construction cost estimating phases (Adapted from Manfredonia 2016).

First, a conceptual cost estimate is developed during the early stages of project development. Since this is an early estimate, it is usually calculated with little information and with a roughly defined scope of work. Conceptual estimates are expected to be the most inaccurate among all estimates developed along the life cycle of construction projects (Phaobunjong 2002). Despite their low accuracy, conceptual estimates are highly necessary to determine the financial viability of candidate projects, to define feasible scopes of work, and to support other strategic business decisions (Liu and Zhu 2007). These estimates are used by both owners and contractors to design project portfolios that match their financial capabilities, as well as to quickly compare the cost implications associated with different construction methods and materials (Manfredonia 2016). The lack of project-specific information at this early phase makes it hard for estimators to produce effective cost estimates (Kim, An, and Kang 2004); however, the existing literature provides a number of tools and methodologies to aid STAs on this matter (Fragkakis et al. 2010; Asmar et al. 2011; Juszczyk 2013; Sonmez 2004; Phaobunjong 2002).

A detailed cost estimate is then developed by the end of the engineering/design phase or at the completion of design work. This estimate is based on a detailed design for a well-defined scope of work, and depending on the type of contract being awarded, it is also based on the anticipated construction methods and materials, schedule constraints, required milestones, and deliverables (among other project-specific characteristics). Due to the detailed project-specific information available at this phase, detailed cost estimates are expected to be considerably more accurate than conceptual estimates (Phaobunjong 2002; Manfredonia 2016). This is the last estimating attempt made by owners before awarding a contract. This is commonly used to verify if the intended project is still feasible and to make any necessary adjustments to the project budget (AASHTO 2013). These estimates are also intended to serve as a point of reference during potential price negotiations with contractors.

Finally, the execution phase begins when the contract is awarded. The definitive cost estimate at this phase is given by the price proposal submitted by the selected contractor and/or any price negotiations held between the owner and the contractor before signing the contract. It is also referred to as the actual contracted price. This estimate is usually compared against the previously developed detailed estimate to determine if further budget adjustments are required (Manfredonia 2016; Phaobunjong 2002). The contracted price is used for payment purposes and to monitor the financial status of the project throughout the construction period (Hendrickson and Au 1989).

After the conceptual estimate, subsequent estimates are usually built using the previous cost estimate as the starting point (Hendrickson and Au 1989). Thus, each subsequent estimate can be considered as a revised version of the previous one, with the revision occurring in the light of the additional information that became available in between phases. It must be noted that all three types of estimates described in this section are equally important at their respective phases.

Cost estimates developed with the system proposed in this study fall within the detailed estimating category. The system is aimed to be applied at design completion, or as soon as the expected quantity of work to be delivered by the selected contractor is known.

2.2 Cost Estimating Approaches Currently used in Transportation Projects

This section discusses four different cost estimating approaches outlined by the American Association of State Highway and Transportation Officials (AASHTO) in its Practical Guide to Cost Estimating (2013): 1) parametric, 2) bid-based, 3) cost-based, and 4) risk-based estimating. The AASHTO guidebook associates each of these estimating approaches with a different project development phase, as shown in Table 2.1. The four project development phases in Table 2.1 correspond to a more detailed configuration of the conceptual and engineering/design phases discussed in the previous section, which are also shown above in Figure 2.1. This table shows the level of project maturity at each project development phase as a percentage of all the planning and design work required to successfully award the contract. This table also shows the most suitable cost estimating approach at each phase with its respective expected estimating accuracy. Table 2.2 summarizes the main activities contained within each project development phase.

Table 2.1 Cost Estimating Classification (Adapted from AASHTO 2013)

Project Development Phase	Project Maturity (% project definition completed)	Estimating Approach		Estimating Accuracy
Planning	0% to 2%	Parametric	Risk-Based (optional combination with other approaches)	-50% to +200%
	1% to 15%	Parametric or Historical Bid-Based		-40% to +100%
Scoping	10% to 30%	Historical Bid-Based or Cost-Based		-30% to +50%
Design	30% to 90%			-10% to +25%
Final Design	90% to 100%			-5% to +10%

Table 2.2 Project Development Phases and Typical Activities (Adapted from AASHTO 2013)

Project Development Phase	Typical Activities
Planning	Purpose and need; improvement or requirement studies; environmental considerations; right-of-way considerations; schematic development; project benefit/cost feasibility; public involvement/participation; interagency conditions.
Scoping	Environmental analysis; alternative analysis; preferred alternative selection; public hearings; right-of-way impact; environmental clearance; design criteria and parameters; funding authorization (programming).
Design	Right-of-way development and acquisition; preliminary plans for geometric alignments; preliminary bridge layouts; surveys/utility locations/drainage.
Final Design	Plans, specifications, and estimate (PS&E) development—final right-of-way acquisition; final pavement and bridge design; traffic control plans; utility drawings; hydraulics studies/final drainage design; final cost estimates.

As mentioned before, the greater the level of project development, the more accurate and reliable the cost estimate. That explains the progressive accuracy improvement in Table 2.1. The risk-based estimating approach seems to be presented in the AASHTO guidebook as an optional version of the other three approaches. The following sections present a more detailed description of each of these cost estimating approaches.

2.2.1 Parametric Estimating

Parametric cost estimating techniques are usually applied during early project development in the planning phase and at a conceptual level. "Parametric estimating techniques are primarily used to support development of planning or early scoping phase estimates when minimal project definition is available. Statistical relationships or non-statistical ratios, or both, between historical data and other project parameters are used to calculate the cost of various items of work (i.e., center lane miles or square foot of bridge deck area)" (AASHTO 2013). The use of parametric estimating models has served as an alternative to the traditional expert-based approach (almost discontinued by STAs), in which conceptual cost estimates are solely the result of the estimator's subjective opinions built from previous construction experiences (Phaobunjong 2002). The expert-based approach may not appropriately account for the main factors influencing the cost estimating process if the estimator's experience does not match the scope of the intended project. As a data-driven approach, parametric cost estimating methods have added some needed objectivity to the development of conceptual estimates and have shown improvement in the estimating accuracy during early project phases (Trost and Oberlender 2003; Kwak and Watson 2005).

Parametric estimating models are usually straightforward, user-friendly models (Bajaj, Gransberg, and Grenz 2002). However, these models have a limited capacity to handle the high cost uncertainty levels during early project development phases. According to Harbuck (2002), the main sources of uncertainty in construction cost estimating are: 1) changes in the scope of work, 2) potential design changes, 3) errors in the calculation of quantities of work and unit costs, and 4) unforeseen site conditions. When considering the nature of these four uncertainty sources, it is easy to understand how difficult it could be for a STA to quantify their potential impacts on early cost estimates developed only with a preliminary scope of work.

2.2.2 Historical Bid-Based Estimates

As shown in Table 2.1, historical bid-based cost estimating could be used at all project development phases. This is actually recognized as the most common cost estimating approach currently used by STAs. This approach is used to some extent by all STAs (Anderson et al. 2009; Schexnayder et al. 2003). The AASHTO guidebook defines bid-based estimating as an approach that "uses data from recently let contracts as the basis for determining estimated unit prices for a future project" (AASHTO 2013). As per AASHTO guidelines, bid-based estimates are usually developed with data from projects awarded during the last one or two years. Longer look-back periods might be considered when the most recent two years of historical data do not provide sufficient relevant data. However, STAs do not count with a mechanism to make objective decisions on the length of look-back periods. The decision of whether to use one, two, or more years of data is mainly based on the subjective judgment of STA estimators.

An advantage of bid-based estimating over the other estimating approaches is that the former requires less previous experience from estimators. Experience is replaced by trends and relevant statistic parameters extracted from the bid data. This advantage becomes very relevant when considering the high retirement rates of seasoned staff experienced by STAs during the last decade. An efficient bid-based cost estimating system would be expected to improve the resilience of cost estimating processes to the effects of the current brain drain situation, allowing estimating systems to perform satisfactorily with fewer, and overall, less experienced staff.

2.2.3 Cost-Based Estimates

Cost-based estimates are composite estimates resulting from the aggregation of seven cost elements: time, equipment, labor, subcontractor, material, overhead, and profit (AASHTO 2013). In comparison to bid-based cost estimating, a cost-based approach demands greater estimating efforts to apply quantitative procedures at a deeper level of detail. Bid-based techniques are frequently used to support cost-based estimates by providing prices for one or more of the seven elements mentioned above (AASHTO 2013). Even though STAs tend to prefer the use of bid-based cost estimating techniques, a cost-based approach should be favored if the estimator perceives a high level of uncertainty in a bid-based estimate at the project level (AASHTO 2013).

Although cost-based estimates are more complex and require greater estimating efforts, if well developed, they could facilitate better planning and design by forcing the project staff to better understand the project. This would allow for the timely identification of issues that otherwise would be discovered during construction. Problems found during construction, and resulting from poor planning or design errors, usually have a negative impact on projects in terms of increased costs, extended project durations, or both. A better understanding of construction projects and the timely identification of potential issues through cost-based estimating, have allowed the Utah Department of Transportation to save about $11 million due to a reduced number of change orders issued during construction (Utah Construction & Design 2013).

2.2.4 Risk-Based Estimates

"Risk-based cost estimation entails developing probable cost for project components, and the project, based on identified known quantities and costs and contingency developed from a list of identified uncertainties from both opportunities and threats and their potential impact on the project" (Shane et al. 2015). In a simpler definition provided by AASHTO (2013), risk-based estimating refers to the combination of risk analysis techniques with any of the estimating approaches described above. A risk-based approach converts a typical deterministic output (parametric, bid-based, or cost-based) into a stochastic cost estimate in the form of a probability distribution function. "This approach is used to establish the range of total project cost and to define how contingency should be allocated among the critical project elements" (AASHTO 2013).

Even though the use of risk-based estimating techniques has not been adopted by most STAs, it is becoming increasingly popular among transportation agencies. Some STAs, including the Washington State Department of Transportation (WSDOT) and Montana Department of Transportation (MDT), have already developed their own risk-based estimating systems (Molenaar 2005; Gardner 2015). WSDOT's risk-based estimating system was developed by Molenaar (2005) and was intended for projects greater than $100 million, referred to as "Highway Megaprojects." Molenaar found that the main benefits provided by this system were better budget control and resource allocation, as well as an increase in public confidence due to a more transparent communication of financial expectations. Molenaar's estimating system was found to be effective; however, it was estimated that its implementation would have a cost of about $3 million. Likewise, its implementation required the employment of a risk-analyst expert, unlike the methodology proposed in this study.

MDT's risk-based estimating system was developed by Gardner (2015) using 189 paving projects previously awarded by this agency. Gardner used multiple regression and artificial neural network models to produce stochastic conceptual cost estimates using 14 input variables. Even though some of the input variables used by Gardner should be considered to refine the estimating methodology proposed in this report, those 14 inputs do not take into consideration adjustments required to counteract the impact of inflation and construction market volatility over time. Moreover, Gardner's system considers specific topographic and geotechnical characteristics of the jobsite, but it fails to consider regional market conditions that might potentially influence construction pricing. As shown later in this report, the research team has proven the significant influence of project specific geographic considerations on transportation construction prices in Alabama.

2.3 Consequences of Inaccurate Cost Estimating

The following four scenarios summarize the existing literature on the potential negative consequences of inaccurate cost estimating (AASHTO, 2013; Sanders et al., 1992).

- Overrun Budgets: When more funds than those originally estimated are required to successfully complete a given project, a STA might be forced to relocate its annual budget affecting or canceling other approved projects scheduled in its construction program.
- Underrun Budgets: Even though some may argue that finishing projects under budget is a sign of effective management and budget control, it might actually be a sign of poor cost estimating. Overestimating construction costs reduces the ability of STAs to maximize the value of their limited budgets since more funds than required are allocated to execute approved projects. This prevents STAs from developing more projects with the same available funding.
- Unreasonably High Estimates: When construction cost estimates are unreasonably high, due to calculation errors or poor estimating, cost-benefit ratios are inflated, leading to the rejection of projects that should be accepted.
- Unreasonably Low Estimates: When construction cost estimates are unreasonably low, due to calculation errors or poor estimating, cost-benefit ratios are understated, leading to the acceptance of projects that should be rejected.

Cost overruns seem to be the most common scenario in the transportation industry (Schexnayder, et al., 2003) and are usually attributed to estimating and design errors (AKinci & Fischer 1998, Molenaar et al., 2007). A study conducted by Flyvbjerg et al. (2002) on 258 transportation infrastructure projects led to the following observations:

- The cost of about 90% transportation infrastructure projects is underestimated.

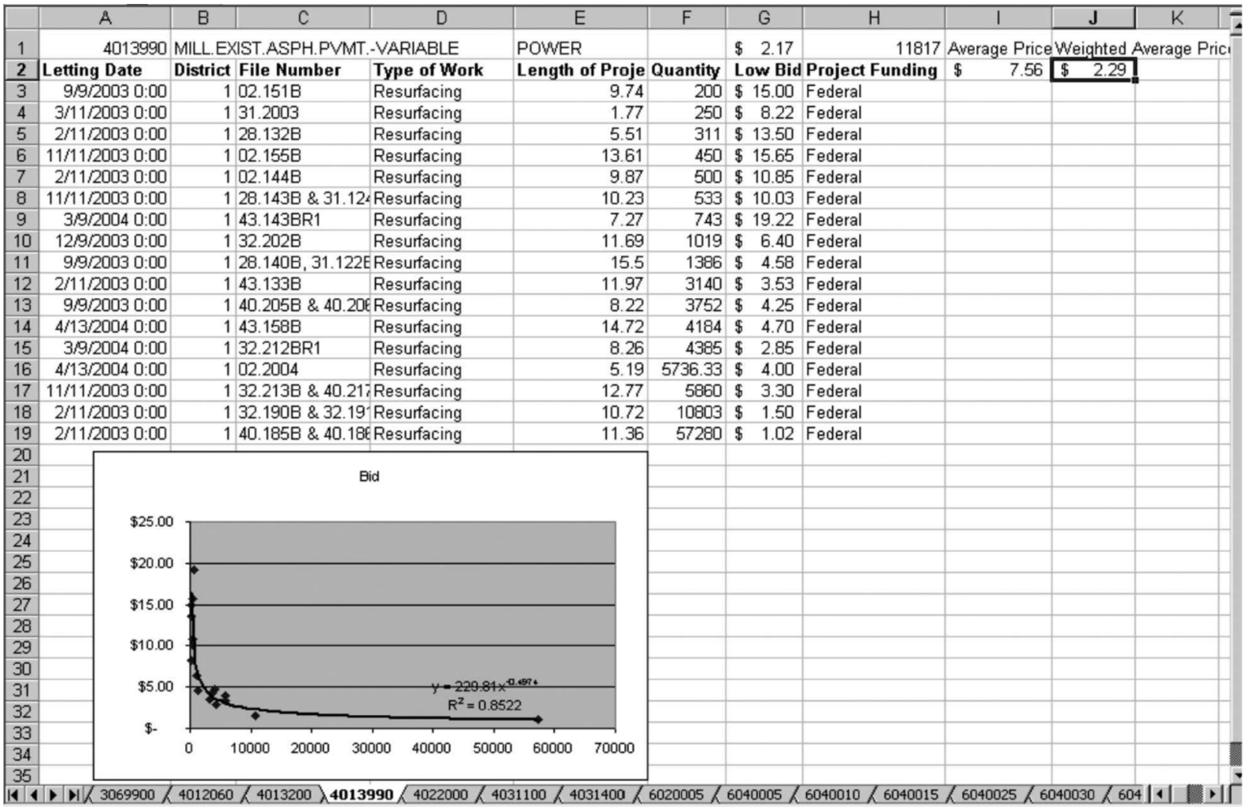
- Actual costs in highway construction projects are about 20% higher than estimated costs, and with a standard deviation of 30%.
- Flyvbjerg et al.'s study was conducted at the international level, finding that cost underestimation seems to be a global phenomenon.

To avoid or mitigate the impact of cost overruns, or any of the other unfortunate estimating scenarios listed above, STAs are required to implement construction cost estimating systems that allow for the recalculation of expected costs at the different project development phases (Anderson et al., 2007; AASHTO 2013). It allows STAs to monitor and control estimates throughout project development, facilitating timely decisions to ensure that projects stay within the approved budgets. As a project moves forward across development phases, more project information and details become available for cost estimating, which allows for greater estimating accuracy (Jui-Sheng Chou, 2009).

2.4 Statistical and Causal Data-Driven Cost Estimating

Previous studies have proposed a number of quantitative methods to estimate construction costs using historical data. Those methods have been classified into two major groups: statistical and causal methods. Statistical methods mainly rely on time series analysis and curve fitting to estimate unit prices based on recent trends (Touran and Lopez 2006; Hanna and Blair 1993). On the other hand, causal methods use mathematical techniques to model the relationship between one or multiple independent variables (also called explanatory or causal variables) and the dependent variable (Hanna and Blair 1993; Makridakis et al. 1998). Under the context of this study, the dependent variable would be the unit price of the pay item under consideration.

Based on the classification of data-driven cost estimating methodologies stated above, it can be said that the system proposed in this report corresponds to a statistical bid-based estimating approach. Although without providing much detail, the AASHTO guidebook shows some examples of statistical bid-based estimating approaches currently used by STAs. Figure 2.2 was taken from the AASHTO guidebook and shows an example of a spreadsheet used by a STA to estimate unit prices using curve-fitting techniques, more specifically, using a non-linear regression model similar to those used in this report as well as to the one shown in Figure 1.1 in Chapter 1.



	A	B	C	D	E	F	G	H	I	J
1	4013990	MILL.EXIST.ASPH.PVMT.-VARIABLE			POWER		$ 2.17	11817	Average Price	Weighted Average Pric
2	**Letting Date**	**District**	**File Number**	**Type of Work**	**Length of Proje**	**Quantity**	**Low Bid**	**Project Funding**	$ 7.56	$ 2.29
3	9/9/2003 0:00	1	02.151B	Resurfacing	9.74	200	$ 15.00	Federal		
4	3/11/2003 0:00	1	31.2003	Resurfacing	1.77	250	$ 8.22	Federal		
5	2/11/2003 0:00	1	28.132B	Resurfacing	5.51	311	$ 13.50	Federal		
6	11/11/2003 0:00	1	02.155B	Resurfacing	13.61	450	$ 15.65	Federal		
7	2/11/2003 0:00	1	02.144B	Resurfacing	9.87	500	$ 10.85	Federal		
8	11/11/2003 0:00	1	28.143B & 31.12	Resurfacing	10.23	533	$ 10.03	Federal		
9	3/9/2004 0:00	1	43.143BR1	Resurfacing	7.27	743	$ 19.22	Federal		
10	12/9/2003 0:00	1	32.202B	Resurfacing	11.69	1019	$ 6.40	Federal		
11	9/9/2003 0:00	1	28.140B, 31.122	Resurfacing	15.5	1386	$ 4.58	Federal		
12	2/11/2003 0:00	1	43.133B	Resurfacing	11.97	3140	$ 3.53	Federal		
13	9/9/2003 0:00	1	40.205B & 40.20	Resurfacing	8.22	3752	$ 4.25	Federal		
14	4/13/2004 0:00	1	43.158B	Resurfacing	14.72	4184	$ 4.70	Federal		
15	3/9/2004 0:00	1	32.212BR1	Resurfacing	8.26	4385	$ 2.85	Federal		
16	4/13/2004 0:00	1	02.2004	Resurfacing	5.19	5736.33	$ 4.00	Federal		
17	11/11/2003 0:00	1	32.213B & 40.21	Resurfacing	12.77	5860	$ 3.30	Federal		
18	2/11/2003 0:00	1	32.190B & 32.19	Resurfacing	10.72	10803	$ 1.50	Federal		
19	2/11/2003 0:00	1	40.185B & 40.18	Resurfacing	11.36	57280	$ 1.02	Federal		

Figure 2.2 Historical bid analysis using non-linear regression modeling (AASHTO, 2013).

