CONCEPTUAL COST ESTIMATION OF HIGHWAY BID ITEMS USING GEOSTATISTICAL INTERPOLATION

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ABSTRACT

Challenges associated with ensuring the accuracy and reliability of cost estimation of highway bid items, especially during the conceptual phase of a project, are of significant interest to state highway agencies. Even with the existing research undertaken on the subject, the problem of inaccurate estimation of highway bid items still exists.

A systematic literature review was performed to determine research trends, identify, categorize the factors influencing highway unit prices, and assess the performance of conceptual cost prediction models.

This research proposes a geographic information system (GIS)–based methodology that leverages vast historical bid data for unit-price estimation and the robust GIS capabilities with consideration of the effects of project-specific location and variations due to cost escalation on different bid items.

A comparison of the three spatial interpolation techniques operationalized in this research revealed that disjunctive and empirical Bayesian kriging models led to more accurate cost prediction than ordinary kriging algorithms.

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DEDICATION

This work is dedicated to the almighty God. I am extremely grateful for His abundant mercies, blessings, and guidance throughout my life.

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CHAPTER 1. INTRODUCTION

1.1. Background

The construction industry in the world, especially in the United States, is one of the largest industry sectors that deliver projects with substantial budgets (Zhang et al. 2017). Historically, the construction sector has been plagued by poor performances, characterized by lagging productivity growth, cost overruns, and low levels of customer satisfaction (Rameezdeen, 2007; Yap et al. 2019; Biörck et al. 2020). State highway transportation agencies (SHAs) require multiple cost estimates for various purposes throughout the life cycle of construction projects (Migliaccio et al. 2015; Zhang et al. 2017). Conceptual cost estimates are vital for decision making, initial appropriation, and economic feasibility studies of capital projects (Sinnette 2007; Hyari et al. 2015; Dursun and Stoy 2016). Developing a reliable and accurate total cost estimate at the preliminary stages of a project is a challenge for any state highway agency (SHA) due to personnel shortages, lack of information and data, and incomplete design (Asmar et al. 2011; Elbeltagi, et al. 2014; Gardner et al 2016). With federal financial aid swirling with uncertainty and the increasing demand for highway construction projects, inaccurate estimates often present challenges in the successful delivery of much-needed highway projects (Baek and Ashuri 2019). The accuracy of conceptual cost estimates is crucial to the success of construction projects.

Improving the accuracy of cost estimates is key to addressing the shortcomings of current cost estimating methods (Zhang et al. 2014) and ensuring the successful planning, execution, and completion of transportation projects. It is even more important for contracting authorities to optimize taxpayer’s money by utilizing it as responsibly as possible. Yet, authorities often must choose between different projects during the feasibility stage. Sometimes, under the pressure of time constraints, funding decisions are made before the project scopes are fully finalized. This presents difficulty in preparing adequate estimates of the probable project costs of highway construction projects. However, it is in the preliminary stages of the project that control over the budget is most necessary.

Conceptual cost estimates are developed based on historical cost data and adjustment factors, which include location, time, size, and complexity. Thus, the accuracy of those adjustment factors directly affects the accuracy of the estimate (Elbeltagi et al. 2014; Zhang et al. 2016). A wide range of construction cost estimation methods exists to verify feasibility studies on facilities or in evaluating design alternatives. Estimating methods at the conceptual phase needs to be quick, economical, and reasonably accurate (Kim et al. 2012). Several studies have been conducted to improve the estimation process, including a geographic information systems estimation based on project location (Le et al. 2019; Martinez 2010; Zhang 2010). Other researchers also applied case-based reasoning (CBR), genetic algorithms(GA), and multiple regression analysis (MRA) to improve the cost estimation process (Shrestha et al. 2014). Existing forecasting models for instance regression and artificial intelligence use binary weight values which are not robust enough to quantify the spatial variation of highway construction costs. However, an important consideration with the selection of any method for cost estimation is the accuracy by which actual costs can be predicted (Ashworth and Skitmore 1982; Elmousalami 2020). Cost estimates expressed as a deterministic value often leads to a false inference of accuracy because of the inability to account for the vagaries associated with the deterministic approach making it difficult for transportation agencies to cater for cost growth (Anderson et al. 2007; Gardner et al. 2017). The communication of a range of values representing the array of probable project costs creates a better understanding of estimation precision (Anderson et al. 2007). The stochastic conceptual estimate approach produces a probability distribution of the likely construction costs and addresses the level of confidence in an estimate (Gardner et al. 2017). Hence, it is necessary to devise a method that would improve the accuracy of construction cost estimation during the planning phase (Shrestha et al. 2014).

1.2. Statement of the Problem

The development of cost estimates that accurately reflect project scope, microeconomic conditions and macroeconomic conditions that provide a reliable baseline cost (Shane et al. 2009) are vital for decision making, preliminary appropriation, and economic feasibility studies of capital projects (Dursun and Stoy 2016). Reliable cost data are often difficult to obtain during the conceptual stages of a project, particularly if the design and cost drivers remain unresolved (Trost and Oberlender 2003; Wilmot and Cheng 2003). Conceptual estimating methods require considerable effort in data collection and analyses before modeling construction costs. The preparation of the estimate takes little time, however, compiling historical cost data is a time-consuming process and is only useful if updated and monitored regularly (Barzandeh and Zealand 2011). Construction and engineering organizations that can successfully collect, store, analyze, and generate insights from historical data and project information are among the winners in this new information age (Huang et al. 2006). Available computing hardware and database technology allow for easy, efficient, and reliable data storage and retrieval. Furthermore, the widespread use of cloud computing and sophisticated database systems enables companies to pool their data together from across different geographical locations using data servers. However, the amount of data generated by these firms presents both a challenge and opportunity- a challenge to traditional methods of data analysis since the data are often complex, and large (Ahiaga-Dagbui and Smith 2013). The actual cost of a project is subject to many variables including scope, location, time, size, capacity, human judgmental factors, market fluctuations, weather, and complexity; which could significantly influence the range of probable projected costs (AASHTO 2013; Zhang et al. 2016; Baek and Ashuri 2019). Geographic location considerations are powerful project characteristics that may substantially affect unit prices (ITD 2020). This is evident in several empirical studies conducted by Shash and Al-Khaldi (1992) in which a number of contractors identified project location as a predominant factor that influences the probable cost of highway projects. A project's location, whether in an urban, suburban, or rural setting should be considered in establishing the probable cost of highway construction projects at the conceptual phase (NJDOT 2019). The geographic location of a highway transportation project is a larger cost driver in asphalt pavement bid unit prices than mix design. Therefore, bid prices for other asphalt bid items in a similarly priced geographical area should be investigated (WisDOT 2020). A location factor is an instantaneous overall project factor for translating all of the project cost elements of a defined construction project scope of work from one geographic location to another (Pietlock 1996). One of the problems that may be encountered in conceptual cost estimation location adjustment is that not all cities or communities are accounted for in published standard cost indices (Martinez 2010). To adjust cost estimates for geographical locations without location adjustment factor, the state of practice is to apply factors from nearby cities with similar economic characteristics. SHA's depend on estimators' judgment and experience to make these adjustments. However, this subjective recommendation does not ensure consistent and reliable location adjustment of cost estimates. Additionally, estimating construction cost using manual comparison and interpolation from historical data is time-consuming and error-prone due to the challenges of two-dimensional interpolation from multiple historical values (Zhang, 2010; Zhang et al. 2016). Furthermore, practical, technical, and economical constraints make it difficult to collect, store, and process historical cost data for every desired point over space and time. Location-cost adjustment factors (LCAF) are commercially available to account for spatial variation in construction cost. However, they do not include all geographic locations. Therefore, LCAFs for unsampled locations need to be inferred through spatial interpolation or prediction methods (Migliaccio et al. 2013). The state of the art has applied interpolation methods to location cost-adjustment factors to adjust the total costs of two similar projects in two different cities. However, existing methods are most beneficial to conceptual cost estimation without considering variances between two projects in the same city and various effects of location on different work items (Le et al. 2019). A recent study conducted by Le, et al. (2019) in a GIS-based framework for estimating and visualizing unit prices used inverse distance weighted (IDW), ordinary kriging (OK), and ordinary cokriging (OCK) methods. The shortcoming of this research, however, is only a deterministic and linear kriging approach were deployed for the study. Invariably, the choice of an optimal kriging method is dependent on how well the variogram model fits the data set (Shamo et al. 2012). Out of the 11 semivariogram models in ArcGIS, only one was fitted for the entire study. Additionally, classical interpolation methods assume that the estimated semivariogram is the true semivariogram for the interpolation region and does not assess the uncertainty introduced by estimating the underlying semivariogram. If a new method can be introduced that can be statistically proven to increase prediction accuracy, this will be a great contribution to construction cost estimation of highway construction bid items (Martinez 2010). This warrants a further study to improve the unit price estimation process for SHAs' estimators by proposing ordinary kriging(linear), Disjunctive kriging (non-linear), and empirical Bayesian kriging(EBK) methods for estimating unit prices based on historical bid data.

1.3. Statement of Purpose

Even with the existing research undertaken on the subject, the problem of inaccurate estimation of highway bid items still exists. Intense competition coupled with the demand for shorter completion times and lower costs have been driving innovative approaches within the construction industry. The accuracy of conceptual cost estimates is a major concern for project sponsors.

This study proposes a geographic information system(GIS)–based methodology that leverages vast historical bid data for unit-price estimation and the robust GIS capabilities with consideration of the effects of project-specific location and variations due to cost escalation and inflation overtime on different bid items. This study will investigate which combination of kriging and semivariogram model would best fit the data since the kriging results are based on the intrinsic properties of the data. Three spatial interpolation methods ordinary kriging(OK), Disjunctive kriging(DJ), and empirical Bayesian kriging(EBK) methods will be combined with several semivariogram models one at a time, to ascertain the best combination of the kriging method and variogram fitting for the historical cost data used in the study.

1.4. Research Questions

1. What context are cost models used to estimate the cost of highway construction bid items and their associated shortcomings?
2. What is the level of accuracy associated with the estimating methods adopted in the selected articles?
3. What were the factors affecting the costs of highway unit prices in the published papers?

4. What are trends of unit prices for the top 5 historical highway bid items from 2013 to 2018?
5. Which combination of ordinary kriging and variogram models yields the best results in estimating unit prices for highway construction bid items?
6. What is the prediction accuracy associated with the ordinary kriging and disjunctive kriging in estimating unit prices of highway construction bid items?
7. Which combination of empirical Bayesian kriging and variogram models yields the best results in estimating unit prices for highway construction bid items and what is the standard prediction error introduced by estimating the underlying semivariogram?
8. How can the validity of the prediction results be checked concerning the actual unit prices bid items?

1.5. Overview of Research Approach

Although the primary research is essential for producing crucial original data and insights, reviews can inform us about what is known, how it is known, how this varies across studies, and thus also what is not known from previous research (Gough et al. 2012). Conducting a systematic literature review on a subject matter provides extensive insight into previous research and limitations. Even with the existing research undertaken on the subject, the problem of inaccurate estimation of highway bid items still exists. A systematic literature review was performed to search, select, and review 105 papers from six electronic databases on conceptual cost estimation of highway bid items. This study used content and non-parametric statistical analyses to determine research trends; identify and categorize the factors influencing highway unit prices; and to assess the combined performance of conceptual cost prediction models from existing literature.

A reliable method of tracking construction costs is to observe the variability in the average unit price of individual highway construction bid items that occur in several contracts; thus, enabling their comparisons yearly (Cheng and Wilmot 2009). The frequency of the bid items of each highway project in the database was determined to identify the common bid items from 2013 to 2018. Bid items whose units were not precisely defined for instance lump sum, were discarded and those with consistent and specific characteristics that allowed a price comparison over time were retained for the analyses. The dataset was visually screened to check for completeness, consistency, and to ensure the location of each bid item corresponded to the precise project location. The bid data were then subjected to exploratory data and statistical analyses to help understand the data and make logical choices and conclusions for further modeling procedures. Two research hypotheses were formulated to further ascertain the impact of competition and project size on unit prices submitted by contractors for 5 common bid items identified in the database.

Three spatial Interpolation algorithms ordinary kriging(OK) will be combined with the three(3) semi-variogram models(exponential, spherical, Gaussian) one at a time, to ascertain the best combination of the kriging method and variogram fitting for the historical cost data used in the study. Subsequently, the prediction performance of ordinary kriging(linear) and disjunctive kriging (non-linear) will be assessed to ascertain which of the two algorithms performs best for the top five highway bid unit prices. To accurately assess the standard prediction error introduced by estimating the underlying semivariogram in quantifying the effect of project-specific location and time on highway bid unit-price estimation, empirical Bayesian kriging(EBK) with three semivariograms (exponential detrended, whittle detrended, and K-Bessel detrended) to model and interpolate top five bid unit prices. Cross-validation will be used to assess the variability and validity of the modeling results and formed the basis of comparison and selection of the optimal results.

