DATA USAGE OPTIMIZATION FOR COST ESTIMATING IN ASPHALT PAVING PROJECTS USING A COST INDEXING SYSTEM

by

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ABSTRACT

During the last decade, the transportation construction industry has seen an increase in the implementation of historical bid-based cost estimating practices by various state transportation agencies (STAs). The American Association of State Highway and Transportation Officials (AASHTO), provides basic guidelines on the preparation of construction cost estimates using bid data from previous transportation construction projects. The process presented in the AASHTO guidebook includes a number of assumptions whose validity does not seem to have been challenged in the existing literature. One of these assumptions, and the one addressed in this thesis, refers to the optimal number of year of historical data to be used for estimating purposes.

The primary objective of this study is to develop a methodology to assist the Alabama Department of Transportation (ALDOT) with the definition of optimal look-back periods for data retrieval to maximize estimating accuracy in asphalt paving projects. According to AASHTO guidelines, a one- or two-year lookback period is commonly used for bid-based estimating purposes, and sometimes, it could be extended if the last two years do not provide sufficient data. However, no guidance is provided on how to determine whether to use one, two, or more years of data. How can a STA estimator know how many years of data would be required to maximize estimating accuracy? This is the main question to be answered in this thesis.

Taking into consideration that the amount of data is irrelevant if it is not appropriately collected, clean, and processed, the proposed look-back determination process is presented along with a data-driven cost estimating methodology designed to maximize the effectiveness of bid-base estimates. The optimal look-back period is determined, and the application and effectiveness of the cost estimating methodology is demonstrated, using ALDOT’s historical bid data for all projects awarded between 2011 and 2016 (2122 contracts). A moving-window analysis algorithm has been designed to measure the performance of the estimating model over 6 years and for different look-back periods ranging from 1 to 5 years. The moving-window algorithm includes a number of research techniques, including advance data cleaning procedures, non-linear regression, time series analysis, and various statistical significance testing approaches.

The proposed bid-based estimating methodology has been designed to counteract the impact of inflation on estimates produced with data from previous projects. Thus, the author has also developed an innovative construction cost indexing system (CCIS) intended to adjust past construction prices based on observed fluctuations in the construction market. The thesis presents a comparative analysis conducted to select the most suitable cost indexing approach among 20 alternatives, including twelve different versions of the CCIS (developed in this study) and eight existing construction cost indexes (CCIs) currently used in the construction industry. The twelve different versions of the CCIS were developed by taking into consideration three different index recalculation periods (i.e. quarterly, semi-annual, and annual) and four types of inputs for each recalculation period (i.e. all bids, median values on a project basis, average values on a project basis, and only awarded bids).

The use of the look-back period determination process and the proposed data-driven cost estimating methodology are illustrated in this thesis as they are applied to the most relevant pay item used in ALDOT’s paving projects: *“Superpave Bituminous Concrete Wearing Surface Layer, 1/2" Maximum Aggregate Size Mix, ESAL Range C/D – Item ID 424A360.”* It was found that unit prices for the case study item (item 424A360) are more accurately estimated using two years of historical bid data and a quarterly CCIS calculated with all bids received by ALDOT for this item. Even though these findings are only applicable to the case study item, the thesis presents the process in a detailed manner, so that it could repeated for other cost items, on an as needed basis.

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Firstly, I would like to thank Dr. Rueda for giving me an opportunity to prove myself. I remain grateful to him for all the guidance and support he provided in the past couple of years. There is no exaggeration in saying that it is because of him, my educational experience at Auburn University has become wonderful and memorable. Secondly, I would like to thank Dr. LaMondia and Dr. Azhar for showing their interest to serve on my committee and providing their valuable suggestions that help shape my thesis. Last but not least, I would like to thank my parents and friends who stood by me in times of need and constantly encouraged me in my endeavors. I truly feel fortunate for having all these people in my life.

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LIST OF ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation Officials
ALDOT	Alabama Department of Transportation
ASCE	The American Society of Civil Engineers
BCI	Building Cost Index
CCI	Construction Cost Indexes
CCIS	Construction Cost Indexing System
ENR	Engineering News Record
FHWA	Federal Highway Administration
LAPV	Largest Average Price Variation
MAPE	Mean Absolute Percentage Error
MCCI	Multilevel Construction Cost Index
NLR	Non-linear Regression
ROUT	Robust Regression and Outlier Removal
STAs	State Transportation Agencies

CHAPTER ONE: INTRODUCTION

The U.S. transportation infrastructure system 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 elements of the American infrastructure. State Transportation Agencies (STAs) play a key role in the planning, design, construction, operation, and maintenance of the highway network in the U.S. To fulfil these responsibilities, STAs are compelled to manage their budgets in a responsible and efficient manner. “A sound budgeting system is one which engenders trust among citizens that government, in the broad sense, is listening to their concerns, has a plan for achieving worthwhile objectives, and will use the available resources effectively, efficiently and in a sustainable manner in doing so” (OECD, 2014). STAs’ budgets are built with funds coming from various sources, including federal-aid programs and vehicle fuel taxes and registration fees collected at the state and federal level (IOWADOT, 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 (ASCE, 2017). Even though it looks like a massive investment in public infrastructure, the same study has revealed that such levels of investment are not sufficient to satisfy the current needs of the 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 conditions of the U.S transportation infrastructure system, which is affecting taxpayers on 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 the limited available resources to offer the best value for taxpayer's money. The ability of STAs to offer the best value-for-money depends, in part, on the effectiveness of their cost estimating systems. Having sound estimates of the expected costs of addressing current and foreseen infrastructure needs would facilitate an effective allocation of resources by allowing a better prioritization of candidate projects based on more reliable cost-benefit analyses. As a contingency measure to mitigate the impact of the unavoidable and increasing funding gap, STAs have been intensifying their efforts towards the improvement of cost estimating practices. This thesis is intended to contribute to those efforts by proposing a methodology to improve what has become the most commonly estimating approach used by STAs: historical bid-based cost estimating (AASHTO 2013) –a estimating method used to some extend by all STAs (Anderson et al. 2009; Schexnayder et al. 2003).

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). The Practical Guide to Cost Estimating, published by the American Association of State Highway and Transportation Officials (AASHTO) (2013), provides basic guidance on the preparation of construction cost estimates using bid data from previous transportation construction projects. However, this guidance relies on various assumptions whose validity does not seem to have been challenged in the existing literature. One critical assumption, and the one addressed in this thesis, refers to the optimal number of years of past data to be used for estimating purposes.

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 lays 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. In an effort to lessen the conflict between these two requirements, and in an attempt to maximize the estimating power of historical bid data, this study also used ALDOT's data to develop a innovative construction cost indexing system (CCIS) used to mitigate the impact of inflation as increasing the length of the look-back period. A similar cost indexing system has been previously developed, and positively validated, for the Minnesota Department of Transportation (Rueda 2016).

Twelve versions of the CCIS were developed in this study considering three different index recalculation frequencies (i.e. quarterly, semi-annual, and annual) and four types of inputs for each recalculation frequency (i.e. all bids, median values on a project basis, average values on a project basis, and only awarded bids). Likewise, the performance of the twelve CCIS's presented in this thesis was compared against the performance of eight existing Construction Cost Indexes (CCIs) currently used by some practitioners in the construction industry. Thus, the CCIS ultimately proposed in this thesis is the one that showed the best performance among all 20 different indexing alternatives.

The proposed look-back period determination process and the data-driven cost estimating methodology are illustrated and validated in this thesis by applying them to estimate unit prices for the most relevant pay item used in ALDOT's asphalt paving contracts: *"Superpave Bituminous Concrete Wearing Surface Layer, 1/2" Maximum Aggregate Size Mix, ESAL Range C/D – Item ID 424A360."* An innovative moving-window analysis algorithm was developed and used as the main research instrument, as well as an advanced validation strategy. This algorithm integrates various research techniques, including advanced data cleaning procedures, non-linear regression modeling, time series analysis, and various statistical significance tests. The optimal look-back period and the best CCIS were selected through comparative analysis by running the moving-window algorithm several times to assess and compare the performance of all possible combinations of look-back periods and cost indexing alternatives (110 combinations –including combinations with no linear regression models and no indexing system)

This study found that unit prices for the case study item (item 424A360) are more accurately estimated using two years of historical bid data and a quarterly CCIS calculated with all bids received by ALDOT for this item. It must be noted that these specific findings are only applicable to the case study item in projects to be awarded by ALDOT. However, the process to determine the optimal look-back period and to develop and select the most suitable CCIS, as well as the overall data-driven cost estimating methodology, are explained in sufficient detail, so that they could be adapted by ALDOT, or other STAs, to estimate unit prices for other items used on a regular basis in transportation construction contracts.

1.1 MOTIVATION AND BACKGROUND

1.1.1. 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% can be 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 to 11% during a 2-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 do not include the additional almost $2 billion a year due to motor vehicle crashes and congestion costs (ASCE, 2015).

ALDOT's current funding situation is not very different from the national funding situation described in the previous section. STAs across the country, including ALDOT, are currently looking for strategies that allow them to support the expanding highway network with a shrinking funding stream (Taylor and Maloney 2013). In view of the lack of sufficient funding, ALDOT has being modifying its resource allocation strategies to spend less to make needed improvements, and more to maintain existing roads and bridges open and in acceptable conditions (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 source of transportation funding. These taxes are collected as a fixed-rate for every gallon of fuel purchased. Federal and Alabama state taxes have not been increased since 1993 and 1992, respectively (ASCE, 2015). It means that the government has been collecting exactly the same amount of cents on every gallon of fuel purchased for more than 15 years. This is probably the main cause of the increasing funding gap (Miller, 2015).

Recognizing their funding constraints and their limited ability to increase their funding capacity, STAs like ALDOT have been investing efforts and resources in the optimization of their resource management systems to ensure that their shrinking budgets are invested in an effective manner and in an attempt to maintain the transportation infrastructure system in the best possible condition. Effective resource management systems require the implementation of reliable procedures to prioritize infrastructure needs based on thoughtful cost-benefit analyses, and these procedures, in turn, rely on the effectiveness of STA’s cost estimating practices. This is how the methodologies proposed in this thesis will contribute to the improvement ALDOT’s budget control and management capabilities –by facilitating a better and more effective use of ALDOT’s historical bid data to produce better construction cost estimates.

1.1.2. FACTORS INFLUENCING UNIT PRICE ESTIMATING

Effective bid-based cost estimating systems must allow for adjustments to the estimating process based on the specific conditions of each project (Anderson et al., 2007). The ASCE has identified the following five factors influencing the estimation of unit prices in construction contracts:

- Scale – project size; quantities of work.
- Time – fluctuations in construction prices over time.

- Geographic Conditions – project location; local labor and materials availability; urban, suburban, or rural setting; local traffic volumes.
- Level of Competition – number of potential bidders qualified to do the work.
- Uncertainty – lack of ability to accurately account for all project-specific conditions affecting cost estimating.

The study presented in this thesis is just the first of a series of research efforts intended to enhance ALDOT's construction cost estimating system. The data-driven cost estimating methodology proposed in this study only takes into consideration the first two factors listed above: scale and time. The other three factors will be addressed in future studies. The scale factor was incorporated through non-linear regression techniques, as usually done by ALDOT and as illustrated in Figure 1. Non-linear regression is used with historical bid data to model the relationship between quantities of work and unit prices. For example, the non-linear regression equation in Figure 1 was created for the hot mix asphalt case study item (424A360) using two years of data, January 2013 – December 2015. Thus, based on ALDOT's current estimating practices, this equation would be used to estimate unit prices for this item around January 2016.

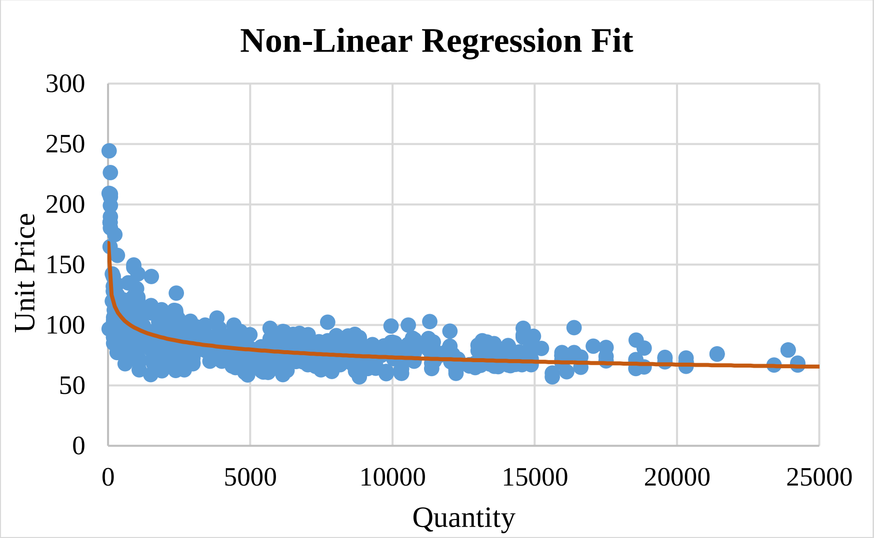


Figure 1. Non-linear Regression Model for Case Study Item (424A360)

Based on a face-to-face meeting held with ALDOT staff involved in cost estimating procedures, it was found that they usually retrieve one or two years of data to create non-linear regression models for bid-based estimates. However, the ultimate decision on how much data to use is a subjective decision based on estimator’s judgement and experience. This is where the proposed look-back period determination methodology will play a critical role. It will allow ALDOT to objectively define look-back periods for data retrieval, maximizing the effectiveness of its bid-based estimates. Moreover, the proposed methodology includes the use of a cost indexing system as a means to incorporate the second of the five price influencing factors listed above: time. The adjustment of bid-based cost estimates for inflation and fluctuations in the construction market over time is something that, to the best knowledge of the author, has not been proposed in the existing literature, at least not for an immediate of short-term use of the estimates, as in this study. Time adjustments in bid-based estimates have been proposed only when the estimated values needs to be forecasted across long time horizons (Gardner et al., 2015). A possible reason to explain why no similar approaches have been proposed before for an immediate of short-term use could be that data from the past one to two years seem to be still considered as “recent” data, so no time adjustments are required. That can be inferred from the definition of bid-based cost estimating stated by AASHTO. “Historical bid-based estimating uses data from *recently* let contracts as the basis for determining estimated unit prices for a future project […] the data retrieval period is often limited to 1 to 2 years, unless there is not sufficient bid data for an item, in which case dated data must be used” (AASTHO, 2013). However, this study has proved that significant construction price changes may occur during those periods of time, affecting the accuracy bid-based estimates, as demonstrated in Chapter 5 of this thesis.

1.2 RESEARCH OBJECTIVES

The research plan followed throughout this study, and described in Chapter 3, was thoughtfully crafted to achieve the following objective and sub-objectives:

- The primary objective of this thesis is to develop a protocol to assist ALDOT with the definition of optimal look-back periods for data retrieval to maximize accuracy of historical bid-based cost estimates in asphalt paving projects. The protocol is to be applied at the pay item level, meaning that unit prices for different pay items in the same contract may be estimated with different look-back periods. To accomplish this primary objective, and maximize the contribution of this study, the following sub-objectives have been established:
    - Develop a methodology to facilitate and ensure an appropriate utilization of datasets retrieved with the proposed look-back determination protocol. This methodology must consider two main factors affecting unit price estimating processes project scale and fluctuations in construction prices over time. At this stage, these two factors are enough to develop and validate the proposed look-back period determination protocol. Future research efforts will be aimed to further refine ALDOT's data-drive cost estimating practices by incorporating additional factors that may influence the pricing process.
    - Develop a construction cost indexing system (CCIS), or select an existing indexing approach (whichever works better), to adjust bid-based estimates according to inflationary trends and observed changes in the construction market. This indexing system is intended to maximize the length of look-back periods allowing the use of

larger amounts of historical data while counteracting the impact of time on construction prices.

1.3 ORGANIZATION OF THESIS

This thesis has been organized into seven chapters, as follows:

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

Chapter 2: Literature Review, provides a summary of the existing literature on bid-based cost estimating, including various research reports, journal articles, and case studies from a number of authors. This chapter also discusses previous studies on the development and appropriate use of CCIs and describes the three algorithms most commonly used in the construction industry to calculate price indexes.

Chapter 3: Methodology, describes the research plan designed and followed for the accomplishment of the research objectives and sub-objectives, including all the research instruments, mathematical procedures, and statistical tests involved in the development and implementation of the look-back period determination protocol, CCIS, and the overall data-driven cost estimating methodology that integrates all the procedures proposed in this thesis. This chapter also describes the techniques used to validate the research results and to demonstrate the effectiveness of the proposed bid-based cost estimating methodology.

Chapter 4: Development of Construction Cost Indexing System (CCIS), presents the twelve different CCIS's developed under this study, as well as the eight existing CCIs considered in this study as a way to adjust bid-based cost estimates to counteract the impact of inflation and fluctuations in the construction market over time.

Chapter 5: Moving-window Data Optimization Algorithm: Analysis of Results, summarizes the results obtained from moving-window optimization algorithm and presents the statistical analysis for the selection of the optimal look-back period and the most suitable CCIS for the case study item.

Chapter 6: Conclusions and Future Research, deals with major results and findings of this extensive study and presents the main contributions to the body of knowledge made in this thesis. Lastly, this section presents some recommendations for future research as a follow-up to the results presented in this study.

CHAPTER TWO: LITERATURE REVIEW

2.1 INTRODUCTION

Chapter 2 summarizes the information gathered during the comprehensive literature review conducted for the development of this thesis. The chapter starts with an overview of the cost estimating challenges faced by STAs and the cost estimating approaches currently used in the transportation construction industry. Specifically, this chapter briefly describes the four main cost-estimating approaches presented in the AASHTO Practical Guide to Cost Estimating (2013): parametric, historical bid-based, cost-based, and risk-based cost estimating. The chapter then focused on historical bid-based cost estimating, providing a more detailed discussion on this estimating approach, which is the main concern of this thesis. Finally, this chapter presents a brief discussion about the use and limitations of traditional cost indexing systems when used to counteract the impact of time on construction cost estimates.

2.2 COST ESTIMATING IN THE TRANSPORTATION CONSTRUCTION INDUSTRY – OVERVIEW

By definition, a project is “a temporary endeavor undertaken to create a unique product, service, or result” (PMI, 2013), and transportation construction projects are not the exception. Each transportation 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 impact of all these factors on a project, makes construction cost estimating a particularly challenging process. The following four possible 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 me be forced to relocate its annual budget, cancelling 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 may be actually a sing 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 the approved projects, preventing 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 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). For example, 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%; and
- 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, from early planning to final design (Anderson et al., 2007; AASHTO 2013;). It allows STAs to monitor and control estimates throughout project development, facilitating timely decision 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, allowing for a greater estimating accuracy (Jui-Sheng Chou, 2009).

Different STAs may have adopted a different configuration of the project development process in terms of phases and activities performed under each phase. However, the AASHTO guidebook has identified and defined four generic project development phases, which are presented in Table 1. Likewise, Table 2 shows the level of project maturity, estimating methodology, and level of estimating accuracy for each phase.

Table 1. Project Development Phases and Typical Activities (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.

Table 2. Cost Estimating Classification (Adapted from AASHTO 2013)

Project Development Phase	**Project Maturity (% project definition completed)**	**Estimating Methodology**	**Estimating Accuracy**
Planning	0% to 2%	Parametric	-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 shows three different estimating methodologies used in the transportation construction industry: parametric; historical bid-based; and cost-based. There is one more estimating methodology mentioned in the ASSHTO guidebook and not shown in Table 2, which is actually an optional version for any of the other three methodologies: risk-based estimating. The following is a brief definition for each of these four estimating methodologies.