The literature review revealed that causal methods, such as multiple regression, are more popular and have been used more frequently by previous authors than statistical methods (Bowen & Edwards, 1985; Khosrowshahi & Kaka, 1996). It could be explained by the fact that, in comparison with causal approaches, statistical methods require a substantial amount of data, which is not usually available to researchers. In a previous study on data-driven cost estimating modeling, Gardner et al. (2015) found that more than 50% of the bid-based estimating models are developed and validated with data from less than 100 previous projects. The largest sample found by that study was 530 projects, which is a small dataset considering the vast databases currently managed by construction owners and contractors. This is also considerably less than the number of projects used in this report.

The literature contains several examples of bid-based cost estimating models. Many of them using multiple regression techniques. In fact, one of the first causal cost estimating models for highway construction projects was developed for ALDOT. In 1987, Bell and Bozai used multiple regression to develop bid-based cost estimating models for ALDOT (at that time known as the Alabama Highway Department). Those models were built and tested with 174 projects and were intended to forecast construction costs over long time horizons. Independent variables for those models included quantities per mile for various pay items. Bell and Bozai's multiple regression equations calculated project costs per mile with an estimating accuracy ranging from ±17% to ±35%. In a subsequent study, also in Alabama, Sander et al. (1992) developed a multiple regression cost estimating model for bridge widening projects on urban highways. With an average accuracy of 6%, Sander et al.'s model could be considered fairly accurate. However, these results are questionable due to the fact the model was developed and validated only with data from 11 previous projects.

Gardner (2015) found that in spite of the fact that some data-driven cost estimating models in the literature show high effectiveness when validated by their respective authors, they have never been implemented by STAs due to their questionable validation processes. Some positive validation results are the result of testing the performance of the models with very small testing samples, in some cases, using only two projects for validation (Gardner 2015).

2.5 Analysis of Current Validation Techniques in Data-Driven Cost Estimating Modeling

Cross validation (CV) is a research approach commonly used to assess the performance of data-driven models, including cost estimating models. A typical CV process is performed in four general steps:

1. The available data is split into a training and a testing dataset.
2. The training dataset is then used to develop the model.
3. The model is applied to each observation in the testing dataset to estimate the values of the dependent variable(s) on each observation.
4. Estimated values are compared against the actual values of the dependent variable(s) in the testing dataset. The result of this comparison is used to assess the performance of the model.

The CV process is intended to simulate the actual implementation of a model so that CV results are assumed to reflect the level of performance that should be expected by the final users. However, the literature review revealed some major issues associated with traditional CV approaches that could compromise the integrity of the validation results in cost estimating models. As mentioned in the previous section, a major issue found in the literature on the validation of cost estimating models is the use of small testing datasets.

Rueda (2016) identified another problem associated with traditional CV procedures used in cost estimating models in the construction industry. Observations for the training and testing datasets are sometimes assigned in a random manner. However, as suggested by Rueda (2016), a random partition of the data might not be appropriate for a bid-based cost estimating model since it implies the use of recent projects to estimate older prices, which would be an impossible scenario during actual implementation. This simulated scenario would be a case in which an estimator uses future prices (which are obviously unknown) to estimate current prices. According to Rueda (2016), model developers should intentionally (instead of randomly) place older projects in the training dataset and the more recent projects in the testing dataset for the validation of bid-based cost estimating models. In that way, the CV process would not only "determine the accuracy of the construction cost estimating models, but also the ability of bid data from previous projects to estimate current construction costs" (Rueda 2016).

Although Rueda's approach is a more accurate representation of the actual model implementation, this study has identified another opportunity to improve CV procedures in bid-based estimating. This allows for an even more appropriate representation of the eventual utilization of a given estimating model. In the actual implementation of bid-based estimating models, the look-back period is formed with historical bid data from the most recent projects so that the look-back period for data retrieval ends just before the current date. Thus, an effective CV process for bid-based estimating should allow for the adjustment of the training period to match the period of time immediately preceding each testing project. That is not possible with the fixed training and testing datasets typically used in CV. The proposed moving-window cross-validation (MWCV) algorithm, described in detail in Chapters 3 and 4, is intended to address this CV limitation by allowing for a dynamic partition for training and testing observations.

2.6 Construction Cost Indexing

As defined by Fisher (1922), who is a pioneer in the development of price indexes, "[a]n index number of prices […] shows the average percentage change of prices from point of time to another" (Fisher 1922). Thus, a construction cost index (CCI) is defined as an instrument to measure average fluctuations of construction prices over time. CCIs are used to adjust prices over time and estimate construction costs based on observed trends in the construction market (Rueda and Gransberg 2015).

Indexes were initially used to track fluctuations in the stock market, wholesale/retail prices, and wages. Their use in the construction industry started in the early 20s with the Aberthaw Index intended to measure changes in the construction cost of a standard seven-story reinforced concrete building (Hubbard 1921; Gill 1933). Since then, CCIs have become more popular, and today it is possible to find different types of cost indexes published and maintained by different public and private participants in the construction industry. There are also other types of indexes aimed to monitor changes in factors other than money, such as safety (Du 2013), quality (Lee 2013), sustainability (Olson 2013).

The literature review revealed several different criteria used to classify CCIs. They can be classified based on their mathematical approach (e.g. arithmetic, geometric, aggregative), index composition and configuration (e.g. simple or unweighted, weighted, composite), updating frequency (e.g. monthly, quarterly, annual), and geographic scope (e.g. national, state, local) (Fisher 1922; Allen 1975; Rueda 2013). CCIs are also classified as input or output indexes. "Input indexes measure the price change in one or more construction components or materials, while output indexes indicate observed changes in construction prices, including general costs, overhead, profit, risk, and other possible external factors" (Rueda and Gransberg 2015). As another criterion to classify CCIs, Rueda and Gransberg (2015) proposed a three-tier classification system based on their intended industry sectors or level of detail. This classification system is illustrated in Figure 2.3.

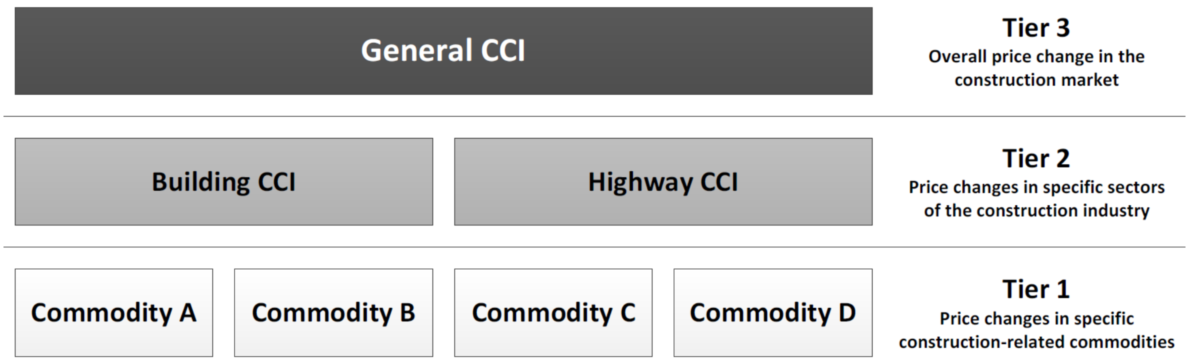


Figure 2.3 Construction cost index classification by industry sector/level of detail (Rueda and Gransberg 2015).

Tier 1 corresponds to indexes designed to track price changes for specific commodities or cost elements (e.g. fuel, asphalt, cement, steel, a specific pay item, etc.). Indexes in Tiers 2 have been classified at a broader scale into either building (vertical construction) or highway (horizontal construction) CCIs. These indexes are commonly used to estimate and forecast costs at the project or program level within their respective construction sectors. Finally, general CCIs at Tier 3 are calculated at the broadest level in an attempt to quantify overall changes in the construction industry, covering all construction sectors. It should be noted that the twelve CCIs developed in this study are only intended to track price changes for the case study item. Therefore, they are classified as Tier 1 cost indexes. The eight existing indexes also evaluated in this report include one Tier 1 and seven Tier 2 indexes.

The literature review for this study has shown several STAs developing and using Tier 1 and 2 indexes to gain a better understanding of the highway construction market, to estimate future highway funding needs, and to predict construction costs (Erickson, 2011; White, 2011; Guerrero, 2003). Tier 2 indexes developed by STAs are usually applied to all types of highway construction projects (e.g. resurfacing, bridge construction, road widening) (Rueda and Gransberg, 2015). To calculate these CCIs, STAs collect historical unit costs from a few relevant construction activities or commodities, and mathematically combine them to obtain a single index number. These are called composite weighted indexes (Rueda and Gransberg, 2015). There are two main challenges associated with the development of composite weighted indexes: 1) the definition of weights and 2) the integration of index inputs into a single index value. The lack of mechanisms to effectively overcome these challenges has prevented STAs from an effective implementation of cost indexes.

Rueda and Gransberg (2015) introduced two important principles that are repeatedly violated when using composite indexes to adjust construction prices: the matching and proportionality principles. The matching principle refers to the degree of similarity between the components used in the calculation of a CCI and the composition of the item or project to be adjusted by the index. Once the matching principle has been fairly met, the proportionality principle appears. It refers to the degree of consistency between the weight of each component in the calculation of the index and the actual weight of its respective matched component in the item or project to be adjusted.

Thus, a perfect application of a CCI implies that each cost element in the adjusted item/project is represented by one component in the CCI, and the weights used in the calculation of the index are proportional to the contribution of each cost element to the total cost (Rueda and Gransberg 2015). It should be noted that a violation of the matching principle implies a violation of the proportionality principle. Rueda and Gransberg (2015) also discuss two assumptions usually made by STAs when using composite CCIs for estimating purposes and how they suppose a strong violation of matching and proportionality principles. These assumptions are:

1. Changes in the construction market from period to period have an equal or similar impact on all kinds of construction activities.
2. Weighted price changes between two construction periods in a few significant materials or construction components represent an overall construction cost change between the same two periods.

STAs usually apply a single CCI to cost estimating procedures in all types of projects or construction activities (assumption 1). These CCIs are calculated with a few commodities or cost elements, assuming that they are suitable to equally represent all types of work (assumption 2). With these two assumptions, STAs are clearly violating the matching and proportionality principles since not all construction activities combine the same elements or cost items, and even if some projects share the same items, they do not necessarily appear in the same proportions (Rueda and Gransberg 2015).

Even though the matching and proportionality principles should prevent the use of traditional composite indexes to adjust prices at the pay item level, this report still evaluates the performance of seven Tier 2 composite indexes in the generation of bid-based cost estimates for the case study item. The other existing index evaluated in this study (the Tier 1 index) is the Asphalt Price Index developed and updated by ALDOT.

Finally, the twelve CCIs developed in this study were calculated following a methodology previously developed by Gransberg and Rueda (2014) for the Minnesota Department of Transportation (MnDOT). This methodology facilitates the creation of a Multilevel Construction Cost Index (MCCI) strategically designed to overcome the limitations of traditional indexing practices and to better meet the matching and proportionality principles. The MCCI consists of a group of pay item indexes (Tier 1 indexes) organized in a multi-level arrangement. Thus, each item in a construction contract can be adjusted with the index from the MCCI that best matches it. Different projects might require different sets of indexes, offering great flexibility to customize price adjustment procedures to the unique characteristics of each project. It should be noted that this study has used Gransberg and Rueda's methodology on a single pay item: the case study item. Therefore, this report does not present a fully developed MCCI for ALDOT. Further data processing efforts should be directed to repeat the same process presented in this report to create a fully functional MCCI as well as to incorporate more pay items into the proposed bid-based cost estimating system.

CHAPTER 3: RESEARCH APPROACH

3.1 Introduction

After gaining a better understanding of the research problem through the literature review summarized in Chapter 2, the authors proceeded to design an appropriate research plan, which illustrated in Figure 3.1. This flow chart guided the research team through the development and validation of the bid-based cost estimating system for the case study item. The process and research activities performed at each step of the research plan are described throughout this chapter.

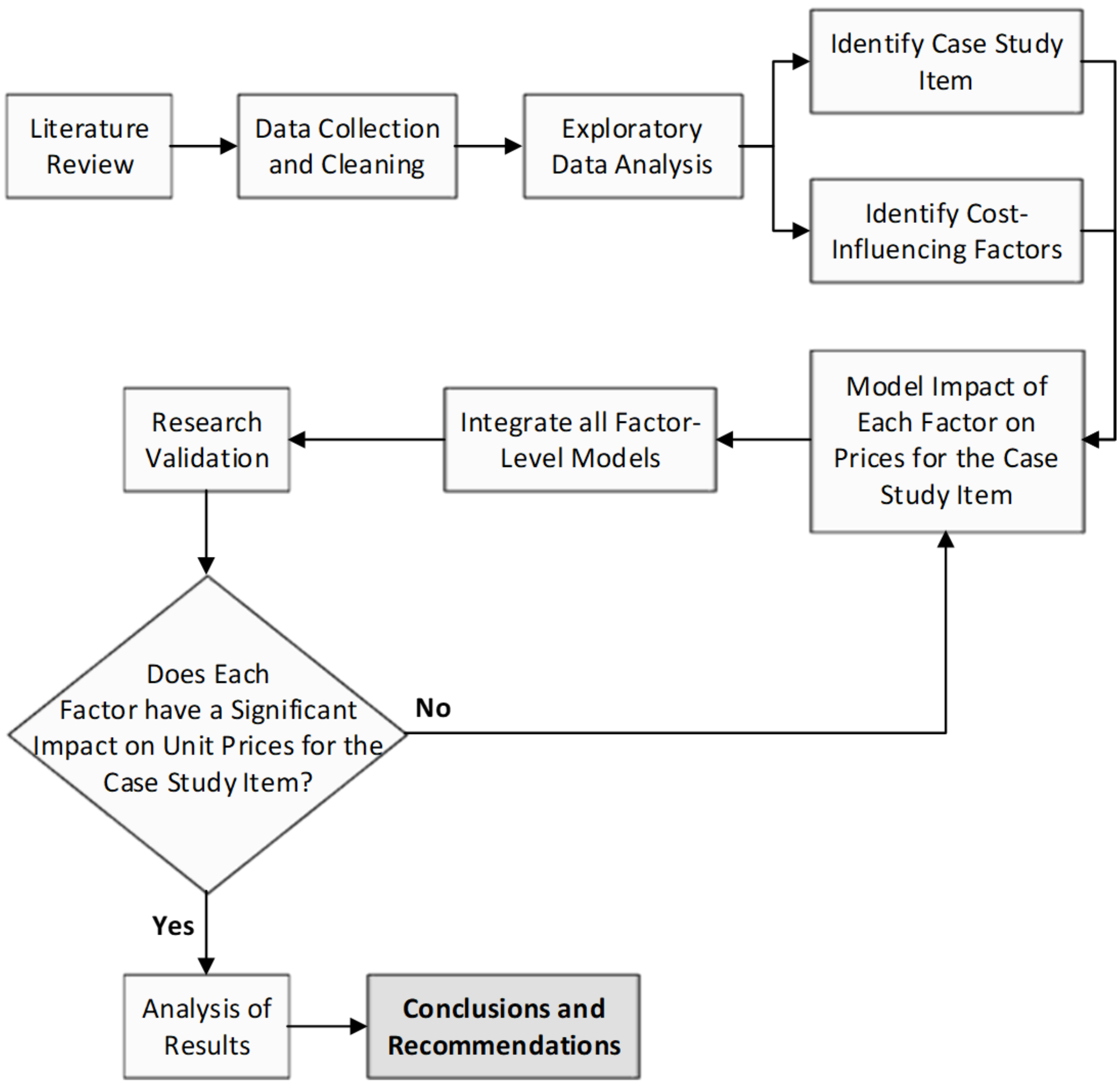


Figure 3.1 Research methodology.

3.2 Data Collecting and Cleaning

Data collection and cleaning efforts in this work consisted of mining historical pricing data from the bid tabulations for all projects awarded by ALDOT between 2006 and 2016. Data from all 3,661 projects awarded during this 11-year period was extracted from ALDOT's Bid Tabulations website. Bid data published on this website is available in Portable Document Format (PDF), which is not a suitable format for data manipulation and processing. Figure 3.2 is a screen capture from one of the PDF files. This figure shows a few unit prices submitted by three bidders for a bridge replacement project in Etowah County, Alabama.

Alabama Department of Transportation
Tabulation of Bids

DATE: 1/29/2016
Page: 1

Call Order: 001 **Contract ID:** 20160129001 **County:** ETOWAH
Letting Date: January 29, 2016 **Area/District:** 0105 **Contract Time:** 310 Working Days
Contract Description: **Project(s):** BR-0001(565)
REPLACEMENT OF DUAL BRIDGES(GRADE, DRAIN BASE, PAVE,SIGNALS) ON SR-1 (US-431) OVER BLACK CREEK TO INCLUDE THE REMOVAL OF A PEDESTRIAN BRIDGE AND RETAINING WALL IN GADSDEN

Line No / Item ID Item Description Alt Set / Alt Member	Quantity and Units	(1) BELL & ASSOCIATES CONSTRUCTION, L.P.		(2) IKAROS, LLC		(3) WRIGHT BROTHERS CONSTRUCTION COMPANY, INC.	
		Unit Price	Ext Amount	Unit Price	Ext Amount	Unit Price	Ext Amount
SECTION: 0001 Total							
0010 206A000 Removal Of Old Bridge, Station 120+58.85, NBR	(1) LS	200,000.00	200,000.00	150,000.00	150,000.00	115,000.00	115,000.00
0020 206A001 Removal Of Old Bridge, Station 120+42.16, SBR	(1) LS	200,000.00	200,000.00	100,000.00	100,000.00	115,000.00	115,000.00
0030 206A002 Removal Of Old Bridge, Station 123+75.00, Pedestrian Bridge	(1) LS	270,000.00	270,000.00	600,000.00	600,000.00	100,000.00	100,000.00

Figure 3.2 ALDOT Bid Tabulations - PDF Format.

A web-based format-conversion application was used to reformat the data into a format compatible with Microsoft Excel (hereinafter referred to as Excel). However, data in the Excel spreadsheets was still arranged as in the original PDF files, which is still not ideal for data processing purposes. Additionally, the converted data presented several critical format inconsistencies such as discontinued or shifted columns and unintended combined cells. Given the large amount of data collected by this study, manual reformatting and correction of inconsistencies was not an option. Part of the data cleaning efforts in this study were aimed to develop an Excel data cleaning spreadsheet carefully designed to identify and correct all formatting inconsistencies while rearranging the data into a tidy format. A screen capture of the tidy dataset is shown in Figure 3.3.