1.6. Research Contribution

The accuracy of conceptual cost estimates for capital projects has been a major concern and the subject of much scrutiny over the last 35 years (Trost and Oberlender 2003). A majority of studies conducted on the subject matter failed to validate their methodology on vast real project cost data. The primary contribution to the body of knowledge of the study is to apply three spatial interpolation algorithms ordinary kriging(OK), disjunctive kriging (non-linear), and empirical Bayesian kriging(EBK) methods for unit-price estimation and geovisualization with consideration of the effects of project-specific location and inflation on different highway bid items at the conceptual phase of projects. This research will validate the proposed methodology using different types of highway construction bid items from WisDOT. The geovisualized maps will help state highway authorities to increase their efficiency in developing and updating conceptual estimates and will serve as a leverage for verifying existing historical bid costs. The generated maps will be integrated into an ArcGIS online platform, in a cloud environment that enables stakeholders involved in planning and delivering transportation projects to easily access complete historical cost data to make better-informed funding decisions. The following are proposed research papers that will be generated from this study;

1. Conceptual Cost Estimation of Highway Bid Items- A Systematic Literature Review
2. Exploratory Data and Statistical Analyses of Highway Construction Bid Items

3. Conceptual Cost Estimation of Highway Unit Prices Using Ordinary Kriging
4. Comparison of Ordinary and Disjunctive Kriging Methods for Conceptual Cost Estimation of Highway Bid Items
5. Conceptual Cost Estimation of Highway Unit Prices: An Empirical Bayesian Kriging Approach

1.7. Organization of the Study

The thesis is organized into seven chapters as illustrated in Figure 1.

1.7.1. Chapter One-Introduction

This chapter sets out the background and context of the research, laying the basis for the problem statement along with the objectives of the research. The research questions have also been stated in this chapter

1.7.2. Chapter Two- Conceptual Cost Estimation of Highway Construction Bid Items- A Systematic Literature Review

This chapter forms the spine of the research where the thesis statement is identified and refined. The systematic literature review provides an exhaustive and comprehensive review of the article on conceptual cost estimation of highway bid items from six major electronic databases. This section's unique contribution to the body of knowledge is its in-depth statistical analysis of the data to assess and provide preliminary insight into the combined accuracy of the cost estimation models identified from the selected literature. This section identified and categorized a comprehensive set of factors that affect highway construction costs. This study serves as a reference for future research in advancing cost estimation modeling at the early stages of highway projects. This chapter answers research questions one, two, and three of this research.

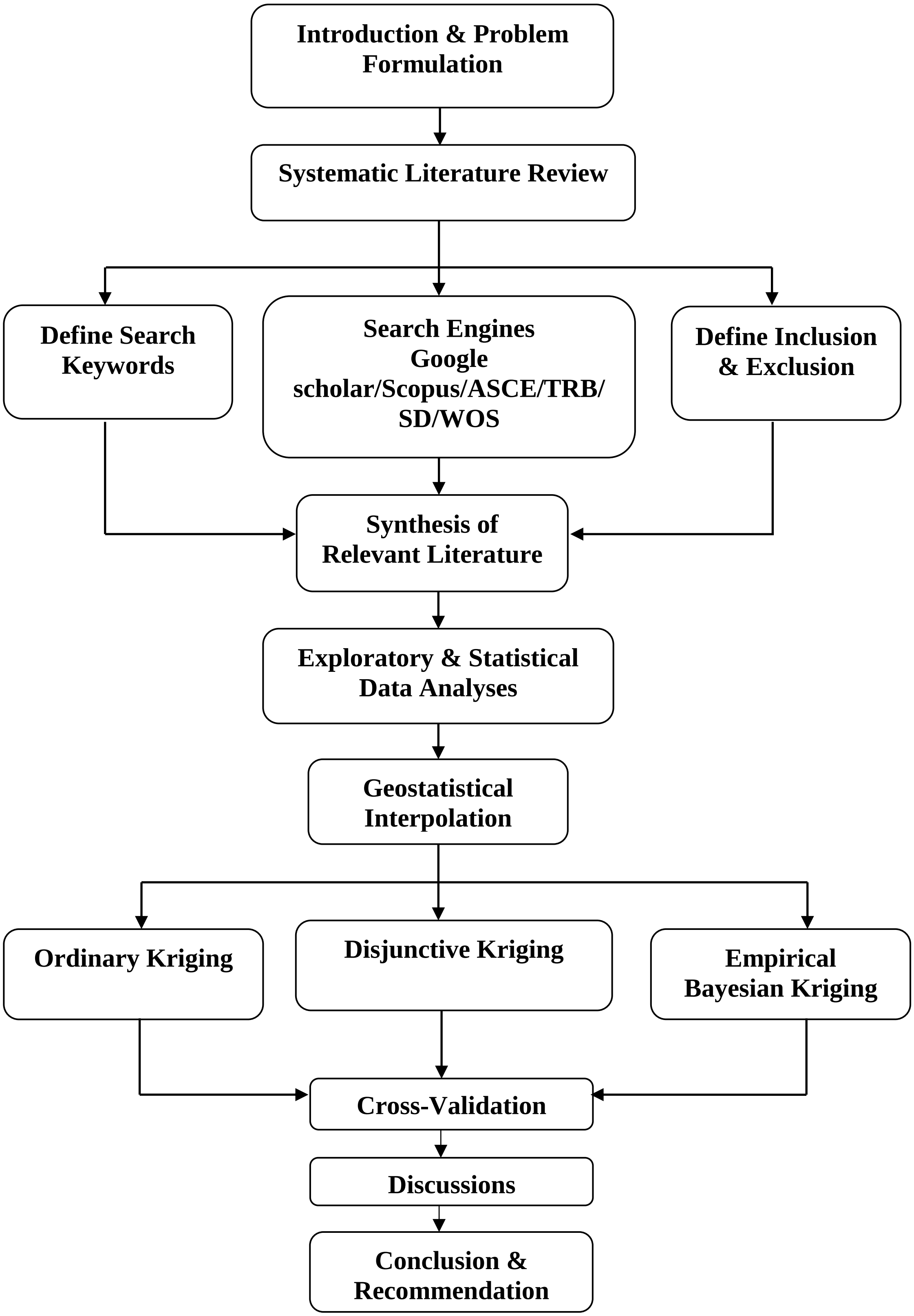

Figure 1. Thesis research methodology

1.7.3. Chapter Three-Exploratory Data and Statistical Analyses of Highway Construction Bid Items

In this chapter, data-driven empirical insights and patterns of historical highway cost data will be generated to enhance the efficacy of conceptual cost estimates. This paper explored and investigated trends in historical highway construction bid data from 2013 to 2018 obtained from the Wisconsin Department of Department (WisDOT), determined the relationship between project size and unit prices, and assessed the impact of competition on unit prices of highway construction bid items using exploratory data and statistical analyses. This chapter answers research question four.

1.7.4. Chapter 4- Conceptual Cost Estimation of Highway Unit Prices Using Ordinary Kriging

Kriging is an optimal spatial regression technique that requires a spatial statistical model, popularly known as a semivariogram, representing the internal spatial structure of the data. It is known as the best linear unbiased estimator (BLUE) (Asa et al. 2012). Although other nonlinear geostatistical algorithms are now vastly deployed, the relative transparency and straightforwardness of the OK algorithm, combined with its good performance in the past, ensure its continued popularity (Van Groenigen 2000). In this paper, ordinary kriging will be combined with three commonly used semivariograms (spherical, exponential, and Gaussian) one at a time to estimate highway construction unit prices from the Wisconsin Department of Transportation (WisDOT) from 2013 to 2018. Chapter 4 answers research question five. Cross-validation will be used to assess the variability and validity of the modeling results and formed the basis of comparison and selection of the optimal results.

1.7.5. Chapter 5- Comparison of Ordinary and Disjunctive Kriging Methods for Conceptual Cost Estimation of Highway Bid Items

Depending on the highway project type and cost data being deployed, the use of nonlinear models could be necessary to capture the nonlinearity inherent in the cost data (Sonmez 2005). The state-of-the-art has applied deterministic and linear geostatistical models to assess the spatial variation on highway cost estimates. However, deterministic and linear approaches assume that the data are from a realization of a Gaussian or nearly Gaussian random field; an assumption that produces linear predictors (Rivoirard et al. 2014). Therefore, these algorithms are not capable of accurately modeling the nonlinear relationship and also handling non-Gaussian distributions associated with construction cost data and the cost drivers influencing highway unit prices. To answer research question six, this study will compare the prediction performance of ordinary and disjunctive kriging methods to model and interpolate six years (2013 to 2018) of the top five common highway bid data: common excavation, base aggregate dense 1 ¼”, base dense aggregate ¾”, tack coat, and asphaltic surface obtained from WisDOT.

1.7.6. Chapter 6- Conceptual Cost Estimation of Highway Unit Prices Using Empirical Bayesian Kriging

Empirical Bayesian kriging(EBK) differs from classical kriging methods by accounting for the error introduced by estimating the semivariogram model. This is done by estimating, and then using a spectrum of semivariogram models rather than a single semivariogram. If the data distribution is Gaussian, the best predictor is one that uses a linear combination of the nearby data values. For other distributions, however, the best predictor is often non-linear and, therefore, more complex (Krivoruchko 2012). EBK models do not require specification of the prior distributions for the model parameters, allow moderate local and large global data non-stationarity, locally transform data to Gaussian distribution, and work reasonably fast and produce reliable outputs with default parameters (Krivoruchko and Gribov 2019). The novel contribution of this study is exploring the potential application of the empirical Bayesian kriging in spatially interpolating the highway bid unit prices. To answer research question seven, this section will investigate which combination of empirical Bayesian kriging and variogram models yields the best results in estimating unit prices for highway construction bid items and investigate whether the same set of kriging and variogram algorithms could be fitted to the unit price data set from year to year.

1.7.7. Chapter 7- Conclusions and Recommendation

In the closing chapter, conclusions will be made based on the findings from the literature review, exploratory and statistical data analyses, and geostatistical modeling chapters. The objectives set out in the initial chapter of the thesis will be revisited and a judgment made on whether these have been achieved, and to what extent. Theoretical and practical contributions of the research will be summarized while detailing the implications of the findings for enhancing the efficacy of cost estimation at the conceptual phase. Some considerations of future research will then be provided to stimulate future studies in improving highway construction cost estimates along with limitations of the current research.

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CHAPTER 2. CONCEPTUAL COST ESTIMATION OF HIGHWAY BID ITEMS- A SYSTEMATIC LITERATURE REVIEW[1]

2.1. Abstract

Challenges associated with ensuring the accuracy and reliability of cost estimation of highway construction bid items, especially during the conceptual phase of a project, are of significant interest to state highway transportation agencies. Even with the existing research undertaken on the subject, the problem of inaccurate estimation of highway bid items still exists. This paper systematically searched, selected, and reviewed 105 papers from six electronic databases on conceptual cost estimation of highway bid items. This study used content and non-parametric statistical analyses to determine research trends, identify, categorize the factors influencing highway unit prices, and to assess the combined performance of conceptual cost prediction models.

Findings from the trend analysis showed that between 1983 to 2019 North America, Asia, Europe, and the Middle East contributed the most to improve highway cost estimation research. Aggregating the quantitative results and weighting the findings using each study's sample size revealed that the average error between the actual and the estimated project costs of Monte-Carlo simulation models(5.49%) performed better compared to Bayesian model(5.95%), support vector machines(6.03%), case-based reasoning(11.69%), artificial neural networks(12.62%), and regression models(13.96%). This paper identified 41 factors and was grouped into three categories, namely: (1) factors relating to project characteristics; (2) organizational factors; and

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(3) estimate factors based on the common classification used in the selected papers. The mean ranking analysis showed that a majority of the selected papers used project-specific factors more when estimating highway construction bid items than the other factors.This paper contributes to the body of knowledge by analyzing and comparing the performance of highway cost estimation models, identifying, and categorizing a comprehensive list of cost drivers to stimulate future studies in improving highway construction cost estimates.

2.2. Introduction

The construction industry in the world, especially in the United States, is one of the largest industry sectors that deliver projects with substantial budgets (Zhang et al. 2017a). State highway transportation agencies(SHAs) require multiple cost estimates for various purposes throughout the life cycle of construction projects (Migliaccio et al. 2015; Zhang et al. 2017a). To prepare reliable highway construction programs, transportation authorities must have accurate estimates of future funding and project costs (Wilmot and Cheng 2003). Estimating the costs of highway bid items at the conceptual stage is critical to the initial decision-making process for the construction of capital projects (Trost and Oberlender 2003). Completing highway projects within budget is essential to SHAs because such performance enables them to fund, manage, and maintain their set of transportation projects (Wilmot and Cheng 2003; Alavi and Tavares 2009; Zhang et al. 2017b). The accuracy of conceptual cost estimates for capital projects has been a major concern and a subject of much scrutiny over the last 35 years (Trost and Oberlender 2003). Because of incessant cost overrun experienced during the construction phase of transportation projects, engineering skill, and judgment invested in project planning is obscured (Schexnayder et al. 2003; Molenaar 2005). Depending on the phase of a project, cost estimates are defined differently (Membah and Asa 2015). Oberlender and Trost (2001) defined a conceptual estimate as an estimate prepared from the inception of a project up to and including when funding is allocated. Asmar et al. (2011) also defined a conceptual cost estimate as an estimate prepared at the point at which only a general idea exists about what the project will entail. As a result, estimators must infer many of the cost components from historical costs associated with past projects of similar scope (Trost and Oberlender 2003; Asmar et al. 2011). The construction sector over the years has focused its efforts and resources on improving the quality of cost estimates (Zhang et al. 2017a). While future funding is fraught with uncertainty, incorrect estimation of transportation costs leads to significant overestimation and underestimation of highway construction costs (Baek and Ashuri 2019) and often presents challenges in the successful planning, execution, and completion of construction programs (Wilmot and Cheng 2003; Bayram and Al-Jibouri 2016). Overestimated cost could cause a misjudgment for the feasibility of a project, which could limit the number of business opportunities an owner can pursue at a time or loss of a contract to competitors (Chou and O'Connor 2007; Liu and Zhu 2007; Migliaccio et al. 2015). In contrast, underestimated cost could later force the owner to secure additional funding, reduce project scope, and probably lead to the suspension or termination of the proposed project (Kyte et al. 2004; Chou and O'Connor 2007; Liu and Zhu 2007; Migliaccio et al. 2015). Over the years, several researchers have conducted studies to improve the estimation of highway bid items at the conceptual phase. However, an important consideration with the selection of any method for cost estimation is the accuracy by which actual costs can be predicted (Ashworth and Skitmore 1982; Elmousalami 2020). Estimating performance is an essential indicator used to assess the quality of highway cost estimates during project development (Meeampol and Ogunlan 2006; An et al. 2007). There is a need to assess the quality of cost estimation models by measuring the deviation between the estimated and actual cost for transportation projects (Odeck 2003; Harper et al. 2014; Bayram and Al-Jibouri 2016).