- Parametric Estimating: "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).

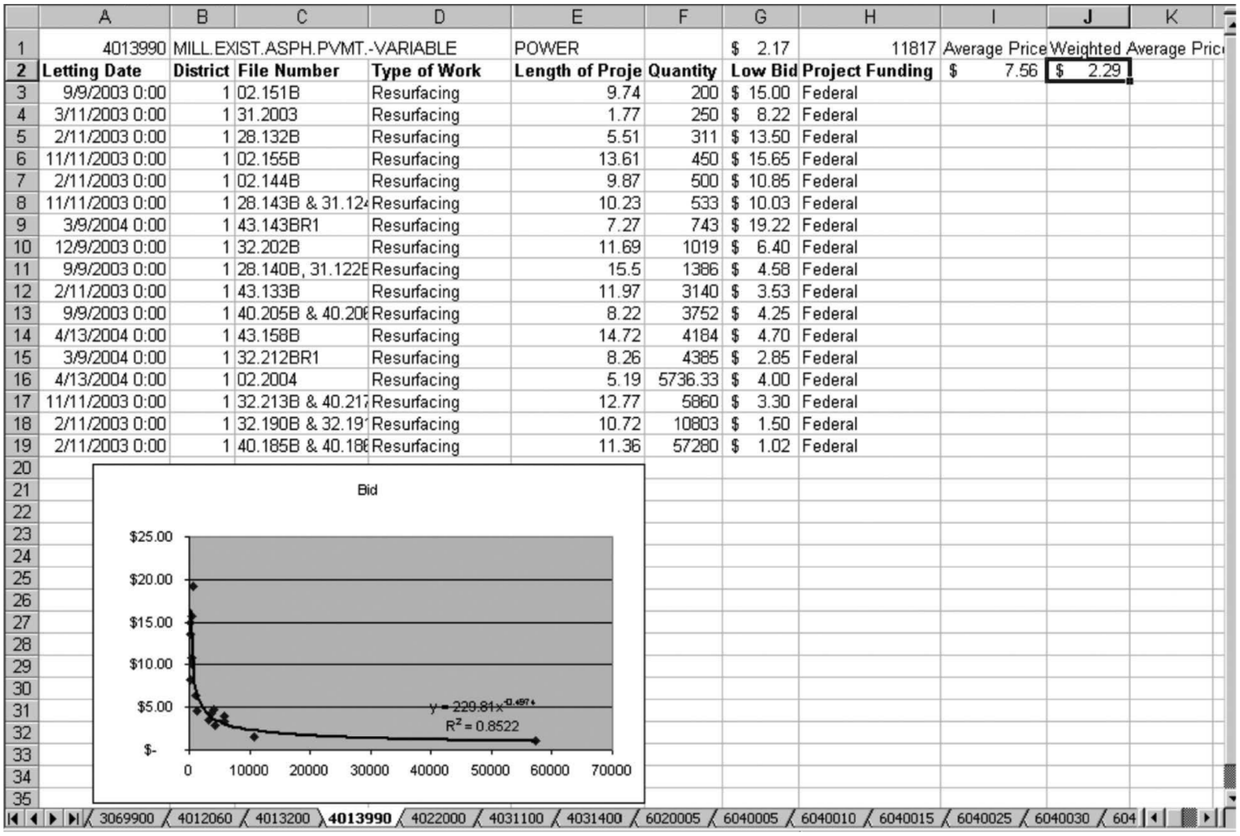
- Historical Bid-Based Estimating: "Historical bid-based estimating uses data from recently let contracts as the basis for determining estimated unit prices for a future project" (AASHTO, 2013). It is recognized as the most common estimating methodology used by STAs (Anderson et al. 2009).
- Cost-Based Estimating: "Cost-based estimating considers seven basic elements: time, equipment, labor, subcontractor, material, overhead, and profit. Generally, a work statement and set of drawings or specifications are used to 'take off' material quantities required for each discrete task necessary to accomplish the project bid items. From these quantities, direct labor, materials, and equipment costs are calculated based on assumed production rates. Contractor overhead and profit are then added to this direct cost. The total cost divided by the quantity gives the estimated unit price for the work item" (AASHTO 2013).
- Risk-Based Estimating: This estimating methodology combines any of the other estimating methodologies with risk analysis techniques in an attempt to quantify uncertainty in construction cost estimates. "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).

Table 2 also shows that bid-based cost estimating can be applied at all four project development phases with different levels of accuracy. The bid-based cost estimating methodology proposed in this thesis is intended to be applied at the final design phase, shortly before advertising the project and after identifying all pay items and calculating their respective quantities of work. However, it could be applied to a single pay item, at any development phase, as soon as having an estimate for its quantity, and as long as having sufficient and reliable historical bid data on that specific item.

2.3 HISTORICAL 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 the existing STAs's 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 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, 2007). However, it does not mean this is a mature approach that has been successfully refined throughout the years. Unfortunately, there is not much guidance for STAs on how to develop, implement, and update bid-based cost estimating systems, which frequently 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).

Previous studies have proposed a number of quantitative methods to estimate construction costs using historical data. These 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), which under the context of this study, would be the unit price of the item under consideration. Based on this classification of data-driven cost estimating methodologies, it can be said that the methodology proposed in this thesis 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 under use by STAs. Figure 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, to develop a non-linear regression model, similar to those used in this thesis.



	A	B	C	D	E	F	G	H	I	J	K
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. Historical bid analysis using non-linear regression modeling (AASHTO, 2013)

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

The literature contains several examples of bid-based estimating models. Most 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). These models were built and tested with 174 projects and were intended to forecast construction costs over long time horizons. The independent variables for this model included the 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 in urban highways. With and average accuracy of 6%, Sander et al.'s model could be considered fairly accurate. However, this results are questionable due to the fact the model was developed and validated only with data from 11 previous projects.

Based on the review of extensive literature on this topic, it can be concluded that historical bid-based cost estimating is a highly effective approach, as long as it is appropriately performed with sufficient and reliable data.

2.4 CONSTRUCTION COST INDEXING

As defined by Fisher (1922), who is a pioneer in the development of index numbers, "[a]n index number of prices […] shows the average percentage change of prices from point of time to another" (Fisher 1922). Thus, for the purposes of this thesis, a CCI is defined as an instrument to measure the average fluctuations of construction price over time. Indexes were initially used to track fluctuations in the stock market, wholesale/retail prices, and wages. Their use in the construction industry started by the early 20s with the Aberthaw Index, which was intended to measure changes in construction costs on standard seven-story reinforced concrete buildings (Hubbard 1921; Gill 1933). Since then, the use of CCIs has been increasing, and today it is possible to find several cost indexes published and maintain by different public and private organizations in the construction industry. There are also other types of indexes aimed to measure changes in factors other than money, such as safety (Du 2013), quality (Lee 2013), sustainability indexes (Olson 2013). However, the main use of CCIs is still focused on the adjustment of unit prices and the estimation of construction costs based on observed trends in the construction market (Rueda and Gransberg 2015).

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), frequency of recalculation (e.g. monthly, quarterly, annual), and scope/location(s) (e.g. national, 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). Moreover, Rueda and Gransberg (2015) propose a three-tier CCI classification system based on their usage. This classification system is illustrated in Figure 3.

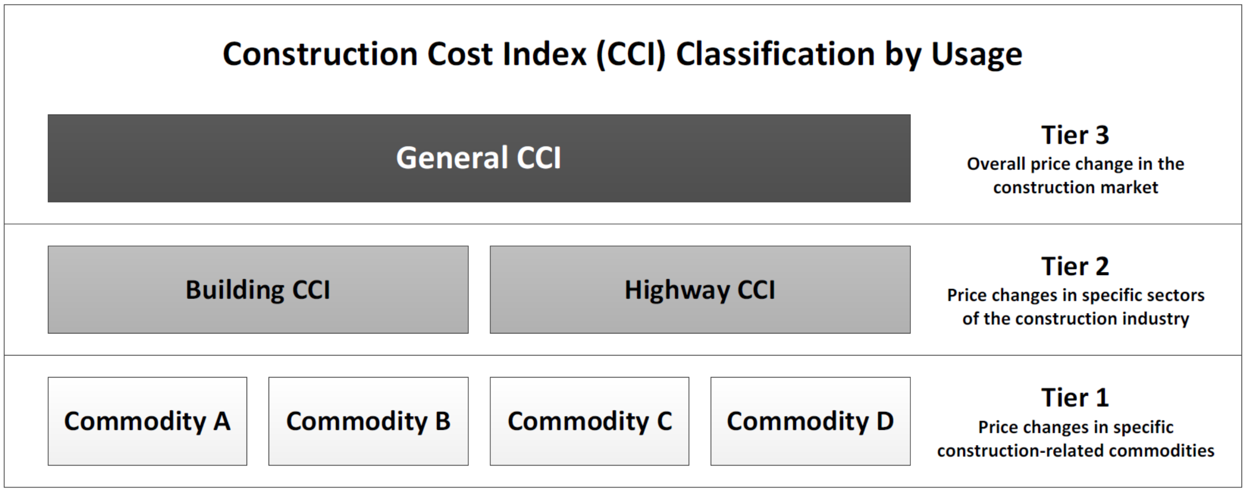


Figure 3. Construction Cost Index Classification by Usage (Rueda and Gransberg 2015)

Tier 1 corresponds to indexes designed to track price changes for specific commodities (e.g. fuel, asphalt, cement, steel, etc.). This tier also includes indexes at the price index level as those developed in this study. Indexes intended to track construction prices as such level of detail, as those in Tier 1, are mainly intended to adjust prices for their respective commodities/pay items over time (Skolnik, 2011). On the other hand, indexes in Tiers 2 have been classified at a broader scale into building (vertical construction) and highway (horizontal construction) CCIs. These indexes are commonly used at a broader scale 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, including all construction sectors.

The literature review for this thesis has found several STAs developing and using Tier 1 and 2 indexes to better understand changes in highway construction costs over time, estimate future highway funding needs, and estimate construction costs at the project level (Erickson, 2011; White, 2011; Guerrero, 2003). A Tier 2 index developed by a STA is usually intended to be applicable to all highway construction projects undertaken by the agency, meaning that there is a single index number to be applied to all types of work (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 (Rueda and Gransberg 2015). These are called composite weighted indexes (Rueda and Gransberg, 2015). The main challenges associated with the development of composite weighted indexes are the definition of weights and the integration of different types of index components. For example, a single index could be calculated using price fluctuations in asphalt (dollars/ton) and changes in labor rates (dollars/hour). How could these two components be combined into a single index? Which of these elements would be more relevant for cost indexing purposes? Fortunately, the econometrics literature offers various mathematical equations to overcome these challenges. The three most common price index equations used in the construction index are Laspeyres, Paasche and Fisher (FHWA 2017). In these equations, the weights of index components are given by their respective quantities of work. Thus, greater weights would be assigned to commodities or construction activities widely used by an STA. Equations 1, 2 and 3 represent these three indexing formulas.

$$Laspeyers\ index, L = \frac{\sum_{i=1}^{n} p_{i,t} q_{i,0}}{\sum_{i=1}^{n} p_{i,0} q_{i,0}} = \sum_{i=1}^{n} w_{i,0} \frac{p_{i,t}}{p_{i,0}} \qquad \textbf{\textit{Eq. 1}}$$

Where, weight, $w_{i,0} = \frac{p_{i,t} q_{i,0}}{\sum_{i=1}^{n} p_{i,0} q_{i,0}}$

$$Paasche\ index, P = \frac{\sum_{i=1}^{n} p_{i,t} q_{i,t}}{\sum_{i=1}^{n} p_{i,0} q_{i,t}} = \left(\sum_{i=1}^{n} w_{i,0} \frac{p_{i,0}}{p_{i,t}}\right)^{-1} \qquad \textbf{\textit{Eq. 2}}$$

Where, weight, $w_{i,0} = \frac{p_{i,t} q_{i,t}}{\sum_{i=1}^{n} p_{i,t} q_{i,t}}$

$$Fisher\ index, F = \sqrt{\frac{\sum_{i=1}^{n} p_{i,t} q_{i,0}}{\sum_{i=1}^{n} p_{i,0} q_{i,0}} X \frac{\sum_{i=1}^{n} p_{i,t} q_{i,t}}{\sum_{i=1}^{n} p_{i,0} q_{i,t}}} = \sqrt{\sum_{i=1}^{n} w_{i,0} \frac{p_{i,t}}{p_{i,0}} X \left(\sum_{i=1}^{n} w_{i,t} \frac{p_{i,0}}{p_{i,t}}\right)^{-1}} \qquad \textbf{\textit{Eq. 3}}$$

Where: $p_{i,t} = Prevailing\ price\ of\ item\ i\ in\ period\ t$
$q_{i,0} = Quantity\ of\ item\ i\ sold\ in\ period\ 0$
$w_{{i,0}_i} = Weight\ of\ the\ item\ i\ for\ period\ 0$
$n = Total\ number\ of\ projects$

These three equations are widely used by STAs for the calculation of their own CCIs. Table 3 shows some examples of the different elements considered by 16 STAs in the calculation of composite CCIs.

Table 3. Examples of CCI Components used by STAs

Agency	**Components used in the Calculation of CCI**
California	Roadway excavation; aggregate base; asphalt concrete pavement; Portland cement concrete pavement; Portland cement concrete structural; bar reinforcing steel; and structural steel.
Colorado	Earthwork; hot mix asphalt; concrete pavement; structural concrete; reinforcing steel.
Florida	Surfacing; earthwork; Portland cement concrete; bituminous concrete structural; reinforcing steel; structural steel; structural concrete.
Iowa	Roadway excavation; hot mix asphalt pavement; Portland concrete cement pavement; reinforcing steel; structural steel; structural concrete.
Minnesota	Excavation; reinforcing steel; structural steel; structural concrete; concrete pavement; plant-mix bituminous.
Mississippi	Unclassified excavation; warm and hot mix asphalt pavement; concrete pavement; reinforcing steel; structural steel; class ‘aa’ bridge concrete.
Montana	Excavation; aggregate base; surfacing; drainage; concrete; reinforcing steel; bridge; traffic; misc. item.
Nebraska	Roadway excavation; concrete pavement; concrete for box culverts; 24” & 36” pipe, culvert; corrugated metal and plastic (cmp), reinforced; concrete for bridges; structural steel; piling, concrete and steel; asphalt concrete; asphalt cement; emulsified asphalt for track coat.
New Hampshire	Roadway excavation; crushed materials; hot mix asphalt, structural concrete, -rebar; structural steel.
Oregon	Excavation; crushed rock; Portland concrete cement; mixed asphalt; reinforcing steel; structural steel; structural concrete.
Ohio	Asphalt; aggregate base; barrier; bridge painting; curbing; drainage; earth work; erosion control; guardrail; landscaping; lightning; maintenance of traffic; pavement marking; pavement repair; Portland cement concrete pavement; removal; signalization; structures; traffic control; unclassified construction items.
South Dakota	Unclassified excavation; liquid asphalt; asphalt concrete; gravel cushion; sub-base and base; Portland cement concrete pavement; class a concrete (structures); reinforcing steel; structural steel.
Texas	Earthwork; excavation; embankment subgrade and base course -lime treated subgrade or base; cement treated subgrade or base; asphalt treated base or foundation course; flexible base surfacing; surface treatment; bituminous mixtures; concrete pavement structures; structural concrete; metal for structures; prestructured concrete beams; foundations; drainage -riprap -retaining walls.
Utah	Roadway excavation; bituminous surface mix; bitumen; Portland cement concrete pavement; reinforcing steel; structural steel; structural concrete.
Washington	Roadway excavation; crushed surfacing; hot mix asphalt; Portland cement concrete pavement; structural concrete; steel reinforcing bar; structural steel.
West Virginia	Unclassified excavation; class 1 aggregate base course; Marshall hot-mix base course, stone; Marshall hot-mix wear course, stone, -class b concrete; reinforcing steel bars; -type 1 guardrail.

Rueda and Gransberg (2015) introduced two important principles that are repeatedly violated when using composite indexes to adjust construction prices at the project level: the matching and the proportionality principles. The matching principle refers to the degree of similarity between the components used in the calculation of a CCI and the actual activities/elements used in the 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 weights of index components and the actual contribution of these components to the total cost of the project to be adjusted. Thus, "a perfect application of a CCI (unlikely situation) implies that each pay item in a given CCI-adjusted contract is represented by one commodity in the CCI and the weights used in the calculation of the index numbers are exactly proportional to the contribution of their respective pay items to the total project cost" (Rueda and Gransberg 2015). It should be noted that a violation of the matching principle implies a violation of the proportionality principle. Likewise, Rueda and Gransberg (2015) discuss how two assumptions usually made by STAs when using composite CCIs for estimating purposes suppose a strong violation of these two principles. These assumptions are:

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

STAs usually assume that a single CCI represents average overall fluctuations in the highway construction industry in their respective states, so that, this CCI can be applied in cost estimating procedures for all types of projects (assumption 1). Then, these CCI are calculated with a few commodities or items, assuming that they are significant enough to represent the entire highway construction market (assumption 2). With these two assumption, STAs are clearly violating the matching and proportionality principles since not all projects are compose by the same elements or pay items, and even if some projects share the same items, they would not be included in the projects in the same proportions (Rueda and Gransberg 2015).

Regardless of the known limitations of traditional cost indexing practices in construction cost estimating, and due to the fact that it is impossible to find an indexing approach that perfectly comply with the matching and proportionality principles, this thesis has considered and assessed the performance of eight existing composite CCIs as an alternative to adjust bid-based cost estimates. However, in this study, the author has also developed twelve different versions of a construction cost index system (CCIS) following a methodology previously developed by Gransberg and Rueda (2014) for the Minnesota Department of Transportation (MnDOT). This methodology is intended to create a Multilevel Construction Cost Index (MCCI) strategically designed to overcome the limitation of traditional indexing practices and to better meet the matching and proportionality principles. The MCCI consists of a group of indexes organized in a multi-level arrangement. Thus, different cost items in a construction contract could be adjusted with different indexes from the MCCI. Therefore, different projects may require different sets of indexes, offering great flexibility to customize price adjustment procedures to the unique characteristics of each project. More information on the development and implementation of this innovative CCIS is presented in Chapter 3. Additionally, a research report authored by Gransberg and Rueda (2014) and submitted to MnDOT presents a detailed description of the methodology followed to produce a MCCI. It should be noted that, for the purposes of this theses, the term Construction Cost Indexing System (CCIS) refers to an arrangement of multiple Tier 1 indexes intended to track price changes at the pay item level. While the term Construction Cost Index (CCI) refers to a single Tier 2 composite index aimed to measure fluctuations at higher level (building/highway construction sector).

CHAPTER THREE: METHODOLOGY

3.1 INTRODUCTION

This chapter describes the research methodology that led to the development of the look-back period determination protocol and data-driven cost estimating approach proposed in this thesis. The flow chart in Figure 4 illustrates the research methodology and illustrates the sequence of work followed throughout this study. The information in this chapter is presented in logical order following the order of activities illustrated in Figure 4, starting with the data collection and cleaning processes, and then guiding the reader through the data processing procedures that allowed the achievement of the research objectives. Finally, this chapter describes the validation strategies used to demonstrate the potential positive impact of this study on ALDOT construction cost estimating practices. As illustrated in Figure 4, this study started with a comprehensive literature review on current and effective bid-based cost estimating procedures. Findings and information gathered during the literature review was already presented in Chapter 2; therefore, that step of the research methodology is not covered in this chapter.