	A	B	F	H	K	CH	CI	CJ	CK	CL	CM	C
1	PostingDate	ContractID	County	Year	Quarter	Item ID	Item Description	Units	Quantity	Unit Price 1	EXT1	Unit P
2	1/17/2006	20060106001	CULLMAN	2006	1	405A000	Tack Coat	GAL	15046	1.35	20312.10	1.24
3	1/17/2006	20060106001	CULLMAN	2006	1	408A053	Planing Existing Pavement (Approximately 2.10" Thru 3.0" Thick)	SQYD	250765	1.53	383670.45	3.9
4	1/17/2006	20060106001	CULLMAN	2006	1	408A054	Planing Existing Pavement (Approximately 3.10" Thru 4.0" Thick)	SQYD	300	3	900.00	18.84
5	1/17/2006	20060106001	CULLMAN	2006	1	410C000	Contractor Retained Profilograph	EACH	1	15000	15000.00	13600
6	1/17/2006	20060106001	CULLMAN	2006	1	410H000	Material Remixing Device	EACH	1	90000	90000.00	12690
7	1/17/2006	20060106001	CULLMAN	2006	1	420A015	Polymer Modified Open Graded Friction Course	TON	11285	61.11	689626.35	58.98
8	1/17/2006	20060106001	CULLMAN	2006	1	423A002	Stone Matrix Asphalt Wearing Layer, 3/4" Maximum Aggregate Size	TON	25077	64.11	1607686.47	46.39
9	1/17/2006	20060106001	CULLMAN	2006	1	424B659	Superpave Bituminous Concrete Upper Binder Layer, Leveling, 1" Maximum Aggre	TON	50	200	10000.00	150
10	1/17/2006	20060106001	CULLMAN	2006	1	600A000	Mobilization	LUMP	1	286995.78	286995.78	28699
11	1/17/2006	20060106001	CULLMAN	2006	1	701A028	Solid White, Class 2, Type A Traffic Stripe (0.06" Thick) (6" Wide)	MILE	17	1737.2	29532.40	1825
12	1/17/2006	20060106001	CULLMAN	2006	1	701A032	Solid Yellow, Class 2, Type A Traffic Stripe (0.06" Thick) (6" Wide)	MILE	17	1737.2	29532.40	1825

Figure 3.3 Tidy Dataset Format.

“Tidy datasets are easy to manipulate, model and visualize, and have a specific structure: each variable is a column, each observation is a row, and each type of observational unit is a table” (Wickham 2014). There is only one observational unit in this study: pay items included in contracts awarded by ALDOT between 2006 and 2016. Therefore, there is only one table, in which each row refers to a single pay item used in a given project, and each column presents all the available attributes and information associated with that pay item as well as with its respective contract. Information provided for each item on each row includes, but is not limited to, item identification number, item description, awarded quantity, unit of measurement, contract number, project location (county[ies]), number of bidders proposing on the project, names of bidders, and the unit price submitted by each bidder.

The final tidy dataset had 169,947 rows and 131 columns. It should be noted that ALDOT has a standard list of pay items and some of them are frequently used in different projects. It means that the same item may appear several times in the dataset, but each time it appears, it corresponds to a different project. A total of 5,246 different pay items have been used by ALDOT in the 3,661 projects contained in this dataset.

Initially, all 11 years of collected and cleaned data were considered in this study. However, a significant trend change was found in the case study’s prices around 2010, suggesting that something may have changed the conditions of the paving construction market in Alabama during that year. Since this study is intended to demonstrate the applicability of the proposed methodology in the current construction market, when this trend change was found, the authors decided to continue the case study only with the most recent six years of data, from 2011 to 2016. Nonetheless, a considerable portion of the data cleaning and analysis efforts were applied the entire 11 years of data.

3.2.1 Outlier Detection and Removal

A critical part of the data cleaning process consisted of removing those observations that do not appear to belong with the rest of the data, generally called outliers. “Usually, the presence of an outlier indicates some sort of problem. This can be a case that does not fit the model under study, or an error in measurement” (Cho et al. 2010). In this study, the authors used two outlier identification methods strategically selected and applied to serve different purposes.

The first outlier detection approach used in this study was the modified Z-score method. This method was applied following the guidelines provided by Iglewicz and Hoaglin (1993) and it was used at the pay item level (to each row) in order to identify outliers among the set of unit prices submitted for the same item under the same contract. These are unit prices estimated for the same quantity and under the same project-specific considerations. While some outliers identified with the modified Z-score method could be the result of typographical errors or the misinterpretation of the pay item associated with the unit price, a number of them are actually the result of unbalanced bids (Rueda 2016). “A bid is considered unbalanced if the unit rates are substantially higher or lower, in relation to the estimate and the rates quoted by other bidders” (JICA 2000). A contractor unbalances a bid to either protect its intended profit or fixed costs, to maximize profits by taking advantage of errors in the bid quantities listed in the solicitation documents, or to inflate prices of early activities to reduce the cost of borrowing money (FHWA 1988). Regardless of the ethical implications typically associated with unbalanced bids, it is a fact that this practice is currently used by construction contractors, and it is also a fact that unbalanced bids might affect the performance of bid-based cost estimating models.

The modified Z-score method was applied using Equation 3.1. The reason behind the use of this method is that outliers are identified using the sample median ($\check{x}$) and the median absolute deviation (MAD) making it more suitable for small samples. Since this method was used on bids submitted by different contractors under the same contract, it was applied to relatively small samples. The average number of bids received by ALDOT for a single contract is between three and four. Other more commonly used outlier detection methods rely on the sample mean and standard deviation to identify outliers. However, these two statistics are more sensitive to extreme values in small samples, increasing the risk of not detecting outliers that should be discarded (Iglewicz and Hoaglin, 1993). Based on Iglewicz and Hoaglin guidelines, all unit prices with absolute modified Z-score greater than 3.5 ($|M_i| > 3.5$) were removed from the dataset.

$$M_i = \frac{0.6745(X_i - \check{x})}{MAD} \qquad \textbf{Eq. 3.1}$$

Where: M_i = Modified Z-Score for Observation i

MAD = Median Absolute Deviation = {$|X_i$ – Median$|$}

x_i = Value of Observation i

$\check{x}$ = Median of All Observations

The second outlier detection approach used in this study was the Robust Regression and Outlier Removal method (ROUT). This method was developed by Motulsky and Brown in 2006 and combines robust regression and non-linear regression techniques to identify values that could be significantly apart from the regression equation. The ROUT method was used to detect outliers during the development of non-linear regression models. These are outliers not detected by the modified Z-score method, including those resulting from unusual project requirements that may have forced all contractors to bid outside the typical unit price ranges. Since the modified Z-score method compares unit prices for the same item under the same contract, this method might find no outliers if unique project conditions force all bidders to submit unit prices substantially higher (or lower) than those typically paid by ALDOT for the same pay item in other projects. Due to their unique circumstances, these unit prices should also be excluded from the process to develop the proposed system.

The ROUT method was applied using GraphPad Prims 7, a statistical software equipped with a ROUT function that can be activated during the development of non-linear regression models. Figure 3.4 shows an example of the output yielded by this software. This is a non-linear regression model developed for the case study item using all unit prices recorded between 2006 and 2016.

All red data points are outliers detected by the ROUT method and excluded from the regression analysis.

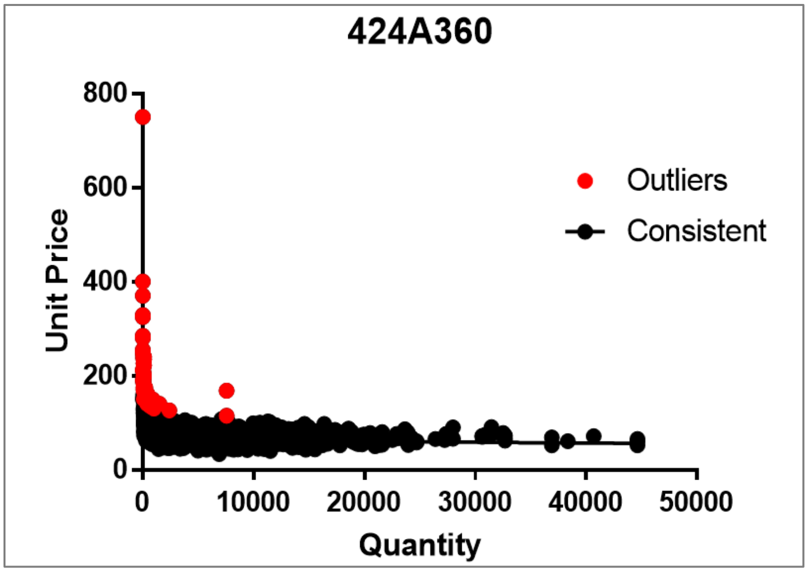


Figure 3.4 GraphPad Prims 7 Output – Example.

3.3 Exploratory Data Analysis

An exploratory data analysis (EDA) is a common step in data-driven research. It is intended to provide researchers with a better understanding of the variables contained in the available data and the relationships among them. In this particular study, EDA facilitated a further identification of inconsistencies and errors in the data, allowing the authors to take the necessary measures to correct them before proceeding with data processing. The EDA also helped with the selection of the case study item and with the identification of potential elements that could be used to model the relationship between each cost-influencing factor and construction prices paid by ALDOT.

With regard to the case study item, the authors were looking for the most relevant pay item used in ALDOT contracts. The EDA showed a single pay item clearly identified as the most relevant in terms of frequency of use and dollar expenditure: "Superpave Bituminous Concrete Wearing Surface Layer, 1/2" Maximum Aggregate Size Mix, Item ID 424A360." This item corresponds to the second highest dollar expenditure in ALDOT's annual construction program. It is only outranked by mobilization expenses. It should be noted that unlike the selected pay item, mobilization costs are paid by ALDOT in almost all contracts, which explains the greater expenditures under that pay item. Having identified the case study item and the four key cost-influencing factors, the authors proceeded with the modeling efforts to quantify the cost impact of each factor on the case study item, as described in the following section.

3.4 Quantitative Modeling

This section refers to the process to quantitatively model the relationship between each of the four cost-influencing factors and unit prices paid by ALDOT for the case study item. The assessment and modeling process for each of the factors is presented in the following subsections.

3.4.1 Project Scale Impact

Based on the economies of scale principle discussed in Section 1.4.1, it was necessary to model case study' unit prices as a function of their bid quantities. This was modeled using non-linear regression techniques. More specifically, the study used power regression models like the one shown in Figure 1.1 in Chapter 1. This regression approach has been successfully used by Rueda (2016) to model unit prices for MnDOT. Moreover, it seems to be a widely accepted approach in the transportation construction industry as inferred from the AASHTO Practical Guide to Cost Estimating (2013) as shown in Figure 2.2. in Chapter 2. Power regression models are defined by Equation 3.2, where 'A' and 'B' are constant values determined for each set of observations to be modeled. The suitability of power regression equations for unit price modeling has been further demonstrated in the first part of the validation process discussed later in this report.

$$Unit\ Price = A * (Quantity)^B \qquad \textbf{Eq. 3.2}$$

Where: A and B are constant values.

3.4.2 Time Impact

Two elements must be defined to incorporate the time factor into the proposed bid-based cost estimating system: 1) a CCI to adjust cost estimates for inflation and price fluctuations over time and 2) an optimal look-back period for data retrieval. This subsection only refers to the selection of the CCI since this is a required element to identify the optimal look-back period later during the first part of the validation process.

The literature review found a number of different cost indexing alternatives that could be used in this study. It was concluded that it would not be possible to objectively select one of these alternatives without a formal comparative analysis among all of them. Thus, Part 1 of the validation process was performed in an iterative manner to test 20 different CCIs. Results of this iterative process were analyzed to identify the CCI that provides the best cost estimating effectiveness for the case study item. The 20 CCIs evaluated in this report include twelve CCIs developed by the authors using ALDOT's historical bid data through a methodology previously developed, and positively validated, by Gransberg and Rueda (2014). The remaining eight indexes correspond to existing CCIs currently used in the construction industry.

The non-linear regression techniques discussed in the previous section were used for two different purposes. At a later stage of the study, they are used to produce deterministic unit price estimates based on expected quantities of work, but they are first used to make sure that price fluctuations in the twelve CCIs developed by the authors are measured between similar quantities of work. The economies of scale concept indicates that a comparison between the unit price for 50 tons of asphalt and the unit price for 50,000 tons of asphalt would not be an "apples to apples" comparison. Thus, to develop cost indexes with ALDOT's bid data, it was first necessary to define quantity ranges for the case study item, so that price changes over time are measured between unit prices from the same quantity ranges (similar quantities of work).

Figure 3.5 illustrates the process proposed by Gransberg and Rueda (2014) to develop 12 out of the 20 CCIs evaluated in this report. This process starts with the definition of quantity ranges for the case study item. According to Gransberg and Rueda's methodology, the quantity ranges for a given item are defined using its non-linear regression model and the largest average price variation (LAPV) between the lowest and the largest bids received for that specific item. The LAPV is calculated as shown in Equation 3.3 and is defined as "the typical maximum difference between two bids for the same pay item and quantity" (Gransberg and Rueda 2014).

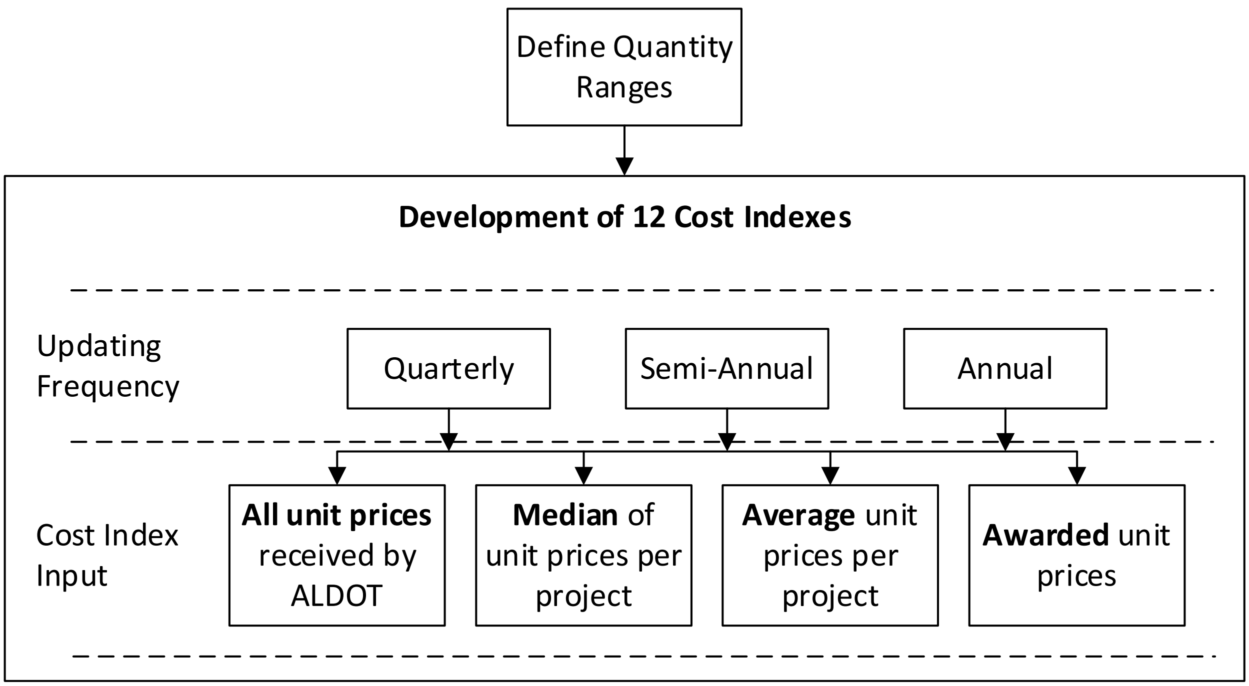


Figure 3.5 Developed of Proposed Construction Cost Indexes

$$LAPV = \frac{\sum_{i=1}^{n} \frac{Largest\ bid_i - Lowest\ bid_i}{Lowest\ bid_i}}{n} \times 100\% \qquad \textbf{Eq. 3.3}$$

Where: $LAPV = Largest\ average\ price\ variation$

$Largest\ bid_i = Largest\ unit\ price\ bid\ for\ item\ under\ consideration\ on\ project\ i$

$Lowest\ bid_i = Lowest\ unit\ price\ bid\ for\ item\ under\ consideration\ on\ project\ i$

$n = Total\ number\ of\ projects\ including\ the\ item\ under\ consideration$

Figure 3.6 and Table 3.1 show the process to define the quantity ranges for the case study item. The application of Equation 3.3 to the available historical bid data yielded an LAPV value of 13.9% for the case study item. Figure 3.6 shows how the LAPV is used along with the regression model to define the quantity ranges. Four quantity ranges have been defined for the selected item. Different pay items may have a different number of quantity ranges. The number of ranges depends on the LAPV value and the regression equation. The lower and upper values for each of the four ranges for the case study item are listed in Table 3.1. As done by Gransberg and Rueda (2014), quantity ranges were defined to cover at least 90% of the observations.

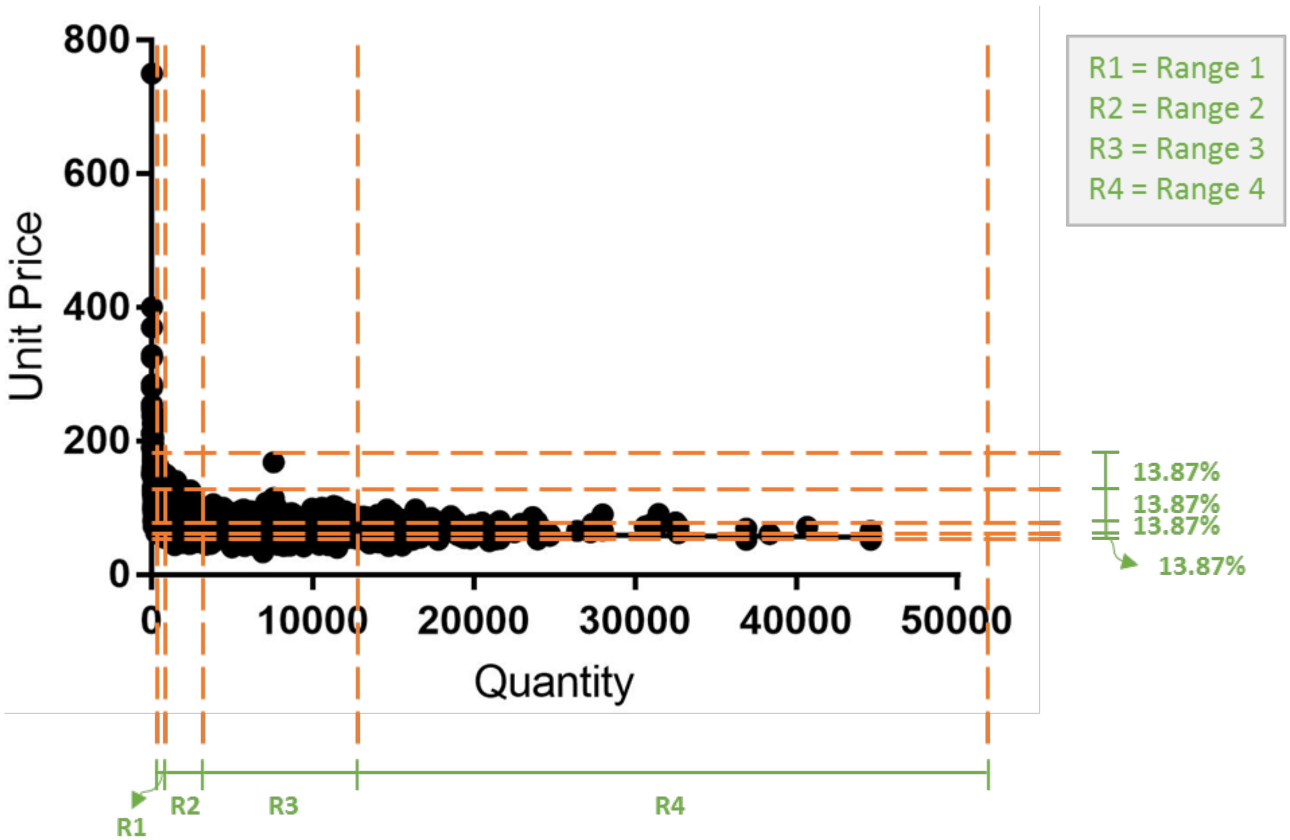


Figure 3.6 Quantity Range Determination – Case Study Item

Table 3.1 Quantity Ranges for Case Study Item

Average Percentage Variation In Unit Price	Quantity Range	Lower Limit of Range (Tons)	Upper Limit of Range (Tons)
13.9%	1	188	766
	2	766	3124
	3	3124	12735
	4	12735	51915