To address these limitations in conceptual cost estimation modeling of highway bid items, this paper aims to answer the following research questions:

1. What is the publication trend of estimating the cost of highway construction bid items at the conceptual phase from 1980 to 2019?
2. What context are the models used to estimate the cost of highway construction bid items and their associated shortcomings?
3. What is the level of accuracy associated with the estimating methods adopted in the selected papers?
4. What were the factors affecting the costs of highway unit prices in the published papers?

To address these research questions, a systematic literature review was used to search several databases and a content analysis approach was employed to identify the context in which the estimation methods are used and their shortcomings. Factors affecting highway unit prices were identified and categorized based on the common classification identified from the selected literature. To assess the accuracy of the cost estimation methods, we performed statistical analyses to compare the mean absolute percent error between the actual and estimated costs. The rest of this paper is organized as follows. First, this study presents an overview of models used in estimating highway bid items, the factors affecting unit prices, and the research method used for the study. Content analysis was used to explore the publication trend in conceptual cost estimation of highway construction bid items from 1980 to 2019, the algorithms adopted by previous studies and their shortcomings, and the evaluation techniques used to assess the level of accuracy of the models. This was followed by assessing the level of accuracy associated with the cost estimation methods and identifying the factors influencing highway construction bid items. Finally, conclusions, limitations, and suggestions for future work are outlined.

2.3. Cost Estimation Modeling during the Conceptual Phase of Highway Construction Projects

The top-down and bottom-up approach which can either be deterministic or stochastic are the predominant methods used to estimate construction costs (Kim and Reinschmidt 2011; El-Sawalhi 2015; Elmousalami 2020). The top-down estimation approach is mainly used in the conceptual phase of construction projects and is based on similar historical project information and cost data to forecast future project costs. Therefore, the accuracy of the top-down approach is contingent on the quality of cost data, project information, the expertise of the estimation team amongst other cost drivers (Kim and Reinschmidt 2011; Elmousalami 2020). In contrast, the bottom-up approach is used when detailed design and work packages are substantially complete to estimate the cost of resources, labor, materials, equipment, and subcontracting (Kim and Reinschmidt 2011; Elmousalami 2020).

Recent advances in computational intelligence have enabled the development of several algorithms; namely artificial neural networks (ANNs), genetic algorithms (GA), support vector machines (SVM), and a multitude of tools that are readily available to model construction cost (Hegazy and Ayed 1998; Hassanein 2006). However, the subjectivity and randomness associated with using modeling techniques and tools to estimate construction costs have been criticized because such randomness is intrinsic in the construction industry (Hassanein 2006). Several researchers have conducted studies to improve the estimation process, including the use of geographic information systems to estimate highway construction bid items (Martinez 2010;

Zhang 2010; Shrestha and Shrestha 2014; Le et al. 2019). Other researchers also applied artificial neural networks (ANNs), case-based reasoning (CBR), genetic algorithms (GA) and regression analysis (RA) to enhance the cost estimation process (Adeli & Wu, 1998; Hegazy and Ayed 1998; Al-Tabtabai et al. 1999; Chou 2009; Kim and Kim, 2010; Cirilovic et al. 2014; Adel et al. 2016). Cost estimation models capable of modeling construction costs as a function of influencing factors are highly likely to generate reliable estimates (Wilmot and Cheng 2003).

With increasing transportation needs, funding limitations at both the federal and state levels, and the high cost of transportation improvement projects, it is important to have a toolbox of techniques that support accurate estimation of project costs (AASHTO 2013). Cost estimates expressed as a deterministic value often leads to a false inference of accuracy because of the inability to account for the vagaries associated with the deterministic approach making it difficult for transportation agencies to cater for cost growth (Anderson et al. 2007; Gardner et al. 2017). The communication of a range of values representing the array of probable project costs creates a better understanding of estimation precision (Anderson et al. 2007). They encourage the adoption of a stochastic conceptual estimate approach to produce a probability distribution of the likely construction costs and address the level of confidence in an estimate (Gardner et al. 2017).

2.4. Cost Estimation in Lump-Sum Contracts

State Highway Transportation agencies have been implementing alternate project delivery and procurement methods for transportation projects (Khalafalla and Rueda-Benavides 2018). Therefore, the impact of these methods on project cost must be considered when preparing estimates and managing estimated costs (Anderson et al. 2007). In lump-sum contracts, a contracting firm delivers a single price either for the entire project, for each bid item, or a group of bid items (Wasserman 2012). Lump-sum contracts will normally require the contractor to break down the project into a variety of work items and estimate cost and contingencies to arrive at the total project cost (Frein 1980; Hinze 2011). Unlike unit rate contracts, lump-sum contracts require estimators to be highly accurate in the quantities and the unit prices of highway construction bid items (Chua and Li 2000). Therefore, using historical bid-based estimating techniques for predicting lump-sum items is a complex and difficult process. Most lump-sum items differ from one project to another. Thus, using past bid history is often not a good indicator of the future price for lump-sum items. In a lump-sum bidding situation, the profit margin of the contractor depends on the accuracy of his or her estimate. If the project is exceptionally large, the loss from an inaccurate estimate on a lump-sum bid might cause a significant loss to the contractor (Dysert and Elliot 2002).

2.5. Factors Affecting Highway Construction Unit Prices

The development of cost estimates that accurately reflect project scope, project economic conditions, and macroeconomic conditions that provide a reliable baseline cost (Shane et al. 2009) is vital for decision making, preliminary appropriation, and economic feasibility studies of capital projects (Dursun and Stoy 2016). Reliable cost data are often difficult to obtain during the conceptual stages of a project, particularly if the design and cost drivers remain unresolved (Trost and Oberlender 2003; Wilmot and Cheng 2003). The actual cost of a project is subject to many variables including scope, location, time, size, capacity, human judgmental factors, random market fluctuations, and weather, and complexity, which could significantly influence the range of probable projected costs(AASHTO 2013; Zhang et al. 2016; Baek and Ashuri 2019). These variables may not all be directly quantifiable and determining the change in cost is often a fuzzy, qualitative, and ill-structured process (Al-Tabtabai et al. 1999). Therefore, there is a need to explore a recognized logical process to quantify cost drivers when assessing project costs (Schexnayder et al. 2003).

Modeling cost as a function of many variables is complex and an opaque process mainly owing to a lack of transparent algorithms capable of incorporating the required variables and the effects of their associated interactions (Hegazy and Ayed 1998; Al-Tabtabai et al. 1999). Traditionally, cost estimation relationships are modeled by applying regression analysis to historical cost information (Hegazy and Ayed 1998) as a linear function using mathematical equations (Al-Tabtabai et al. 1999). In addition, cost drivers are highly correlated to each other, resulting in multicollinearity when more than one factor is included in the modeling procedure (Wilmot and Mei 2005). However, the variables affecting highway construction costs function in a linear or non-linear form (Adeli and Wu 1998; Al-Tabtabai et al. 1999; Wilmot and Mei 2005).

While estimators may address this through a transformation of variables, the assumption of a specific mathematical formulation limits the ability of the model to fit the data on which it is estimated (Wilmot and Mei 2005). Highway construction cost data are very noisy because only a few of the major factors are considered in the mathematical modeling of the cost-estimation problem (Adeli and Wu 1998; Wilmot and Cheng 2003). Therefore, improving the accuracy of predicted costs is contingent on finding a properly fitted approximation for factors influencing highway construction unit prices and selecting an appropriate model that can quantify the relationship between these factors (Adeli and Wu 1998; Trost and Oberlender 2003).

2.6. Methodology

The research methodology is a systematic literature review of previous work related to the conceptual cost estimation of highway bid items. Systematic literature review (SLR) is a logical approach of presenting findings across multiple research studies on a research question through a systematic collection, critical evaluation, and integration of previous work (Pati and Lorusso 2018; Linnenluecke et al. 2019). To ensure adequate coverage of articles on the subject matter, the title, abstract, and keyword (T/A/K) field of Scopus, Google Scholar, American Society of Civil Engineers (ASCE), Transportation Research Board (TRB), and Science Direct (SD) were searched. The search string used to identify relevant articles were "cost estimates", "conceptual cost estimates", "early cost estimates", "preliminary cost estimates" based on the research topic, and was limited to "highway projects". The databases were selected to ensure that a broad range of published literature on highway construction projects was retrieved (Membah and Asa 2015).

The inclusion and exclusion criteria used to select the articles include: (1) the article should be specifically related to cost estimation of highway bid items; (2) the article should report estimation accuracy (error matrices); (3) the article should mention, discuss, or list factors affecting highway bid items in the key text, tables, or figures; (4) the selected article must be a peer-reviewed paper; and (5) it must be published in English. However, some peer-reviewed conference papers, reports which met the criteria were included in the study.

Selected articles for the content analysis were profiled based on the journal, year of publication, and the geographical distribution. The values derived from the analysis were determined based on the ratio of references per each journal to the total number of articles considered for the review. This was followed by the categorization of the methods used in estimating construction costs and identifying the factors affecting unit prices in highway construction projects. After categorizing the methods, quantitative findings were collected, and statistical analyses were performed to assess the collective performance of the methods adopted in estimating highway construction cost.

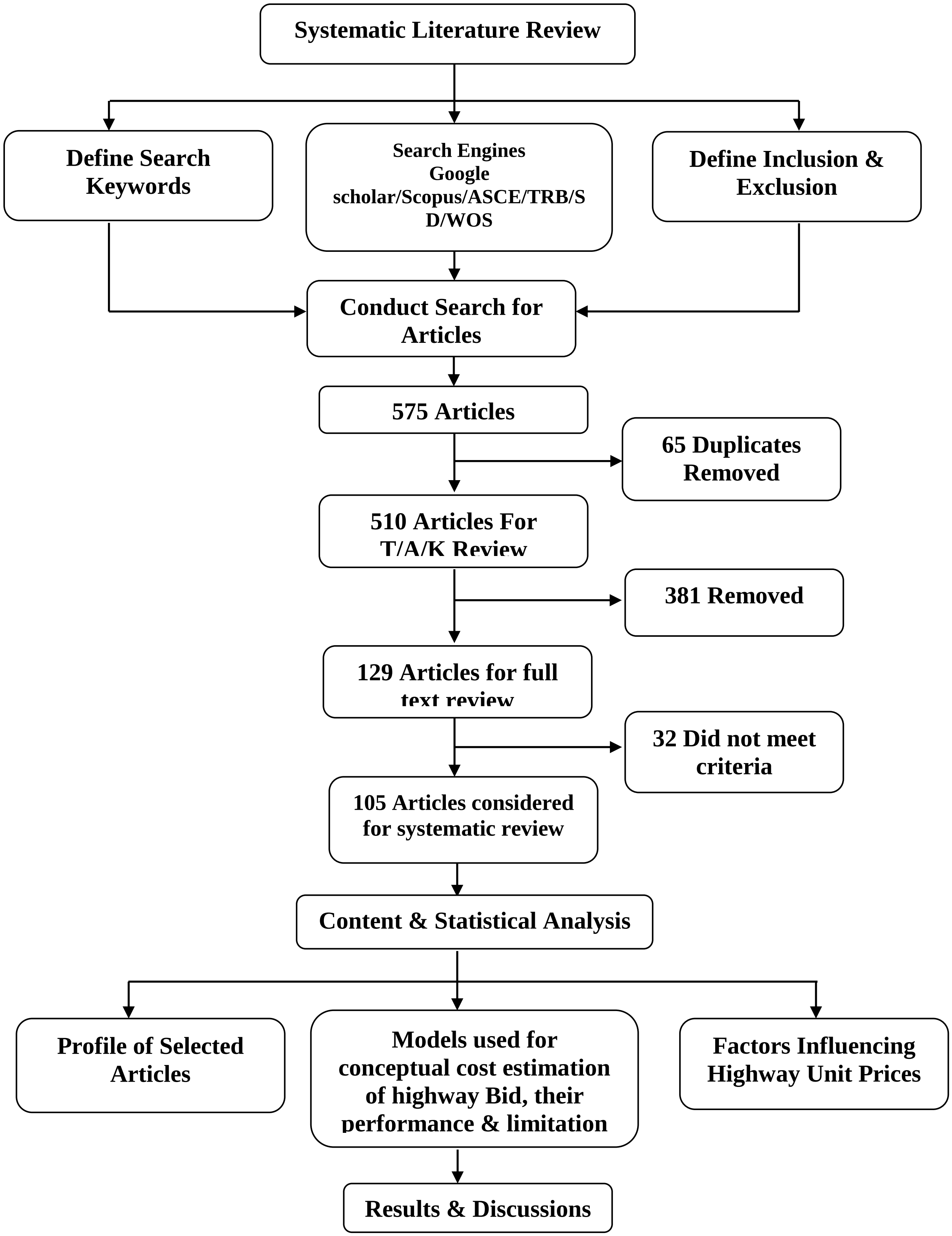

Figure 2. Systematic literature review research methodology

2.6.1. Content Analysis

Content analysis has been adopted for various research studies across different disciplines because it is useful for examining trends and patterns in documents (Stemler 2001; White and Marsh 2006). The qualitative content analysis examines data that is the product of open-ended data collection techniques aimed at detail and depth, rather than measurement(Forman and Damschroder 2007). This paper adopted a qualitative content analysis approach to categorize the methods used in estimating construction costs at the conceptual stages of highway projects and to identify factors affecting unit prices in highway construction projects.