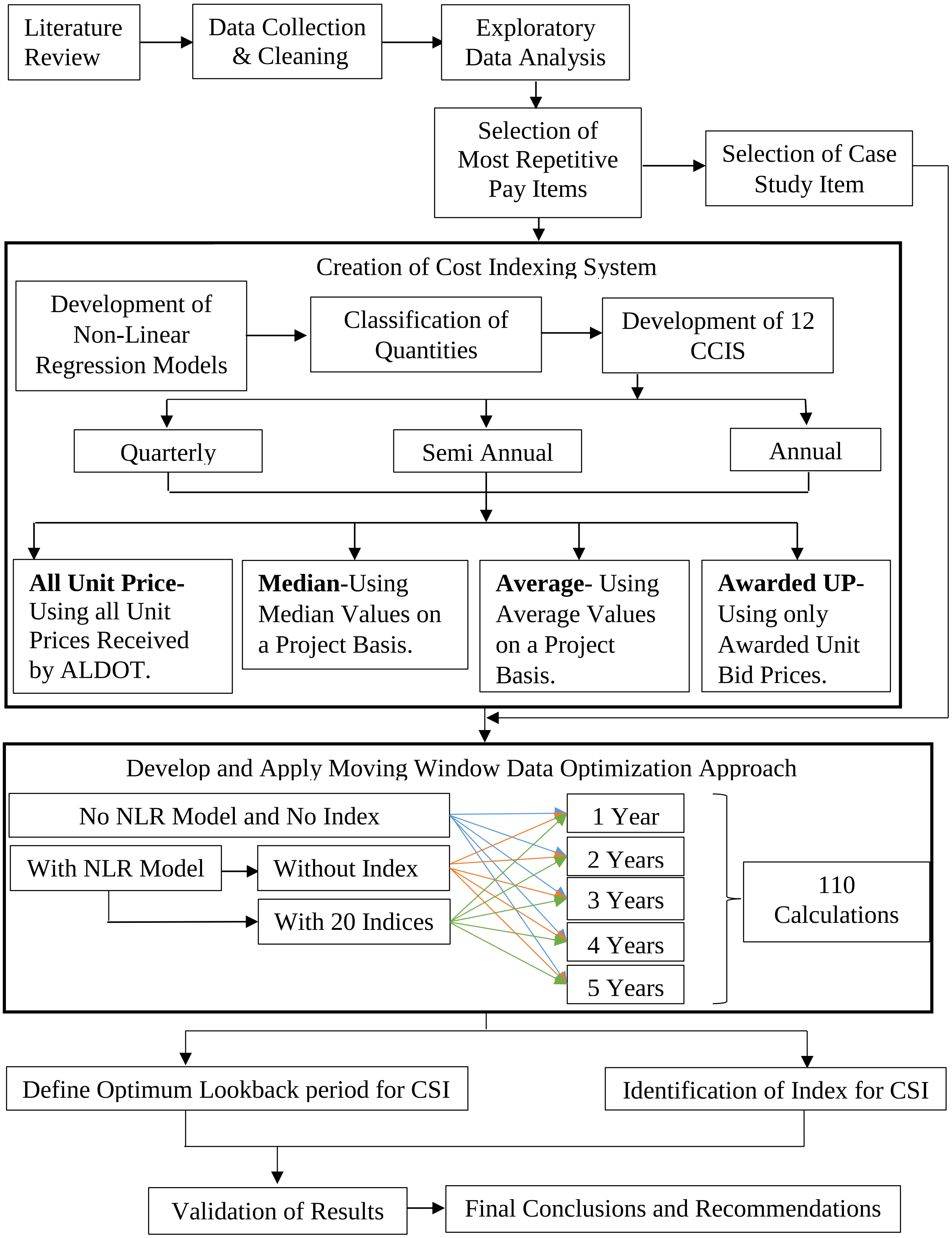


Figure 4. Illustration of Research Methodology

3.2 DATA COLLECTION & CLEANING

> *"State highway agencies invest a large amount of resources in collecting, storing and managing various types of data ranging from roadway inventory to pavement condition data during the life cycle of a highway infrastructure project. Despite this huge investment, the current level of data use is limited and is raising concerns whether the growing amount of data adds value to users and offers meaningful return on data collection efforts." (Woldesenbet, 2014)*

Taking into consideration the issue highlighted by Woldesenbet in the quote above, this study has paid special attention and has invested a considerable amount of research time and efforts to fully exploit and appropriately use the large amounts of cost data stored by ALDOT during the last decade. This section summarizes the data collection and cleaning procedures implemented in this study to successfully develop and validate the look-back period determination protocol and the proposed CCIS, as well as to develop the overall data-driven cost estimating methodology that integrates the quantitative approaches proposes in this this. Data collection efforts were directed to extracting bid tabulations from ALDOT's databases for all construction projects awarded from 2006 to 2016 (eleven years of data). 3661 contracts were awarded during that period. Figure 5 is a rough representation of the structure of the bid tabulations collected for this study. In addition to some project-specific information, such as project description, contract ID, location, letting date, etc., the bid tabulations present all the unit prices submitted by each bidder for each pay item listed in the Requests for Proposals (RFPs). It should be noted that the list of pay items and quantities are provided by ALDOT in the RFP; therefore, all contractors are bidding on the same items and quantities. All 3,661 projects have been awarded on a low-bid basis, meaning that the contractor that submits the lowest total bid price –after adding all extended prices (Extended Price = Quantity x Unit Price)– is awarded the contract. Bid tabulations sort bidders in an ascending order, from the lowest (the winner) to the highest bid. Depending on the project complexity, the number of items in a project may vary from 10 to 200. Likewise, the number of bidders competing for a project may vary from one bidder to twenty.

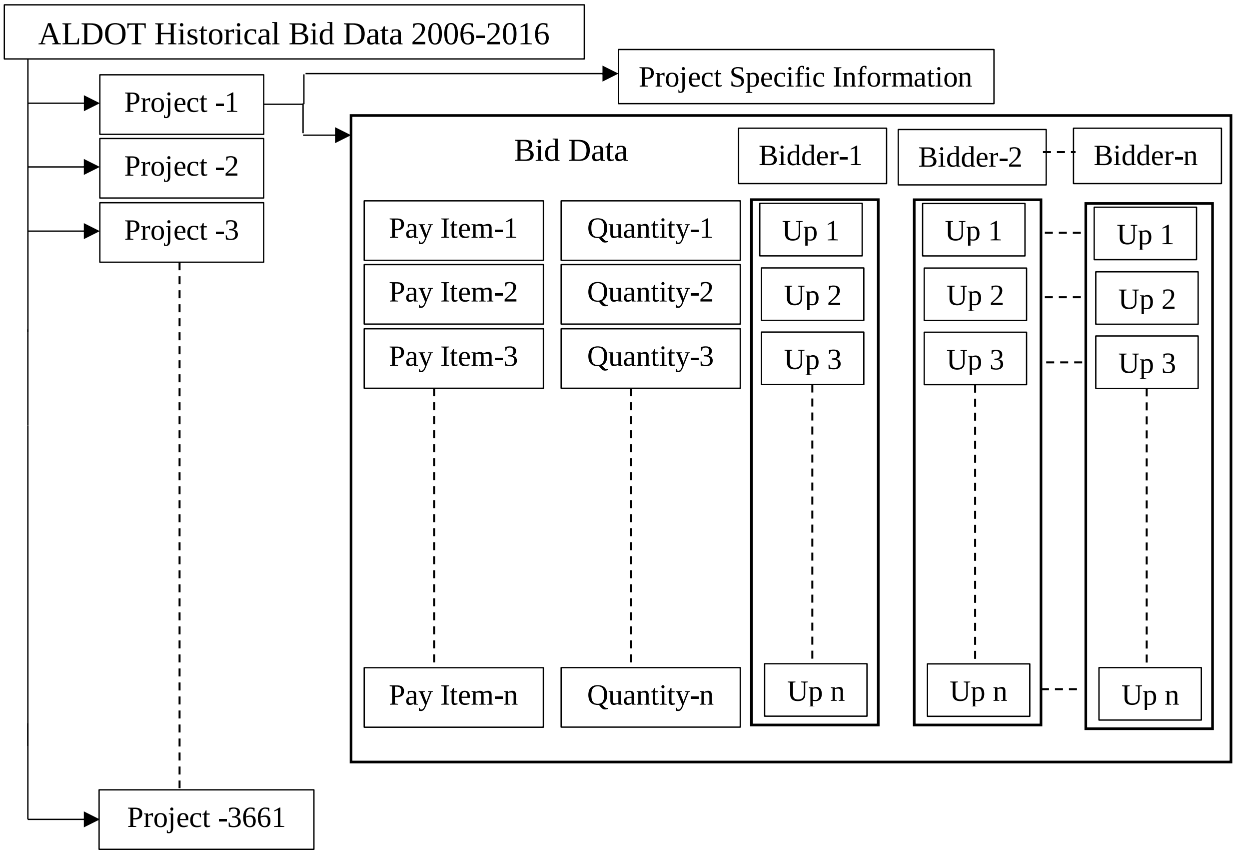
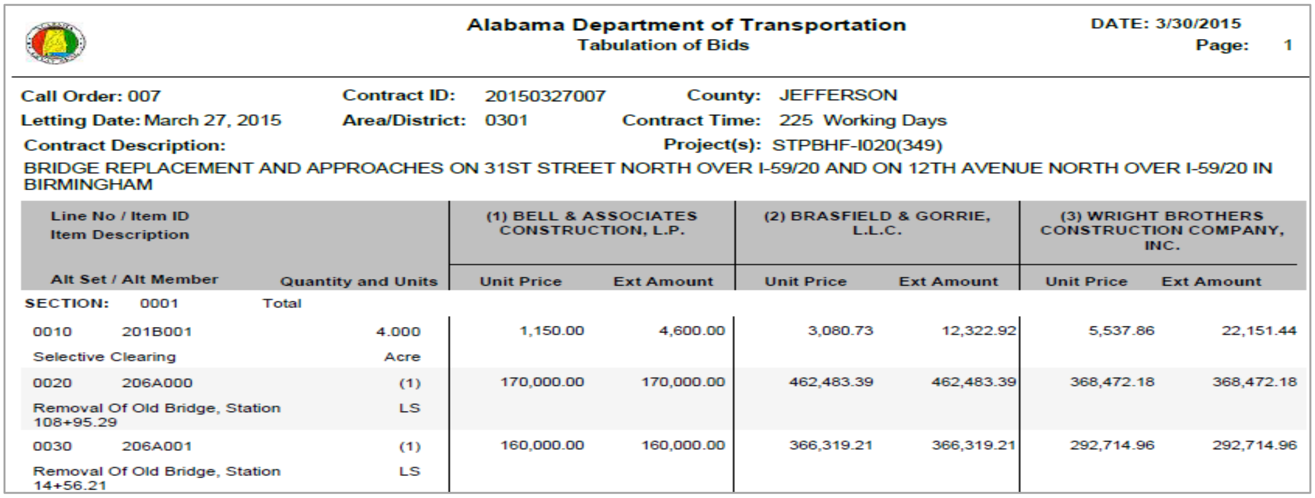


Figure 5. ALDOT Structure of the Bid Tabulations

Historical bid data was extracted directly from ALDOT's letting website in Portable Document Format (PDF). Figure 6 shows a screen capture of the PDF file for a given project. For data manipulation and processing purposes, it was necessary to convert all PDF files into Microsoft Excel (hereinafter referred to as Excel) format. The format conversion process was carried out using an internet-based free software application. The conversion process was not perfect and the Excel files had some critical consistency issues, making data processing virtually impossible for such a large database. Even with a perfect format conversion, data processing would have been extremely difficult with the data arrangement used in ALDOT's bid tabulations. Therefore, it was necessary the development of a meticulous and complex Excel spreadsheet to bring the poorly formatted data into a data processing-friendly format. This spreadsheet used a series of algorithms to reformat, in a semi-automatic fashion, all PDF-to-Excel converted data into a tidy database.

Data tidying is a critical part of the data cleaning process (Wickham, 2014). It refers to the arrangement of a dataset into a tabular format, so that each observation is assigned a single row and each column represents a different attribute of the observations. Thus, a user of a tidy dataset should be able to find all the characteristics of an observation on a single row. Part of the tidy dataset for this project is shown in Figure 7. In this dataset, each row corresponds to a pay item included in a construction contract and the columns include 24 data attributes on each pay item. Data attributes include letting date, contract ID, county, project title, contract time, number of bidders, total bid for the contract, pay item ID, item description, unit of measurement, quantity, unit prices submitted by all bidders on that specific item, etc. The final collected data includes bid data of 3,661 projects with 5,246 different pay items and 169,947 observations (rows). Some of the 24 data attributes are presented in multiple columns, such the bidders name and bids summited by each of them for the same item. Thus, the final tidy dataset was arranged into 131 columns. It should be noted that some pay items appear multiple times throughout the datasets as they are used in different projects. The twelve CCIS developed in this study track construction price fluctuation across all eleven years of data (using all 3,661 projects). However, the look-back determination period protocol and the bid-based estimating methodology are developed and validated using only 2122 projects, which are all the projects awarded by ALDOT between 2011 a 2016 (six years of data). This decision was made because the CCIS revealed what seemed to be a trend change in historical bid prices for asphalt paving project in 2010. Therefore, the results of the application of the proposed methodologies before 2010 might not effectively represent the expected results from their potential application in today's construction industry.



Alabama Department of Transportation
Tabulation of Bids

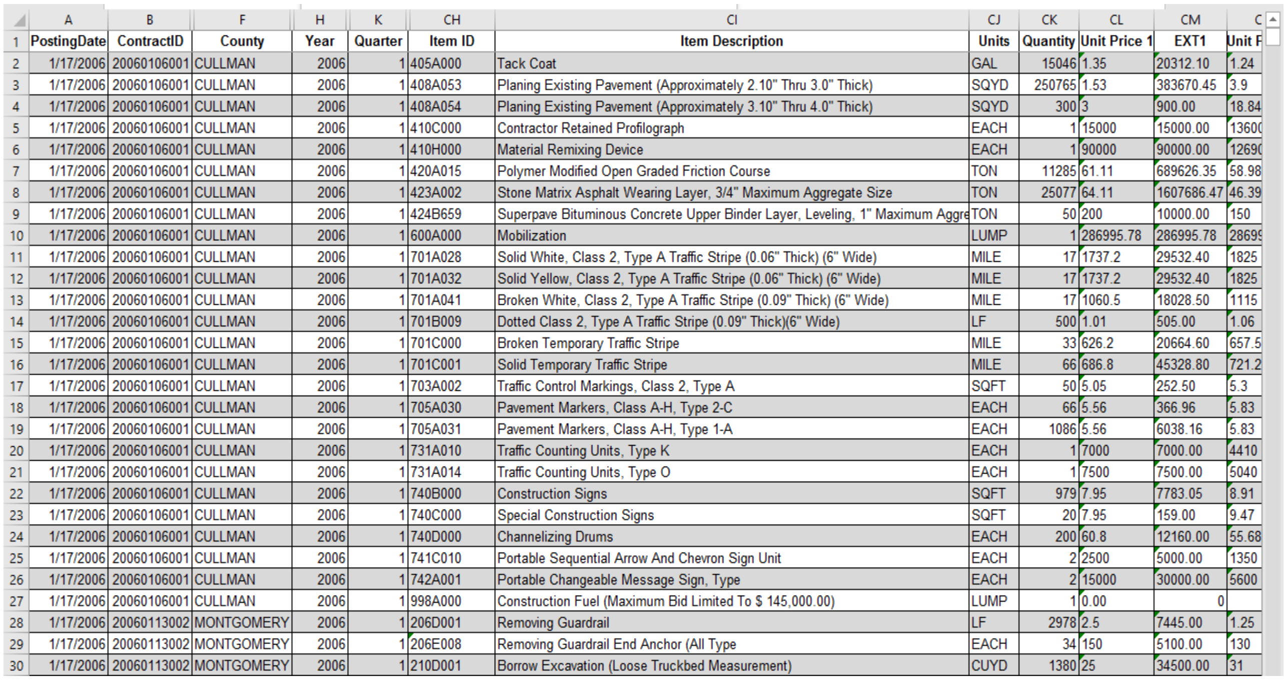
DATE: 3/30/2015
Page: 1

Call Order: 007
Contract ID: 20150327007
County: JEFFERSON
Letting Date: March 27, 2015
Area/District: 0301
Contract Time: 225 Working Days
Contract Description:
Project(s): STPBHF-I020(349)

BRIDGE REPLACEMENT AND APPROACHES ON 31ST STREET NORTH OVER I-59/20 AND ON 12TH AVENUE NORTH OVER I-59/20 IN BIRMINGHAM

Line No / Item ID Item Description Alt Set / Alt Member	Quantity and Units	(1) BELL & ASSOCIATES CONSTRUCTION, L.P.		(2) BRASFIELD & GORRIE, L.L.C.		(3) WRIGHT BROTHERS CONSTRUCTION COMPANY, INC.	
		Unit Price	Ext Amount	Unit Price	Ext Amount	Unit Price	Ext Amount
SECTION: 0001 Total							
0010 201B001 Selective Clearing	4.000 Acre	1,150.00	4,600.00	3,080.73	12,322.92	5,537.86	22,151.44
0020 206A000 Removal Of Old Bridge, Station 108+95.29	(1) LS	170,000.00	170,000.00	462,483.39	462,483.39	368,472.18	368,472.18
0030 206A001 Removal Of Old Bridge, Station 14+56.21	(1) LS	160,000.00	160,000.00	366,319.21	366,319.21	292,714.96	292,714.96

Figure 6. Screen Capture of Project Data in PDF Format



	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	1360
6	1/17/2006	20060106001	CULLMAN	2006	1	410H000	Material Remixing Device	EACH	1	90000	90000.00	1269
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	2869
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
13	1/17/2006	20060106001	CULLMAN	2006	1	701A041	Broken White, Class 2, Type A Traffic Stripe (0.09" Thick) (6" Wide)	MILE	17	1060.5	18028.50	1115
14	1/17/2006	20060106001	CULLMAN	2006	1	701B009	Dotted Class 2, Type A Traffic Stripe (0.09" Thick)(6" Wide)	LF	500	1.01	505.00	1.06
15	1/17/2006	20060106001	CULLMAN	2006	1	701C000	Broken Temporary Traffic Stripe	MILE	33	626.2	20664.60	657.5
16	1/17/2006	20060106001	CULLMAN	2006	1	701C001	Solid Temporary Traffic Stripe	MILE	66	686.8	45328.80	721.2
17	1/17/2006	20060106001	CULLMAN	2006	1	703A002	Traffic Control Markings, Class 2, Type A	SQFT	50	5.05	252.50	5.3
18	1/17/2006	20060106001	CULLMAN	2006	1	705A030	Pavement Markers, Class A-H, Type 2-C	EACH	66	5.56	366.96	5.83
19	1/17/2006	20060106001	CULLMAN	2006	1	705A031	Pavement Markers, Class A-H, Type 1-A	EACH	1086	5.56	6038.16	5.83
20	1/17/2006	20060106001	CULLMAN	2006	1	731A010	Traffic Counting Units, Type K	EACH	1	7000	7000.00	4410
21	1/17/2006	20060106001	CULLMAN	2006	1	731A014	Traffic Counting Units, Type O	EACH	1	7500	7500.00	5040
22	1/17/2006	20060106001	CULLMAN	2006	1	740B000	Construction Signs	SQFT	979	7.95	7783.05	8.91
23	1/17/2006	20060106001	CULLMAN	2006	1	740C000	Special Construction Signs	SQFT	20	7.95	159.00	9.47
24	1/17/2006	20060106001	CULLMAN	2006	1	740D000	Channelizing Drums	EACH	200	60.8	12160.00	55.68
25	1/17/2006	20060106001	CULLMAN	2006	1	741C010	Portable Sequential Arrow And Chevron Sign Unit	EACH	2	2500	5000.00	1350
26	1/17/2006	20060106001	CULLMAN	2006	1	742A001	Portable Changeable Message Sign, Type	EACH	2	15000	30000.00	5600
27	1/17/2006	20060106001	CULLMAN	2006	1	998A000	Construction Fuel (Maximum Bid Limited To $ 145,000.00)	LUMP	1	0.00	0	
28	1/17/2006	20060113002	MONTGOMERY	2006	1	206D001	Removing Guardrail	LF	2978	2.5	7445.00	1.25
29	1/17/2006	20060113002	MONTGOMERY	2006	1	206E008	Removing Guardrail End Anchor (All Type	EACH	34	150	5100.00	130
30	1/17/2006	20060113002	MONTGOMERY	2006	1	210D001	Borrow Excavation (Loose Truckbed Measurement)	CUYD	1380	25	34500.00	31

Figure 7. Tidy Project Data in Excel

3.3 OUTLIER DETECTION AND REMOVAL

"An outlying observation is numerically distant from other members of the sample in which it occurs. Although it may occur by chance in any distribution, it often stems from unmodeled factors or anomalous causes" (Agamennoni et al. 2011). Two main outlier detection methods were used in this study as part of the data cleaning process: 1) the modified Z-score method and 2) robust regression and outlier removal (ROUT). Both methods are used under the assumption that values are normally distributed around the mean value. These methods are described in the following two sections

Modified Z-Score Method

Even though the outlying condition of unit prices in historical bid datasets may be due to data entry errors or unreasonable unit prices mistakenly submitted by contractors, most outliers in these datasets are probably the result of unbalanced bids (Rueda 2016). According to Manzo (1997), a price proposal is considered to be unbalanced if each of its bid items "fails to carry its proportionate share of the overhead and profit in addition to the necessary costs for the item. The results are understated prices for some items and enhanced or overstated prices for others." The presence of outliers in datasets used to build data-driven models can potentially affect the performance of the models. It is a common practice to implement outlier detection mechanisms at an early stage during the development of this type of models in an attempt to discard unbalanced bids, as well as other unintentional outliers (FHWA 1988).