The twelve cost indexes developed in this study correspond to the combination of three different index updating frequencies (i.e. quarterly, semi-annual, and annual) with four types of inputs (i.e. average values on a project basis, median values on a project basis, only awarded bids, and all bids), as shown in Figure 3.5. Table 3.2 shows the updating dates for each updating frequency. The twelve cost indexes developed with ALDOT historical bid data are the following:

- Quarterly updated with average values (Quarterly Average)
- Quarterly updated with median values (Quarterly Median)
- Quarterly updated only with awarded bids (Quarterly Awarded Bids)
- Quarterly updated with all bids (Quarterly All Bids)
- Semi-Annual updated with average values (Semi-Annual Average)
- Semi-Annual updated with median values (Semi-Annual Median)
- Semi-Annual updated only with awarded bids (Semi-Annual Awarded Bids)
- Semi-Annual updated with all bids (Semi-Annual All Bids)
- Annual updated with average values (Annual Average)
- Annual updated with median values (Annual Median)
- Annual updated only with awarded bids (Annual Awarded Bids)
- Annual updated with all bids (Annual All Bids)

Table 3.2 Index Updating Dates

Updating Periods		Updating Date
Quarterly	**Quarter 1 (Q1)**	31st March
	Quarter 2 (Q2)	30th June
	Quarter 3 (Q3)	30th September
	Quarter 4 (Q4)	31st December
Semi Annual	**Semester 1 (S1)**	30th June
	Semester 2 (S2)	31st December
Annual	**Year (Y)**	31st December

Table 3.3 shows the quarterly, semi-annual, and annual cost indexes for the case study item for the years 2006 and 2007. The index values in this table correspond to the CCIs calculated with all bids (index input) received by ALDOT for this item during these two years. All cost indexes have a base period used as a point of reference to measure price changes, which is usually assigned an index value of 100 (Gransberg and Rueda 2014). In this study, the reference base periods for the quarterly, semi-annual, and annual indexes are Q1-2006, S1-2006, and Y-2006, respectively (see Table 3.3). Variations in index values are intended to proportionally represent average price

changes between periods. Thus, the quarterly index in Table 3.3 has perceived an average change of -2.71% between the fourth quarter of 2006 and the fourth quarter of 2007 ([120.87 – 124.24]/124.24). Table 3.3 only shows the first two years of the "all bids" indexes for the three updating frequencies. These CCIs were actually calculated until 2016 for all index inputs.

Table 3.3 Construction Cost Index for Case Study Item 2006-2007 (All bids)

Annual Index	**2006**				**2007**			
	100				99.76			
Semi-Annual Index	**S1**		**S2**		**S1**		**S2**	
	100		111.42		104.23		107.14	
Quarterly Index	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
	100	104.33	115.78	124.24	120.31	118.47	122.71	120.87

The average price variation between indexing periods is calculated as a weighted average of the variations for all quantity ranges, as shown below in Equation 3.4. Quantity ranges are weighted based on the total number of bids at each range. The larger the number of bids used to calculate the price variation, the more reliable the measure of variability, and the greater the weight. Once the average price variation between two consecutive periods has been calculated, the new index value is established using Equation 3.5.

$$APV_{PC} = \frac{\sum_{i=1}^{n}\left((PB_{Ri}+CB_{Ri})\times\frac{CAP_{Ri}-PAP_{Ri}}{PAP_{Ri}}\right)}{\sum_{i=1}^{n}(PB_{Ri}+CB_{Ri})} \qquad \textbf{Eq. 3.4}$$

$$Current\ Index\ Value = Past\ Index\ Value\ \times(1+APV_{PC}) \qquad \textbf{Eq. 3.5}$$

Where: $APV_{PC} =\ Average\ price\ varation\ between\ past\ and\ current\ period$

$PB_{Ri} =\ Number\ of\ bids\ in\ the\ past\ period\ under\ quantity\ range\ i$

$CB_{Ri} =\ Number\ of\ bids\ in\ the\ current\ period\ under\ quantity\ range\ i$

$CAP_{Ri} =\ Current\ average\ price\ under\ range\ i$

$PAP_{Ri} =\ Past\ average\ price\ under\ range\ i$

$n =\ Number\ of\ quantity\ ranges\ for\ hte\ item\ under\ considertion$

In addition to the 12 cost indexes developed by the authors, the study has evaluated eight existing CCIs currently used in the construction industry. Table 3.4 outlines the existing CCIs, which include indexes published and maintained by private organizations, such as the Building Cost Index (BCI) and CCI developed by the Engineering News Record (ENR), and the CCI published by the RSMeans. The ENR provides a national CCI, as well as local CCIs for 20 cities across the country. This study has assessed the performance of both the ENR National CCI and a CCI developed to track changes in the construction market in Birmingham, Alabama. As shown in Table 3.4, the selected existing CCIs include two indexes mainly intended to be used in the vertical construction industry: the ENR-BCI and the RSMeans CCI. Even though these two indexes are aimed for a different construction sector, they have been considered in this study because the literature review revealed that some building CCIs are being used by STAs or by other authors for cost estimating purposes (Rueda 2016).

Table 3.4 Existing Construction Cost Indexes

Index	Components	Applicability	Frequency
Engineering News Record: Building Cost Index (BCI)	• Cement • Structural Steel • Lumber • Labor	National	Monthly
Engineering News Record: Construction Cost Index (CCI)	• Cement • Structural Steel • Lumber • Labor (more labor intensive than BCI)	National	Monthly
Engineering News Record: Construction Cost Index (CCI)- Birmingham, AL	• Cement • Structural Steel • Lumber • Labor (more labor intensive than BCI)	Birmingham, AL	Monthly
RSMeans Construction Cost Index (CCI)	• 9 types of buildings - 66 construction materials - Wage rates for 21 different trades - 6 types of construction equipment	National	Quarterly
Federal Highway Administration: National Highway Construction Cost Index (NHCCI)	• Nations Highway Projects - Standard Pay Items - Material - Labor	National	Quarterly
California Department of Transportation: Price Index for Selected Highway Construction Items	• Roadway excavation per cubic yard • Aggregate base per ton • Asphalt concrete pavement per ton • Portland cement concrete (Pavement) per cubic yard • Portland cement concrete (Structure) per pound • Bar reinforcing steel per pound • Structural steel per pound	California	Quarterly
Washington State Department of Transportation: Price Index for Highway Construction Items	• Roadway excavation per cubic yard • Crushed Surfacing per ton • Hot Mix Asphalt per ton • Concrete Pavement per cubic yard • Structural concrete per cubic yard • Steel Reinforcing bar per pound • Structural steel per pound	Washington State	Annual
Alabama Department of Transportation: Price Index for Asphalt	• Asphalt – Price per gallon	Alabama	Monthly

3.4.3 Location Impact

To model the relationship between geographic location and construction prices with a location cost index (LCI), it was first necessary to split the available historical bid data into comparable regions. Counties within each region are assumed to share similar market conditions. Likewise, each region was required to provide sufficient data to allow for reliable analysis, and at the same time, they could not be too large, so that, they would become meaningless geography-wise. The study initially considered the five geographic regions used by ALDOT to organize its operations: north (N), east-central (EC), west-central (WC), south-central (SC), and south-west region (SW). Figure 3.7 shows the partition of the state of Alabama according to these five regions.

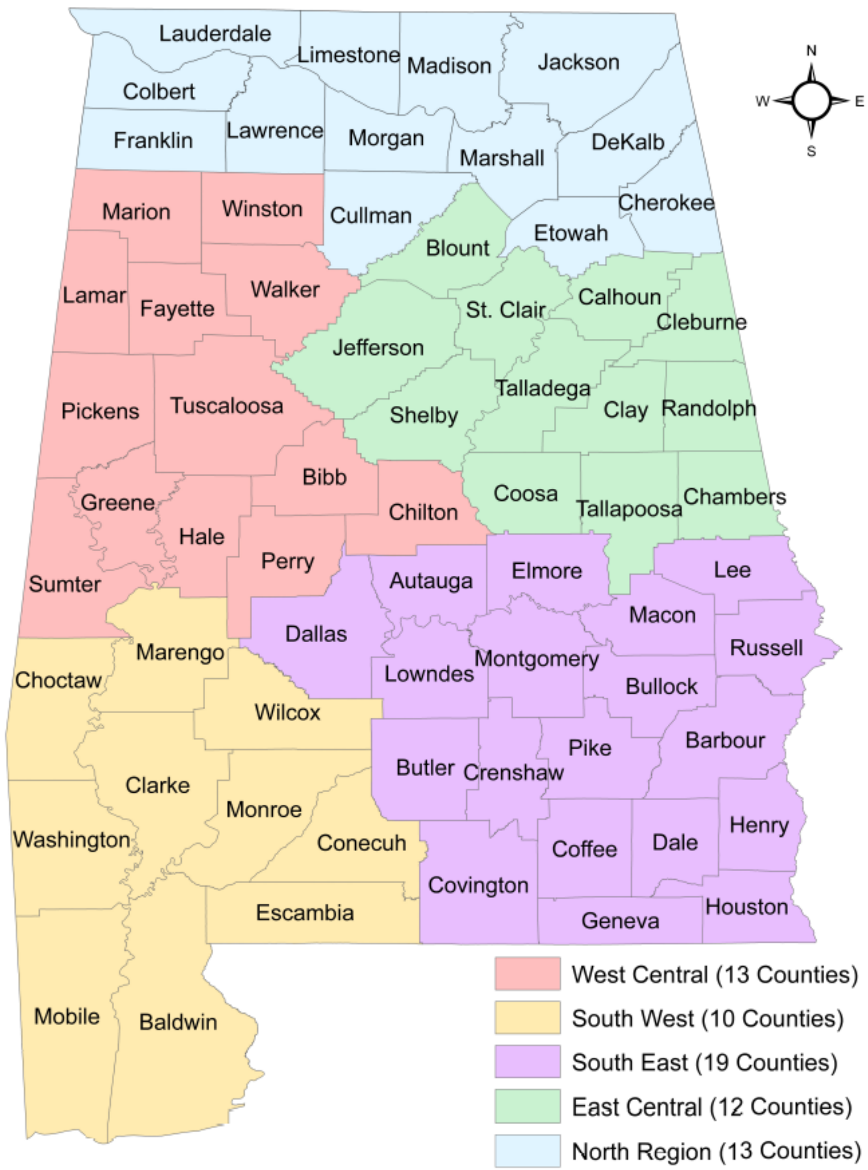


Figure 3.7 ALDOT geographic regions: Five-region classification.

The decision to use the partition shown in Figure 3.7 had to be reevaluated when the EDA revealed that some of these regions were not providing a constant stream of pricing data for the case study item throughout the period of time considered in this study. The lowest count of paving projects corresponded to the WC and SW regions. This issue was solved by rearranging this partition into three regions: north, central, and south region. The final partition is shown in Figure 3.8.

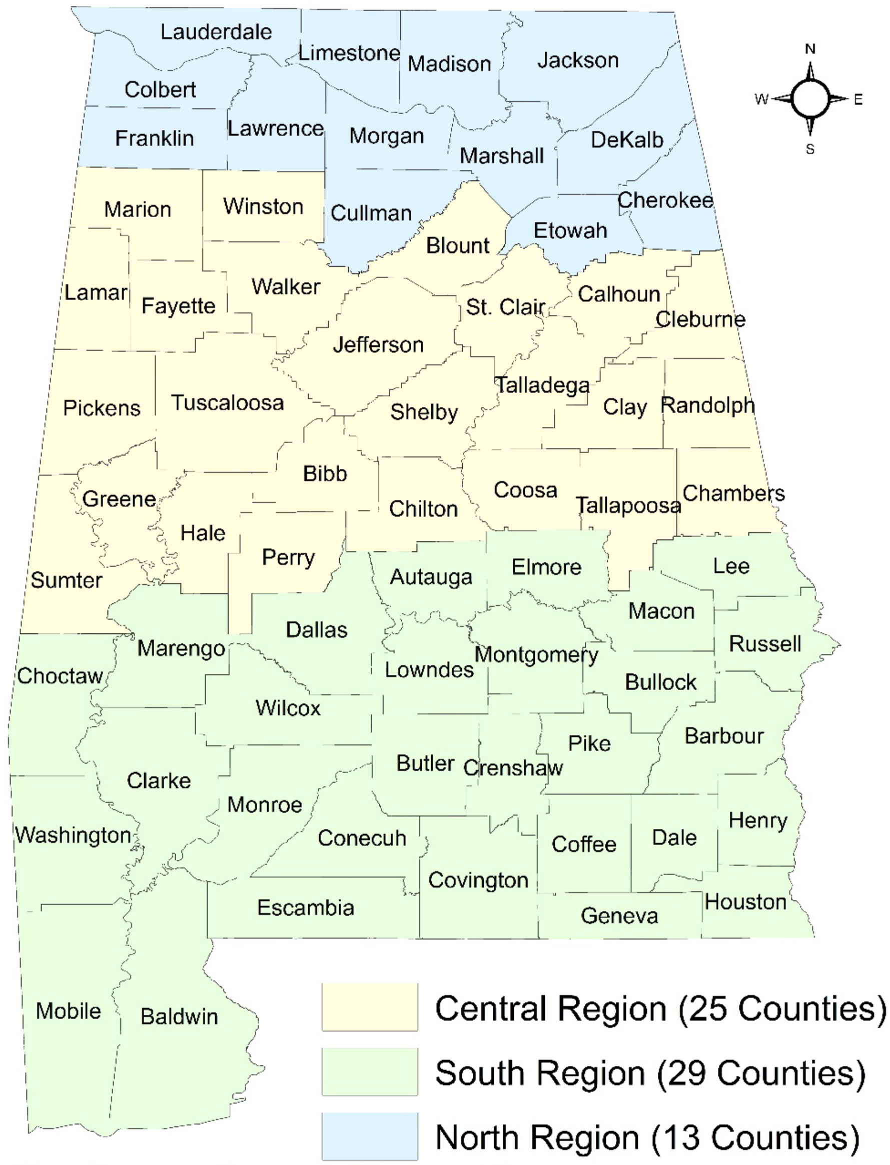


Figure 3.8 Final geographic regions: Three-Region Classification.

After defining the three geographic regions for the LCI, the research team used time series analysis to determine if significant differences in unit prices for the case study item should be expected for the same bid quantity across the three regions. The study identified a typical paving project awarded by ALDOT and used the collected bid data to determine the annual average unit price for case study item in that project in each region. Figure 3.9 shows how the average unit price for

8,715 tons of the case study item (bid quantity in a selected project) changed between 2006 and 2016 in each region.

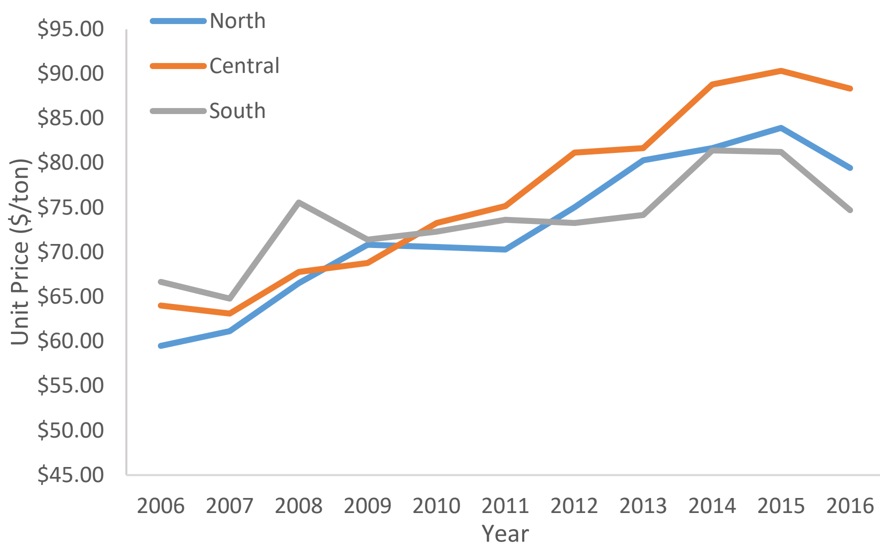


Figure 3.9 Annual average unit price for case study item per region.

The next step was to determine if there is a significant difference between the three time series in Figure 3.9. The location factor would not be necessary for the proposed cost estimating methodology if no significant differences are found between regions. A visual inspection of this figure seems to show that unit prices for the case study item across the three regions started to increasingly spread out after 2010. A series of ANOVA tests applied to different time frames were used to validate this statement. The results of these tests are presented in Table 3.5.

The first test was conducted to compare the 11-year average unit price (2006-2016) between the three regions and it revealed no significant difference with a 5% significance level. The time frame was then reduced by one year (2007-2016), and the ANOVA test was run again with the same results. This process was repeated a number of times, reducing the time frame by one year at a time, showing that significant differences between these regions started to appear after 2010.

Two important findings were derived from this statistical analysis. First, it can be assumed that unit prices for the case study item change significantly between regions in the current construction market. The second finding is that some sort of event(s) affected the paving construction market in Alabama around 2010. Therefore, the authors decided to continue developing and validating the proposed system using only data from projects awarded between 2011 and 2016 (2,122 projects) since old pricing trends might affect the results of the study, misleading ALDOT on the expected performance of the proposed system in today's construction market. Thus, the authors proceeded to develop an annual LCI to quantify the price differences between these regions starting in 2011.

Table 3.5 ANOVA Test Results to Compare Average Unit Prices per Region

Years	Time Frame	Region	Average Unit Price	P-value	Conclusion
11	2006-2016	North	67.05	0.607	Not enough information to prove a significant difference with a significance level of 5%
		Central	74.74		
		South	73.00		
10	2007-2016	North	68.41	0.549	
		Central	76.15		
		South	74.12		
9	2008-2016	North	69.90	0.394	
		Central	77.87		
		South	75.31		
8	2009-2016	North	71.36	0.215	
		Central	79.19		
		South	74.96		
7	2010-2016	North	72.43	0.076	
		Central	81.27		
		South	75.66		
6	2011-2016	North	73.72	0.034	Significant difference with a significance level of 5%
		Central	82.86		
		South	76.44		
5	2012-2016	North	75.48	0.005	
		Central	84.41		
		South	77.37		
4	2013-2016	North	76.59	0.007	
		Central	84.89		
		South	78.57		
3	2014-2016	North	76.42	0.018	
		Central	86.29		
		South	79.58		

Finally, the LCI was developed following a similar approach adopted by the RSMeans for the calculation of its City Cost Index (RSMeans 2018). The RSMeans City Cost Index compares average construction costs among 731 U.S. and Canadian cities. The index values for all U.S. cities are calculated using the U.S. national average as a reference. Every year, the U.S. national average is assigned an index value of 100, and index values at the city level are calculated in a proportional manner around the national index. For example, if the index value for a given city is 95, that would mean that the average construction costs in that city are 5% lower than the national average. Likewise, an index value of 102 would indicate that local average costs are expected to be 2% above the national average.