2.6.2. Estimation Performance

This paper collected the findings from studies that quantitatively assessed the accuracy of the estimation methods and combined them to measure the performance of the methods adopted by the authors in producing realistic forecasts of highway construction bid items. Estimating accuracy is a performance measure of the spread between a current cost estimate and estimates prepared earlier during project development (Harper et al. 2014). Articles selected for the analysis were based on data available on the variable of interest, mean absolute percentage error (MAPE) a performance metric which is a common measure used for assessing the level of accuracy of the algorithms used to estimate the cost of highway bid items shown in equation 1 (Choi et al. 2014):

$$MAPE = \left(\frac{100\%}{n}\right)\sum_{i=1}^{n}\left|\frac{P_i - A_i}{A_i}\right| \qquad (1)$$

where n= number of data points; P_i = predicted construction cost A_i = Actual construction cost for the *ith* project.

However, MAPE was calculated for studies that reported their actual and estimated construction costs. After collecting the quantitative findings from selected studies, descriptive statistics were determined for the cost estimation methods. Weighted averages are common when combining and analyzing results from multiple studies to factor sample size, quality of the study, variance, or other characteristics. MAPE values extracted from each study were converted to weighted averages to account for the difference in study characteristics by weighting the results based on the total number of studies considered for the analysis. Studies that considered a larger sample have a greater influence on the weighted average since larger samples tend to generate more robust results (Sullivan et al. 2017).

Outliers were identified and removed from the quantitative findings extracted from the selected studies. Based on an assessment of the normal distribution and variance of the data extracted, statistical analysis (t-test, Mann-Whitney U-test, and Moods median test) was performed to determine the level of significance of the combined results between the different estimating methods identified from the selected articles. The weighted average is given in equation 2 (Sullivan et al. 2017):

$$Weighted\ average = \frac{\sum(original\ MAPE)_i \times (study\ sample\ size)_i}{\sum all\ study\ sample\ sizes} \tag{2}$$

After identifying and categorizing the factors influencing unit prices of highway construction bid items, a mean ranking system was determined based on the individual frequencies identified in the papers, and a mathematical calculation was used to determine the mean scores of each category. The category with the highest mean was ranked first and follows in that order. For instance, project-specific factors (PF) was calculated as follows;

$$Mean\ Score = \frac{\sum PF}{N} \tag{3}$$

where *PF*= the number of Project-Specific factors identified in each article and *N* = total number of measures per variable.

2.7. Results and Discussion

2.7.1. Profile of Selected Articles

The selected articles for the content analysis were profiled based on the journal and year of publication. About 37% of the total articles were selected from six journals in the American Society of Civil Engineers database (ASCE); namely Journal of Construction Engineering and Management (27%), Journal of Management in Engineering (3%), Journal of Infrastructure Systems (3%), Journal of Risk and Uncertainty in Engineering Systems (1%), Journal of transportation engineering (1%), and Journal of Computing in Civil Engineering (3%). The remaining 63% of the selected articles were published in the other 51 journals as shown in Figure 3.

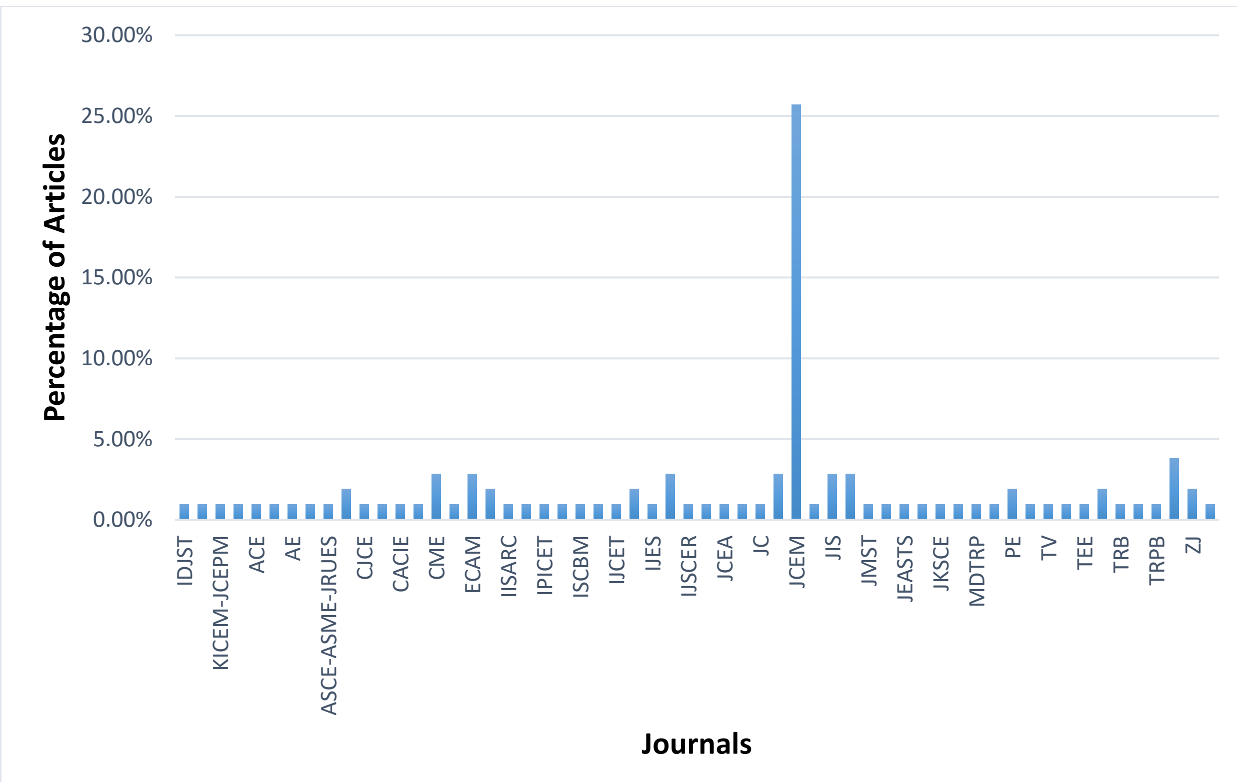

Figure 3. Distribution of selected articles published in each journal

2.7.2. Overview of Conceptual Cost Estimation of Highway Projects Publication Trend

Figure 4 depicts the distribution of conceptual cost estimation of highway-related articles that were published from 1983 to 2019. The period between 1983 to 1986, 1986 to 1990, and 1992 to 1996 showed no record of conceptual cost estimation publications. However, several studies were conducted to improve cost estimation in highway projects between 1999 and 2019 with the highest number of publications recorded in 2011(8.6%), followed by 2009(7.62%), and 2006 (7.62%). Despite an increase in publication over the years, the number of studies recorded in 1999, 2004, 2008, 2012, 2014, and 2019 fluctuated from the previous years.

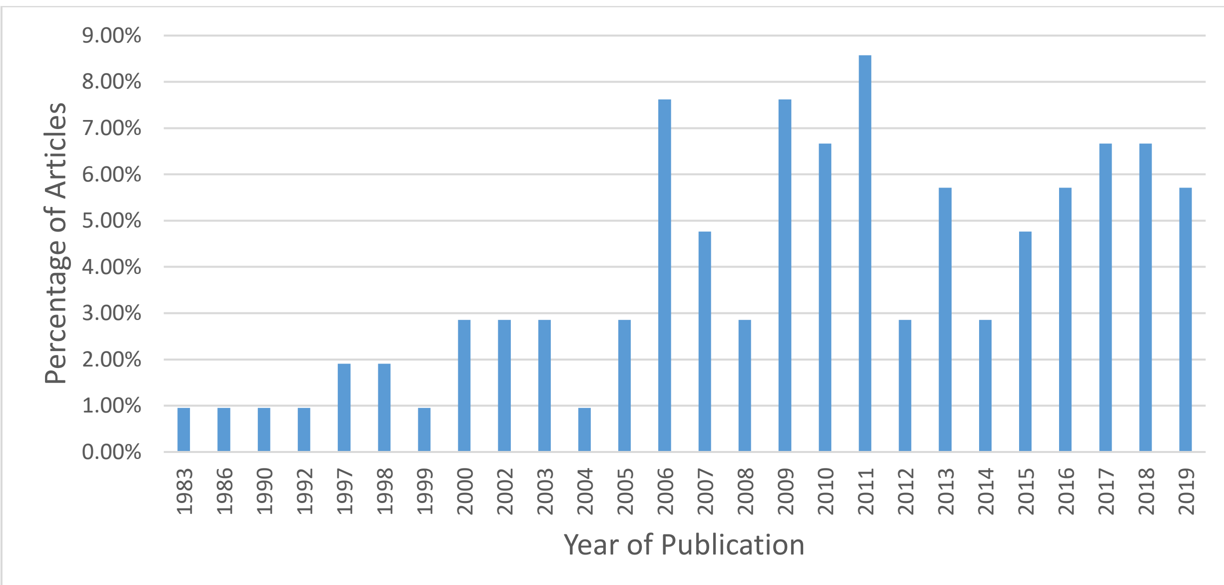

Figure 4. Trend of conceptual cost estimation of highway related articles trend from 1983 to 2019

Figure 5 shows the geographical distribution of the 105 selected articles. The results show that 41% of the studies were conducted in North America with the United States contributing 38% of the total articles to improve the estimation of highway construction bid items at the conceptual stage. About 25% of the studies were conducted in Asia, and 16% of the articles were published in Europe. About 8% of the studies were conducted in the Middle East, 5% in Africa, 4% in Australia, and 1% in South America.

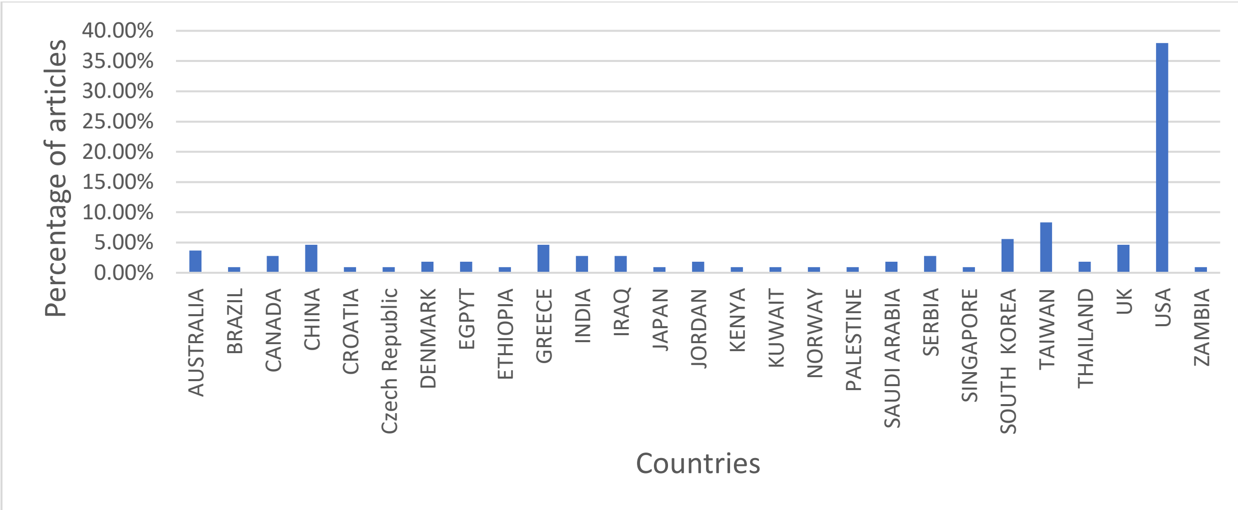

Figure 5. Profile of selected publications by geographical location

2.8. Artificial Intelligence

Artificial Intelligence(AI) algorithms are modeling techniques that can automatically develop and quantify the relations among cost drivers and the project costs for which the final prediction error can be minimized. Therefore, AI can diminish human interventions to estimate the cost of projects (Elmousalami 2020).

2.8.1. Artificial Neural Networks (ANNs)

ANNs are artificial intelligence algorithms based on the adjustment of sets of parameters (adjustment of weights), making it able to learn, through training, and to generalize the behavior of a problem(Barros et al. 2018). ANNs can be categorized into two major categories based on the direction of the flow of information within the network: feed-forward neural networks and recurrent neural networks (Basheer and Hajmeer 2000; Elmousalami 2020). Recurrent Neural Networks (RNN) are unique in that they store previous calculations and use them to improve the accuracy of future calculations. Neural networks comprise a network architecture (topology), a neuron binding scheme, a neuronal transfer function, and learning laws. Architecture represents the specific arrangement and connection of neurons in the form of a network. By architecture, different feedforward neural networks are distinguished as multilayer perceptron (MLP), radial basis function neural network (RBFNN), generalized regression neural network (GRNN), and belief networks (Tijanić et al. 2019; Elmousalami 2020). The choice of ANN architecture depends on several factors such as the nature of the problem, data characteristics, complexity, and the number of sample data (Sodikov 2005). ANNs can perform with superior accuracy in forecasting the cost of construction projects to other AI-based algorithms because of their ability to be trained on historical information and real-time data to generalize solutions (Tijanić et al., 2019). Highway construction costs are affected by many factors, but only a few key factors are usually recorded and can be considered in the mathematical modeling of the cost-estimation problem (Hegazy and Ayed 1998; Adeli and Wu 1998). Artificial neural networks help to eliminate the need to manually identify the relationship and to quantify the interactions between variables influencing highway cost estimates. They do not also limit the number of variables that can be incorporated into the modeling procedure(Wilmot and Mei 2005). However, there are drawbacks, such as the need to determine the correct ANN architecture, which is a complex, time-consuming, and tedious process in explaining the effects of the variables on the unit price bids (Baek and Ashuri 2019).