The modified Z-score method was mainly used in an attempt to remove the outliers resulting from unbalanced bids. If for example, five bidders submit proposals on a given contract, this method can be applied to determine whether or not a given unit price submitted by one of the bidders for a specific pay item is unbalanced, by comparing it against the other four bids for the same item. As shown in this example, the sample size to be assessed for outlier detection is given by the number of bidders on each contract, which is usually a small number. The reason for using the modified Z-score method in this study is because it is more suitable for small samples since it uses the median of the values under consideration ($\tilde{x}$) and the absolute deviation of the median (MAD) to identify outliers, while other more commonly used methods are based on mean and standard deviation values (Iglewicz and Hoaglin, 1993). Mean and standard deviation values in small datasets are very sensitive to extreme values, so that outliers could be masked and pass undetected (Seo, 2006). Equation 4 was used for the calculation of the modified Z-score (Seo, 2006). As recommended by Iglewicz and Hoaglin (1993), all unit prices whose absolute modified Z-score was greater than 3.5 ($|M_i|$ >3.5) were marked as outliers and removed from the study.

$$M_i = \left(\frac{0.6745(x_i - \check{x})}{MAD}\right) \qquad \textbf{\textit{Eq. 4}}$$

Where: $x_i = Observation$
$MAD = Means\ Absoulte\ Deviation$
$\tilde{x}_i = Median\ of\ Observations$
$M_i = Modified\ Z\ Score$

Robust Regression and Outlier Removal (ROUT) Method

This method was proposed by Motulsky and Brown in 2006. It uses robust regression techniques to optimize non-linear regression models by discarding extreme values that significantly differ from the other values in the sample, allowing for regression models that better fit the data. In this study, ROUT was mainly intended to remove outliers not detected by the modified Z-score method. These outliers are removed during the development of the non-linear regression models used to correlate quantities and unit prices. Outliers not detected by the first method might be the result of unusual project conditions/requirements, forcing all bidders to submit atypical unit prices. If all unit prices for a given pay item in a contract are equally deviated from the typical price range, no outliers would be detected by the modified Z-score method since it is applied at the project level. However, the non-linear regression models in this thesis are developed with data from several projects, allowing for the identification and removal of those unusual projects that may affect the effectiveness of the proposed data-driven methodologies. This method was applied to this study using a statistical software package called GraphPad Prism 7, which, to the best knowledge of the author, and at this writing, is the only software package that offers a ROUT function.

3.4 EXPLORATORY ANALYSIS AND DATA SELECTION

The exploratory data analysis was conducted to gain a better understanding of the available historical bid data and to characterize the variables. It also allowed the author to identify and address data formatting and quality issues. By better understanding the data, the author was also able to adjust the research plan to ensure that the data requirements of the plan matched the actual condition and configuration of the available data. However, the main purpose of the exploratory data analysis was the selection of the items to be considered for the CCIS and the case study item to be used to illustrate the development and implementation of the look-back period determination protocol and the overall bid-based cost estimating methodology.

As mentioned above, the CCIS developed and tested in this study consists of multiple cost indexes for a number of pay items. The CCIS is used to adjust prices at the pay item level by selecting from the pool of indexes the one that best matches each pay item. Thus, the greater the number of items included in the CCIS the greater the expected accuracy of the price adjustments. However, not all 5,246 pay items used by ALDOT between 2006 and 2016 can be considered for the CCIS since not all of them are frequently included in ALDOT’s construction contracts, making it difficult to track their pricing behavior over time. Therefore, at this stage, the study was focused on finding the largest possible group of significant repetitive pay items to build the CCIS. The following steps followed to select frequently used pay items suitable for the CCIS:

1. Discard those items whose units are not precisely defined (e.g. each, lump sum), and keep those with consistent and specific characteristics that allow a price comparison over time. Unit prices for these types of items are usually not comparable across projects and cannot be modeled through non-linear regression techniques; therefore, it is not possible to track their prices over time with traditional indexing techniques or with the innovative approach used in this thesis. For example, while two projects may include in their RFPs the same mobilization pay item, which is usually paid once and on a lump sum basis (quantity = 1), the unit prices for this item could be very different between the projects due to the fact that each lump sum value might comprise different mobilization requirements.
2. Identify those used by ALDOT at least once in every quarter since 2006 to 2016. For this study, the calendar year is divided into four quarters as follows: Quarter 1 (Q1) from January 1 to March 31; Quarter 2 (Q2) from April 1 to June 30; Quarter 3 (Q3) from July 1 to September 30; and Quarter 4 (Q4) from October 1 to December 31. Since a quarterly index was the shortest recalculation period considered for the CCIS, it is necessary to include only pay items that are used at least once per quarter.
3. Discard those items that show no apparent correlation between their unit prices and their respective quantities of work. In other words, those items whose quantity-unit price relationship cannot be reasonably modeled using non-linear regression techniques (models similar to those shown in Figure 1 and 2).

Fifty three (53) pay items remained after following the three steps listed above. Although this number of items (about 1% of all 5,246 items) does not seem to be sufficient to represent the transportation construction industry in Alabama, these 53 pay items actually consume, on average (annual average from 2011-2016), over 20.41% of ALDOT's annual construction budget between 2011 and 2016. Several of the other 5,193 pay items are used just a few times, many of them only in one or two projects, in the 11-year period comprised in the available data. The list of all 53 items with their item identification numbers, descriptions, and units of measurement is presented in Appendix 1.

On the other hand, the case study item, which is also one of the 53 items used in the CCIS, corresponds to the most relevant pay item used in ALDOT's paving projects: *"Superpave Bituminous Concrete Wearing Surface Layer, 1/2" Maximum Aggregate Size Mix, ESAL Range C/D – Item ID 424A360."* In fact, this item has the second largest participation in ALDOT's annual construction budget, with only mobilization consuming a larger portion of the budget. It should be noted that mobilization is paid to contractors in almost all projects, not only asphalt paving projects, which explains why more dollars are spent in mobilization than on the case study item.

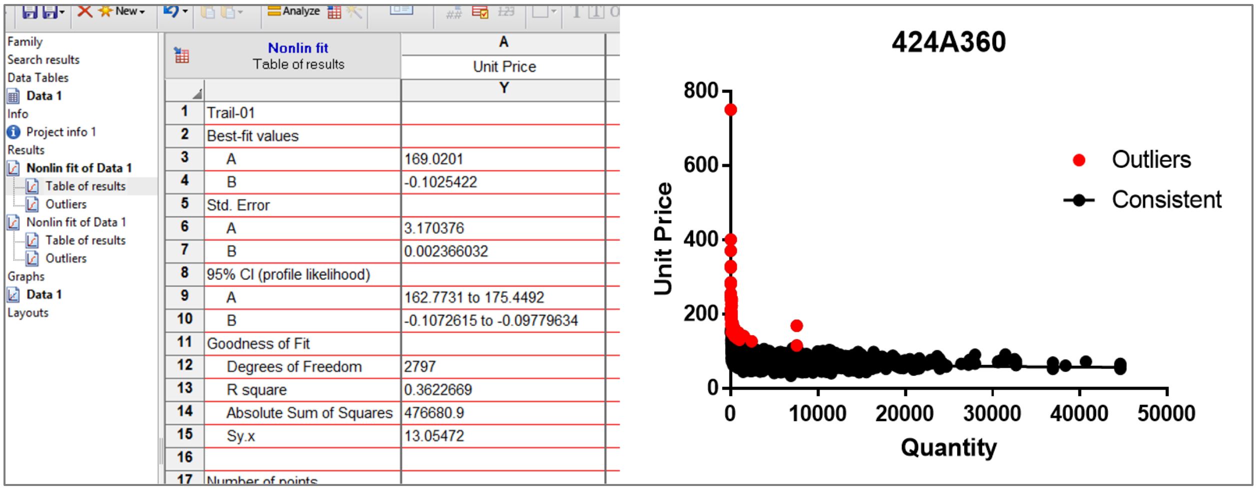
3.5 NON-LINEAR REGRESSION MODELS

To understand the non-linear relationship between quantities of work and unit prices, it is important to first understand the concept of economies of scale. According to this concept, lower unit prices should be expected from larger quantities of work (Zuoyi Zhang 2007). It happens because the fixed costs can be distributed among a greater number of units of work (Camacho and Garcia, 2011). Figure 1, in Chapter 1, illustrates the impact of economies of scale on the case study item. Unit prices decrease at a lower ratio as the number of units of work increase. That is why the curve is almost horizontal for large quantities of work (see Figure 1 and 2).

Research conducted by Rueda (2013; 2016) and the AASHTO guidebook (2013) suggest that power regression models are more suitable to explain quantity-unit price relationships for pay items in transportation construction contracts. These are non-linear regression models defined by Equation 5 (A and B are constant values). These model were created using GraphPad Prism 7, a statistical software that facilitates the use of the ROUT method for the identification and removal of outliers (see Section 3.3). The screen capture in Figure 8 shows an example of a power regression model developed with this software for the case study item using bid data from projects awarded between 2006 and 2016.

$$Unit\ Price = A * (Quantity)^{B} \qquad \textbf{Eq. 5}$$

Where: $A = Constant$
$\mathrm{B} = Constant$



	Nonlin fit Table of results	A Unit Price Y
1	Trail-01	
2	Best-fit values	
3	A	169.0201
4	B	-0.1025422
5	Std. Error	
6	A	3.170376
7	B	0.002366032
8	95% CI (profile likelihood)	
9	A	162.7731 to 175.4492
10	B	-0.1072615 to -0.09779634
11	Goodness of Fit	
12	Degrees of Freedom	2797
13	R square	0.3622669
14	Absolute Sum of Squares	476680.9
15	Sy.x	13.05472
16		
17	Number of points	

Figure 8. Power Regression Model for case study item in GraphPad Prism 7

Non-linear regression techniques are used for two different purposes in this thesis. Later in the study, they are used to produce initial unit price estimates based on the quantities of work to be included in ALDOT’s RFPs, but these regression models initially are used to make sure that price fluctuations are measured in the CCIS using comparable unit prices for similar quantities of work. This was the reason to include the third step in the selection of items for the CCIS (see Section 1.2). The economies of scale concept suggests that a comparison between the unit price for 50 tons of asphalt and the unit price for 50,000 tons of asphalt is not an “apples to apples comparison. Thus, the next step in this study was to define quantity ranges for each of the 53 items used in the CCIS, so that price changes over time are measure between unit prices from the same quantity ranges.

3.6 QUANTITY RANGES

Following the same approach used by Gransberg and Rueda (2014) for the development of a similar CCIS for MnDOT, the quantity ranges for a given item were defined using its non-linear regression model and the largest average price variation (LAPV) between the lowest and the largest bids received by ALDOT for that specific. The LAPV is calculated as shown in Equation 6 and is defined as “the typical maximum difference [in dollars] between two bids for the same pay item and quantity” (Gransberg and Rueda, 2014).

$$LAPV = \frac{\sum_{i=1}^{n} \frac{Largest\ bid_i - Lowest\ bid_i}{Lowest\ bid_i}}{n} \times 100\% \qquad \text{Eq. 6}$$

Where: $LAPV = Largest\ average\ price\ variation$
$Largest\ bid_i = Largest\ unit\ price\ received\ for\ the\ item\ under\ consideration\ on\ project\ i$
$Lowest\ bid_i = Lowest\ unit\ price\ received\ for\ the\ item\ under\ consideration\ on\ project\ i$
$n = Total\ number\ of\ projects\ including\ the\ item\ under\ consideration$

Figure 9 and Table 4 illustrate the process to define the quantity ranges for the case study item. Using Equation 6 and the available historical bid data, it was found that the LAPV for this item is 13.87%. Figure 9 shows how to use this LAPV and the values given by the regression model to define the quantity ranges for this item. Four quantity ranges have been defined for this item. Different pay items may have a different number of quantity ranges. The minimum and maximum numbers of quantity ranges among the 53 CCIS items are 1and 41 respectively. The number 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 summarized in Table 4. As done by Gransberg and Rueda (2014), quantity ranges were defined to cover at least 90% of the observations.

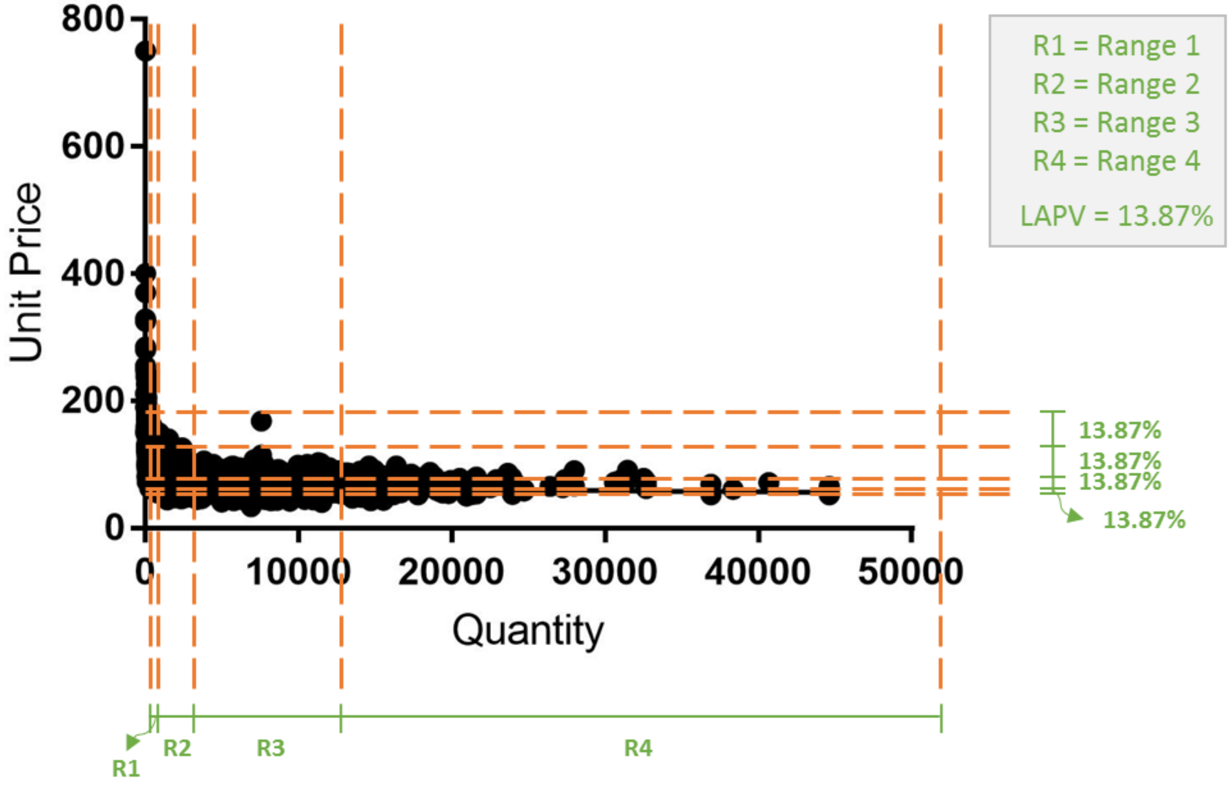


Figure 9. Case study item – Quantity range determination.

Table 4. Quantity Ranges for Case Study Item (Item 424A360)

Pay Item	Average Percentage Variation In Unit Price	Quantity Range	Lower Limit of Range	Upper Limit of Range
424A360	13.87%	1	188.00	766.38
424A360		2	766.38	3124.10
424A360		3	3124.10	12735.28
424A360		4	12735.28	51914.93

3.7 CONSTRUCTION COST INDEXING SYSTEM

As mentioned in Chapter 2, the proposed CCIS is based on multi-level cost indexing system previously developed by Gransberg and Rueda (2014) for MnDOT. The CCIS developed in this thesis, and illustrated in Figure 10, consists of 88 cost indexes arranged on four different levels. The lowest level is the Pay Item Level and it contains cost indexes for the 53 CCIS items. This is the level with the most specific indexes since each of 53 indexes at this level is only intended to be used on its respective pay item.

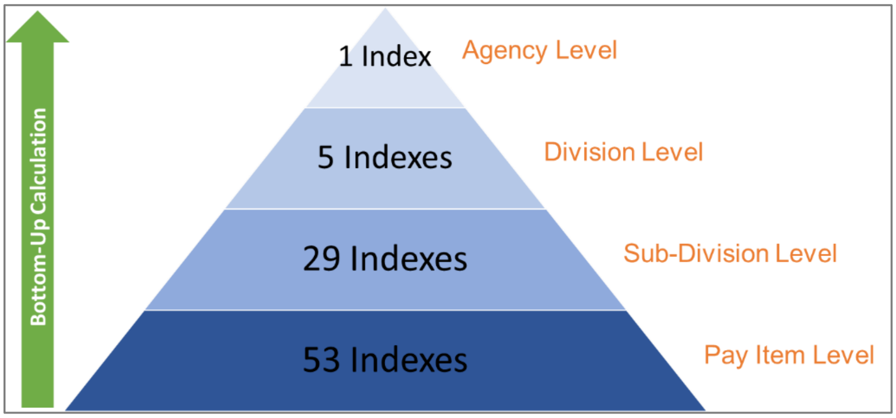


Figure 10. Structure of Construction Cost Indexing System

Following a bottom-up calculation approach, indexes at the Pay Item Level are then used to calculate the 29 indexes at the Sub-Division Level, which are less specific. Similarly, the indexes at the Sub-Division Level are used to calculate five broader indexes at the Division Level, which are then used to calculate a single general index to be used at the Agency Level.