Figure 3.10 shows the same three time series from Figure 3.9 as well as the addition of one more series for the state average unit price for 8,715 tons of the case study item. The values plotted in this figure for each region were compared against the state average at their respective years. The results of these comparisons were then translated into index values in a similar fashion as in the RSMeans City Cost Index. The resulting LCI is shown in Table 3.6.

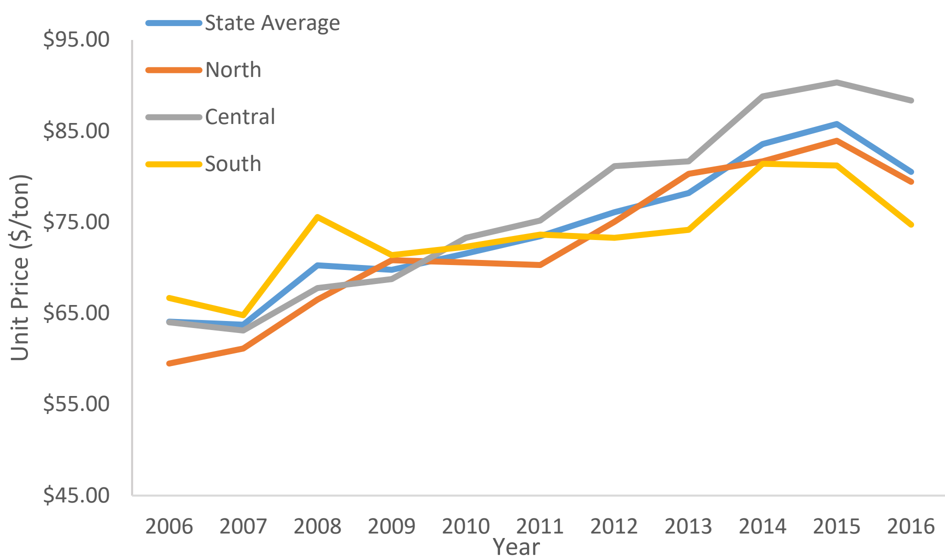


Figure 3.10 Annual average unit price for case study item per region and state average.

Table 3.6 Location Cost Index for Case Study Item

Year	State	North	Central	South
2011	100.00	95.15	102.56	100.21
2012	100.00	97.53	106.98	96.35
2013	100.00	102.02	104.51	94.93
2014	100.00	97.12	106.75	97.37
2015	100.00	97.80	105.70	94.22
2016	100.00	98.46	110.25	92.42

While it does not seem to be a clear pattern to define the difference in prices for the case study item between the north and south regions, Figure 3.10 and the LCIs shown in Table 3.6 show a clear trend of higher prices in the central region in comparison with the other two regions. On average, among the six years shown in Table 3.6, unit prices for the case study item in the central region are 8.3% and 10.8% higher than in the north and south regions, respectively. Further research is required to attempt to explain the reason behind the price differences between regions.

3.4.4 Estimating Uncertainty Impact

Unlike the scale, time, and location factors described above, the estimating uncertainty factor is not incorporated as an input to the proposed estimating system. It is essentially a byproduct of the validation process, as illustrated in Figure 3.11. To implement the proposed system on a given pay item, ALDOT's estimators must perform the same process presented in this report for the case study item, but with the most recent historical bid data for the intended pay item. After Part 1 of the validation process, estimators shall produce a set of percentage errors by applying Equation 3.6 on each testing project. These percentage errors are then used to create a probability distribution function intended to represent the level of uncertainty of the estimating system for the pay item under consideration. This distribution is then saved for future use during the actual implementation of the system to account for the uncertainty factor within the cost estimating process, as discussed in the next section. The same process should be followed for every pay item to be incorporated into the bid-based cost estimating system. Therefore, each item should have its own distribution of percentage errors.

$$PE = \frac{A_i - E_i}{E_i} \times 100\% \qquad \textbf{Eq. 3.6}$$

Where: PE = Percentage Error

A_i = Actual unit price in testing project i

E_i= Estimated unit price in testing project i

Testing Projects	Actual Unit Price	Estimated Unit Price	Percentage Error
Project 1	$89.06	$84.56	5.3%
Project 2	$67.10	$71.06	-5.6%
Project 3	$87.77	$93.60	-6.2%
…	…	…	…
Project n	$78.10	$72.85	7.2%
n = Number of project in testing dataset			

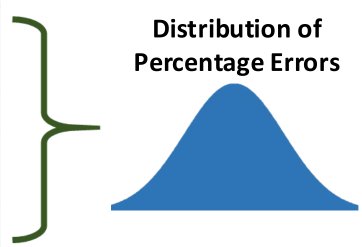


Figure 3.11 Generation of distribution of percentage errors.

It should be noted that the errors in this distribution are calculated as percentages of the estimated values, unlike APEs, which are percentages of the actual values. The distribution of percentage errors is intended to represent all possibilities for the actual values around the estimated value, while APEs are calculated around actual values. For example, if the estimated unit price for the case study item on a testing project is $71/ton and the actual price paid by ALDOT is $67/ton, the APE for this estimate according to Equation 1.1 would be 6.0%, which means that the percentage difference with respect to the actual price is 6.0%. It is irrelevant whether it is greater or lower since the APE is an absolute value, but in this case, the estimated price is 6.0% greater than the actual price. If the same percentage difference were calculated with respect to the estimated value, as in the values used to create the distribution of percentage errors, it would be -5.6%, meaning that the actual price is 5.6% lower than the estimated price.

3.5 Integration of Factor-Level Models

The previous section has presented all the elements and models used to consider the impact of each cost-influencing factor on the proposed bid-based cost estimating process. Now it is necessary to establish a framework to integrate and facilitate the use of all these elements and models. That framework is illustrated in Figure 3.12.

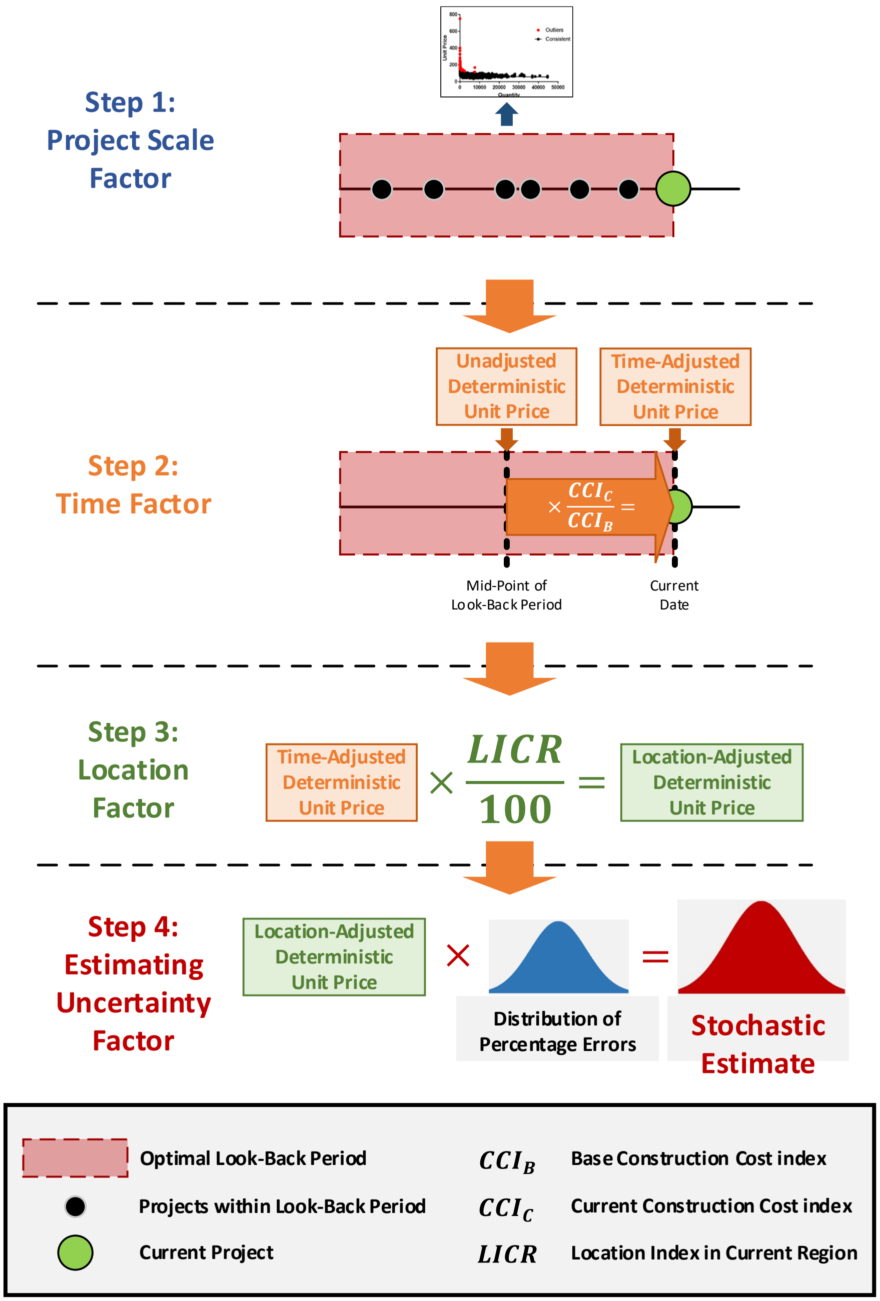


Figure 3.12 Integration of Factors for Implementation.

This framework shows how the system should be implemented by ALDOT's estimators on a pay item that has already been subjected to the development process in Figure 1.3 from Chapter 1 and also presented again in the next chapter. It means that upon using this framework, the optimal look-back period, the CCI, and the LCI for the intended pay item have already been defined. This figure only refers to the actual implementation of the system. All the steps in Figure 3.12 are described below.

1. **Step 1 – Project Scale Factor:** Develop a power regression model using unit prices for the intended pay item from all previous projects contained in the optimal look-back period.
2. **Step 2 – Time Factor:** Use the power regression model to estimate a deterministic unit price (unadjusted) for the expected units of work to be delivered under the current project. Assume that the unadjusted deterministic unit price corresponds to the mid-point of the look-back period, and use the selected CCI to bring this estimate into current dollars using Equation 3.7 (time-adjusted deterministic unit price).

$$TADUP = UADUP \times \frac{Current\ CCI}{Base\ CCI} \qquad \textbf{Eq. 3.7}$$

Where: TADUP = Time-adjusted deterministic unit price
UADUP = Unadjusted deterministic unit price
Current CCI = Last CCI value known at current date
Base CCI = Last CCI value known at the mid-point of the look-back Period

3. **Step 3 – Location Factor:** Use the LCI and Equation 3.8 to adjust the time-adjusted deterministic unit price for the region in which the current project is to be constructed. The time-adjusted deterministic unit price from Step 2 was estimated with projects awarded across the entire state. Therefore, it is assumed to be a state average unit price.

$$LADUP = TADUP \times \frac{Location\ Index\ in\ Current\ Region}{100} \qquad \textbf{Eq. 3.8}$$

Where: LADUP= Location-Ajusted Deterministic Unit Price
TADUP= Time-Ajusted Deterministic Unit Price

4. **Step 4 – Estimating Uncertainty Factor:** Develop the final stochastic unit price by multiplying the location-adjusted deterministic unit price by the distribution of percentage errors obtained during the system development process.

Since the three-part research validation process adopted in this study is intended to simulate the actual implementation of the system, the four steps in Figure 3.12 are also applied to the testing projects during the development phase in the same fashion described above. The main difference between the development and implementation phases for a give pay item lies in the fact that the three-part research validation process is only used during development to ensure that all system elements and factor-level models will work properly during implementation. The system development and validation processes are illustrated in the next chapter using the case study item.

CHAPTER 4: DEVELOPMENT AND VALIDATION OF STOCHASTIC BID-BASED COST ESTIMATING SYSTEM

4.1 Introduction

This chapter presents an in-depth discussion of the process to develop the proposed bid-based cost estimating system as well as a careful analysis of the validation results obtained from the case study item. The system development process, which is to be applied to each pay item to be incorporated into the system, is illustrated in Figure 4.1. This process includes the three-part research validation approach.

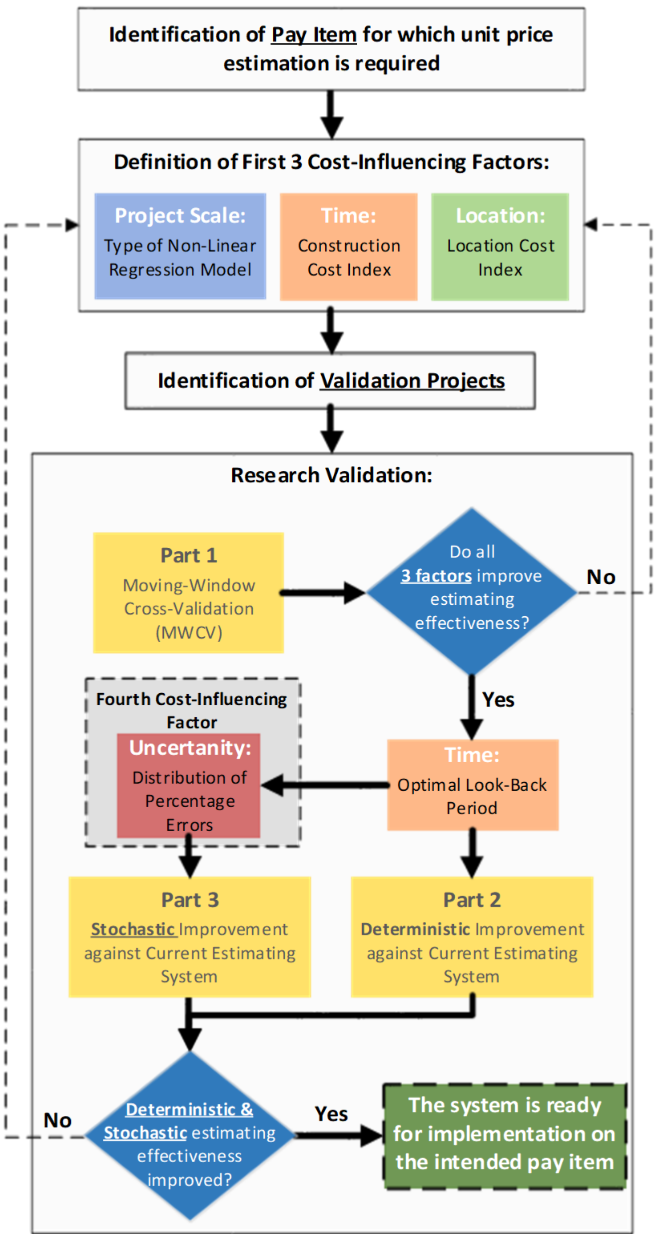


Figure 4.1 Development of proposed bid-based cost estimating system.

Most of this chapter is concerned with Part 1 of the research validation process, which consists of the use of the MWCV algorithm. This algorithm was applied in a systematic, iterative fashion in an attempt to fulfill three different purposes:

- Demonstrate the contribution of each cost-influencing factor towards the improvement in cost estimating effectiveness.
- Identify the optimal look-back period for data retrieval (in years).
- Identify the most suitable cost indexing approach.

Upon completion of the first part of the validation process, the research team proceeded to determine if the deterministic estimating effectiveness offered by the proposed system is superior to the level of estimating accuracy and reliability achieved with ALDOT's current practices. This was Part 2 of the validation process. Finally, after demonstrating the deterministic performance of the bid-based estimating system, the third validation part consisted of a second "proposed systems vs. current practices" comparison, but this time from a stochastic perspective. All three parts of the validation process yielded positive results, indicating that the case study item was successfully incorporated into the system. Although the results presented in this chapter are only applicable to the selected pay item, the following sections present the development and validation process with a sufficient level of detail to guide ALDOT on the incorporation of other pay items into the system.

4.2 Definition of First Three Cost-Influencing Factors

As shown in Figure 4.1, the first step in the system development process is to define the non-linear regression equation that will represent the scale factor as well as to identify suitable cost and location cost indexes to account for the time and location cost impacts associated with the pay item under consideration. Section 3.4.1 has already explained the decision of using a power regression equation to consider the scale factor. Likewise, Section 3.4.3 has presented the quantitative analysis that led to the development of the LCI for the case study item. What has not yet been addressed in this report is the identification of the most suitable CCI for the case study item among the 20 cost indexing alternatives listed in Section 3.4.2. This will be addressed in the next section through additional iterations of the MWCV algorithm during Part 1 of research validation.

4.3 Research Validation Process

Figure 4.1 shows the role played by the three-step research validation process during the system development phase. This process must be repeated for every pay item to be incorporated into the system. The following subsections describe each of the three parts of the research validation approach as they are applied to the case study item.

4.3.1 Research Validation Part 1: Moving-Window Cross-Validation

Part 1 of the research validation process consists of the MWCV algorithm. This algorithm is illustrated in Figure 4.2. This is basically an advanced version of the cross-validation (CV) techniques described in Section 2.5, and it is designed to overcome the limitations of traditional

CV procedures described in the same section. The term “moving-window” refers to a time window of fixed width moving across the testing period (period of time containing the testing projects), which has been defined as the year 2016 for this study. After discarding outliers, the testing dataset was formed by 97 projects that used the case study item during 2016. The width of the time window corresponds to the optimal look-back period. To determine the optimal window width for the case study item, the MWCV in Figure 4.2 was applied a total of five times, once for a different look-back period ranging from one to five years. The optimal look-back period for the selected pay item was then the one that yielded the best estimating effectiveness.

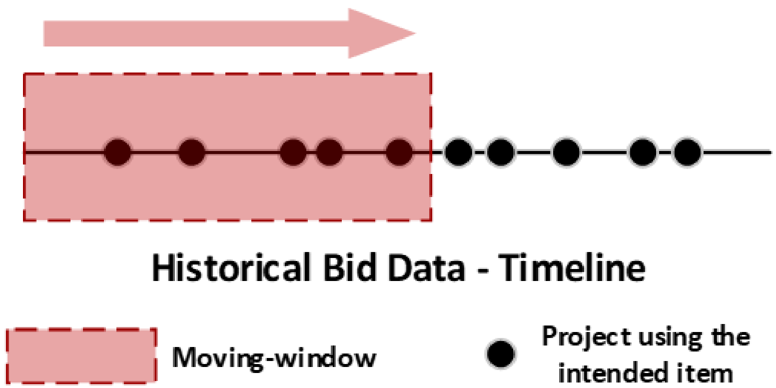


Figure 4.2 Moving-window cross-validation algorithm.

The MWCV process started by placing the right-end of the time window at the beginning of the testing period (January 1, 2016). It was then moved towards the end of the testing timeline. Every time that the right-end of the moving-window found a project, it stopped, the unit price for the case study item in that project was estimated using the bid data contained in the moving-window (following Steps 1 to 3 from Figure 3.12), and the APE was calculated. After that, the fixed time window continued moving until finding the next project. At the end of the MWCV process, the MAPE and standard deviation of the APEs (97 APE values– one for each project in the testing period) were calculated to determine the overall estimating accuracy and reliability of the system on the case study item. The MWCV algorithm allowed for the calculation of the MAPE and standard deviation values that ALDOT would have actually experienced if the proposed cost estimating methodology would have been used to estimate unit prices for the case study item during 2016. This would not be possible with traditional CV techniques.