2.8.2. Case-Based Reasoning (CBR)

CBR is a widely used AI-algorithm by construction managers not only in estimating costs but also in many decision-making models. The principle of CBR assumes that similar problems have similar solutions. For a new problem, the CBR model first retrieves previous similar cases from its case base to reuse their solutions as a proposed solution for the new problem. Then, the model examines and revises the proposed solution and confirms it. Finally, the model retains the revised, confirmed solution as a new case in the case base for future use (Kim et al., 2004; Kim

& Kim, 2010; Kim 2013; Choi et al. 2014). The case similarity score for case *n* can be computed as follows (Chou 2009; Choi et al. 2014):

$$Case\ Similarity\ = \frac{\sum_{a=1}^{m} |sim(x_a^I, x_a^n) \times w_a|}{\sum_{a=1}^{m} w_a} \tag{4}$$

where m= number of attributes; and w_a = weight of the attribute a.

The revised step is used to predict and confirm the cost of the input cases. This step consists of adjusting by similarity score, road length, and construction price index which can be calculated at once as follows (Choi et al. 2014):

$$Predicted\ \text{cost}\ = \sum_{i=1}^{n} \frac{\left(C_i\ \times \frac{score_i}{\sum score}\ \times \frac{length}{length_i} \times \frac{CPI}{CPI_i}\right)}{n} \tag{5}$$

where C_i = direct cost of the ith top-scored case, $score_i$ = similarity score of the ith top-scored case, *score* = sum of $score_i$, *length* = road length of the input case, $length_i$ = road length of the ith top-scored case, *CPI* = construction price index of the input case, and CPI_i = construction price index of the ith top-scored case.

2.8.3. Support Vector Machines(SVMs)

SVMs are machine learning techniques based on the minimization of structural risk and statistical learning theory (Wang et al. 2012). SVMs help to minimize misclassification cases by optimizing the margins and hyperplanes distances (Elmousalami 2020). SVMs solve a convex optimization problem in a relatively short time, provides excellent generalization performance, and sparse representation with acceptable accuracy; making it more advantageous than other machine learning algorithms (El-Sawalhi 2015). The following steps are required to construct a cost model using support vector machine include; (1) model building, (2) data collection and organization, (3) dividing the data into sets and building the network, model training, and testing, and (4) model validation. The objective function for SVM optimization can be expressed as (Wang et al. 2012; Elmousalami 2020):

$$Min \sum_{i=0}^{i=m} \frac{1}{2} w \times w^T + c \sum_{i=0}^{i=m} \xi_i \tag{6}$$

2.8.4. Rough Set Theory(RST)

RST is a rule-based algorithm used to model uncertain knowledge(Hongwei 2009). A rough set model can identify and estimate the significance of specific attributes to be utilized as input variables for other cost estimation models (Choi et al. 2014). The concept of rough set algorithm is described as follows(Hongwei 2009; Choi et al. 2014):

As an Information system (*IS*) let (U, A) be an information system where: $U = \{x_1, x_2, \cdots, x_n\}$ is a finite non-empty set of *n* cases, called the universe, $A = \{a_1, a_2, \cdots, a_m\}$ is the finite set of *m* attributes. The information system can be deduced as a decision table, assuming that C, $D \subset A$, and C ∩ D= ∅, where C, D are subsets of attributes denoted as condition attributes and decision attributes, respectively. As an Indiscernibility relation (*IR*), let $a = C$ and $B \subseteq C$, where *B* is a subset of attributes. The indiscernibility relation is defined as:

$$IND(B) = \{(x_i, x_j) \in U \times U | \forall\, a \in B, f_a(x_i) = f_a(x_j)\} \tag{7}$$

where (x_i, x_j) is a pair of cases, and the information function is $f_a : U \to V_a$ for any $a \in C$, where V_a is the set of values of *a*, called the domain of attribute *a*.

2.8.4.1. Regression Models (RM*)*

RM are well established and widely used in estimating construction costs at the conceptual phase (Sodikov 2005; Fragkakis et al. 2011) because they are easy and relatively fast to implement and can determine how well a fitted curve matches a given data set (Kim et al. 2004; Sodikov 2009). In addition, they are effective due to a well-defined mathematical expression, as well as being able to explain the significance of each variable and relationship between independent variables (Sodikov 2005; Sodikov 2009). When there is only one predictor variable it is called simple linear regression, and when there are several predictors, it is referred to as multiple linear regression (Petruseva et al. 2017). Regression model equations can be expressed as follows(Kim et al. 2004; Sodikov 2009):

$$Y = C + B_1 X_1 + B_2 X_2 + \dots \dots \dots B_n X_n \tag{8}$$

where *Y*= dependent variable; *C*= constant *Bi* = variable coefficient and X_i = independent variable. The following steps are required to construct a cost model using regression models include: (1) Collect and prepare historical cost data, (2) Identify cost drivers and project variables (3) Check for normality and linearity of the data, (4) Develop regression model and check for significance in results, (5) Check homoscedasticity, and (6) Model Validation

2.9. Evaluation Techniques for Assessing Highway Cost Estimation Accuracy

One of the crucial and difficult aspects of developing a prediction model is to obtain a model that provides realistic estimates(Kim et al. 2004; Bayram and Al-Jibouri 2016). The performance measures of a model are considered in terms of bias, consistency, and accuracy. Measures of bias, consistency, and accuracy are concerned with the average of the deviation between the actual costs and the estimated costs, with the degree of variation around the average, and with the combination of bias and consistency (Kim et al. 2004).

To measure the accuracy of cost estimation models, estimators need to monitor key performance indicators which include elements such as targets, benchmarks, milestone dates, numbers, percentages, variances, distributions, rates, time, cost, indexes, ratios, survey data, and report data (Molenaar and Navarro 2011). The common performance metrics used to assess the performance of data-driven cost estimation models are mean absolute error (MAE), mean absolute percentage error (MAPE) and mean squared error (MSE).

Mean Absolute Error (MAE) measures how close the predicted is to the actual. The absolute value of the difference between the predicted and actual costs is summed and normalized over each data point (Aminikhanghahi and Cook 2017). It is the average size of forecasting errors when negative signs are ignored. If MAE approaches zero, it is an indication of the model's high accuracy (Azadi and Karimi-Jashni 2016; Bayram and Al-Jibouri 2016). MAE is given in equation 9:

$$MAE = \frac{\sum_{i=1}^{n} |P_i - A_i|}{n} \tag{9}$$

where n= number of cases; i= case number; P_i = predicted construction cost A_i = Actual construction cost for the *ith* project.

Mean Squared Error (MSE) is an alternative to MAE. However, because the errors are squared, the resulting measure will be exceptionally large if a few outliers exist in the data (Aminikhanghahi and Cook 2017). MSE can be expressed as follows (Aminikhanghahi and Cook 2017):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} |P_i - A_i|^{2} \tag{10}$$

where n= number of cases; i= case number; P_i = predicted construction cost A_i = Actual construction cost for the *ith* project

Mean Absolute Percentage Error (MAPE) is the mean or average of the sum of the percentage errors for a given data set taken without regard to sign (Ryu 2002). The closer MAPE is to zero, the better the performance of the model. This method of validation is traditionally used by authors of data-driven conceptual estimating models (Gardner et al. 2017).

$$MAPE = \left(\frac{100\%}{n}\right) \sum_{i=1}^{n} \left|\frac{P_i - A_i}{A_i}\right| \tag{11}$$

where n= number of data points; P_i = predicted construction cost A_i = Actual construction cost for the *ith* project.

2.10. Performance of Cost Estimation Models

Performance measures are powerful tools used to establish the quality of highway project cost estimates and help to improve a state transportation agency's(STA's) estimating processes. Estimating accuracy is a measure of the spread between a current cost estimate and estimates prepared earlier during project development (Harper et al. 2014). Studies on the accuracy of specific estimation approaches rather than a mixture of approaches would define a fruitful path in developing theories and practices for effective estimation (Liu et al. 2010).

With the inadequate provision of state and federal funding and the need for new transportation infrastructure, estimation performance measures will assist STAs to improve cost estimation practices, manage construction costs, and make informed funding decisions (Harper et al. 2014; Bayram and Al-Jibouri 2016). Therefore, this study seeks to synthesize the performance of cost estimating methods for highway projects. A total of 70 studies reported the performance of the models used to estimate highway construction costs. Models were grouped into (1) artificial intelligence algorithms, (2) regression models, and (3) statistical models. The results are compared and discussed in the subsequent sections. Studies that used more than one method were reported as separate results. For instance, Tijanić et al. (2019) used three neural network architectures MLPNN, GRNN, and RBFNN and therefore were reported separately to distinguish amongst their associated MAPE results.

2.10.1. Artificial Intelligence-Based Cost Estimation Performance

Thirty-three studies identified from the selected articles used ANNs to estimate highway construction costs. However, Adeli and Wu (1998) and Cirilovic et al. (2014)'s studies reported a coefficient of determination(r^2) as their matrix for measuring estimation performance. Also, the estimated and actual amount was not reported to compute MAPE values and therefore, their study was excluded from the analysis. The estimation performance for the rest of the thirty-one ANNs studies is shown in Figure 6.

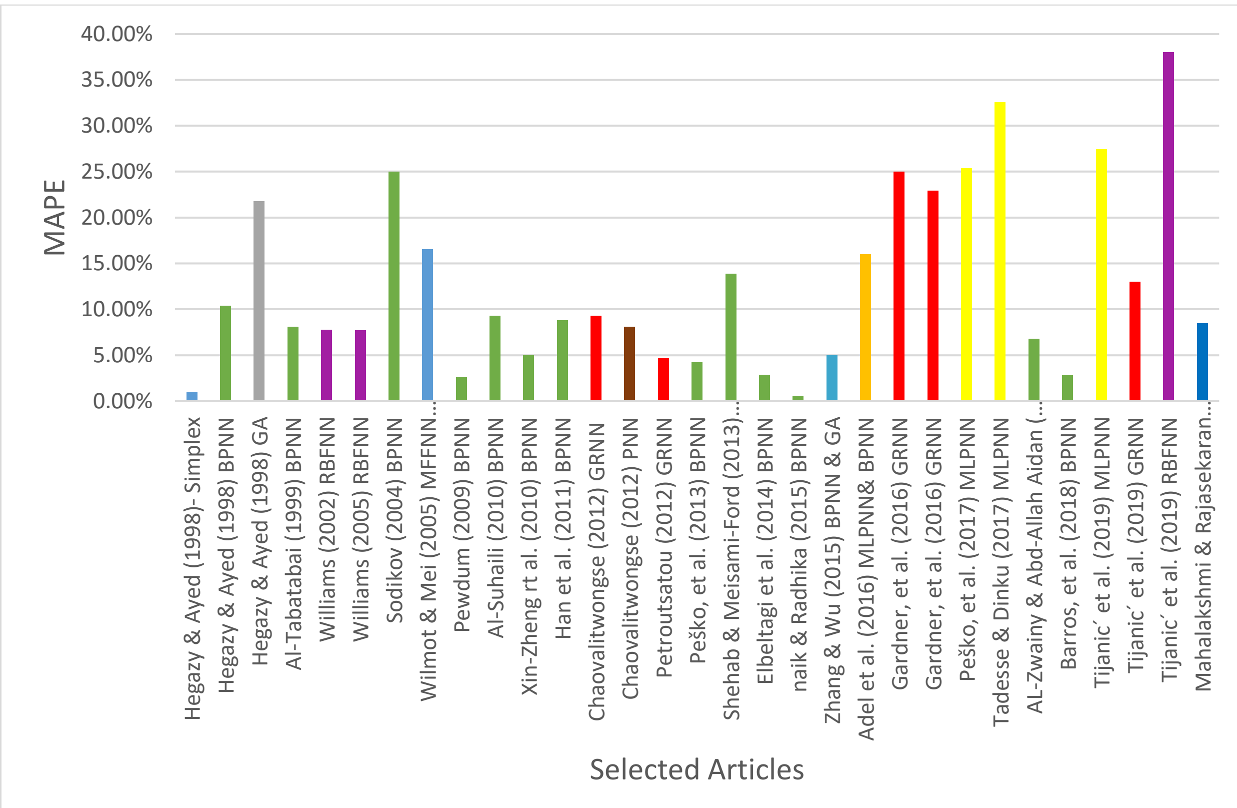

Figure 6. Quantitative findings for the performance of ANNs cost estimation algorithm

The MAPE values recorded between the predicted cost estimate and the actual cost estimate ranged between 0.57%(BPNN) and 38.04%(RBFNN), respectively. The average estimation error measured by the MAPE for the entire ANN algorithm is 12.62% with a median value of 9.05%, and the standard deviation for the magnitude of estimation error is 10.04%. Mood's Median test was performed on the data to compare the significance of the differences in the estimated growth for the ANNs algorithms identified from the selected literature. However, there is insufficient evidence to reject the null hypothesis of equal means between the ANNs at a confidence level of 95% (p=0.133). A Levene's test of equal variance was applied to test whether there is significant variability between the different ANN projects. The significance of Levene's test was p=0.001 indicating there is significant evidence of unequal variance between the different ANN projects. After weighting the results of the common ANN architectures adopted in the studies by sample size, BPNN (7.75%) had the least amount of error between the estimated and the actual amount.