Chapter 4 presents a comparative analysis conducted to select the most suitable cost indexing approach among 20 alternatives in order to identify the alternative that maximizes estimating accuracy. The 20 alternatives include twelve different versions of the CCIS (developed in this study) and eight existing construction cost indexes (CCIs) currently used in the construction industry. It means that the author has developed twelve different versions of the CCIS illustrated in Figure 10. All of them with the 88 cost indexes arranged in the same way, and with the same 53 items at the pay item level. The twelve versions of the CCIS were developed by taking into consideration three different index recalculation periods (i.e. quarterly, semi-annual, and annual) and four types of inputs for each recalculation period (i.e. average values on a project basis, median values on a project basis, only awarded bids, and all bids). Table 5 shows the recalculation dates for each of the recalculation periods. The twelve CCIS's are listed below:

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

Table 5. Index Recalculation Dates

Recalculation Period		**Recalculation 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

The calculations required to develop the CCIS’s can be classified into two major steps. The first step consists of the calculation of the all indexes at the Pay Item Level. Table 6 presents the quarterly, semi-annual, and annual cost indexes for case study item for 2006 and 2007. The index values in this table correspond to the CCIS calculated with all bids received by ALDOT for this item during these two years. All cost indexes have a start period used as a point of reference to measure price changes, and which is usually assigned an index value of 100 (Gransberg and Rueda, 2014). In this study, the start periods for the quarterly, semi-annual, and annual indexes are Q1-2006, S1-2006, and Y-2006, respectively (see Table 6). Variations in the index values are intended to proportionally represent average price changes between periods. Thus, based on Table 6, the annual index indicates that between 2006 and 2007 there was an average increase of -0.24% in the price of this item. Similarly, the semi-annual index shows an average price increase of 4.23% between first semester of 2006 and the first semester of 2007, and the quarterly index have measured and average increase of -2.71% between the fourth quarter of 2006 and the fourth quarter of 2007 ([120.87 – 124.24]/124.24). Cost indexes shown in Table 6 were calculated from 2006 to 2016 for all 53 CCIS items and for all types of inputs.

Table 6. CCIS 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 two periods is calculated as a weighted average of the variations at each quantity range, as shown below in Equation 7. In this equation, quantity ranges are weighted based on the total number of bids used to calculate the variation at each range. The larger the number of bids used to calculate the price variability, the more reliable the measure of variability, and the greater the weight. Once the average price variation between two periods has been calculated, the new index value for the current period is calculated using Equation 8.

$$APV_{PC} = \frac{\sum_{i=1}^{n}\left((PB_{Ri}+CB_{Ri})\times\frac{CAP_{Ri}-PAP_{Ri}}{PAP_{Ri}}\right)}{\sum_{i=1}^{n}(PB_{Ri}+CB_{Ri})} \qquad \text{Eq.7}$$

$$Current\ Index\ Value = Past\ Index\ Value\ \times (1 + APV_{PC}) \qquad \text{Eq.8}$$

Where: $APV_{PC} =$ $Average\ price\ varation\ between\ past\ and\ current\ period$
$PB_{Ri} =$ $Number\ of\ bids\ in\ the\ past\ period\ under\ quantity\ range\ i$
$CB_{Ri} =$ $Number\ of\ bids\ in\ the\ current\ period\ under\ quantity\ range\ i$
$CAP_{Ri} =$ $Current\ average\ price\ under\ range\ i$
$PAP_{Ri} =$ $Past\ average\ price\ under\ range\ i$
$n =$ $Number\ of\ quantity\ ranges\ for\ hte\ item\ under\ considertion$

The second major step in the development of the CCIS refers to bottom-up calculations used to define the indexes for the three upper level. To calculate the indexes at the Sub-Division Level, the 53 indexes were grouped based on similar characteristics and the indexes within each group were aggregated to produce one index per group. It means that 29 groups were form out of the original 53 indexes, resulting in the 29 indexes at the Sub-Division Level. In a similar way, these 29 indexes were arranged into 5 groups to produce the 5 indexes at the Division Level, which were then used to produce the general index at the Agency Level. The characterization of indexes was performed using the item identification numbers. Pay item identification numbers are assigned based on the nature of the work, materials, and activities associated with each item and according to the classification or activities and the construction divisions defined in ALDOT's Standard Specifications for Highway Construction (ALDOT, 2018). Therefore, it can be assumed that similar item identification numbers refer to similar pay items. Table 7 shows an example of how indexes were grouped al label across the CCIS. The description for the items in this table can be found in Appendix 1.

Table 7. Grouping of Indexes based on Levels

Pay Item Level	Sub-Division Level	Division Level	Agency Level
408A051	408	4	General Cost Index (calculated using all 53 indexes at the Pay Item Level)
408A052			
424A360	424		
424B650			
424B655			
424B659			
424B681			

The five indexes at the Division Level correspond to five major construction division defined in ALDOT's construction specifications (2018). ALDOT's specifications book is divided into the eight divisions listed below:

- **Division 100** – General Provisions
- **Division 200** – Earthwork
- **Division 300** – Bases
- **Division 400** – Surfacing and Pavements
- **Division 500** – Structures
- **Division 600** – Incidentals
- **Division 700** – Traffic Control Devices And Highway Lighting
- **Division 800** – Materials

Item identification numbers are associated with the number of their respective divisions. For example, all items with identification numbers starting with 4 are related to Division 400 – Surfacing and Pavements. The divisions not included in the CCIS are Divisions 100, 300 and 800. ALDOT construction contract include no pay items associated with Divisions 100 and 800, so that, these divisions do not need to be considered in the CCIS. On other hand, this study found not suitable items for the CCIS within Division 300.

The proposed CCIS is designed to allow for the adjustment of unit prices at the pay item level using the cost index that best matches the characteristics of the item under consideration. If a given pay item is not included among the indexes at the Pay Item Level, it still can be adjusted with one of indexes at the upper levels. For example, if pay item *408B001 - Micro-Milling Existing Pavement (Approximately 1.10" Thru 2.00" Thick)* is to be adjusted, it cannot be adjusted with an index form the Pay Item Level since this is not one of the 53 CCIS items. However, it could be adjusted with the index 408 at the Sub-Division Level (see Table 7). Likewise, pay items under Division 300 could be adjusted with the general cost index at the Agency Level, which is not different to what some STAs are currently doing. The Agency Level index could also be used as a macroeconomic indicator of the overall situation of the transportation construction market or to support strategic decisions made at upper management levels.

The combination of similar indexes into higher-level indexes is performed using the aggregate price index method shown in Equation 9 (FHWA, 2017). This is just the weighted sum of the indexes of the grouped items at the lower level. Weights for this equation are proportional to the dollar amount spent on the items under consideration at a given period of time.

$$I_{upper\ level} = \sum_{i=1}^{n} w_i \times I_i \qquad \text{Eq.9}$$

Where: $I_{upper\ level} = Index\ to\ be\ calculated\ a\ the\ upper\ level$
$w_i = Weight\ for\ item\ i\ at\ the\ lower\ level$
$I_i = Index\ for\ imte\ i\ at\ the\ lower\ level$
$n = Number\ of\ items\ grouped\ at\ the\ lower\ level$

3.8 MOVING-WINDOW DATA OPTIMIZATION ALGORITHM

The main purpose of the moving-window data optimization algorithm is roughly illustrated in Figure 11, which is to aid ALDOT in the identification of optimal look-back periods for specific pay items, as well as in the selection of suitable indexing alternatives to facilitate the development of effective bid-based construction cost estimates. Figure 11 shows the 20 indexing alternatives considered in this project: 12 CCIS'S developed in this study and 8 existing CCIs. In this thesis, the moving-window algorithm is presented through its application to the case study item (424A360) using data from all projects awarded by ALDOT between 2011 and 2016 and considering different look-back periods ranging from 1 to 5 years.

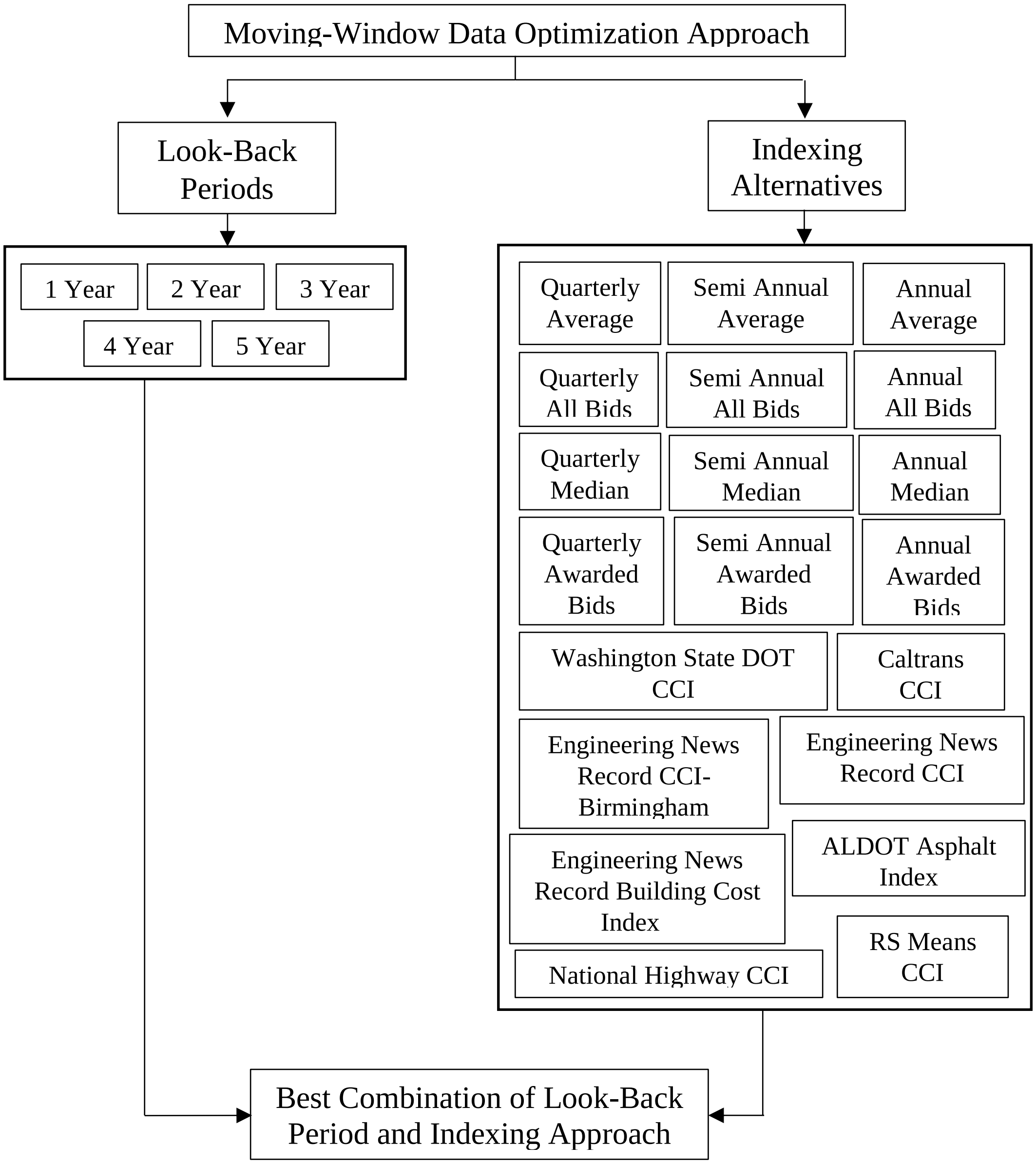


Figure 11. Look-Back Periods and Indexing Alternatives

The algorithm was run several times to consider all possible combinations of look-back periods and indexing alternatives (20 indexing alternatives x 5 different look-back periods = 100 possible combinations]). The algorithm was run ten more times: five times to demonstrate the importance of the non-linear regression models (once for each look-back period) and five more times using no indexing approach (once for each look-back period). These additional ten calculations were intended to demonstrate the importance of using non-linear regression to model quantity-unit price relationships, as well as to prove the importance of adjusting bid-based estimates to counteract the impact of time. It was run a total of 110 times.

Figures 12 and 13 better illustrate the methodological procedure contained in the moving-window algorithm. The algorithm is basically intended to use real data from previous projects to show what would have happened if ALDOT would have actually used the proposed data-driven methodology along a given period of time in the past.

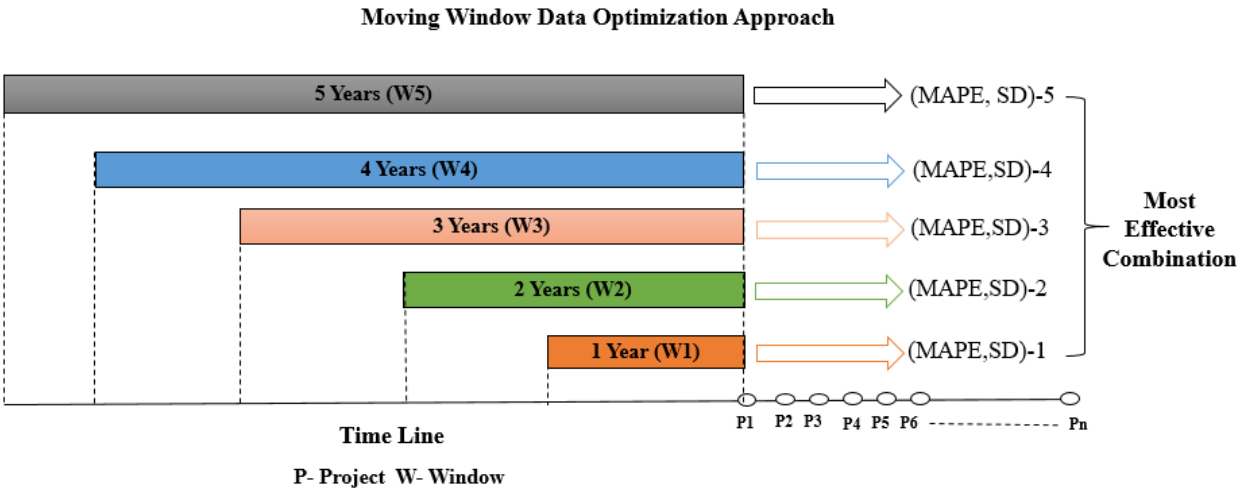


Figure 12. Moving-Window Data Optimization Algorithm

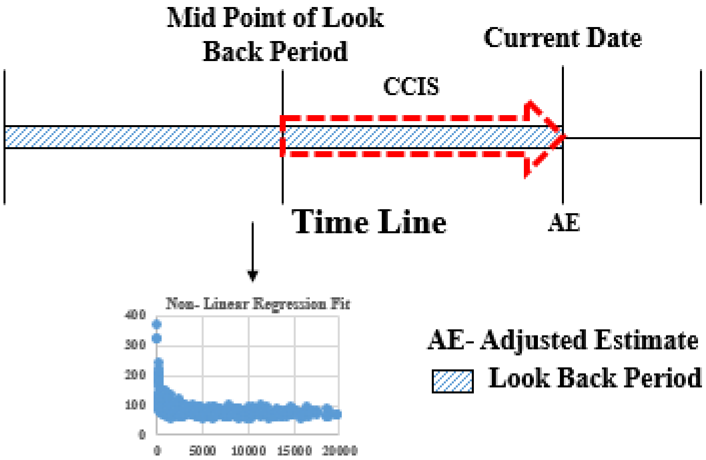


Figure 13. Time adjustment with indexing system.

At each run of the algorithm, the author produced bid-based unit price estimates for all the times the case study item was actually used during a given period of time. In this thesis, that period of time was the year 2016. The case study item was used 97 times in 2016, which would be once per project from Project 1 (P1) to Project n (Pn) in Figure 12 (n=97). Thus, each run in this study consisted of 97 estimated unit prices compared against the 97 actual unit prices submitted to ALDOT by the selected contractors. In other words, the estimated values were compared against the prices actually paid by ALDOT every time this item was used in 2016. The result of this comparison is a Mean Absolute Percentage Error (MAPE) for each iteration. MAPE values, calculated with Equation 10, are commonly used to assess the effectiveness of construction cost indexes (Gardner, 2015). After all the 110 calculations, the lowest MAPE corresponds to the combination of look-back period and indexing approach that would offer to ALDOT the best average accuracy for the case study item. Figure 13 shows how each of the indexing alternatives was used to adjust every estimated unit prices. Basically, the estimate produced with the non-linear regression models are assumed to represent expected unit prices at the mid-point of the look-back period, so that, cost indexes are then used to adjust unit price estimates by "moving" them from the mid-point date to the current date (end of look-back period). The term "moving-window" refers to the use of a fixed period of time (look-back period) that moves forward in time, stopping each time that the item under consideration is used in a construction project to provide the required historical bid data. Thus, the process illustrated in Figure 13, is performed every time that the "moving-window" finds a project using the given pay item, and this is also proposed data-driven methodology that should be used to ensure in practice to ensure an appropriate utilization of the identified look-back period and CCIS.

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|A_i - E_i|}{A_i}}{n} \times 100\% \qquad \text{Eq.10}$$

Where: $MAPE = Mean\ Absolute\ Percentage\ Error$
$A_i = Actual\ unit\ price\ for\ case\ study\ item\ in\ project\ i$
$E_i = Estimated\ unit\ price\ for\ case\ study\ item\ in\ project\ i$
$n = Number\ of\ projects\ using\ case\ study\ item\ during\ period\ under\ consideration$

The proposed moving-window algorithm may be easier to understand with a more specific example. Figure 14 shows one of the 110 algorithm calculations for the case study item. The one conducted to calculate the MAPE value for a one-year look-back period when using the Quarterly Annual CCIS. The algorithm started by finding the first time that the case study was used in 2016. It was found that this item was first used in January 22 of that year. One year of historical bid data was then retrieved; from January 22, 2015, to January 21, 2016. The retrieved data was then used to develop a non-linear regression model, which, in turn, was used to estimate the unit price for the case study item in July 22, 2015 (mid-point of look-back period), and based on the given quantity for this item (quantity listed in January 21, 2016). The Quarterly Annual CCIS was then used to adjust this unit prices for inflation and all construction market changes that may have happened between the mid-point of the look-back period and the current date. Equation 11 shows how index values at these two points in time are used to adjust unit prices. The accuracy of the adjusted unit price was measured by the absolute percentage error resulting by comparing the estimated value against the actual unit price (|Actual Unit Price – Estimated Unit Price|/Actual Unit Price). This value was stored and the window was moved forward until finding the second time the case study item was used in 2016. When found, the window stops and the same process is carried out to get the second absolute percentage error. This process was repeated every time that the case study item was used in 2017: 97 times. Finally, all 97 absolute percentage errors were used as shown above in Equation 10 to calculate the MAPE associated with the use of a one-year look-back period and the Quarterly Annual CCIS.