In addition to the iterations to test the different look-back periods, the MWCV algorithm was also run multiple times to determine if each of the three input elements (non-linear regression equations, CCI, and LCI) was actually contributing to the improvement in estimating accuracy and reliability at the deterministic level. The MWCV approach was applied before and after incorporating each of the first three factors into the cost estimating process, as they were added one-by-one. The comparison of “before” and “after” estimates allowed for the quantification of the estimating improvement attributed to each factor.

Assuming that the regression approach, CCI, LCI, and the optimal look-back period are already known, the MWCV approach would have been applied four times (hereinafter referred to as passes) as described below and as shown in Figure 4.3. An APE value is obtained from each testing project on each MWCV pass. Thus, each MAPE and standard deviation value in Figure 4.3 was calculated in this study with 97 APEs. The following is the description of each MWCV pass:

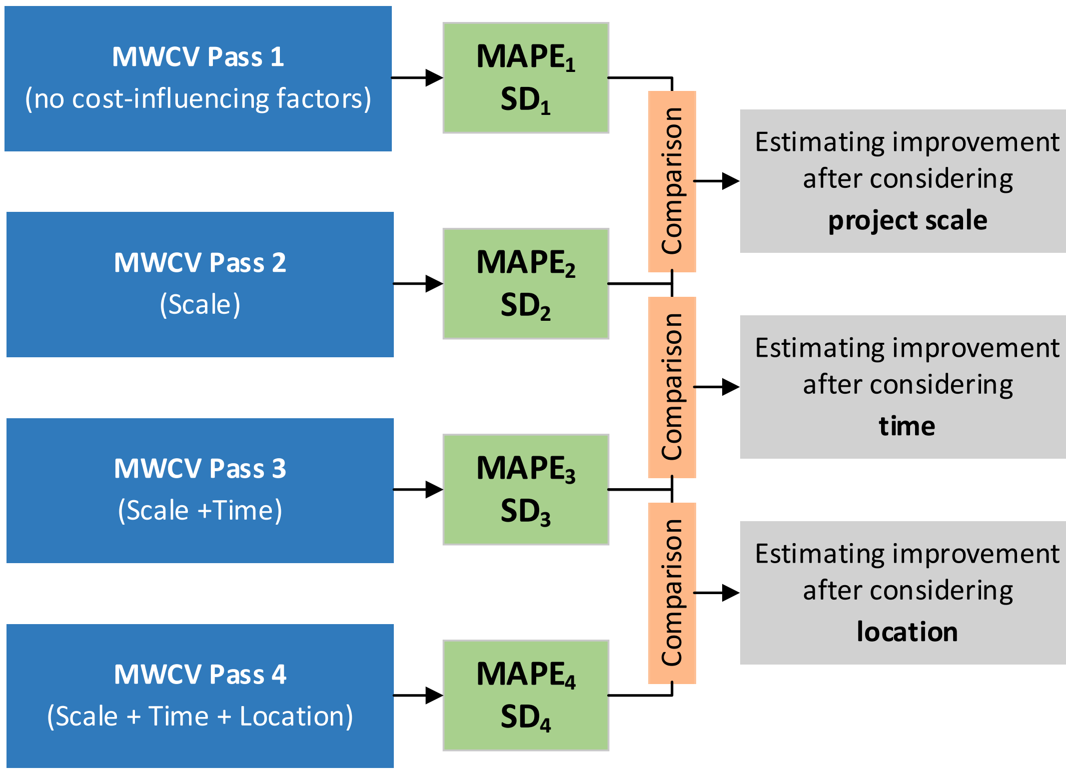


Figure 4.3 Four passes of moving-window cross-validation algorithm.

1. MWCV Pass 1 (no cost-influencing factors): Unit prices for the intended pay item in the validation projects are estimated as the average of the historical unit prices contained in the look-back period. This pass disregards the potential impacts of the four cost-influencing factors.

2. MWCV Pass 2 (project scale): Unit prices for the intended pay item in the testing projects are estimated using the non-linear regression equation (as shown in Step 1 in Figure 3.12) and according to the quantities of work contracted under each testing project. The improvement in cost estimating effectiveness attributed to the incorporation of the project scale factor is determined by comparing accuracy and reliability measures between Passes 1 and 2.

3. MWCV Pass 3 (project scale + time): Unit prices for the intended pay item in the testing projects are estimated using the non-linear regression equation and the selected CCI to bring old prices into current dollars (up to Step 2 in Figure 3.12). The improvement in

estimating effectiveness attributed to the incorporation of the time factor is determined by comparing accuracy and reliability measures between Passes 2 and 3.

4. MWCV Pass 4 (project scale + time + location): Unit prices for the intended pay item in the testing projects are estimated using the non-linear regression model, the CCI, and the LCI to adjust prices according to the geographic location of each testing project (up to Step 3 in Figure 3.12). The improvement in estimating effectiveness attributed to the incorporation of the location factor is determined by comparing accuracy and reliability measures between Passes 3 and 4.

In order to determine the optimal look-back period, the sequence of MWCV passes described above was repeated five times, one for each of the five look-back periods under consideration. It would imply a total of 20 MWCV iterations (4 passes x 5 look-back periods = 20 iterations). However, there are still additional iterations required to identify the most suitable CCI among the 20 cost indexing alternatives described in Section 3.4.2. It means that 10 of those 20 iterations, those corresponding to MWCV Passes 3 and 4, had to be repeated 20 times. In other words, MWCV Passes 3 and 4 were each performed 100 times (5 look-back periods x 20 CCIs = 100 iterations), increasing the total number of iterations to 210 (5 iterations first pass + 5 iterations second pass + 100 iterations third pass + 100 iterations fourth pass = 210 iterations).

In a similar way, some of the four MWCV passes could have been performed additional times to evaluate the cost estimating performance of the system under different regression equations and/or LCIs. A systematic iterative application of the MWCV algorithm could help to identify the look-back period, regression approach, CCI, and LCI combination that would offer the best total improvement in estimating accuracy and reliability for the intended pay item, but this study only evaluated different alternatives for the look-back period and the CCI.

Table 4.1 shows the MAPE and standard deviation values for each of the five look-back periods before and after using the non-linear regression models to account for the scale factor (MWCV Passes 1 and Pass 2).

Table 4.1 Research Validation Part 1 – MWCV Passes 1 and 2

MWCV Pass	Look-Back Period	MAPE	SD of APEs
MWCV Pass 1 No Cost-Influencing Factors	1 Year	19.46%	14.79%
	2 Year	21.62%	16.18%
	3 Year	20.61%	15.30%
	4 Year	20.19%	15.24%
	5 Year	19.31%	14.60%
MWCV Pass 2 Scale	1 Year	14.95%	10.30%
	2 Year	16.62%	10.85%
	3 Year	16.16%	10.44%
	4 Year	15.47%	9.99%
	5 Year	14.96%	9.63%

Improvements in cost estimating performance between MWCV Passes 1 and 2 were measured via statistical significance testing. Two different statistical tests were used: 1) the paired two-sample t-test to determine the level of significance in accuracy improvement (reduction of MAPE) and 2) the F-test to assess the improvement in reliability (reduction in the standard deviation of APEs). The paired two-sample t-test was appropriate in this case because both MWCV calculations were applied to each of the 97 testing projects.

After the second MWCV pass, it was still difficult to anticipate which of the five look-back periods would offer the best cost estimating performance. However, the statistical analysis allowed to conclude (with a 99% confidence level) that, regardless of the number of years used to develop regression models, the incorporation of the scale factor significantly improved cost estimating accuracy and reliability for the case study item. The statistical test showed a significant reduction in MAPE and standard deviation values between MWCV Passes 1 and 2 under all look-back periods.

Table 4.2 shows the results of the 100 iterations under MWCV Pass 3. A closer look at this table seems to point to a two-year look-back period as the optimal amount of data for bid-based cost estimating for the case study item. Most of the top ten cost estimating performances on both effectiveness parameters (MAPE and standard deviation) were obtained with two years of data. However, it is too early to make a conclusion regarding the most appropriate look-back period. That conclusion should be made after the application of the LCI in MWCV Pass 4 since it could change the performance ranking.

MWCV Pass 3 is mainly intended to determine if the use of a CCI to bring bid-based cost estimates into current dollars would improve cost estimating effectiveness. To make this determination it is not necessary to demonstrate an estimating improvement by each of the 100 iterations, which is obviously not the case. Showing improvement with a single iteration would be sufficient. Among the 100 iterations in Table 4.2, the one showing the lowest MAPE and standard deviation is the one that uses the Quarterly All Bids index with a two-year look-back period. Statistical testing results allowed to assert (with a 95% confidence level) that the levels of accuracy and reliability under this iteration are significantly better than those from any of the five iterations from Pass 2. In conclusion, these results have demonstrated the importance of using CCIs to address the fact that historical bid data does not reflect current pricing levels. The statistical analysis described in this paragraph was similar to the one applied above to compare the results of MWCV Passes 1 and 2.

Table 4.2 Research Validation Part 1 – MWCV Pass 3

Indexing Approach	Look-Back Period	MAPE	SD of APEs	Indexing Approach	Look-Back Period	MAPE	SD of APEs
Quarterly All Bids	1 Year	13.33%	8.94%	Annual Average	1 Year	15.05%	10.43%
	2 Year	12.52%	8.21%		2 Year	16.89%	10.99%
	3 Year	13.53%	10.41%		3 Year	19.04%	12.28%
	4 Year	14.64%	10.05%		4 Year	19.84%	12.54%
	5 Year	14.75%	9.90%		5 Year	21.02%	12.99%
Quarterly Median	1 Year	14.32%	8.92%	Annual Awarded Bid	1 Year	15.53%	10.99%
	2 Year	13.12%	8.43%		2 Year	18.07%	11.56%
	3 Year	13.49%	9.66%		3 Year	19.84%	12.52%
	4 Year	15.23%	10.11%		4 Year	20.34%	12.76%
	5 Year	15.78%	10.16%		5 Year	21.31%	13.13%
Quarterly Average	1 Year	14.36%	8.89%	National Highway CCI	1 Year	14.56%	9.41%
	2 Year	13.15%	8.46%		2 Year	15.17%	9.91%
	3 Year	13.57%	9.67%		3 Year	15.12%	9.75%
	4 Year	15.34%	10.21%		4 Year	16.07%	10.74%
	5 Year	16.08%	10.34%		5 Year	16.52%	10.53%
Quarterly Awarded Bid	1 Year	14.49%	9.31%	Caltrans CCI	1 Year	20.91%	15.34%
	2 Year	12.90%	8.29%		2 Year	22.42%	15.40%
	3 Year	12.86%	9.02%		3 Year	25.63%	16.09%
	4 Year	14.80%	9.91%		4 Year	27.25%	17.79%
	5 Year	15.35%	9.60%		5 Year	33.27%	28.47%
Semi Annual All Bid	1 Year	13.44%	9.36%	Washington State DOT CCI	1 Year	19.91%	13.34%
	2 Year	12.73%	8.90%		2 Year	20.52%	15.83%
	3 Year	15.08%	11.68%		3 Year	16.22%	10.54%
	4 Year	16.24%	11.23%		4 Year	27.40%	16.56%
	5 Year	16.21%	11.19%		5 Year	40.04%	23.18%
Semi Annual Median	1 Year	13.72%	9.45%	Engineering News Record -Birmingham CCI	1 Year	15.28%	10.54%
	2 Year	13.24%	8.84%		2 Year	17.80%	11.49%
	3 Year	15.36%	11.62%		3 Year	17.39%	11.22%
	4 Year	16.95%	11.21%		4 Year	17.21%	10.90%
	5 Year	16.93%	11.21%		5 Year	17.64%	11.20%
Semi Annual Average	1 Year	13.70%	9.39%	Engineering News Record CCI	1 Year	15.85%	10.72%
	2 Year	13.22%	8.81%		2 Year	18.72%	11.90%
	3 Year	15.21%	11.48%		3 Year	18.80%	11.95%
	4 Year	16.88%	11.18%		4 Year	18.97%	12.10%
	5 Year	16.94%	11.19%		5 Year	19.31%	12.28%
Semi Annual Awarded Bid	1 Year	13.53%	9.29%	Engineering News Record Building Cost Index	1 Year	15.65%	10.63%
	2 Year	13.09%	9.05%		2 Year	18.21%	11.64%
	3 Year	15.63%	11.87%		3 Year	18.36%	11.70%
	4 Year	17.06%	11.44%		4 Year	18.63%	11.88%
	5 Year	16.79%	11.23%		5 Year	18.69%	11.93%
Annual All Bid	1 Year	15.31%	10.74%	RSMeans CCI	1 Year	15.07%	10.27%
	2 Year	17.54%	11.31%		2 Year	17.03%	11.07%
	3 Year	19.68%	12.51%		3 Year	16.71%	10.74%
	4 Year	20.43%	12.80%		4 Year	16.63%	10.70%
	5 Year	21.91%	13.46%		5 Year	16.56%	10.53%
Annual Median	1 Year	15.07%	10.46%	ALDOT Asphalt Index	1 Year	15.24%	11.30%
	2 Year	16.95%	11.02%		2 Year	22.51%	12.07%
	3 Year	19.02%	12.26%		3 Year	34.78%	11.28%
	4 Year	19.78%	12.51%		4 Year	37.09%	9.83%
	5 Year	21.09%	13.03%		5 Year	36.84%	9.59%

Table 4.3 shows the results of the 100 iterations under MWCV Pass 4 after applying the LCI for the last price adjustment. This table shows the total cumulative improvement after applying the first three cost-influencing factors with four different look-back periods and 20 different cost indexing alternatives. After applying the LCI in Pass 4, the two-year Quarterly All Bids iteration is still the one showing the best cost estimating performance. The paired two-sample t-test showed a statistical significant reduction of 9.61% in the MAPE value for this "look-back period/CCI" combination due to the adjustments for location. On the other hand, this combination showed an increase in the standard deviation of APEs, which would suppose a reduction of 11.08% in the level of reliability after using the LCI. However, the F-test did not show this reduction as statistically significant, meaning that, in the long run, the level of reliability before and after applying the LCI could be similar. Therefore, this study can conclude that the implementation of the LCI would have a significant positive impact on construction cost estimating accuracy without affecting estimating reliability.

Before moving forward with the validation process, it is necessary to make a decision regarding the most suitable look-back period and CCI for the case study item. As mentioned before, the use of a two-year look-back period and the Quarterly All Bids CCI has yielded the best total improvement. Nonetheless, it is difficult to conclude with a visual inspection of Table 4.3 if the MAPE and standard deviation values under this iteration are significantly lower than those obtained with other look-back period/CCI combinations. So far, statistical testing techniques have been used to analyze cost estimating improvements between MWCV passes, and they are now required to compare the results from all iterations at the end of Pass 4. Due to the nature of this statistical analysis, the paired two-sample t-test and F-test are not applicable this time. Other two statistical tests were used in this analysis: the two-way ANOVA test to compare MAPE values and the Levene's test to evaluate the variances among the iterations.

Levene's test was used to maximize reliability. The null hypothesis tested with the Levene's test was that the variances across all look-back period/CCI combinations are equal. This test was systematically used in this study to reduce the number of possible look-back period/CCI combinations into the subset of combinations that offered the lowest comparable variance. The look-back periods and indexing approaches showing the higher variability were discarded one-by-one until having a subset of combinations with the lowest comparable variances. Subsequently, an in a similar systematical manner, the two-way ANOVA test was applied on this subset to form a smaller subset with the combinations offering the lowest comparable MAPEs. After applying both statistical tests, the original 100 look-back period/CCI combinations were of 18 combinations with the lowest comparable MAPEs and standard deviation values. These 18 combinations are listed in Table 4.4.

Table 4.3 Research Validation Part 1 – MWCV Pass 4

Indexing Approach	Look-Back Period	MAPE	SD of APEs	Indexing Approach	Look-Back Period	MAPE	SD of APEs
Quarterly All Bids	1 Year	12.15%	11.90%	Annual Average	1 Year	13.83%	10.52%
	2 Year	11.31%	9.12%		2 Year	15.68%	11.00%
	3 Year	12.42%	10.24%		3 Year	17.71%	12.37%
	4 Year	13.50%	10.08%		4 Year	18.63%	12.34%
	5 Year	13.49%	10.06%		5 Year	19.76%	12.91%
Quarterly Median	1 Year	13.00%	9.55%	Annual Awarded Bid	1 Year	14.28%	11.04%
	2 Year	12.08%	9.17%		2 Year	16.81%	11.55%
	3 Year	12.27%	9.75%		3 Year	18.50%	12.58%
	4 Year	14.07%	10.34%		4 Year	19.11%	12.58%
	5 Year	14.60%	10.30%		5 Year	20.05%	13.02%
Quarterly Average	1 Year	13.02%	9.56%	National Highway CCI	1 Year	13.08%	9.87%
	2 Year	12.13%	9.19%		2 Year	13.86%	10.04%
	3 Year	12.30%	9.81%		3 Year	13.61%	10.07%
	4 Year	14.19%	10.42%		4 Year	14.62%	10.94%
	5 Year	14.89%	10.48%		5 Year	15.27%	10.47%
Quarterly Awarded Bid	1 Year	13.36%	9.64%	Caltrans CCI	1 Year	19.43%	14.98%
	2 Year	11.88%	9.12%		2 Year	20.75%	14.97%
	3 Year	11.72%	9.35%		3 Year	24.31%	15.85%
	4 Year	13.67%	10.20%		4 Year	25.45%	17.08%
	5 Year	14.17%	9.94%		5 Year	32.42%	29.63%
Semi Annual All Bid	1 Year	12.37%	9.74%	Washington State DOT CCI	1 Year	18.45%	13.24%
	2 Year	11.68%	9.37%		2 Year	19.34%	15.61%
	3 Year	14.33%	11.50%		3 Year	14.97%	10.89%
	4 Year	15.07%	11.30%		4 Year	26.28%	16.14%
	5 Year	15.10%	11.21%		5 Year	38.97%	21.95%
Semi Annual Median	1 Year	12.56%	9.77%	Engineering News Record -Birmingham CCI	1 Year	13.97%	10.66%
	2 Year	12.04%	9.35%		2 Year	16.54%	11.53%
	3 Year	14.36%	11.62%		3 Year	16.22%	11.11%
	4 Year	15.74%	11.25%		4 Year	15.88%	11.00%
	5 Year	15.76%	11.24%		5 Year	16.43%	11.16%
Semi Annual Average	1 Year	12.54%	9.72%	Engineering News Record CCI	1 Year	14.51%	10.87%
	2 Year	12.01%	9.34%		2 Year	17.50%	11.84%
	3 Year	14.22%	11.47%		3 Year	17.61%	11.81%
	4 Year	15.67%	11.22%		4 Year	17.80%	11.90%
	5 Year	15.77%	11.21%		5 Year	18.15%	12.05%
Semi Annual Awarded Bid	1 Year	12.37%	9.70%	Engineering News Record Building Cost Index	1 Year	14.33%	10.79%
	2 Year	11.97%	9.48%		2 Year	16.99%	11.62%
	3 Year	14.61%	11.91%		3 Year	17.09%	11.66%
	4 Year	15.85%	11.48%		4 Year	17.46%	11.72%
	5 Year	15.63%	11.25%		5 Year	17.57%	11.71%
Annual All Bid	1 Year	14.08%	10.79%	RSMeans CCI	1 Year	13.81%	10.41%
	2 Year	16.30%	11.31%		2 Year	15.81%	11.08%
	3 Year	18.34%	12.58%		3 Year	15.53%	10.71%
	4 Year	19.19%	12.62%		4 Year	15.40%	10.79%
	5 Year	20.68%	13.30%		5 Year	15.36%	10.59%
Annual Median	1 Year	13.85%	10.54%	ALDOT Asphalt Index	1 Year	15.48%	10.99%
	2 Year	15.73%	11.03%		2 Year	23.21%	11.75%
	3 Year	17.69%	12.35%		3 Year	35.42%	10.81%
	4 Year	18.57%	12.31%		4 Year	37.71%	9.39%
	5 Year	19.83%	12.95%		5 Year	37.45%	9.16%

Table 4.4 Research Validation Part 1 – MWCV Pass 4

Indexing Approach	Look-Back Period	MAPE	SD of APEs
Quarterly All Bids	1 Year	12.15%	11.90%
	2 Year	11.31%	9.12%
Quarterly Median	1 Year	13.00%	9.55%
	2 Year	12.08%	9.17%
Quarterly Average	1 Year	13.02%	9.56%
	2 Year	12.13%	9.19%
Quarterly Awarded Bid	1 Year	13.36%	9.64%
	2 Year	11.88%	9.12%
Semi Annual All Bid	1 Year	12.37%	9.74%
	2 Year	11.68%	9.37%
Semi Annual Median	1 Year	12.56%	9.77%
	2 Year	12.04%	9.35%
Semi Annual Average	1 Year	12.54%	9.72%
	2 Year	12.01%	9.34%
Semi Annual Awarded Bid	1 Year	12.37%	9.70%
	2 Year	11.97%	9.48%
National Highway CCI	1 Year	13.08%	9.87%
	2 Year	13.86%	10.04%

In general, all quarterly and semi-annual indexes outperformed the annual and existing cost indexes, demonstrating the suitability of the cost indexing methodology proposed by Gransberg and Rueda (6) to track price fluctuations at the pay item level in Alabama. Only one of the existing CCIs was not discarded by the statistical analysis: the National Highway CCI. However, it showed the worst performance among the remaining 18 combinations.