The weighted averages for the GRNN, RBFNN, and MLPNN were 11.81%, 12.24%, 27.09% respectively. Mann-Whitney U test was performed to compare the significance of the difference between estimation performance for the common ANN architectures identified. The results indicate there are significant differences between the estimated and actual costs of BPNN and MLPNN (p= 0.011) and GRNN and MLPNN(p=0.037). However, insufficient differences were observed between the estimated and actual costs of the BPNN and GRNN (p= 0.085), BPNN and RBFNN (p=0.346), RBFNN and GRNN(p=1.00), RBFNN and MLPNN(p=0.663). Estimation performance of case-based reasoning, support vector machines, Monte-Carlo simulation, Bayesian models, and other algorithms as measured by MAPE values are shown in Table 1 and Figure 7. From the selected articles, five studies used CBR to estimate highway projects with an average estimation error of 11.69%, a median value of 9.17%, and a standard deviation of 5.26%. MAPE of the other algorithms identified from the selected articles were PIREM (8.49%), and Kalman filter (3.19%).

Table 1. Descriptive statistics of aggregated cost accuracy of estimation models from the selected articles

Descriptive Statistics	ANN	CBR	MCS	BAY.M	SVM	RM
Number of studies	31	5	2	2	2	19
Number of Projects	7764	491	1472	76	236	4647
Median	8.79%	9.17%	5.40%	5.95%	6.03%	11.54%
Standard Deviation	9.93%	5.26%	6.30%	1.65%	1.50%	7.55%
Q1	5%	7.31%	0.00%	0.00%	0.00%	8.62%
Q3	21.80%	17.33%	0.00%	0.00%	0.00%	21.44%
minimum	0.57%	7%	1%	4.30%	5.00%	3.04%
maximum	38.04%	18.40%	9.86%	7.60%	7.10%	33.00%
Number of outliers	0	0	0	0		0
Mean	12.62%	11.69%	5.40%	5.95%	6.03%	13.96%
Weighted Average	12.99%	13.29%	9.43%	5.95%	6.45%	12.13%

Note: Includes Only studies using a common measure of assessing estimation accuracy (MAPE)

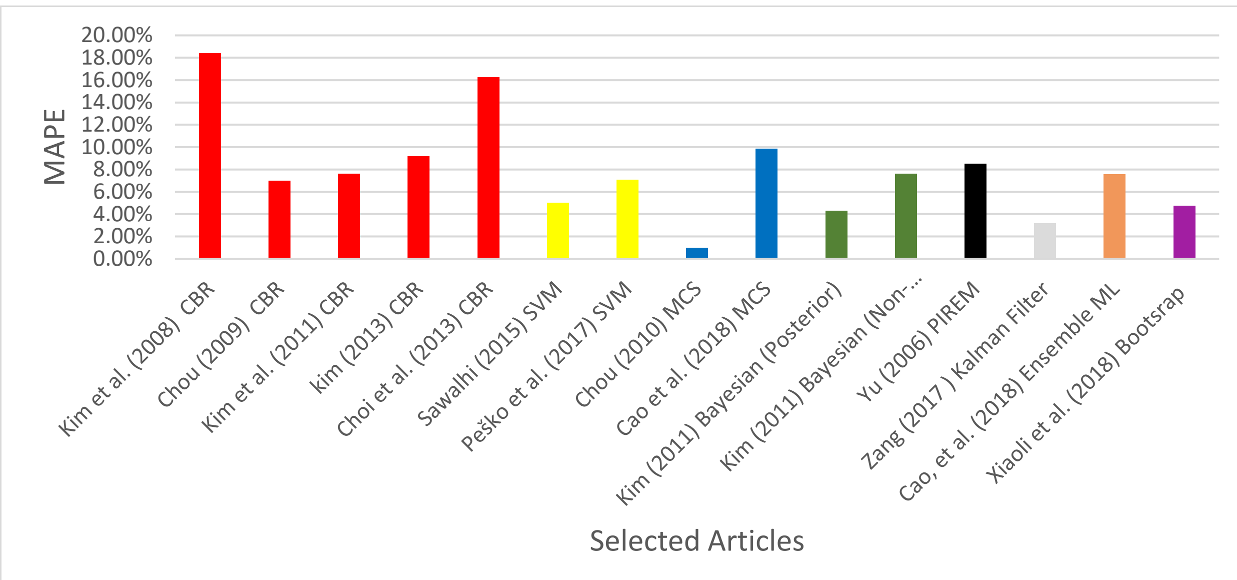

Figure 7. Quantitative findings of performance for other AI-based cost estimation algorithm.

Yu (2006) proposed Principal Item Ratios Estimating Method (PIREM) that integrates several existing conceptual estimating methods (parametric estimating, ratios estimating, and cost significant model) with advanced nonlinear mapping techniques and adopts a scheme that separates unit prices from the quantities of a cost item. It allows estimators to predict highway construction costs based on the prevailing market unit prices, thus accounts for price fluctuation on a real-time basis. The error between the estimated and actual cost was approximately 8.49%.

The study by Cao et al. (2018) used an ensemble machine learning algorithm to model bid prices for more than 1,400 projects, along with 57 related variables. A total of 20 variables were selected using the Boruta feature analysis to train and test the model. The results showed that the ensemble learning model has a mean absolute percentage error of approximately 7.56%.

Based on 10 projects, Zang et al. (2017) modeled highway historical cost using the Kalman filter algorithm. The resulting model predicted the actual cost with an average error of 3.15% as shown in Figure 7.

2.10.2. Performance of Regression Models in Estimating Highway Construction Cost

Twenty-two studies identified from the selected publications used regression models to estimate highway construction costs. However, two studies conducted by Fragkakis et al. (2011) and Cirilovic et al. (2014), reported a coefficient of determination(r^2) to measure the estimation performance of their regression models. Also, Chou and O'Connor (2007) and Swei et al. (2017) used a different form of sensitivity analysis and therefore could not be combined with the other regression models identified from the selected articles. Their estimated and actual amount was not reported to compute MAPE value and therefore four studies were excluded from the analysis.

The estimation performance for the eighteen regression models is shown in Figure 8. The MAPE values recorded between the predicted cost estimate and the actual cost estimate ranged from 3.04%(generalized linear models) to 38.04%(multiple linear regression), respectively. The average estimation error measured by the MAPE for the entire regression models is 13.96% with a median value of 11.54%, and the standard deviation for the magnitude of estimation error is 7.55%. The arithmetic means of the cost growth performance for multiple linear regression

(17.90%) was greater than the simple linear regression (14.43%). However, when weighted by the study sample, multiple linear regression (11.83%) performed better than simple linear regression (15.01%). The variances in the MAPE values for the multiple and simple linear regression models were the same: the significance level of the Levene's test *p* =0.233. Mann-Whitney test was performed to compare the difference between MAPE values for multiple and simple linear regression. The results of the Mann-Whitney U test revealed no statistically significant difference in the MAPE values between multiple and simple linear regression (*p*-value= 0.478).

Figure 8. Quantitative findings of performance for regression models

Williams (2002) used a regression model to estimate the cost of 276 highway construction projects from the New Jersey Department of Transportation. The models produced reasonable results with a MAPE of 7.96%.

Kyte et al. (2004) developed a tool to estimate highway construction cost using 132 completed highway projects collected from the Virginia Department of transportation. To improve the accuracy of the models, the project scope was used as an input to calibrate the model to account for cost variations. Validation of the estimation model yielded results that on average differed from actual final project costs by 22%.

Yu et al. (2006) developed a web-based intelligent cost estimator (WICE) based on the neuro-fuzzy system and data mining to estimate highway construction costs. The proposed WICE is a real-time conceptual cost estimating system in practical use. Using 30 highway pavement projects, the validation results showed MAPE of 8.49%. The testing results show that the proposed system provides not only a globally accessible and promptly responding means for cost estimation but also an effective and reliable tool for real-time decision-making.

Huntington and Ksaibati's (2009) developed a method for generating estimates of annualized maintenance and construction costs incurred by small agencies. These inputs are used to generate annualized network-level cost estimates for each county. The models generated reasonable results with a MAPE of 36.03%.

Liu et al. (2010) assessed the estimation accuracy using a hybrid estimating approach blending primarily reference class forecasting(RCF) with a fixed contingency approach on 74 road projects conducted by an Australian State Road & Traffic Authority. The model performed better when compared with historical results from selected literature on infrastructure projects and samples of two other dominant estimation methods, namely, the conventional fixed contingency approach and risk-based estimating (RBE).

Asmar et al. (2011) used an analysis similar to the program evaluation and review technique (PERT), to assign certainty factors to cost estimates. The approach used a combination of 77 historical highway projects for major roadway items whose quantities can be estimated early in the development process and historical percentages called allowance and contingency factors. The results of the PERT-type technique showed that construction costs were accurately predicted at the conceptual stage within 20% of the actual construction costs (Figure 9).

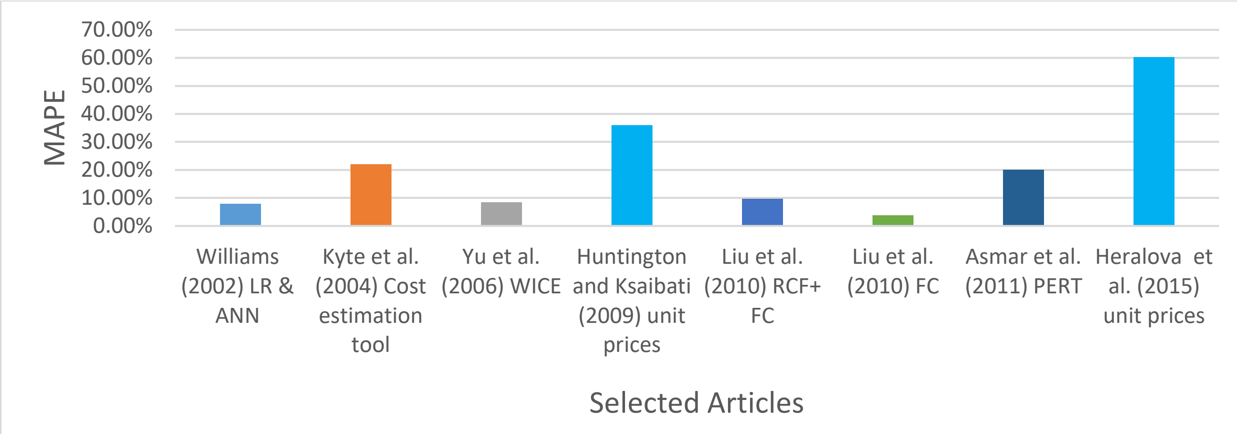

Figure 9. Quantitative findings of performance for cost estimation tools and other statistical methods

2.10.3. Comparison of the Accuracy for the Top Cost Estimation Models

Figure 10 shows the accuracy of the top estimation methods from the selected studies. The MAPE values show that Monte-Carlo simulation models(5.49%), performed better compared to Bayesian model (5.95%), support vector machines (6.03%), case-based reasoning (11.69%), artificial neural networks (12.62%), and regression models (13.96%) on the average. However, when these results are weighted by sample size, Bayesian models (5.95%), performed better followed by support vector machines (6.45%), Monte-Carlo simulation (9.43%), regression models (12.13%), artificial neural networks (12.99%), and the Case-based reasoning (13.29%) shown in Figure 10.

Mann-Whitney U test was performed to compare the significance of the difference in the accuracy of the six cost estimation models. Insignificant differences were found between the estimation accuracy for ANNs and CBR at a confidence level of 95% (p=0.891), CBR and Bayesian models (p=0.175), CBR and MCS(p =0.561), RM and SVM(p-value=0.082), ANN and RM(p=0.289), RM and CBR(p-value= 0.522), ANN and SVM(p-value=0.346), ANN and MCS(p-value=0.407), and RM and MCS(p-value=0.168).

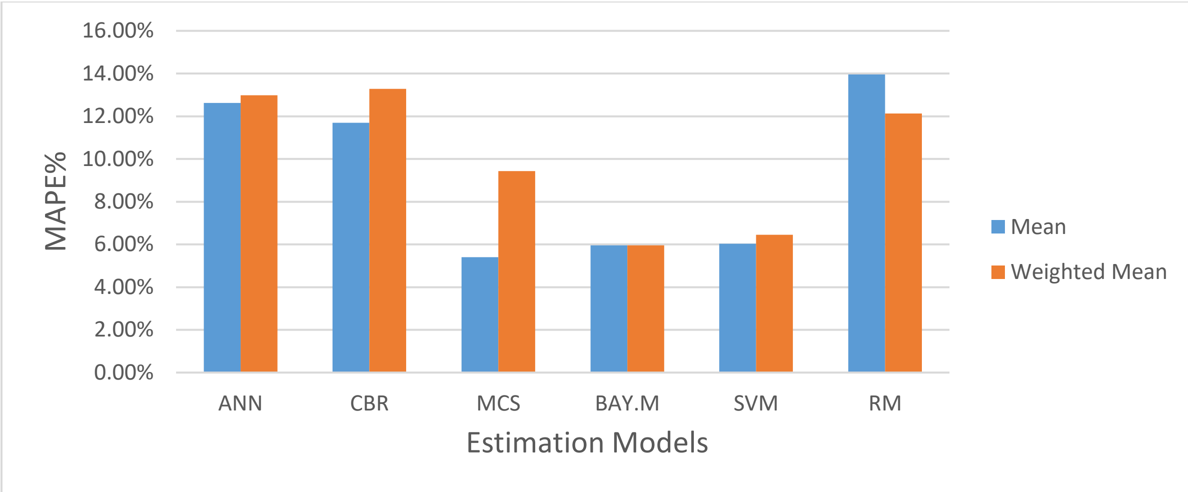

Figure 10. Quantitative findings of performance for the top cost estimation algorithms.