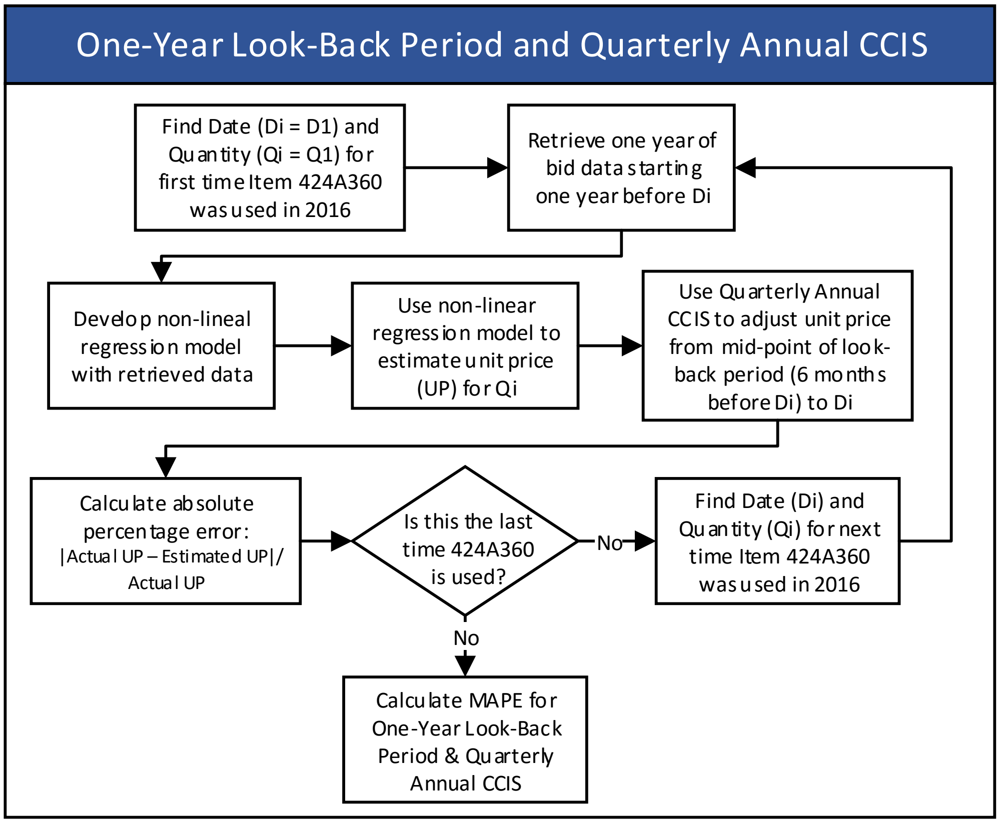


Figure 14. Moving-window algorithm example – One-year look-back period & Quarterly Annual CCIS.

$$Unit\ Price_{Current\ Date} = Unit\ Price_{Mid-Point\ of\ LBP} \times \frac{Index\ Value_{Current\ Date}}{\text{Index Value}_{Mid-Point\ of\ LBP}} \quad \text{Eq. 11}$$

3.9 IDENTIFICATION OF OPTIMAL LOOK-BACK PERIOD AND INDEXING APPROACH

After applying the moving-window algorithm as described in the previous section, and after discarding the “no non-linear regression and no indexing approach” and the “no indexing approach” alternatives (the 10 additional calculations mentioned in the previous section) due to their inferior performance, the author had to develop a system to identify the best look-back period/indexing approach combination. Even though MAPE values are good indicators of the average accuracy of each combination, this is only a measure of central tendency. It is the expected average accuracy to be expected after applying a given combination several times. In quantitative modeling, the MAPE value would be used to measure the validity of a model, which is the degree to which a given model truly measures what it is intended to measure (Glafshani 2003). Thus, a model with a lower MAPE can be assumed to offer greater validity. However, two models could be equally valid, but it does not mean that they are equally reliable. Reliability refers to the degree of consistency or uncertainty in the outputs of quantitative models (Glafshani 2003). Therefore, an ideal quantitative model must be both valid and reliable. Recognizing the fact, that it is impossible to develop construction cost estimating models that are 100% valid and reliable, this study made efforts to identify the look-back period/indexing approach combination that best satisfies both principles.

Given that all 9,700 absolute percentage errors calculated with the moving-window algorithm (97 projects x 100 possible combinations = 9,700 absolute percentage errors) can be classified according to two different categorical variables (look-back period [1-5] and indexing approach). Two-way ANOVA is a suitable statistical test to compare MAPE values across both categorical variables, as well as to determine if there is any interaction between them (Laerd

Statistics 2013). Two-way ANOVA is performed under the assumption that the dependent variable (i.e. absolute percentage error) is normally distributed and that variances across all combinations of the two categorical variables are equal. The normality assumption was not challenged in this study. This assumption will be reviewed in future research efforts. On the other hand, the assumption of homogenous variables was tested using the Levene's test, following the guidelines provided by Glass (1966). The Levene's test is a statistical test intended to test the homogeneity of variances among multiple samples, and is commonly used before using two-way ANOVA to validate this assumption. Besides being used to comply with the conditions of the two-way ANOVA test, this test was also used to maximize reliability. The null hypothesis tested with the Levene's test was that the variances across all look-back period/indexing approach combinations are equal. This test was systematically used in this study to reduce the number of possible look-back period/indexing approach combinations into the subset of combinations that offered the lowest variance. The look-back periods and indexing approaches yielding the higher average variability were discarded one-by-one until having a subset of combinations with the lowest homogenous variances. After applying this test, the original 100 combinations were reduced to 18 combinations of 9 cost indexes (8 CCIS's and 1 existing CCI) and only two possible look-back periods: one and two years.

Two- way ANOVA was then applied to the remaining 18 combinations, failing to reject the three null hypotheses associated to this test:

1. The means of the absolute percentage errors across the two look-back periods are the same;
2. The means of the absolute percentage errors across all nine indexing approaches are the same;

3. There is no interaction between the look-back periods and the indexing approaches. It means that both categorical variables are independent, which is a requirement for this test.

More information about the statistical tests used in this study and results of the quantitative analysis described in this section are presented in the following chapters.

3.10 RESEARCH VALIDATION

Research validation efforts in this study were conducted at two different stages. Initial validation efforts were conducted during the implementation of the moving-window algorithm. This algorithm is the main research instrument in this thesis and it served as an advanced validation strategy. While comparing the performance of the different look-back period/indexing approach combinations using the results of the moving-window algorithm and the Levene's and two-way ANOVA tests, the author is not only identifying the best combination(s), but also demonstrating how this combination(s) outperforms the other alternatives. Likewise, by including the "no non-linear regression" and "no indexing approach" alternatives in the moving-window calculations, the author was able to demonstrate the importance of modeling and considering both scale (using non-linear regression) and time (using the cost indexes) impacts in bid-based cost estimating.

Unfortunately, the author had no access to actual estimates made by ALDOT for each time that the case study item was used. It would have allowed a direct comparison of the proposed bid-based cost estimating methodology and ALDOT's current estimating system. However, further validation efforts were made to compare the estimated unit prices against the unit prices submitted by the unsuccessful bidders. This is a valuable validation approach when taking into consideration that the proposed methodology is intended to estimate unit prices submitted by low bidders (successful contractors selected to execute the contracts), which, in fact, is also the goal of all bidders. A bidder would only invest time in the preparation and submission of a bid package if there were a reasonable probability of winning the contract. Therefore, it can be assumed that all price proposals submitted for a given contract correspond to the best efforts made by the bidders to estimate what would be the lowest bid for that contract. Thus, by demonstrating that the estimated unit prices produced in this study are closer to the unit prices submitted by the lowest bidders than the prices submitted by the unsuccessful contractors, it can be said that proposed methodology outperforms the estimating practices of the non-selected contractors. The positive results from this validation are even more relevant when considering that contractors' estimating practices are designed to assess unit prices with a better understanding of specific project requirements, while unit prices with the proposed methodology were produced only with the quantities of work listed in the RFP.

CHAPTER FOUR: DEVELOPMENT OF CONSTRUCTION COST INDEXING SYSTEMS AND EXISTING CONSTRUCTION COST INDEXES

4.1 INTRODUCTION

This short chapter starts by proving detailed information on the twelve CCIS's developed in this study. Specifically, this chapter presents the non-linear equations, the LAPV values, and the number of quantity ranges for each of the 53 CCIS items, and used to develop the twelve CCIS's. The chapter also presents the twelve different versions of the cost index for the case study item (only one of the 53 CCIS items). Finally, the chapter includes a summary of the characteristics of the eight existing composite indexes considered in this study, including the components used in their calculation, their geographical applicability and their frequency of recalculation.

4.2 DEVELOPMENT CONSTRUCTION COST INDEXING SYSTEMS

This section presents the non-linear regression equations, the LAPV values, and number of quantity ranges for all 53 CCIS items, which were fundamental in the development of the twelve CCIS's assessed in this study. Even though the proposed look-back period determination protocol and data-driven cost estimating methodology are illustrated in this thesis only for the case study item, the CCIS's were fully developed for all 53 pay items and at all four levels, so that, these methodologies can be applied by ALDOT to develop bid-based estimates for any pay item. All processes has been explained in sufficient detail so they can be replicated by ALDOT on an as needed basis.

4.3 NON-LINEAR REGRESSION MODELS & QUANTITY RANGES

As mentioned in Chapter 3, non-linear regression models were used in this thesis for two main purposes. Later in the study, they are used to estimate unit prices based on expected quantities of work, but at this stage, these models are used, along with LAPV values, to define the quantity ranges for each of the 53 CCIS items, which are critical to ensure that CCIS's are built by measuring fluctuations between comparable quantities of work. Table 8 presents the number of ranges, the parameters of the non-linear regression equations, and the LAPV values for all 53 CCIS items. A description of each of 53 CCIS items listed below can be found in Appendix 1.

Table 8. Summary of Non-linear Regression Models

Non-Linear Regression Model – Power Regression Equation

$$Unit\ Price = A * (Quantity)^B$$

Item Id	No of Ranges	Largest Average Price Variation	A	B	Item Id	No of Ranges	Largest Average Price Variation	A	B
206C010	3	1.250	126.470	-0.412	**620A000**	2	0.436	1030.656	-0.111
206D000	1	1.321	15.985	-0.102	**630A001**	5	0.091	29.109	-0.052
206D001	6	0.103	3.554	-0.079	**650A000**	3	0.709	46.198	-0.170
210A000	3	0.972	24.096	-0.129	**650B000**	2	0.925	21.047	-0.163
210D021	2	0.729	45.024	-0.172	**652A100**	4	0.211	932.512	-0.108
212A000	3	0.571	144.649	-0.235	**652C000**	6	0.214	153.175	-0.146
214A000	2	1.319	20.205	-0.118	**654A000**	3	0.261	9.142	-0.092
214B001	2	0.530	63.085	-0.085	**654A001**	3	0.319	7.688	-0.075
230A000	1	0.776	502.448	-0.067	**656A010**	5	0.245	894.685	-0.168
401A000	4	0.250	3.481	-0.121	**665A000**	4	0.348	701.219	-0.204
405A000	2	0.321	5.184	-0.048	**665E000**	1	1.340	3.639	-0.096
408A051	7	0.550	61.795	-0.399	**665I000**	1	0.467	51.768	-0.044
408A052	6	0.574	55.073	-0.365	**665L000**	1	0.776	20.951	-0.054
424A360	4	0.139	155.183	-0.092	**665O001**	2	0.655	3.268	-0.161
424B650	4	0.136	123.282	-0.075	**666A001**	3	0.592	65.085	-0.244
424B655	3	0.357	199.628	-0.130	**701C000**	4	0.071	796.668	-0.048
424B659	3	0.203	130.898	-0.092	**701C001**	4	0.080	884.271	-0.058
424B681	4	0.154	127.839	-0.085	**701H001**	41	0.063	9.758	-0.308
502A000	3	0.464	2.583	-0.092	**701H006**	27	0.068	4.434	-0.240
505M002	1	0.376	54.903	-0.030	**703A002**	7	0.084	7.466	-0.079
508A000	1	0.592	5.478	-0.034	**703B002**	5	0.081	6.330	-0.061
510A000	1	0.636	743.829	-0.056	**703D001**	13	0.073	4.208	-0.136
510E000	1	0.517	1271.267	-0.108	**710A115**	2	0.206	21.165	-0.045
530A001	2	0.567	56.539	-0.090	**710A126**	2	0.200	22.577	-0.037
610C001	2	0.382	56.045	-0.058	**730H001**	3	0.097	3.577	-0.049
610D003	1	0.732	4.730	-0.073	**740B000**	1	0.200	10.245	-0.047
614A000	3	0.283	460.505	-0.084	-	-	-	-	-

4.4 CONSTRUCTION COST INDEXES FOR CASE STUDY ITEM

As mentioned in Chapter 3, each of the twelve CCIS versions consists of multiple cost indexes at different levels. Due to the number of pages required to contain all CCIS, it would be impractical to present all of them in this thesis. However, this section presents all twelve versions of the cost index for the case study item (only one of the 53 CCIS items), which are at the Pay Item Level (lowest level) of their respective CCIS's. Table 9, 10, and 11 show the quarterly, semi-annual, and annual indexes for the case study item (item 424A360), respectively. Each table presents the index values for the four different types of inputs (i.e. all bids, average values on a project basis, median values on a project basis, and only awarded bids).

Table 9. Quarterly Construction Cost Indexes – Case Study Item (Item 424A360)

Year	Quarter	All Bids	Average	Median	Awarded Bids
2006	**Q1**	100.00	100.00	100.00	100.00
	Q2	104.33	105.36	105.57	105.91
	Q3	115.78	117.37	117.79	116.18
	Q4	124.24	121.91	121.54	124.61
2007	**Q1**	120.31	121.78	121.26	119.25
	Q2	118.47	120.36	120.99	107.26
	Q3	122.71	124.36	125.91	126.52
	Q4	120.87	120.79	121.41	118.93
2008	**Q1**	128.95	125.34	125.71	128.77
	Q2	129.38	130.17	131.37	125.94
	Q3	191.03	185.04	187.68	193.60
	Q4	169.11	161.68	161.52	162.22
2009	**Q1**	160.34	152.56	153.53	149.91
	Q2	148.40	141.95	142.15	138.21
	Q3	145.04	143.29	143.94	141.36
	Q4	147.06	147.20	147.95	144.11
2010	**Q1**	146.61	149.57	150.43	146.53
	Q2	152.48	150.73	150.73	144.60
	Q3	151.77	151.47	152.08	146.31
	Q4	153.04	153.37	152.17	155.67
2011	**Q1**	150.45	149.57	150.13	153.68
	Q2	161.44	159.07	160.31	161.01
	Q3	171.34	174.61	176.19	178.55
	Q4	164.69	166.31	166.46	167.25
2012	**Q1**	170.42	169.45	170.83	173.51
	Q2	175.08	178.35	177.45	181.40
	Q3	162.06	162.52	163.48	164.23
	Q4	169.67	170.50	171.84	178.32
2013	**Q1**	175.35	176.65	178.09	179.98
	Q2	172.78	175.33	176.87	181.73
	Q3	176.72	178.23	179.94	183.02
	Q4	173.91	177.02	177.58	176.49
2014	**Q1**	179.59	180.08	180.51	179.56
	Q2	173.83	178.41	179.42	183.73
	Q3	195.06	198.87	200.49	201.19
	Q4	196.49	200.11	200.35	201.91
2015	**Q1**	192.02	195.18	195.78	201.46
	Q2	189.49	192.18	192.53	192.87
	Q3	189.33	195.21	196.02	202.41
	Q4	177.23	177.58	178.14	176.47
2016	**Q1**	174.54	181.02	180.87	179.97
	Q2	173.03	183.42	183.54	183.68
	Q3	169.09	175.13	173.57	173.00
	Q4	184.68	196.08	195.70	204.99

Table 10. Semi Annual Construction Cost Indexes – Case Study Item (Item 424A360)

Year	Semester	All Bids	Average	Median	Awarded Bids
2006	**S1**	100.00	100.00	100.00	100.00
	S2	111.42	111.81	112.02	111.45
2007	**S1**	104.23	105.84	105.57	103.43
	S2	107.14	108.45	108.71	105.41
2008	**S1**	109.91	110.58	110.79	107.96
	S2	152.27	149.58	150.24	149.07
2009	**S1**	123.87	121.33	121.82	119.51
	S2	120.99	120.82	121.45	119.15
2010	**S1**	125.22	125.01	125.41	122.83
	S2	128.18	126.79	126.92	125.79
2011	**S1**	128.83	125.82	125.89	126.59
	S2	140.40	140.35	140.28	139.81
2012	**S1**	141.73	141.37	141.02	141.90
	S2	137.40	136.62	136.87	137.55
2013	**S1**	145.91	144.35	144.63	144.99
	S2	147.24	145.94	146.23	145.64
2014	**S1**	148.84	147.41	147.29	146.81
	S2	163.83	162.41	162.68	161.63
2015	**S1**	159.82	157.45	157.49	158.99
	S2	153.92	152.10	152.54	153.05
2016	**S1**	144.37	147.27	147.30	145.81
	S2	141.31	141.70	140.63	139.68

Table 11. Annual Construction Cost Indexes – Case Study Item (Item 424A360)

Year	All Bids	Average	Median	Awarded Bids
2006	100.00	100.00	100.00	100.00
2007	99.76	100.31	100.13	99.63
2008	112.57	111.99	112.00	111.69
2009	111.90	111.17	111.26	110.41
2010	114.97	115.92	115.86	115.19
2011	120.43	120.24	119.81	121.34
2012	126.15	127.24	126.85	128.46
2013	131.60	132.04	131.95	132.76
2014	139.37	140.14	139.83	139.50
2015	141.18	140.69	140.49	142.30
2016	128.31	131.25	130.59	129.91

4.5 EXISTING CONSTRUCTION COST INDEXES

Table 12 summarizes the eight existing CCIs considered in this study. It includes indexes published and maintained by private organization, such 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 CCIs for 20 cities across the country. This study has assessed the performance of both the ENR National CCI and one specifically developed to track changes in the construction market in Birmingham, Alabama. Table 12 includes 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 that literature review has revealed that some building CCIs has been considered for cost estimating purposes by STAs or by other authors (Rueda 2016).

Three of eight indexes in Table X have been developed by public transportation agencies: 1) the National Highway Construction Cost Index published by the Federal Highway Administration (FHWA); 2) the Price Index for Selected Highway Construction Items published by the California Department of Transportation (CALTRANS); and 3) the Price Index for Highway Construction Items published by the Washington State Department of Transportation (WSDOT). The last index in the Table 12 is not actually a composite index. This is the Asphalt Price Index maintained and published by ALDOT. It only tracks the market of asphalt per gallon (single index component). ALDOT’s Asphalt Price Index was included in this study because it is closely related to the case study item. However, it should not be considered for other pay items.

Table 12. 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

CHAPTER FIVE: MOVING-WINDOW DATA OPTIMIZATION ALGORITHM: ANALYSIS OF RESULTS

5.1 INTRODUCTION

As mentioned in Chapter 3, the main purpose of the moving-window data optimization algorithm is to aid ALDOT in the identification of optimal look-back periods for specific pay items, as well as in the selection of a suitable indexing alternative to facilitate the development of effective bid-based construction cost estimates. This chapters presents the results obtained from the 110 calculations of moving-window algorithm: 100 calculations from combining all look-back periods and indexing alternatives; 5 calculations from the “no non-linear regression and no indexing approach” alternative (once for each look-back period); and 5 calculations from the “no indexing approach” alternative (once for each look-back period).

After discarding the “no non-linear regression and no indexing approach” and “no indexing approach” alternatives due to their inferior performance, the chapter presents the exhaustive statistical analysis conducted to identify the best loo-back period/indexing approach set among the 100 combinations. Two main statistical tests were used in this analysis: Levene’s test to evaluate the variances among the alternatives and the two-way ANOVA test to compare their MAPE values. Figure 15 clearly illustrates the systematic statistical analysis applied to the 100 combinations and elimination of alternatives until obtaining a set of alternatives whose performance is not significantly different from each other, in terms of validity and reliability. As show in Figure 15 the Levene’s test allowed for the reduction of the number of alternative to 18 (9 indexing approaches x 2 look-back periods = 18), which is the set of alternatives with the lowest homogenous variance.