Even though the statistical tests did not reveal significant differences in the performance of the remaining 18 combinations, the final recommendation made by the authors regarding the most suitable combination for the case study item is still to select the top-ranked combination: the two-year look-back period with the Quarterly All Bids index. This combination showed the lowest cumulative MAPE and standard deviation values. Rather than proving that all 18 combinations would have the same performance, the statistical tests failed to prove that there are significant differences among them. It is still possible that the test failed to detect actual significant differences in the performance of the top combinations. If that were the case, the top-ranked combination (two-year/Quarterly All Bids) would still most likely be the one offering the best cost estimating performance. It was still important to conduct the statistical analysis to identify the top 18 combinations to inform ALDOT about other possible combinations with comparable effectiveness, which could be used in case of not having access to the elements required to use to top-ranked alternative.

The study has now demonstrated the importance of factoring scale, time, and location impacts into bid-based cost estimating processes and has identified the look-back period and CCI that offer the best cost estimating effectiveness for the case study item. However, this "best cost estimating effectiveness" was determined among other iterations of the proposed cost estimating system.

Positive validation results from Part 1 would not necessarily mean that the proposed system is superior to ALDOT's current cost estimating system in terms of estimating accuracy and reliability. In order to make such statement, it is still necessary to prove that cost estimates for the testing projects obtained with the proposed system are more accurate and reliable than the actual estimates calculated by ALDOT's estimators for the same pay item in the same projects. The comparison of the system against ALDOT's current estimating practices is performed in Parts 2 and 3 as described below.

4.3.2 Research Validation Part 2: Deterministic Validation against ALDOT's Current Cost Estimating System

Validation efforts on Parts 2 are simpler than those undertaken in Part 1. Part 2 compares the deterministic estimating effectiveness of the system against the levels of accuracy and reliability observed in ALDOT's deterministic estimates in the testing projects for the selected pay item. Even though the authors did not have access to the unit prices estimated by ALDOT for the case study item in the 97 testing projects, it was possible to reasonably approximate ALDOT's unit prices using ALDOT's cost estimates at the project level (total construction cost estimate including all pay items) and all bids received for each project. The process to infer ALDOT's unit prices for the case study item is illustrated in Table 4.5. This table shows the process for three of the 97 projects in the testing period. In all three contracts in Table 4.5, ALDOT only received bids from three different contractors.

Table 4.5 ALDOT's Unit Price Estimates for Case Study Item

Project	Quantity Item 424A360 (tons) [A]	Percentage of 424A360 in Total Bid Price			Average % [B]	ALDOT's Total Cost Estimate [C]	Inferred Unit Price Estimate for Item 424A360* [D]
		Bidder 1	Bidder 2	Bidder 3			
1	16,045	43.7%	44.0%	41.9%	43.2%	$2,252,826	$60.68/ton
2	7,809	17.8%	18.2%	16.9%	17.6%	$3,001,141	$67.74/ton
3	3,959	48.8%	50.5%	49.7%	49.7%	$560,736	$70.33/ton

* D = C x B / A

The process shown in Table 4.5 was repeated for all 97 observations in the testing period. This inference process is based on the assumption that ALDOT's estimators would be able to determine similar proportions between total bid prices and the portion of the total price that corresponds to the case study item. The authors consider that this is a strong assumption given that ALDOT's estimates and contractors' bids are both prepared with the same plans and specifications, and are based on the same project specific information. Likewise, a visual review reveals an apparent low variability in this proportion among bidders competing for the same project (e.g. all contractors in Project 1 seem to know that this proportion is around 42%-44%), suggesting that an average estimator should be able to foresee this proportion with reasonable accuracy. In other words, total bid-case study item proportions obtained by ALDOT's estimators are expected to be similar to those obtained by the contractor's estimators.

Inferred unit price estimates were compared against those unit prices actually paid by ALDOT (submitted by the low bidder) under each project. MAPE and standard deviation values resulting from this comparison were 13.3% and 9.2%, respectively. When compared against the outputs from MWCV Pass 4 for the two-year/Quarterly All Bids combination, it was found that the cost estimating system proposed in this study has the potential to increase ALDOT's estimating accuracy by 15% ([0.133-0.113]/0.133 x 100%). Statistical tests show this MAPE reduction as a significant improvement in cost estimating accuracy when using the proposed bid-based cost estimating system instead of ALDOT's current practices. In terms of reliability, both the proposed and ALDOT's cost estimating systems showed a similar performance with similar values for the standard deviations of the 97 APEs. Although the two-year/Quarterly All Bids combination in MWCV Pass 4 yielded a lower standard deviation, these difference is not significant, suggesting that both systems offer similar levels of reliability. Based on these results, it can be concluded that the implementation of the proposed bid-based cost estimating system would have a significant positive impact on ALDOT's construction cost estimating accuracy without significantly affecting estimating reliability.

4.3.3 Research Validation Part 3: Stochastic Validation against ALDOT's Current Cost Estimating System

Part 3 of the validation efforts correspond to the assessment of the performance of risk-based estimates obtained by combining the deterministic estimates with the distribution of percentage errors defined with the results from Part 1. The risk-based estimate generated for the intended item on each testing project is compared against the bracket estimate generated by ALDOT for the same project. The term "bracket estimate" is used by ALDOT to refer to a range of possible construction costs defined by a minimum and a maximum expected value. The bracket estimates, as well as the total cost estimates in Table 4.5, were extracted from the Notice to Prospective Bidders issued by ALDOT for each of the testing projects.

To generate risk-based cost estimates for each testing project, it is first necessary to define the distribution of percentage errors as explained in Section 3.4.4. Table 4.6 shows the percentage errors calculated for each of the 97 testing projects using Equation 3.6. The inputs for this equation are the actual unit prices submitted by the successful bidders and the most accurate and reliable unit prices obtained from MWCV Pass 4 (those from the two-year look-back period/Quarterly All Bids combination). Figure 4.4 corresponds to the empirical probability distribution built with the percentage errors listed in Table 4.6.

Even though this empirical probability distribution could be used to produce risk-based estimates, it is important to consider that this distribution is to be saved and distributed among ALDOT estimators for future use during the actual implementation of the system. Sharing an empirical probability distribution is usually more complicated than sharing a standard distribution with two or three parameters. For example, if ALDOT uses a normal distribution instead of the empirical distribution in Figure 4.4, all the information needed for future use and to be shared with ALDOT's estimators would be the mean and standard deviation values of the distribution.

Table 4.6 Percentage Errors for Testing Projects

Testing Project	Actual Unit Price	Estimated UP MWCV 4	% Error	Testing Project	Actual Unit Price	Estimated UP MWCV 4	% Error
1	$115.00	$71.76	60.2%	50	$60.58	$61.91	-2.2%
2	$108.98	$106.36	2.5%	51	$81.25	$73.09	11.2%
3	$60.00	$64.19	-6.5%	52	$80.46	$83.23	-3.3%
4	$70.00	$69.85	0.2%	53	$115.00	$74.30	54.8%
5	$87.77	$88.26	-0.6%	54	$79.20	$81.75	-3.1%
6	$67.10	$59.69	12.4%	55	$74.90	$90.38	-17.1%
7	$88.75	$76.23	16.4%	56	$82.60	$82.51	0.1%
8	$89.06	$68.26	30.5%	57	$110.92	$75.50	46.9%
9	$64.34	$68.01	-5.4%	58	$77.50	$75.91	2.1%
10	$80.00	$72.83	9.9%	59	$81.08	$74.59	8.7%
11	$53.89	$60.12	-10.4%	60	$78.86	$73.19	7.7%
12	$80.00	$98.85	-19.1%	61	$88.11	$73.71	19.5%
13	$79.16	$68.74	15.2%	62	$56.50	$59.94	-5.7%
14	$87.38	$82.05	6.5%	63	$72.62	$74.83	-3.0%
15	$72.75	$60.24	20.8%	64	$64.00	$65.16	-1.8%
16	$69.85	$69.70	0.2%	65	$65.19	$66.26	-1.6%
17	$59.46	$67.53	-11.9%	66	$80.02	$85.92	-6.9%
18	$71.06	$67.87	4.7%	67	$63.68	$60.06	6.0%
19	$78.10	$68.33	14.3%	68	$54.45	$61.05	-10.8%
20	$62.77	$80.64	-22.2%	69	$60.00	$66.21	-9.4%
21	$78.77	$65.78	19.8%	70	$85.65	$83.78	2.2%
22	$62.90	$63.09	-0.3%	71	$59.75	$60.65	-1.5%
23	$66.00	$70.05	-5.8%	72	$56.14	$64.75	-13.3%
24	$65.87	$71.28	-7.6%	73	$56.00	$72.18	-22.4%
25	$58.00	$75.55	-23.2%	74	$60.00	$68.40	-12.3%
26	$72.15	$84.34	-14.5%	75	$84.33	$67.60	24.8%
27	$79.15	$60.59	30.6%	76	$62.41	$71.23	-12.4%
28	$68.85	$58.55	17.6%	77	$72.25	$66.75	8.2%
29	$64.99	$65.54	-0.8%	78	$87.25	$66.73	30.7%
30	$75.75	$71.74	5.6%	79	$68.86	$69.59	-1.1%
31	$82.50	$71.00	16.2%	80	$70.13	$74.49	-5.9%
32	$54.25	$60.39	-10.2%	81	$88.33	$86.12	2.6%
33	$95.00	$97.85	-2.9%	82	$75.00	$82.75	-9.4%
34	$57.07	$67.24	-15.1%	83	$78.00	$77.59	0.5%
35	$67.23	$78.10	-13.9%	84	$56.85	$69.56	-18.3%
36	$70.06	$90.03	-22.2%	85	$106.26	$96.98	9.6%
37	$66.01	$62.82	5.1%	86	$70.64	$72.72	-2.9%
38	$80.25	$69.97	14.7%	87	$92.00	$68.25	34.8%
39	$56.00	$62.42	-10.3%	88	$80.30	$77.15	4.1%
40	$66.86	$62.59	6.8%	89	$66.00	$73.51	-10.2%
41	$63.00	$62.01	1.6%	90	$57.24	$66.64	-14.1%
42	$69.75	$72.15	-3.3%	91	$61.23	$70.02	-12.5%
43	$53.25	$56.93	-6.5%	92	$56.95	$57.43	-0.8%
44	$55.82	$66.39	-15.9%	93	$115.00	$98.68	16.5%
45	$55.79	$68.58	-18.7%	94	$73.11	$73.37	-0.4%
46	$90.25	$63.32	42.5%	95	$73.23	$67.60	8.3%
47	$83.92	$74.62	12.5%	96	$58.50	$55.83	4.8%
48	$55.00	$64.76	-15.1%	97	$90.00	$70.85	27.0%
49	$85.00	$87.43	-2.8%	-	-	-	-

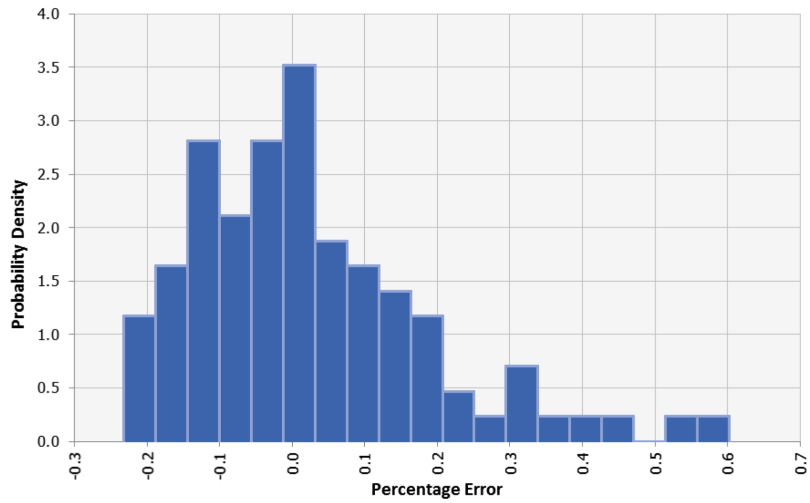


Figure 4.4 Empirical Distribution of Percentage Errors – Case Study Item.

Although the simplicity of a normal distribution function would be convenient for the implementation of the cost estimating system, it seems clear that the distribution of percentage errors in Figure 4.4 does not fit a normal distribution. Thus, the chi-square goodness of fit statistical test was used to infer the most suitable standard probability distribution for these percentage errors. This test was conducted using @Risk, a statistical software package that facilitates the identification of the most suitable distribution among several possible options. The test found that the distribution of percentage errors for the case study item most probably follows an extreme value distribution, which is defined by two parameters: alpha (location parameter; α) and beta (scale parameter; β). The extreme value distribution that best fits the empirical distribution of percentage errors is shown in Figure 4.5. The alpha and beta parameters for these distributions are -0.049 and 0.125, respectively.

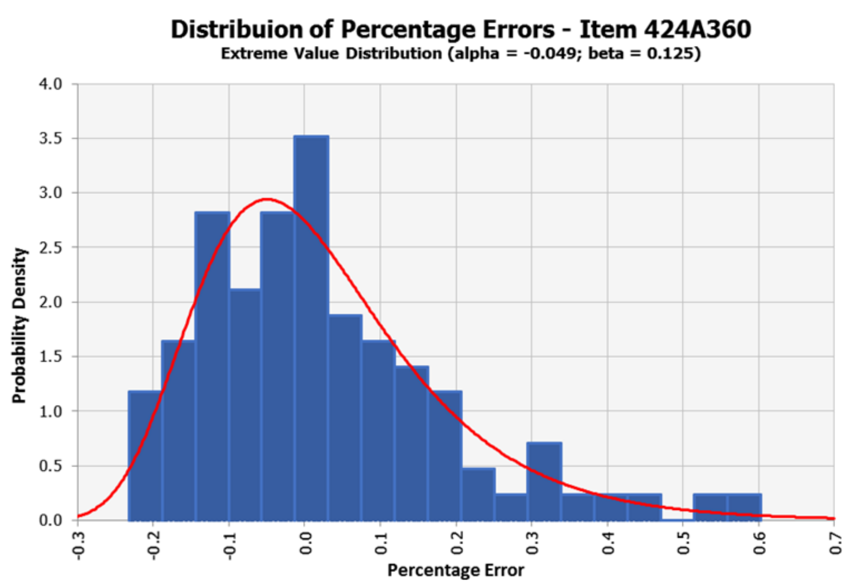


Figure 4.5 Extreme Value Distribution of Percentage Errors – Case Study Item.

The extreme value distribution in Figure 4.5 can now be used to generate risk-based estimates for the case study item in the 97 testing projects. These estimates are produced by multiplying the deterministic outputs of the system by the distribution of percentage errors. It should be noted that different pay items might require different types of distributions to model estimating uncertainty. Likewise, the rules for arithmetic operations between constants and probability distributions may also vary depending on the type of distribution. Equation 4.1 shows how to use the deterministic estimate and the extreme value distribution of percentage errors to produce risk-based estimates for the case study item. All estimates produced with this equation will also follow an extreme value distribution. After a positive validation of the stochastic performance of the system, ALDOT can start using the validated distribution of percentage errors to develop risk-based estimates for intended projects using the same equation (Equation 4.1).

$$RBE = DE \times \left(1 + EV(\alpha_{DPE}; \beta_{DPE})\right) = EV(\alpha_{SE}; \beta_{SE}) = EV(DE \times (1+\alpha); DE \times \beta) \qquad \textbf{Eq. 4.1}$$

Where: RBE = Risk-based estimate
DE = Deterministic Estimate
EV(α_{DPE}; β_{DPE})= Extreme Value Distribution of Percentage Errors
EV(α_{SE}; β_{SE})= Extreme Value Distribution for Risk-Based Estimate

If for example, ALDOT wants to develop a risk-based estimate for the case study item given a deterministic unit price estimate of $80/ton, the alpha and beta values of the risk-based estimate would be 76.08 (α_SE=80×[1+[-0.049]]) and 10.00 (β_SE=80×0.125), respectively. This risk-based estimate is illustrated in Figure 4.6.

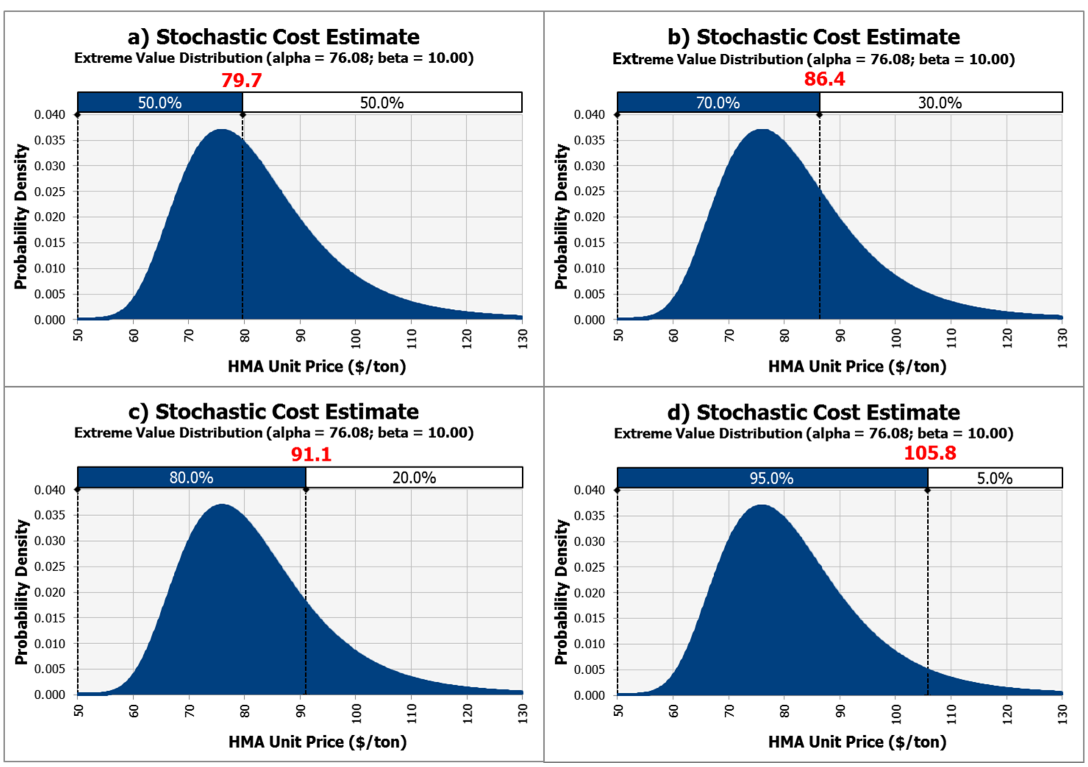


Figure 4.6 Risk-Based Estimate Example – Case Study Item.