2.11. Factors Influencing Highway Construction Unit Prices

Identification and selection of the appropriate input variables that affect highway construction prices can enhance the accuracy of the construction cost estimate, especially at the preliminary stages of project development (Meharie et al. 2019). Due to a lack of preliminary information or a comprehensive database (Tijanić et al. 2019) and difficulty associated with collecting information on the qualitative conditions surrounding each construction contract (Wilmot and Cheng 2003), most of the construction cost models developed in the past have used only a few of the many influential factors that affect construction costs (Adeli & Wu 1998; Wilmot and Cheng 2003).

In this paper, the factors identified from the selected publications were categorized into three groups: (1) factors related to project characteristics, (2) organizational factors, and (3) estimate factors because it was the most common classification method used in the selected articles. A total of 41 factors were identified from the 105 articles selected for the literature review. The intensity of the factors influencing highway unit prices was determined using mean ranking analysis (Equation 3) as shown in Table 2.

2.11.1. Project Specific Factors

Project-specific factors are directly related to the characteristics of the project which affects cost performance (Akintoye 2000; Chou 2009). Project-specific characteristics help estimators define each project in the database which aids the development of the required project scope resulting in the uniqueness of each construction project (Walton and Stevens 1997). These project-specific factors include project type, project size, project location, duration of the project, market conditions, and project complexity (Akintoye 2000; Trost and Oberlender 2003; Chou 2009).

The project type defines the type of work to be executed during the construction phase. Various highway projects include grading, draining, surfacing, and resurfacing, new construction, rehabilitation projects (Walton and Stevens 1997). It is assumed that different project types, due to possible differences in their construction methods and management practices, would have a different impact on construction cost (Gkritza and Labi 2008).

Project size can be categorized based on the total dollar amount of the project (Gkritza and Labi 2008). On larger projects, more care may be exercised in the estimating and planning process; thus, the cost overruns may be reduced (Jahren and Ashe 1991). Therefore in developing a cost estimation relationship, the size of the historical projects compared with the estimated projects must be factored in (Anderson et al. 2007).

Project duration has a direct influence on construction cost because several agencies have fixed annual or biannual budgets and project schedules must often be adjusted to ensure that project funding is available for all projects as needed (Shane et al. 2009). Therefore, project owners must think in terms of the time value of money and recognize the inflation rate and the timing of project expenditures. Estimators frequently do not know what expenditure timing adjustments will be made in the course of project development (Shane et al. 2009).

Table 2. Factors influencing highway construction bid items

Category	Factors	Frequency	Mean	Rank
Project-Specific Factors			**41.13**	**1**
	Project Type	99		1
	Project Location	60		7
	Project Size	80		2
	Year of Construction	56		8
	Project Capacity (1-lane, 2-lane, others)	80		2
	Duration of Project	66		5
	Project Complexity	38		12
	Design	61		6
	Project Scope	71		4
	Inflation	43		10
	Market Conditions	34		14
	Site Restrictions	40		11
	Annual Average Daily Traffic Data	25		15
	Scope Changes	25		15
	Technological Innovation	16		19
	Scope Creep	14		20
	Financial Capacity of the Owners	14		20
	Soil Type	35		13
	Ground Conditions	45		9
	Construction Season	8		30
	Hauling Distance	14		20
	Labor Productivity	8		30
	Construction Method	14		20
Organizational Factors			**11.0**	**2**
	Contract Type	24		17
	Expertise of Consultants	12		26
	Poor Communication	6		35
	Lack of site Familiarity	6		35
	Political Requirements	5		39
	Risk Sharing Strategy	4		41
	Contractors Bidding Strategy	7		32
	Owners Experience level	12		26
	Environmental Requirements	20		18
	Contractors Past Performance	14		20
Estimate Factors			**8.25**	**3**
	Estimating team experience	12		26
	Quality of Cost Information	10		29
	Review of estimate by management	6		35
	Data processing Techniques	6		35
	Adequate Guidelines for estimating	5		39
	Time allowed for preparing cost estimates	7		32
	Contingency Determination	13		25
	Procedure for Updating Cost Information	7		32

Year of construction is an adjustment factor that is applied to account for the difference in time between when the estimate is created and the actual timing for construction to account for the time value of money (Anderson et al. 2007). It is also perceived that contracts let in the fourth quarter of the fiscal year tended to result in higher bid prices. This was due to a tendency for projects to accumulate in the fourth quarter due to various delays, and the increased volume of projects resulting in decreased competition among contractors (Wilmot and Cheng 2003).

Project location distinguishes between urban and rural locations (Ilbeigi et al. 2016). However, districts are not consistently cheaper or more expensive than other districts as districts that are cheaper on one item may be more expensive on other bid items, and vice versa. Certain patterns can be discerned concerning conditions in each project location. For instance, asphalt pavement construction is more expensive in those districts furthest removed from asphalt production sites, and embankment material is cheaper in districts with fewer wetlands or clay material due to the greater potential to use in situ material and the greater likelihood of having shorter linehaul distances. However, not all variations have logical explanations, and interpretations from them should be performed with caution (Wilmot and Cheng 2003; Ilbeigi et al. 2016).

Scope creep is the tendency for the accumulation of many minor scope changes to increase the project cost. While individual scope changes have only minimal cost effects, the accumulation of these minor changes, which may not be essential to the intended function of the facility, can result in a significant cost increase over time (Anderson et al. 2007; Shane et al. 2009).

Annual average daily traffic data helps in planning and managing traffic in construction work-zones and is a significant challenge in projects such as widening and resurfacing projects, including associated safety and travel time conditions (Hassanein 2006).

Project complexity is important because it may determine when, and to what extent, a specific cost estimation method and the tool should be used (Anderson et al. 2007). Engineering and construction complexity caused by the project's location or purpose can make early design work particularly challenging and lead to internal coordination problems and project component errors. Internal coordination problems can include conflicts or problems between the various disciplines involved in the planning and design of a project. (Shane et al. 2009; Hatamleh et al. 2018) .

Market conditions must be assessed when estimating construction costs to take into account the trends in the financial market and their implications on the costs of the resources for a project (Akintoye, 2000). Specifically, economic fluctuation causes changes in highway construction costs. During economic booms, for instance, when there are more projects available in the market, contractors might accumulate an extensive backlog and become more selective when bidding for jobs, which increases completed construction costs. In contrast, during economic recessions, available jobs in the market are scarce, but contractors do not want to lay off their productive crews and efficient management teams because they want to survive these difficult times and begin making profits again when the economy recovers. During these times, contractors hungry for new jobs are willing to take jobs with small profits or even no profit to keep the crews and management team working (Zhang et al. 2017b).

2.11.2. Organizational Factors

Cost estimation is a multifaceted process impacted by the unique characteristics of an agency's organizational structure, policies, and operational capabilities. Managing the capital construction of megaprojects requires the coordination of a multitude of human, organizational, and technical resources (Molenaar 2005). These unique characteristics make the problems associated with cost estimation practices different among agencies (Alavi and Tavares 2009). Projects can be influenced by organizational factors, including, contract type, political requirements, communication, lack of site familiarity (Chou 2009)

Contract type influences construction costs differently because of the uniqueness of the various contracts used in construction contracts. Estimation must be geared towards the proposed contract to cater for the specific contract provisions. Ambiguous contract provisions dilute responsibility and cause misunderstanding between an owner, design team, and contractors. Providing too little information in the project documents can lead to cost overruns during the execution of the project. The accuracy of the prediction result is affected when the core assumptions underlying an estimate are based on ambiguous contract provisions (Wilmot and Cheng 2003; Shane et al. 2009).

Communication is dependent upon the stakeholder who is receiving the information but should consider the mechanism for communicating the cost estimate for its intended purpose, level of uncertainty to be communicated in the estimate given the information upon which it is based, and a mechanism to communicate the estimate to external parties (Anderson et al. 2007)**.**

2.11.3. Estimate Factors

Estimate factors include time allowed to prepare the cost estimate, the experience of the estimation team, lack of data processing techniques, and quality of cost historical cost data (Akintoye 2000; Trost and Oberlender 2003; Chou 2009).

Cost estimation review is conducted to ensure the validity of the base estimate during the project development process. However, the formality and depth of the review will vary depending on the type of project and its complexity. Reviews of construction cost estimates will determine whether estimation criteria and requirements have been met and that a well-documented estimate has been developed (Dysert and Elliot 2002). Also, an estimate review can establish whether the construction cost estimate accurately reflects the project's scope, items are not missing, that historical data reasonably reflects project scope and site conditions, and that cost driver assumptions are appropriate for the project. Upper management reviews often focus on substantiating the overall adequacy of the estimate regarding its intended use (Dysert and Elliot 2002; Trost and Oberlender 2003). This process is to assure management that the level of detail available for the estimate, the estimating methods employed, and the skills of the estimating and project teams support their decision-making process on whether to bid on the proposed project (Dysert and Elliot 2002). State highway agencies must approach estimation development in the same manner as design and construction with documented processes to guide cost estimation practice and cost estimation management throughout project development (Anderson et al. 2007).

Experience of the estimation team highlights the importance of human factors in estimate preparation. This factor emphasizes the importance of the experience level not only of the estimating team but also of the engineering staff (Trost and Oberlender 2003). Estimation of costs demands considerable amounts of experience and a well-founded understanding of the limitations imposed on equipment and personnel under many diverse field conditions(Hicks 1993).

Time allowed to prepare the estimate enables estimation team to adequate scope definition, an experienced project team, and good cost information does not fully explain the estimate accuracy picture but must be combined with an adequate allotment of time (Trost and Oberlender 2003).

Contingency determination is meant to cover a variety of possible events and problems that are not specifically identified or to account for a lack of project definition during the preparation of early planning or programming estimates. Misuse and failure to define what cost contingency amounts cover can lead to inadequate cost estimates. In many cases, it is assumed that contingency amounts can be used to cover added scope and planners seem to forget that the purpose of the contingency amount in the estimate is to cover lack of design definition (Shane et al. 2009).

2.12. Summary of Efficiency of Cost Estimation Models from the Selected Articles

Comparing the aggregated results from the selected literature showed that on average, Monte-Carlo simulation models, Bayesian model, support vector machines, Case-based reasoning, artificial neural networks, and Regression models gave MAPE values of 5.49%, 5.95%, 6.03%, 11.69%, 12.62%, and 13.96% respectively. However, when these results were weighted by sample size, Bayesian models, performed better followed by support vector machines, Monte-Carlo simulation, regression models, artificial neural networks, and Case-based reasoning in that order. Mann-Whitney U test and Levene’s test were performed to assess the significance level of the error between the cost estimation models. The results showed insignificant differences between the estimation accuracy for ANNs, CBR, Bayesian models, Monte-Carlo simulation, Regression Models, and SVM. When the MAPE for the common ANN architectures adopted in the studies were weighted by sample size, and the BPNN had the least amount of error between the estimated and the actual amounts. This is followed by GRNN, RBFNN, and MLPNN, respectively. This finding is consistent with previous studies. For instance, Petroutsatou et al. (2012) and Tijanić et al. (2019) accentuated that GRNN has proven to be a promising approach to use in the preliminary phase of road projects when there is usually a limited or incomplete set of data, and could yield much more accurate results corroborating the results obtained from the analysis.

Mann-Whitney U test was performed to compare the significance of the difference between estimation performance for the common ANN architectures identified. The results indicate there are significant differences between the estimated and actual costs of BPNN versus MLPNN and GRNN versus MLPNN. However, insufficient differences between the MAPE for the BPNN versus GRNN, BPNN versus RBFNN, RBFNN versus GRNN, and RBFNN versus MLPNN. The arithmetic mean of the cost growth performance for multiple linear regression was greater than the simple linear regression. However, multiple linear regression performed better than simple linear regression when weighted by the study sample size. A Mann-Whitney U test performed revealed an insignificant difference in the MAPE values between multiple and simple linear regression.

2.13. Summary of Factors Influencing Highway Unit Prices

This study systematically identified and classified the factors influencing the conceptual cost estimation of highway bid items under 3 categories; (1) project-specific, (2) organizational, and (3) estimate factors. The results from the mean ranking analysis showed that most of the studies used project-specific factors more than the other factors in predicting highway construction costs. Project type was the highest-ranked project-specific factor identified from the 105 articles followed by project capacity, project size, project capacity, project scope, duration of the project, design, project location, year of construction, ground conditions, soil type, inflation, market conditions, and site restrictions in descending order of importance.

The results from ranking the organizational factors showed that the contract type, environmental requirements, contractors' past performance, owners' level of experience, the expertise of consultants, and contractors bidding strategy were the most prevalent factors affecting the cost of highway construction bid items. Among the estimate factors, contingency amount ranked first, followed by the experience of estimating team, quality of cost information, lack of review of estimate by management, lack of data processing techniques, the time allowed for preparing cost estimates, and procedure for updating cost information.

2.14. Gaps and Opportunities for Future Research

Using a combination of dissimilar highway projects to model construction costs may not provide an accurate assessment of the probable project cost because the project type influences cost differently. Some studies identified from the selected literature used heterogeneous projects where unit prices for unique highway projects were collected and combined to model cost. Due to different methods of construction for each type of project, pricing for new construction projects differs from reconstruction works. Also, the levels of unit-price variations of different bid items are often diverse, the optimal methods for two separate items may not be the same (Le et al. 2019). Future research must distinguish between different highway construction projects or work type by using homogenous projects (Tijanić et al. 2019). This will provide a clear indication of the level of accuracy and enhance the generalization for each project or work type (Zhang et al. 2017b).