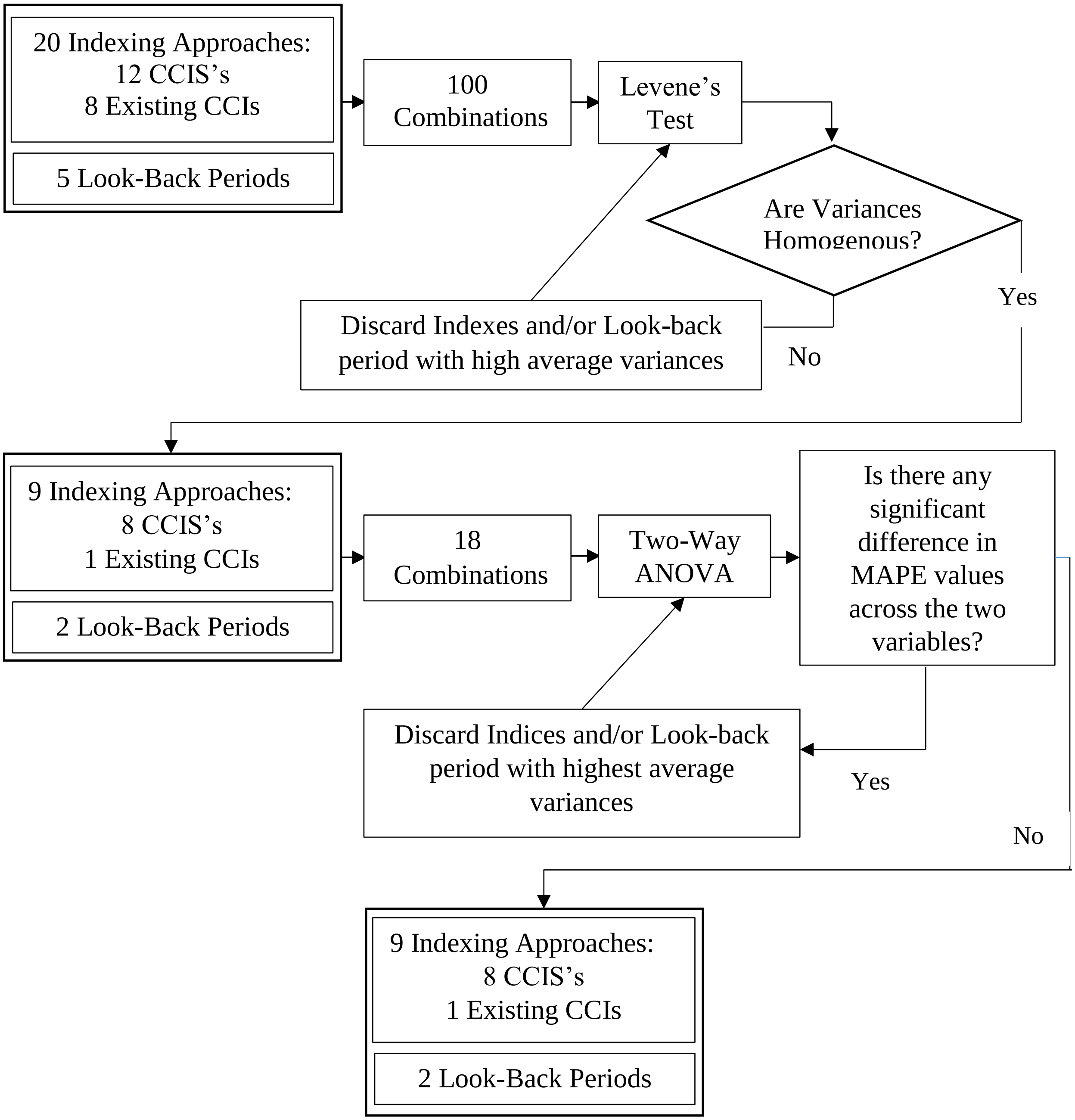


Figure 15. Methodology for Statistical Analysis

The two-way ANOVA test was then used to compare the MAPE values for the 18 combinations finding no significant difference among them. It should be noted that since no significant differences were found among the 18 MAPE values, the loop in two-way ANOVA test shown in Figure 15 was not actually used. However, it was still included in this figure given that this thesis is intended to provide a framework to be applied to other pay items different than the case study item, in which case the loop may be required.

5.2 MOVING-WINDOW ALGORITHM – SUMMARY OF RESULTS

Table 13 represents the summary of results that were generated by the 110 calculations of moving-window algorithm. Each iteration was used to estimates unit prices for the case study item for all projects awarded in 2016. The table shows the MAPE and standard deviation of the average percentage errors (APEs) for each combination, as well as a ranking of combinations by MAPE value and a ranking by standard deviation.

Table 13. Results of Moving-window Data Optimization Algorithm

Approach	Look-Back Period	MAPE	SD of APEs	Ranking by MAPE	Ranking by SD
No No-Linear Regression Model & No Indexing Approach	1 Year	19.46%	14.79%	84	99
	2 Year	21.62%	16.18%	99	106
	3 Year	20.61%	15.30%	94	101
	4 Year	20.19%	15.24%	90	100
	5 Year	19.31%	14.60%	82	98
No Indexing Approach	1 Year	14.95%	10.30%	25	35
	2 Year	16.62%	10.85%	55	51
	3 Year	16.16%	10.44%	49	39
	4 Year	15.47%	9.99%	41	29
	5 Year	14.96%	9.63%	26	21
Quarterly All Bids	1 Year	13.33%	8.94%	10	10
	2 Year	12.52%	8.21%	1	1
	3 Year	13.53%	10.41%	13	37
	4 Year	14.64%	10.05%	22	30
	5 Year	14.75%	9.90%	23	26
Quarterly Median	1 Year	14.32%	8.92%	18	9
	2 Year	13.12%	8.43%	6	3
	3 Year	13.49%	9.66%	12	22
	4 Year	15.23%	10.11%	34	31
	5 Year	15.78%	10.16%	45	32
Quarterly Average	1 Year	14.36%	8.89%	19	7
	2 Year	13.15%	8.46%	7	4
	3 Year	13.57%	9.67%	15	23
	4 Year	15.34%	10.21%	38	33
	5 Year	16.08%	10.34%	48	36

Table 13. Results of Moving-window Data Optimization Algorithm (Cont.)

Approach	Look-Back Period	MAPE	SD of APEs	Ranking by MAPE	Ranking by SD
Quarterly Awarded Bid	1 Year	14.49%	9.31%	20	14
	2 Year	12.90%	8.29%	4	2
	3 Year	12.86%	9.02%	3	11
	4 Year	14.80%	9.91%	24	28
	5 Year	15.35%	9.60%	39	20
Semi Annual All Bid	1 Year	13.44%	9.36%	11	15
	2 Year	12.73%	8.90%	2	8
	3 Year	15.08%	11.68%	30	75
	4 Year	16.24%	11.23%	52	65
	5 Year	16.21%	11.19%	50	58
Semi Annual Median	1 Year	13.72%	9.45%	17	18
	2 Year	13.24%	8.84%	9	6
	3 Year	15.36%	11.62%	40	73
	4 Year	16.95%	11.21%	64	61
	5 Year	16.93%	11.21%	61	62
Semi Annual Average	1 Year	13.70%	9.39%	16	16
	2 Year	13.22%	8.81%	8	5
	3 Year	15.21%	11.48%	33	70
	4 Year	16.88%	11.18%	59	57
	5 Year	16.94%	11.19%	62	59
Semi Annual Awarded Bid	1 Year	13.53%	9.29%	14	13
	2 Year	13.09%	9.05%	5	12
	3 Year	15.63%	11.87%	43	77
	4 Year	17.06%	11.44%	66	69
	5 Year	16.79%	11.23%	58	64
Annual All Bid	1 Year	15.31%	10.74%	37	49
	2 Year	17.54%	11.31%	69	68
	3 Year	19.68%	12.51%	85	88
	4 Year	20.43%	12.80%	92	92
	5 Year	21.91%	13.46%	100	97
Annual Median	1 Year	15.07%	10.46%	29	40
	2 Year	16.95%	11.02%	63	55
	3 Year	19.02%	12.26%	80	84
	4 Year	19.78%	12.51%	86	87
	5 Year	21.09%	13.03%	97	94
Annual Average	1 Year	15.05%	10.43%	27	38
	2 Year	16.89%	10.99%	60	53
	3 Year	19.04%	12.28%	81	85
	4 Year	19.84%	12.54%	87	90
	5 Year	21.02%	12.99%	96	93
Annual Awarded Bid	1 Year	15.53%	10.99%	42	54
	2 Year	18.07%	11.56%	72	72
	3 Year	19.84%	12.52%	88	89
	4 Year	20.34%	12.76%	91	91
	5 Year	21.31%	13.13%	98	95

Table 13. Results of Moving-window Data Optimization Algorithm (Cont.)

Approach	Look-Back Period	MAPE	SD of APEs	Ranking by MAPE	Ranking by SD
National Highway CCI	1 Year	14.56%	9.41%	21	17
	2 Year	15.17%	9.91%	32	27
	3 Year	15.12%	9.75%	31	24
	4 Year	16.07%	10.74%	47	50
	5 Year	16.52%	10.53%	53	41
Caltrans CCI	1 Year	20.91%	15.34%	95	102
	2 Year	22.42%	15.40%	101	103
	3 Year	25.63%	16.09%	103	105
	4 Year	27.25%	17.79%	104	108
	5 Year	33.27%	28.47%	106	110
Washington State DOT CCI	1 Year	19.91%	13.34%	89	96
	2 Year	20.52%	15.83%	93	104
	3 Year	16.22%	10.54%	51	43
	4 Year	27.40%	16.56%	105	107
	5 Year	40.04%	23.18%	110	109
Engineering News Record -Birmingham CCI	1 Year	15.28%	10.54%	36	44
	2 Year	17.80%	11.49%	71	71
	3 Year	17.39%	11.22%	68	63
	4 Year	17.21%	10.90%	67	52
	5 Year	17.64%	11.20%	70	60
Engineering News Record CCI	1 Year	15.85%	10.72%	46	47
	2 Year	18.72%	11.90%	77	79
	3 Year	18.80%	11.95%	78	81
	4 Year	18.97%	12.10%	79	83
	5 Year	19.31%	12.28%	83	86
Engineering News Record Building Cost Index	1 Year	15.65%	10.63%	44	45
	2 Year	18.21%	11.64%	73	74
	3 Year	18.36%	11.70%	74	76
	4 Year	18.63%	11.88%	75	78
	5 Year	18.69%	11.93%	76	80
RSMeans CCI	1 Year	15.07%	10.27%	28	34
	2 Year	17.03%	11.07%	65	56
	3 Year	16.71%	10.74%	57	48
	4 Year	16.63%	10.70%	56	46
	5 Year	16.56%	10.53%	54	42
ALDOT Asphalt Index	1 Year	15.24%	11.30%	35	67
	2 Year	22.51%	12.07%	102	82
	3 Year	34.78%	11.28%	107	66
	4 Year	37.09%	9.83%	109	25
	5 Year	36.84%	9.59%	108	19

The MAPE value for each combination was calculated by considering the average of absolute percentage errors resulting by comparing the estimated values against the prices actually awarded by ALDOT. Generally, the lowest MAPE corresponds to the combination of look-back period and indexing approach that would offer ALDOT the highest estimating accuracy. On the other hand, the standard deviation is assumed to be a measure of reliability. The lower the standard deviation, the more reliable the combination. From table 13, and based on the rankings of MAPE and standard deviation values, it could be said that a two-year look-back period and the Quarterly All Bids CCIS would offer ALDOT the highest accuracy and reliability in the estimation of unit prices for the case study item. However, the next combinations in the raking do not seem to be too far from the front-runner. Therefore, it is necessary to determine if the gaps between the top ranked are statistically significant. It would prove if a two-year look-back is indisputably the best combination, or if there other combinations as good as that one that could be considered by ALDOT. That is what this chapter is aimed to determine, but before that, it is important to review the results of the "no non-linear regression and no indexing approach" and "no indexing approach" to understand the importance of considering the scale and time cost influencing factors in bid-based cost estimating.

5.3 IMPORTANCE OF CONSIDERING SCALE AND TIME IN BID-BASED ESTIMATING

As shown in Figure 15, out of all 110 alternatives only 100 combinations were considered for statistical analysis. It is because the 10 "no non-linear regression and no indexing approach" and "no indexing approach" were discarded due to their inferior performance. The main purpose of considering these 10 alternatives in this model was to demonstrate the importance of using non-linear regression to model quantity-unit price relationships, as well as to prove the importance of adjusting bid-based estimates to counteract the impact of time. A closer look at the results in Table 13 shows an improvement in estimating accuracy and reliability. First, there was an improvement when incorporating the non-linear regression models, and then improves even more when applying an indexing approach.

"*No non-linear regression and No indexing approach" Vs "No indexing approach"*

The first iteration of the moving-windowing algorithm corresponds to the "no non-linear regression and no indexing approach" alternative, in which estimated unit prices are the unadjusted average of all unit prices contained within each look-back period, disregarding the scale and time effects. The second iteration was the "no indexing approach," in which the non-linear regression models are introduced, but no adjustments for inflation are performed. Theoretically, the MAPE from "no indexing approach" should be less than the one from the "no non-linear regression and no indexing approach" alternative given that the latter considers the concept of economies of scale. Table 14 presents the MAPE and standard deviations for these two approaches, which demonstrate this theoretical assumption. Both the MAPE and standard deviation values are reduced when the nonlinear regression model is considered. There accuracy of the estimates is improved by 22.5% and their reliability improves by 34.0%. A statistical F-test was performed to measure the level of significance in the reduction of the standard deviation showing at it was statistically significant at a 5% significance level (p-value = 3.04×10^{-4}). Likewise, a paired two-sample t-test was performed to compare the MAPE values revealing also a statistically significant improvement in accuracy (p-value = 5.1×10^{-4}). These results allow to strongly conclude that the consideration of project scale effects (through non-linear regression) facilitates a significant improvement in accuracy and reliability in bid-based estimating for the case study item.

Table 14. Comparison of results (“No non-linear regression and No indexing approach” Vs “No indexing approach”)

	MAPE	**Standard Deviation of APEs**
No nonlinear regression and No indexing approach (A)	19.31%	14.60%
No indexing approach (B)	14.95%	9.63%
Percentage Reduction (A-B)/A	22.5%	34.0%
Significance of Improvement at 99% Confidence Level	Statistically Significant	Statistically Significant
P-value	<0.01	<0.01

“No indexing approach” Vs “Indexing approach”

“Indexing approach” in the title of this subsection refers to the 100 combinations that include an indexing approach. In a similar way as done in the previous subsection. This study has demonstrated the importance considering time effects in cost estimating by comparing the performance of the “no indexing approach” alternative against the performance of the combinations that used an indexing approach.

Even though the use of no indexing approach seems to outperform the results obtained with some of the cost indexes considered in this study, such as the Caltrans and ALDOT Asphalt CCI, it is only necessary to find one indexing approach that improve estimating performance to demonstrate that inflation and price fluctuations along look-back periods affect estimating accuracy and reliability. Thus, the “no indexing approach” was compared against the combination that seems to offer the best performance” a two-year look-back period with a Quarterly All Bids CCIS. The results of this comparison are shown in Table 15. The values in this table show that the incorporation of a CCIS to adjust bid-based estimates for inflation and market fluctuations could improve accuracy by 16.3% and reliability 14.7%. Even though the F-test does not show a significant increase in reliability at a 5% significance level, it can by assumed at a 6% significance level (p-value = 0.059), which is still considered highly significant by the author. The paired two-sample t-test allows to make a stronger conclusion regarding the reduction in the MAPE value, showing a significant improvement with a p-value of 1.17×10^{-4}.

Table 15. Comparison of results (“No indexing approach” Vs “Moving-window data approach)

	MAPE	**Standard Deviation of APEs**
No indexing approach (A)	14.95%	9.63%
Two-Years Look-Back Period & Quarterly All Bids CCIS (B)	12.52%	8.21%
Percentage Improvement (A-B)/A	16.3%	14.7%
Significance of Improvement at 99% Confidence Level	Statistically Significant	Statistically Significant
P-value	<0.01	<0.01

5.4 IDENTIFICATION OF SUBSET WITH LOWEST HOMOGENEOUS VARIANCES – LEVENE’S TEST

In order to determine if there is a top group of combinations with comparable performance, the author decided to first focus on the combinations that offer the highest reliability (lowest variance). The Levene’s test was used for this purpose. The reason to assess variances before comparing MAPEs lays in the fact that the two-way ANOVA test used for MAPE comparisons works under the assumption of homogenous variances, so that, the Levene’s test is usually performed before a two-way ANOVA test.

The Levene’s test was applied within a loop to systematically eliminate the look-back periods and indexing approaches that show the highest variability until obtaining a p-value greater that 0.05, which would mean that the variances for the remaining combinations could be considered equal at a significance level of 5%. Thus, the remaining set of combinations would correspond to the combinations with the lowest homogenous variances. In other words, the combinations in this set would offer a similar level of reliability. Figure 16 and 17 show the average variability offered by each of the 5 look-back periods and 20 indexing approaches, respectively. This figures also highlight the look-back periods and indexing approaches that were discarded by the Levene's loop due to their high variances. Tables 16 and 17 show the values plotted in Figures 16 and 17, respectively. It should be noted that the values in these figures and tables do not correspond to variances of individual combinations, but to average variances within each group. For example, the average variance of 0.095 for the three-year look-back period (see Figure 16 and Table 16) is the average of the variances from all indexing approaches with a three-year look-back period (the average of 20 variances). Likewise, the average variance of 0.08 for the NHCCI index (see Figure 17 and Table 17) is the average of the variances for this index with each of the five look-back periods (the average of 5 values).