Figure 4.6 also shows the estimated unit price for the case study item at four different confidence levels. For example, if ALDOT wants to be 70% sure of allocating enough funds to cover the costs for this pay item, the unit price for this item should be around \$86.4 per ton (Figure 4.6b). Similarly, for an 80% and 95% confidence level, the unit price should be \$91.1 and \$105.8 per ton, respectively (Figures 4.6c and 4.6d). Equation 4.1 was used in the same manner on each testing project, and each resulting risk-based distribution was then used to create a bracket estimate of similar magnitude as the one originally established by ALDOT on each project, but the new bracket estimates were set around the median of each risk-based estimate. A comparison between the two sets of bracket estimates showed that actual prices paid by ALDOT for the case study item in 2016 (according to the winning proposal) fall outside of ALDOT's bracket estimates 59% of the time. The proposed methodology reduced this number to 45%.

The stochastic validation process concludes the study, demonstrating that the proposed bid-based cost estimating methodology was successfully applied to the case study item, improving estimating accuracy and reliability. However, as mentioned a few times throughout this report, this research project was not intended to develop a cost estimating methodology for a single pay item. The study was aimed to create a framework that could be applied to pay items with sufficient historical bid data. Although this study's results are very promising, the proposed methodology can still be further improved if supplemented with the experience and knowledge of ALDOT's experts and estimators. The results presented in this report were obtained only from the analysis of ALDOT's historical bid data, without the input of ALDOT's experts and estimators, which would most likely enhance estimating accuracy and reliability even more.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

This report has presented the exhaustive research efforts undertaken to develop a bid-based cost estimating methodology for ALDOT. The proposed methodology is applied at the pay item level. It uses a number of mathematical and statistical techniques to incorporate three major factors into the cost estimating process: 1) scale, 2) time, and 3) location, and 4) estimating uncertainty. This report describes the development and validation of the proposed methodology as it is applied on a case study pay item frequently included in ALDOT's construction contracts. This is a hot mixed asphalt pay item (Item ID 424A360), and is considered by the authors as the most relevant pay item used by ALDOT.

The study was conducted using bid data from all projects awarded by ALDOT between 2006 and 2016 (over 3,600 projects). The relationship between unit prices for the selected pay item and the cost-influencing factors under consideration was modeled using non-linear regression techniques, an innovative Multilevel Construction Cost Index (MCCI), a location cost index (LCI), and an advanced cross-validation approach.

Estimating uncertainty was considered by developing a distribution of percentage errors with the results from the research validation process presented in Chapter 4. The distribution of percentage errors is intended to be used during the implementation of the proposed methodology to generate risk-based estimates by quantifying the uncertainty associated with deterministic estimates produced by the first three cost-driven factors.

All the cost-influencing factors were integrated through the four-step framework outlined below, which facilitates the implementation of the proposed methodology by ALDOT. ALDOT's estimators can apply this four-step framework after calculating the expected amount of work for the intended pay item.

1. **Step 1 – Project Scale Factor:** Develop a power regression model using unit prices for the intended pay item from all previous projects contained in the optimal look-back period.
2. **Step 2 – Time Factor:** Use the power regression model to estimate a deterministic unit price (unadjusted) for the expected units of work to be delivered under the current project. Assume that the unadjusted deterministic unit price corresponds to the mid-point of the look-back period, and use the selected CCI to bring this estimate into current dollars.
3. **Step 3 – Location Factor:** Use the LCI to adjust the time-adjusted deterministic unit price for the region in which the current project is to be constructed.
4. **Step 4 – Estimating Uncertainty Factor:** Develop the final risk-based unit price by multiplying the location-adjusted deterministic unit price by the probability distribution of percentage errors obtained during the system development process.

Research validation was systematically performed through a three-part process involving the iterative application of an innovative Moving-Window Cross-Validation (MWCV) approach. The MWCV process was intended to demonstrate and quantify the improvement in estimating accuracy and reliability offered by each cost-driven factor, as they were incorporated into the system one-by-one. The iterative MWCV approach was performed 210 times to meet the objectives of this study. The study found that each of the four factors significantly improves cost estimating accuracy and reliability for the case study item. The use of the LCI showed a significant improvement in estimating accuracy, but a statistical F-test found no evidence to prove a significant change in estimating reliability due to the LCI. Thus, it is reasonable to conclude that the use of the proposed LCI would have a significant positive impact on cost estimating accuracy for the selected pay item without significantly affecting estimating reliability.

Initial research validation efforts showed an overall improvement in estimating effectiveness at a deterministic level (after incorporating the first three cost-driven factors). The study proved this improvement to be statistically significant in comparison with a cost estimating model that does not consider any of the cost-driven factors under consideration. However, that would not necessarily mean an improvement for ALDOT's current cost estimating practices. Further validation efforts demonstrated that the proposed methodology was 15% more accurate than ALDOT's current cost estimating practices. This increase in estimating accuracy was proven to be statistically significant. In terms of reliability, both the proposed and ALDOT's cost estimating systems showed similar performance. The stochastic effectiveness of the risk-based cost estimates produced by the proposed methodology was also compared against the effectiveness of ALDOT's bracket estimates for the 97 projects considered in the research validation process. The study found that unit prices for the case study pay item submitted to ALDOT by successful contractors fall outside of their respective bracket estimates 59% of the time. This number was reduced to 45% with the proposed methodology.

It should be noted that besides proving the importance of considering the scale, time, location, and uncertainty impacts on construction cost estimating, the study has also demonstrated the effectiveness of the tools and methods used to model those impacts, as well as the effectiveness of the framework used to combine those factors. The incorporation of each factor into the cost estimating process only improves estimating effectiveness if each factor is properly assessed and modeled, as explained in this research report.

5.1 Study Limitations

The following are the main limitations associated with this study, which must be considered when interpreting the results presented in this report and during the implementation of the proposed cost estimating methodology:

- The cost estimating system presented in this report is intended to maximize accuracy and reliability in estimating original contract amounts. It is not aimed to estimate construction costs at project completion, which may differ from original contract amounts due to scope creep, design errors or omissions, differing site conditions, and/or change orders issued by ALDOT during the project construction phase.

- The specific quantitative results presented in this study are only applicable to the case study item in contracts to be awarded by ALDOT. However, every step of the study is presented in great detail to make it possible for ALDOT to develop and implement this methodology for other pay items or by other transportation agencies.

5.2 Recommendations for Future Research

During the study, the authors identified some research questions that should be considered in future studies. These questions are outlined below:

- What factors are causing price differences across geographic regions in Alabama?
    - The LCI developed in this study revealed significant differences in prices across the state of Alabama. However, the factors causing price differences among geographic regions have not been clearly defined at the time of this writing. A better understanding of these factors could improve the performance of the cost estimating system proposed in this report.
- Does "level of competition" impact transportation construction prices in Alabama?
    - Initial research efforts also considered "level of competition" as a cost-driven factor. The impact of the level of competition was assumed to be related to the number of vendors competing on ALDOT's projects in each geographic region. No substantial differences were found on the average number of vendors per project per region; therefore, this factor was not further considered in the proposed cost estimating system since it was assumed to impact all ALDOT's projects equally. However, the research team recognizes that further research is needed in this area. The level of competition is not only a result of the number of vendors competing on a project. The level of competition is relative to the perception of each bidder. Even though an anticipated large number of bidders may drive vendors to submit lower price proposals, other factors may have a similar effect. Some of those factors could be anticipated competitors with access to cheaper suppliers/subcontractors or more cost-effective materials or construction methods.
- How would the proposed cost estimating system perform for other pay items different from the case study item?
    - The proposed MCVW approach has proven its ability to improve cost estimating for the case study item in terms of accuracy and reliability. Further research is needed to determine if the proposed system would have a similar effect on cost estimating procedures for other ALDOT's pay items.

REFERENCES

Akanni, P. O., Oke, A. E., & Akpomiemie, O. A. (2015). Impact of environmental factors on building project performance in Delta State, Nigeria. *HBRC Journal*, 11(1), 91-97

Akinci, B., & Fischer, M. (1998). Factors affecting contractors' risk of cost overburden. *Journal of Management in Engineering*, 14(1), 67-76.

Akintoye, A. (2000). Analysis of factors influencing project cost estimating practice. *Construction Management & Economics*, 18(1), 77-89

Alabama Department of Transportation (ALDOT) (2015), *104th Annual Report Fiscal Year 2015*

Alabama Department of Transportation (ALDOT) (2018). *Standard Specifications for Highway Construction 2018 Edition*

Allen, R. (1975). *Index numbers in theory and practice*. Chicago: Aldine

American Association of State Highway and Transportation Officials (AASHTO). (2013). *Practical Guide to Cost Estimating.* AASHTO

Anderson, S. D., Molenaar, K. R., & Schexnayder, C. J. (2007). *Guidance for cost estimation and management for highway projects during planning, programming, and preconstruction* (Vol. 574). Transportation Research Board

Anderson, I. Damnjanovic, A. Nejat, and S. Ramesh. (2009) *Synthesis on Construction Unit Cost Development*, Texas Department of Transportation, Report Number FHWA/TX-09/0-6023-1, Texas Transportation Institute, College Station, Texas.

American Society of Civil Engineering (ASCE) (2015), *Alabama Infrastructure Report*

American Society of Civil Engineering (ASCE) (2017), *Americas Infrastructure Report* Accessed on March 5, 2018.
https://www.infrastructurereportcard.org/

Arafa, M., & Alqedra, M. (2011). Early stage cost estimation of buildings construction projects using artificial neural networks. *Journal of Artificial Intelligence*, 4(1), 63-75.

Betts, M. (2007). Standardization in Information Technology Industries: Emerging Issues under Section Two of the Sherman Antitrust Act. *Oklahoma Journal of Law and Technology*, 3(1), 6.

Boris Iglewicz and David Hoaglin (1993), "Volume 16: How to Detect and Handle Outliers", *The ASQC Basic References in Quality Control: Statistical Techniques*, Edward F. Mykytka, Ph.D., Editor.

Bowen, P. A., and P. J. Edwards. (1985) "Cost modelling and price forecasting: practice and theory in perspective." *Construction Management and Economics* 3.3 199-215.

Byrnes, J. E. (2002). Best practices for highway project cost estimating. Arizona State Univercity, Tempe, AZ.

Cho, Y. K., Youn, J. H., & Martinez, D. (2010). Error modeling for an untethered ultra-wideband system for construction indoor asset tracking. *Automation in Construction*, 19(1), 43-54.

Congress, U. S. (2012). *Moving ahead for progress in the 21 st century act*. Washington, DC.

Cuervo, J. C., & Sui Pheng, L. (2003). Significance of location factors for Singapore transnational construction corporations. *Engineering, Construction and Architectural Management*, 10(5), 342-353

Du, X. (2013). *Traffic Safety Evaluation Model for Highway in Cold Region Based on Fuzzy Theory.* Research Journal of Applied Sciences, Engineering and Technology, (6), 1048.

Erickson, R., & White, K. (2011). *Description of the Federal Highway Administration's National Highway Construction Cost Index* (NHCCI) (No. 11-0218).

Fakültesi, M., & Zeynep, D. (2004). A Neural Network Approach for Early Cost Estimation of Structural Systems of Buildings. *International Journal of Project Management*, 595-602.

Federal Highway Administration (FHWA) (1988). *"Bid Analysis and Unbalanced Bids,"* Memorandum HHO-32, US Department of Transportation, May 16, 2988.
http://www.fhwa.dot.gov/programadmin/contracts/051688.cfm

Fisher, I. (1922). *The making of index numbers; a study of their varieties, tests, and reliability*, Boston, New York: Houghton Mifflin Company.

Fragkakis, N., Lambropoulos, S., & Tsiambaos, G. (2010). Parametric model for conceptual cost estimation of concrete bridge foundations. *Journal of Infrastructure Systems,* 17(2), 66-74.

Gardner, B. J. (2015). *Applying artificial neural networks to top-down construction cost estimating of highway projects at the conceptual stage*. Iowa State University

Gardner, B., Gransberg, D. D., and Jeong, H. S. (2015). *"Rationally Selecting Data for Highway Construction Cost Estimating at the Conceptual Stage."* To be submitted to ASCE Journal of Computing in Civil Engineering.

Gill, C. (1933). *Construction Statistics*. Journal of the American Statistical Association,(181), 31-54.

Golafshani, N. (2003). Understanding reliability and validity in qualitative research. *The qualitative report*, 8(4), 597-606

Gransberg D.D., and J. A. Rueda (2014). *Indefinite Delivery/Indefinite Quantity Final Report,* MnDOT Contract 99/004/Work Order.

Guerrero, P. F. (2003). *Comparison of States' Highway Construction Costs*. US General Accounting Office.

Hanna, A. S., and Blair, A. N. (1993). *"Computerized approach for forecasting the rate of cost escalation."* Proc., Compute. Civ. Build. Tech. Conf., 401–408.

Hendrickson, C., & Au, T. (1989). *Project management for construction: Fundamental concepts for owners, engineers, architects, and builders*. Chris Hendrickson.

Hubbard, J. (1921*). The Aberthaw Index of Building Costs.* The Review of Economics and Statistics, (10), 342-344.

Iowa Department of Transportation (Iowa DOT) (2017). "*Highway Finance"* Accessed on March 5, 2018.
https://iowadot.gov/about/HighwayFinance

JICA (Japan International Cooperation Agency). (2010). Evaluation guide for prequalification and bidding under Japanese ODA loans: Procurement of goods and services.

Juszczyk, M. (2013, October). The use of artificial neural networks for residential buildings conceptual cost estimation. In *AIP Conference Proceedings* (Vol. 1558, No. 1, pp. 1302-1306). AIP.

Kaming, P. F., Olomolaiye, P. O., Holt, G. D., & Harris, F. C. (1997). Factors influencing construction time and cost overruns on high-rise projects in Indonesia. *Construction Management & Economics*, *15*(1), 83-94

Khosrowshahi, F., and Ammar P. Kaka. (1996). "*Estimation of project total cost and duration for housing projects in the UK*." Building and Environment 31.4 375-383.

Kim, G. H., An, S. H., & Kang, K. I. (2004). Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning. *Building and environment,* 39(10), 1235-1242

Lee, Y. (2013). *Assessment of expressway construction using Quality Performance Index (QPI).* KSCE Journal of Civil Engineering, (2), 377-385.

Liu, L., & Zhu, K. (2007). Improving cost estimates of construction projects using phased cost factors. *Journal of Construction Engineering and Management,* 133(1), 91-95.

Makridakis, S., Wheelwright, S. C., and Hyndman, R. J. (1998). *Forecasting methods and applications,* Wiley, New York.

Miller, M. C. (2015). *Develop a social return on investment framework for Iowa rural bridge transportation asset management*. (Doctoral dissertation, Iowa State University).

Molenaar, Keith, Stuart Anderson, and Clifford Schexnayder. (2013). "*AASHTO practical guide to estimating*."

Olson, M. (2013). *Quantification of sustainability index for underground utility infrastructure projects. (Author abstract).* Journal of Construction Engineering and Management.

Phaobunjong, K. (2002). *Parametric cost estimating model for conceptual cost estimating of building construction projects* (Doctoral dissertation).

Project Management Institute (PMI) (2013). *A Guide to the Project Management Body of knowledge (PMBOK® Guide), Fifth Edition*, ANSI/PMI 99-001-2013, pp 589.

Rueda, J. A. (2013). *Develop a Price Escalation Method for Minnesota Department of Transportation Indefinite Delivery/Indefinite Quantity: AxE Bidding* (Master's Thesis), Iowa State University, Ames, IA.

Rueda-Benavides, J.A., and D.D. Gransberg. (2015). "*Suitability Analysis of Existing Construction Cost Indexes for Minnesota Department of Transportation Construction Projects*," Transportation Research Board Annual Meeting Compendium of Papers, Paper 15-2293, National Academies, January 2015, Session 237, 16 pp.

Rueda-Benavides, J. A. (2016). *Indefinite Delivery/Indefinite Quantity project selection framework using stochastic techniques* (Doctoral dissertation, Iowa State University).

Sanders, S. R., Maxwell, R. R., & Glagola, C. R. (1992). *Preliminary estimating models for infrastructure projects*. Cost Engineering (Morgantown, West Virginia), 34(8), 7-13.

Schexnayder, C. J., S. L. Weber, and C. Fiori. (2003). NCHRP Project 20-07/Task 152 Report, *Project Cost Estimating a Synthesis of Highway Practice*, Transportation Research Board, National Research Council, June 2003.

Shane, J. S., Molenaar, K. R., Anderson, S., & Schexnayder, C. (2009). Construction project cost escalation factors. *Journal of Management in Engineering*, 25(4), 221-229.

Taylor, Timothy RB, and William F. Maloney. (2013). *Forecasting Highway Construction Staffing Requirements*. No. Project 20-05, Topic 43-13. 2013.

Touran, A., and R. Lopez. (2006). *Modeling Cost Escalation in Large Infrastructure Projects. Journal of Construction Engineering and Management*, ASCE, Vol. 132, No.2, pp. 853–860.

TRIP (2016). *Key Facts about Alabama's Surface Transportation System and Federal Funding.*

Trost, S. M., & Oberlender, G. D. (2003). Predicting accuracy of early cost estimates using factor analysis and multivariate regression. *Journal of Construction Engineering and Management*, 129(2), 198-204

Utah Construction & Design. (2013). UDOT - Cost-Based Estimates. *Utah Construction & Design*, 41-42.

White, K., & Erickson, R. (2011). *New cost estimating tool.* Public Roads, *75*(1).

Wickham, H. (2014). *Tidy data.* Journal of Statistical Software, *59*(10), 1-23.

William Manfredonia, J. P. (2016, 11 02). *Cost Estimating.* Retrieved from WBDG: https://www.wbdg.org/design-disciplines/cost-estimating

Woldesenbet, Asregedew Kassa, (2014). *"Highway Infrastructure Data and Information Integration & Assessment Framework: A Data-Driven Decision-Making Approach"*.
Graduate Theses and Dissertations. 14017.

Xu, J. W., & Moon, S. (2011). Stochastic forecast of construction cost index using a cointegrated vector autoregression model. *Journal of Management in Engineering*, 29(1), 10-18.

Zhang, Zuoyi, and Yuliang Sun. (2007). "Economic potential of modular reactor nuclear power plants based on the Chinese HTR-PM project." *Nuclear Engineering and Design*, 237.23 2265-2274.

Zou, P. X., Zhang, G., & Wang, J. (2007). Understanding the key risks in construction projects in China. *International Journal of Project Management*, 25(6), 601-614.