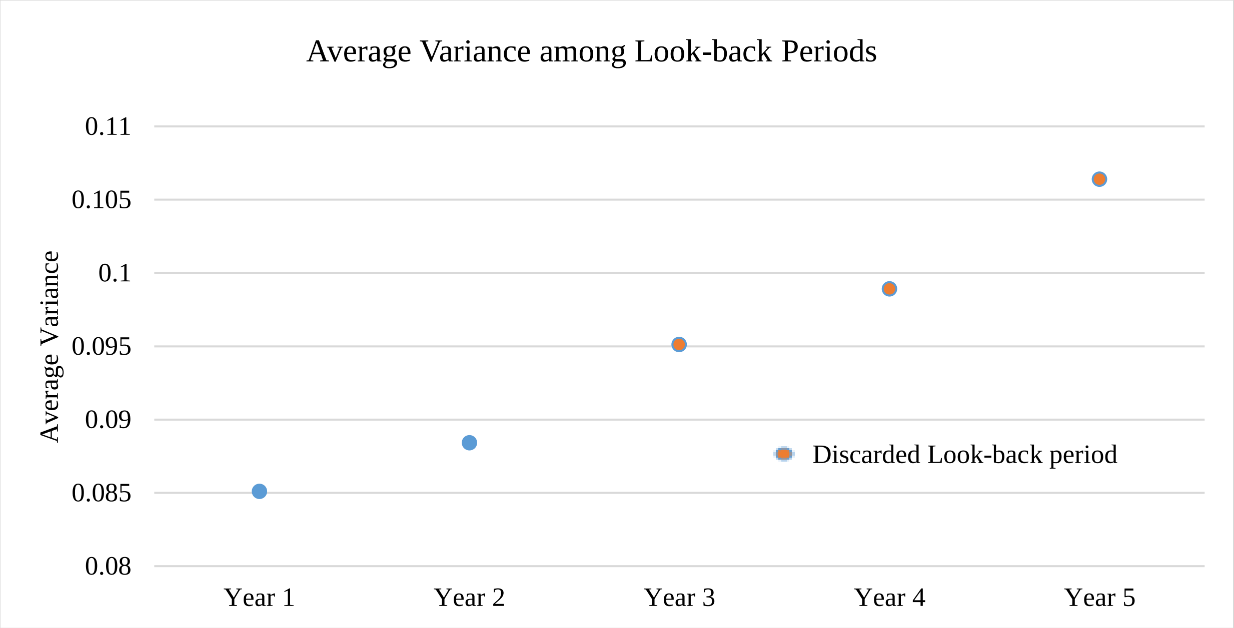


Figure 16. Average Variance among Look-back periods

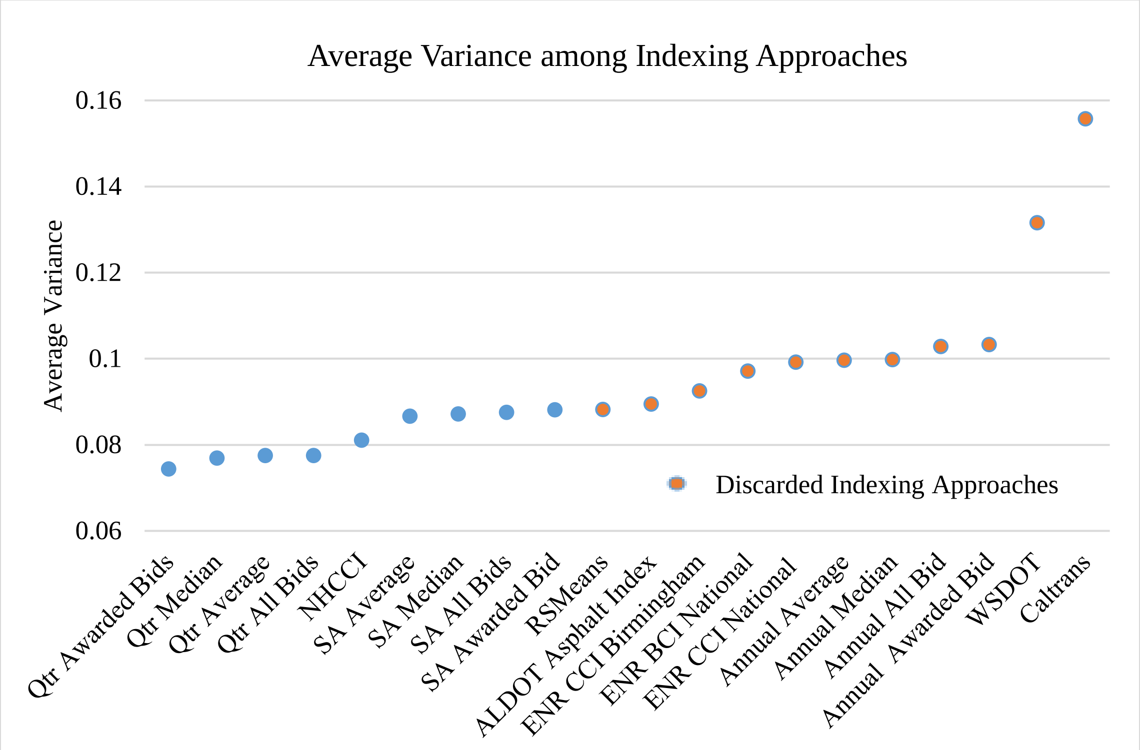


Figure 17. Average Variance among Indexing Approaches

Table 16. Average Variance among Look-back Periods (Ranked)

Year	Average Variance
1	0.085
2	0.088
3	0.095
4	0.099
5	0.106

Table 17. Average Variance among Indexing Approaches (Ranked)

Index	Average Variance	Index	Average Variance
Quarterly Awarded Bid	0.0744	ALDOT Asphalt Index	0.0895
Quarterly Median	0.0769	ENR- CCI Birmingham	0.0925
Quarterly Average	0.0775	ENR BCI National	0.0971
Quarterly All Bid	0.0775	ENR CCI National	0.0991
NHCCI	0.0811	Annual Average	0.0997
Semi Annual Average	0.0867	Annual Median	0.0997
Semi Annual Median	0.0872	Annual All Bid	0.1028
Semi Annual All Bid	0.0875	Annual Awarded Bid	0.1032
Semi Annual Awarded Bid	0.0881	WSDOT	0.1316
RS Means	0.0882	Caltrans	0.1557

Table 18 shows step-by-step how the Levene's test loop eliminated look-back periods and indexing approaches, as well as how the p-value from the test was increasing until getting over 0.05. Finally, Table 19 presents the remaining 18 combinations which offer the lowest homogenous variances. The 18 combinations have been re-ranked by MAPE and standard deviation value.

Table 18. Systematic elimination of factors Based on Levene's Test

Step	P Value	Discarded Look-Back Period and/or indexing Approach
Initial sample	7.87E-196	-
Step -1	3.71E-32	Caltrans, WSDOT
Step-2	1.85E-20	Years 4 &5
Step-3	9.41E-18	Annual All Unit Bid & Annual Awarded Bid
Step-4	2.39E-14	Annual Median & Annual Average & ENR-CCI
Step-5	7.04E-12	ENR-CCI Birmingham & ENR BCI
Step-5	9.48E-09	RS Means & ALDOT Asphalt
Step-6	0.908	Year 3

Table 19. Rankings of Indexing Approaches based on MAPE and Standard Deviation

Indexing Approach	Look-Back Period	MAPE	Standard Deviation of APEs	Ranking by MAPE	Ranking by SD
Quarterly All Bid Unit Prices	1 Year	13.33%	8.94%	9	10
	2 Year	12.52%	8.21%	1	1
Quarterly Median of Unit Prices	1 Year	14.32%	8.92%	14	9
	2 Year	13.12%	8.43%	5	3
Quarterly Average of Unit Prices	1 Year	14.36%	8.89%	15	7
	2 Year	13.15%	8.46%	6	4
Quarterly Awarded Bid Unit Prices	1 Year	14.49%	9.31%	16	13
	2 Year	12.90%	8.29%	3	2
Semi Annual All Bid Unit Prices	1 Year	13.44%	9.36%	10	14
	2 Year	12.73%	8.90%	2	8
Semi Annual Median of Unit Prices	1 Year	13.72%	9.45%	13	17
	2 Year	13.24%	8.84%	8	6
Semi Annual Average of Unit Prices	1 Year	13.70%	9.39%	12	15
	2 Year	13.22%	8.81%	7	5
Semi Annual Awarded Bid Unit Prices	1 Year	13.53%	9.29%	11	12
	2 Year	13.09%	9.05%	4	11
National Highway CCI	1 Year	14.56%	9.41%	17	16
	2 Year	15.17%	9.91%	18	18

5.5 ANALYSIS OF MAPE VALUES – TWO-WAY ANOVA

Having identify the 18 combination with the lowest homogenous variances (see Table 19), the next step was to compare the MAPE values with the two-way ANOVA test. This statistical process allowed to author to test the following three null hypothesis:

1. The means of the absolute percentage errors across the two look-back periods are the same;
2. The means of the absolute percentage errors across all nine indexing approaches are the same;
3. There is no interaction between the look-back periods and the indexing approaches. It means that both categorical variables are independent, which is a requirement for this test.

Table 20 summarizes the results of the two-way ANOVA test for remaining 18 combinations. With a p-value of 0.696, it is possible to assume, with a high level of confidence, that a similar level of accuracy would be achieved with a one- or two-year look back period (first null hypothesis). The same could be said about the accuracy of the remaining nine indexing approaches (with a p-value of 0.127). Finally, a p-value of 0.982 allows to conclude that there is no interaction between the remaining look-back periods and indexing approaches, meaning that these are independent variables. In summary, none of the null hypothesis could be rejected, meaning that all the 18 remaining combinations offer similar accuracy and reliability.

Table 20. Results of Two-way ANOVA Test for 18 Combinations

Source of Variation	***SS***	***df***	***MS***	***F***	***P-value***	***F crit***
Indexing Approach	0.0149	8	0.0019	0.6955	0.696	1.9438
Look-Back Period	0.0062	1	0.0062	2.3284	0.127	3.8468
Interaction	0.0053	8	0.0007	0.2472	0.982	1.9438
Within	4.6327	1728	0.0027			
Total	4.6591	1745				

5.6 VALIDATION AGAINST CURRENT ESTIMATING SYSTEMS

This thesis has successfully proved that the 18 look back period/indexing approach combinations listed in Table 19 offer a superior performance for the estimation of unit prices for the case study item in comparison with the other 82 combinations considered in this study. However, it is still necessary to prove if these 18 combinations are also better, in term of accuracy and reliability, than the current cost estimating techniques used in the transportation construction industry. Given that the author had no access to actual estimates made by ALDOT for the case study item, it is not possible to determine if the proposed methodology to ALDOT's current cost estimating system. However, as discussed in Section 5.6, it can be compared against the performance of the estimating systems adopted by the contractors doing business with ALDOT. This is a significant validation considering the fact that all the bidders have a common goal of submitting least minimum possible cost, so that, rather than trying to estimate actual construction costs they are trying to determine what would the lowest bid for a given construction project. They can decided later if they would be able to do the work with the estimated lowest bid.

Table 21 compares the MAPE's and standard deviation between the second lowest bids and the estimates obtained with the top ranked combination: two-year look-back period with a Quarterly All Bids Index. Even though the seems to be significant reduction in the MAPE and standard deviation values in Table 21, the magnitude of these improvements was also tested through statistical testing. The F-test showed a significant improvement in reliability at a 5% significance level (p-value = $7.21\text{x}10^{-11}$). This time the paired two-sample t-test was not suitable for the comparison of the means since some contracts have multiple bids for the same item; therefore, this is not a one-to-one comparison. The two-sample t-test assuming unequal variances was used in this case, showing a significance improvement in accuracy at a 5% significance level (p-value = 0.042). I should be noted outliers had been already removed from the unsuccessful bids, discarding unit prices unreasonable low or high.

Table 21. Comparison of Results Using Unsuccessful Bidders

	MAPE	Standard Deviation of APEs
Unsuccessful Bids (A)	15.09%	15.51%
Two-Years Look-Back Period & Quarterly All Bids CCIS (B)	12.52%	8.21%
Percentage Improvement (A-B)/A	15.24 %	49.01%
Significance of Improvement at 99% Confidence Level	Statistically Significant	Statistically Significant
P-value	<0.01	<0.01

Even though the results in Table 21 and the statistical tests on these results do not allow to conclude that the proposed methodology is more effective than the estimating system of any contractor doing business with ALDOT (it was not compared against every single contractor), it is possible to conclude that methodology presented in this study offer greater accuracy and reliability in the calculation of unit prices for the case study item than the average estimating techniques used by transportation construction contractors in Alabama.

Finally, even though no statistically significant differences were found in the performance of the 18 alternatives listed in Table 19. The final recommendation made by the author regarding the selection of the most suitable combination is still to select the top ranked combination. In the case of this study, that would be the two-year look-back period with the Quarterly All Bids CCIS. Rather than proving that all 18 combination would have the same performance, the statistical test failed to prove the opposite –that there are significant differences. It is still possible that the test failed to detect actual significant gaps in the performance of the top combinations. If that were the case, the top-ranked alternative would most likely be the one offering the significantly superior performance. It is still important to conduct the statistical analysis after ranking all combinations, because that would tell ALDOT if there are other combinations with a comparable effectiveness in case of not having access to the elements required to use to top ranked alternative.

CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

6.1 CONCLUSIONS

The main contribution to the body of knowledge made by this thesis is a comprehensive data-driven estimating methodology that takes into consideration the scale of projects and the impact of time to improve the accuracy and reliability of bid-based estimates for paving projects executed by ALDOT. The scale and time cost influencing factors were introduced into the cost estimating process using non-linear regression models, a look-back period determination protocol, and cost indexing mechanism to adjust bid-based estimates for inflation and market fluctuations.

The development and validation of the proposed system was illustrated by applying it to a case study item: *"Superpave Bituminous Concrete Wearing Surface Layer, 1/2" Maximum Aggregate Size Mix, ESAL Range C/D – Item ID 424A360."* This is the most relevant pay item used in ALDOT's paving projects. The author has used a moving-window data optimization algorithm to identify the optimal look-back period for data retrieval and the most suitable indexing approach for the case study item. A total of 5 look-back periods, ranging from 1 to 5 years, and 20 indexing approach have been considered in this study. Twelve of these indexing approaches were developed in this study and are referred to as CCIS's, which are arrangements of several cost indexes organized in a multilevel arrangement. Statistical tests failed to find significant differences between the estimating performance of the top 18 look-back period/indexing approach combinations. However, the study recommends the use of a two-year look-back period and a Quarterly All Bids CCIS to maximize the estimating accuracy and reliability for the case study item. This combination showed the highest accuracy and reliability among the 100 combinations evaluated in this study (5 look-back periods x 20 indexing approaches = 100 combinations).

Besides being used to identify the best look-back period/indexing approach combination, the moving-window algorithm was used to demonstrate the importance of considering scale a time effects into the cost estimating process. It was achieved by adding 10 more calculations to the moving-window algorithm: five for each of the look-back period and using no non-linear regression and no indexing approach; and five more for each of the look-back periods using non-linear models but no indexing approach. The best accuracy and reliability among the five "no non-linear regression and no indexing approach" calculations were compared against the best accuracy and reliability among the five "no indexing approach" calculations, which include non-linear regression models. It showed an increase in estimating accuracy and reliability of 22.5% and 34.0%, respectively, which is attributed to the used of the non-linear regression models. This improvement was found statistically significant with a 99% confidence level. Similarly, a statistically significant improvement was obtained after incorporating the time adjustments into the bid-based cost estimating process, showing the importance of considering this cost-influencing factor. The improvement in estimating accuracy and reliability associated with the use of the CCIS was 16.3% and 14.7%, respectively.

It should be noted that the specific quantitative results presented in this study are only applicable to the case study item in projects to be awarded by ALDOT. However, the process that led the author to these findings has been explained in great detail through this thesis, so that it could repeated by ALDOT for other pay items.

6.2 RECOMMENDATIONS FOR FUTURE RESEARCH

This thesis is the first of a series of research efforts intended to enhance ALDOT's construction cost estimating system. The data-driven cost estimating methodology presented in this research considers only two factors; scale and time. However, other factors like geographic conditions, level of competition, and uncertainty may have a potential influence on the accuracy and reliability of construction cost estimating systems. Further research is required to assess the impact of other cost-influencing factors to facilitate the incorporation of these impacts into the cost estimating process.

There is also a need for further research to analysis the reasons behind the outlying condition of the unit prices discarded in this study during the data cleaning process. Some of these unit prices may be substantially higher or lower than normal price ranges due to unique project requirements. A better understanding of the circumstances that force bidders to submit abnormal unit prices would allow ALDOT to identify those projects in which the proposed cost estimating methodology, or could also help model developers to improve this methodology making it applicable to those projects with special requirements.

Finally, part of the process used in this thesis to identify the best look-back period/indexing approach combinations was based on visual inspections. More specifically, the elimination of look-back periods and indexing approaches through visual inspection was conducted during the Levene's test and ANOVA test loops. The author recognizes that the application of an objective process, instead of the visual inspection, could have yielded different and stronger conclusions. Thus, future research efforts towards the improvement of ALDOT cost estimating system should address this issue.

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APPENDICES

Apendix-1. 53 Pay Items Specifications

Item id	Unit of Measurement	Description
206C010	Square Yard	Removing Concrete Driveway
206D000	Linear Foot	Removing Pipe
206D001	Linear Foot	Removing Guardrail
210A000	Cubic Yard	Unclassified Excavation
210D021	Cubic Yard	Borrow Excavation (Loose Truck bed Measurement)(A4 or Better)
212A000	Station	Machine Grading Shoulders
214A000	Cubic Yard	Structure Excavation
214B001	Cubic Yard	Foundation Backfill, Commercial
230A000	Roadbed Station	Roadbed Processing
401A000	Square Yard	Bituminous Treatment A
405A000	Gallon	Tack Coat
408A051	Square Yard	Planing Existing Pavement (Approximately 0.00" Thru 1.0" Thick)
408A052	Square Yard	Planing Existing Pavement (Approximately 1.10" Thru 2.0" Thick)
424A360	Ton	Superpave Bituminous Concrete Wearing Surface Layer, 1/2" Maximum Aggregate Size Mix, ESAL Range C/D
424B650	Ton	Superpave Bituminous Concrete Upper Binder Layer, 3/4" Maximum Aggregate Size Mix, ESAL Range C/D
424B655	Ton	Superpave Bituminous Concrete Upper Binder Layer, Patching, 1" Maximum Aggregate Size Mix, ESAL Range C/D
424B659	Ton	Superpave Bituminous Concrete Upper Binder Layer, Leveling, 1" Maximum Aggregate Size Mix, ESAL Range C/D
424B681	Ton	Superpave Bituminous Concrete Lower Binder Layer, 1" Maximum Aggregate Size Mix, ESAL Range C/D
502A000	Pound	Steel Reinforcement
505M002	Linear Foot	Steel Piling Furnished And Driven (HP 12x53)
508A000	Pound	Structural Steel
510A000	Cubic Yard	Bridge Substructure Concrete, Class A
510E000	Square Yard	Grooving Concrete Bridge Decks
530A001	Linear Foot	18" Roadway Pipe (Class 3 R.C.)
610C001	Ton	Loose Riprap, Class 2
610D003	Square Yard	Filter Blanket, Geotextile

Item id	Unit of Measurement	Description
614A000	Cubic Yard	Slope Paving
620A000	Cubic Yard	Minor Structure Concrete
630A001	Linear Foot	Steel Beam Guardrail, Class A, Type 2
650A000	Cubic Yard	Topsoil
650B000	Cubic Yard	Topsoil From Stockpiles
652A100	Acre	Seeding
652C000	Acre	Mowing
654A000	Square Yard	Solid Sodding
654A001	Square Yard	Solid Sodding (Bermuda)
656A010	Acre	Mulching
665A000	Acre	Temporary Seeding
665E000	Square Yard	Polyethylene
665I000	Ton	Temporary Riprap, Class 2
665L000	Linear Foot	Floating Basin Boom
665O001	Linear Foot	Silt Fence Removal
666A001	Acre	Pest Control Treatment
701C000	Mile	Broken Temporary Traffic Stripe
701C001	Mile	Solid Temporary Traffic Stripe
701H001	Linear Foot	Solid Traffic Stripe Removed (Plastic)
701H006	Linear Foot	Broken Traffic Stripe Removed (Plastic)
703A002	Square Foot	Traffic Control Markings, Class 2, Type A
703B002	Square Foot	Traffic Control Legends, Class 2, Type A
703D001	Square Foot	Temporary Traffic Control Markings
710A115	Square Foot	Class 4, Aluminum Flat Sign Panels 0.08" Thick Or Steel Flat Sign Panels 14 Gauge (Type III Or Type IV Background)
710A126	Square Foot	Class 8, Aluminum Flat Sign Panels 0.08" Thick Or Steel Flat Sign Panels 14 Gauge (Type IX Background)
730H001	Linear Foot	Loop Wire
740B000	Square Foot	Construction Signs