The number of data points is integral to the efficacy of data-driven cost estimation models and tools as more data allows for better performance. One possible reason for the poor performance of construction costs estimation models is because there is not enough data for training and validation purposes (Setyawati et al. 2003). With the proliferation of data-driven modeling tools and techniques for highway construction cost estimation, future research could expand the size of datasets used in the modeling procedure to create a generalized and accurate highway construction estimate. In addition, future studies could investigate how the number of data points influences the accuracy of data-driven estimation models. Furthermore, the selection of modeling techniques is contingent on the intrinsic properties of the data. There is a need to develop a framework to preprocess historical cost data and project information before modeling future costs. This will enable the selection of the appropriate algorithm to optimize the modeling process.

The cost drivers are interrelated and do not influence the cost of the project independently. However, a majority of the studies identified from the selected literature did not account for the interaction effects between the factors affecting highway construction costs. Adopting fuzzy intelligent systems will yield an accurate and realistic representation of expert reasoning of incorporating cost drivers in modeling the cost estimation problem. Therefore, further studies could use fuzzy intelligent systems with other AI-based modeling techniques such as neural networks, case-based reasoning, genetic algorithm, and support vector machines to assess the interaction effects of the factors identified in this paper (Kim 2011; Kim 2013; Ilbeigi et al., 2016; Barros et al. 2018).

This paper found areas of potential improvement in standardizing the way highway construction estimation performance metrics are reported. The studies reviewed in this paper used several statistical measures to assess the performance of the cost estimation models. However, the disparate performance metrics reported do not enable an exhaustive comparison of results among empirical highway cost estimation studies. There is a need to standardize estimation performance measures to monitor the differences between a current cost estimate to previous estimates for highway construction projects. Future research could focus on creating a framework for developing and implementing cost-estimating performance measures and generating additional performance measures for highway cost estimation. Future studies could also provide a longitudinal assessment of how these performance measures improve the estimation accuracy of highway construction projects (Harper et al. 2014).

2.15. Conclusion and Limitations

Accurate forecast of highway construction cost enables state highway transportation agencies to plan, execute, complete, and maintain their set of transportation assets. Even with the existing research undertaken to improve the accuracy of highway construction cost predictions, the problem of inaccurate estimates still exists. To address this research gap, this paper provides a systematic review and synthesizes previous articles on highway bid items to determine research trends, identify the factors affecting highway construction unit prices, and to compare the combined performance of the estimation models. The results of the trend analysis showed that from 1983 to 2019, North America, Asia, Europe, and the Middle East made significant research contributions to improve highway cost estimation practice.

Non-parametric statistical analyses were performed to assess the efficacy of the common cost estimation models identified from the selected literature. On average, Monte-Carlo simulation models performed better compared to the Bayesian model, support vector machines, case-based reasoning, artificial neural network, and regression models in that order when weighted by sample size. A comparison between artificial neural networks showed that back-propagation neural network and generalized regression neural network performed superior to multilayer perceptron neural network when weighted by sample size. From the content analysis, 41 factors influencing highway unit prices were identified and classified into three categories, (1) factors relating to project characteristics; (2) organizational factors; and (3) estimate factors based on the common classification used in the selected articles. The results obtained from the mean ranking analysis showed that most of the studies incorporated project-specific factors than the other factors in predicting highway construction costs.

In view of a lack of published empirical studies and standardized performance metrics to measure the accuracy of cost estimates, the small sample size in SVM, Bayesian, and Monte-Carlo simulation models could lead to type II error, not being able to detect the differences in hypothesized relationships. Findings should be interpreted with caution as a further validation on a larger sample is required to reach a generalization and a more accurate assessment of the combined performance of the cost estimation models.

This paper’s unique contribution to the body of knowledge is its in-depth statistical analysis of the data to assess and provide preliminary insight into the combined accuracy of the cost estimation models identified from the selected literature. In addition, this paper identified and categorized a comprehensive set of factors that affect highway construction costs. This study will serve as a reference for future research in advancing cost estimation modeling at the early stages of highway projects.

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CHAPTER 3. EXPLORATORY DATA AND STATISTICAL ANALYSES OF HIGHWAY CONSTRUCTION BID ITEMS

3.1. Abstract

Challenges associated with ensuring the accuracy and reliability of conceptual cost estimation of highway construction bid items are of significant interest to transportation agencies. State highway transportation agencies are increasingly storing vast amounts of data generated during their operations. Therefore, generating data-driven empirical insights and patterns of highway cost data is of great importance for enhancing the efficacy of conceptual cost estimates. This paper explored and ascertained trends in historical highway construction bid data from 2013 to 2018 obtained from the Wisconsin Department of Department (WisDOT), determined the relationship between project size and unit prices, and assessed the impact of competition on unit prices of highway construction bid items using exploratory data and statistical analyses. The results of the exploratory data analysis showed that the unit price of tack coat and asphaltic surface bid items to be more volatile than common excavation, base aggregate 1 ¼", and base aggregate ¾" bid items. The changing instability of crude oil market conditions presents a challenge to accurately predict the cost of asphaltic surface and tack coat within budget during project development. This study confirmed that larger highway construction contracts yield economies of scale. However, the findings suggest that there is a threshold beyond which the unit cost of the top five bid items starts increasing with an increase in project size due to inherent complexity and uncertainty causing contractors to increase their variable cost. The results of the correlational analysis showed a trend in which the number of bidders increased, the unit price decreased from 2013 to 2017. However, for common excavation,

asphaltic surface, and tack coat bid items, the number of bidders did not significantly influence the probable cost.

3.2. Introduction

Infrastructure projects are essential to support the world's economic development(Martins et al. 2015). Conceptual cost estimates are vital for business unit decisions that include strategies for asset development, potential project screening, and resource commitment for further project development (Oberlender and Trost 2001). Completing highway projects within budget is essential to (Wilmot and Cheng 2003; Zhang et al. 2017) state highway transportation agencies (SHAs) because such performance enables them to fund, manage, and maintain their set of transportation projects (Wilmot and Cheng 2003; Zhang et al. 2017). SHAs require accurate cost data to predict future highway infrastructure costs to effectively plan and fund highway construction programs (Huntsman et al. 2017).

Historical cost data is useful for preparing accurate cost estimates at the conceptual phase if collected and prepared in a way that is compatible with future applications (Antinuke 2010; Chou 2009; Ji et al. 2010). The development of an effective conceptual estimate can be a challenging task because these estimates are conducted before the design phase with minimal scope definition. In addition, the accuracy of highway construction estimates is closely correlated to the extent of historical cost data and project information available at the time the estimate is established (Chou 2009). Selecting appropriate historical data for accurately predicting the probable construction cost is vital to project prioritization, selection of design alternatives, and budget allocations (Kunt 2003; AASHTO 2013). Therefore, it is germane to evaluate cost data and its source because it can greatly influence the accuracy of an estimate (Martinez et al. 2009). Conceptual estimating methods are characterized as requiring considerable effort in data collection and data analysis before modeling construction costs. The preparation of the estimate takes little time, however, compiling historical cost data is a time-consuming process and is only useful if updated and monitored regularly (Barzandeh and Zealand 2011). In addition, there is a need of defining more objective and consistent criteria for the selection of historical construction data for estimating construction cost (Riquelme and Serpell 2013). Vast data are being produced at faster rates due to the explosion of internet-related information and the increased use of operational systems to collect business, engineering, and scientific data, as well as measurements to make timely decisions in the construction industry (Myatt and Johnson 2014). Despite huge investments in data collection and archiving efforts, these data remain underutilized and are not adequately prepared. Due to a multitude of available methods, selecting the appropriate algorithm which will result in high prediction accuracy and facilitate data interpretation is not an easy and straightforward task (Konopka et al. 2018). The lack of properly treated historical cost data further amplifies the inaccuracy of conceptual cost estimates (Chou and O'Connor 2007). Therefore, developing accurate conceptual cost estimates for highway construction projects is very challenging (Chou 2009).

Bid unit price is the sum of all direct costs, allocated indirect costs, and the contractor's profit for a given item of work divided by the total number of units of work (Gransberg and Riemer 2009). Highway construction costs are made up of different bid items and therefore, diverse factors influence bid prices of individual items, or the overall contract price (Cheng and Wilmot 2009). Preprocessing historical cost data is a precedent practice of cost modeling for denoising internal errors or abnormal values. However, few cost estimation approaches have considered preprocessing historical cost data prior to estimating construction costs (Ji et al. 2010). A majority of studies assessed the impact of quantity on the unit price of construction projects(Gransberg and Riemer 2009; Shrestha et al. 2014). However, several factors influence unit prices, and therefore, there is a need to identify and evaluate the impact of these factors on the unit price of highway bid items.

The objective of this paper was to explore and ascertain trends in historical highway construction bid data between 2013 to 2018 obtained the from Wisconsin Department of Department (WisDOT), to determine the relationship between project size and unit prices, and to assess the impact of competition on unit prices of highway construction bid items using exploratory data and statistical analyses. The remaining parts of the paper are as follows. The literature review section examined previous related research in exploratory and statistical analyses of highway cost data. A detailed description of the data, the data exploration and statistical analyses used in the study are presented in the methodology section. The final part of the paper discusses the results and conclusions derived from the analyses of the study, limitations, and also presents ideas for future work.

3.3. Literature Review

Historical project data is essential for planning capital projects at the early stages (Pickett and Elliott 2007) and are important for learning from past projects for accurate cost estimation of construction projects (Kiziltas and Akinci 2009). Construction organizations including state highway transportation agencies are increasingly storing large amounts of data generated during their operations. Therefore, conducting proper analyses through data exploration to detect patterns that indicate the effectiveness of the various processes is of great importance for effective decision making (Nassar 2007).

Ji et al. (2010) addressed the issue of noise, errors, and abnormal values in cost data, using a combination of correlation analysis, principal component analysis, normalization, interval estimation, and regression analysis for data preprocessing. This led to further development of an alternative cost model, a statistically preprocessed data-based parametric (SPBP) cost model. The cost model was operationalized based on case studies from Korean construction projects, and the results showed that the model enhances cost estimate accuracy and reliability than conventional statistical cost models.

Nassar (2007), explored the applicability of data mining to Illinois DOT’s database containing information about asphalt paving projects such as cost and schedule data to discover patterns within the data. Association learning, a data-mining technique was adopted to discover interesting patterns in the data by determining association rules. The study showed that data mining can provide information on a dataset beyond some conventional statistical methods only and provides a source of valuable information that could not have been detected otherwise to support decision-making. However, one limitation of the proposed framework is that it is a computationally time-consuming and complex process. However, if the time-consuming data collection process can be reduced, the method can extract information faster than other statistical analysis methods.

Sheng et al. (2008) analyzed historical cost data from 927 projects in Utah to explore trends in the dataset. The results indicated that owners can partially offset the effect of a reduced number of bidders by timing their projects to seasonal or cyclical periods of construction slowdown or by bundling their projects together into a single, larger project to yield the benefits of economies of scale.

Shrestha and Pradhananga (2010) analyzed 435 bids on 113 public projects between 1991 and 2008 worth $554 million in construction value to determine a correlation between the lowest bid price and construction cost growth in Clark County, Nevada. Their study also determined a correlation between the number of bidders and the deviation of the bid cost from the engineers' estimate. Their study results showed no correlation between the lowest bid price and construction cost growth. However, they found that public owners would have received the lowest construction bid price if more bidders had been involved in the bidding process.

Shrestha et al. (2014) estimated the cost of highway construction bid items of 151 Design-bid build road projects which cost approximately $841 million undertaken by the Clark County Department of Public Works in southern Nevada from 1991 through 2008. Their study developed regression models to predict a future project's bid cost of unit price items, based on the quantities of items. The validation of models also showed that these models predicted the unit bid cost accurately.

Cao and Ashuri (2017) used a non-parametric framework to explore long-term trends of bid price on resurfacing projects in Georgia. The non-parametric analysis framework adopted identified the variation in a trend of the unit bid price in different segments and then assessed the relation of trend pattern among unit bidding price and other selected indicators. The results showed that the national highway construction cost index (NHCCI) could be a useful indicator to reflect the trend changes in unit bidding prices.

Qiao et al. (2018) used a data-driven approach that involved initial comparisons of the unit average project costs of single and bundled projects, preliminary investigations of the potential influential variables of project cost, the development of project cost statistical models, and an analysis of past and possible future bundling strategies. Their study found that the primary drivers of project cost include the project size (economies of scale), bundling strategy (economies of bundling), and bidding market conditions (demand and supply). In addition, their results showed that the similarity between different project types in terms of their constituent pay items is an influential factor in project cost. The study confirmed that larger contracts yielded economies of scale but also lead to less competition thereby discouraging all but the largest firms from bidding. This finding suggests the existence of a contract-size threshold beyond which the unit project cost increases with increasing project cost.

3.4. Project Size (Economies of Scale)

Economies of scale are probably the most dominant factor among all the variables that may affect the cost of a project (Qiao et al. 2018). Economies of scale happen due to size, output, or operation scale for an enterprise which results in cost advantages, where fixed costs are spread out over more units of output thus lowering down their cost (Gruneberg 1997; Ariffin et al. 2016; Qiao et al. 2018). It can be hypothesized that large projects typically attract higher class contractors and therefore, are managed more efficiently, resulting in lower project costs. Construction economies of scale occur when construction costs rise as construction size increases, though in a manner that is less proportional(Gkritza and Labi 2008; Kishore and Abraham 2009; Qiao et al. 2018). However, it may be argued that large projects typically involve several subcontractors and are more vulnerable to construction management problems such as communication lapses that translate to a higher likelihood of cost overrun (Gkritza and Labi 2008).

Project costs do not always vary linearly with different facility sizes. Screening cost estimates are often based on a single variable representing the capacity or some physical measure of the design such as floor area in buildings, length of highways, the volume of storage bins, and production volumes of processing plants. Empirical data are sought to establish the economies of scale for various types of facilities, if they exist, to take advantage of lower costs per unit of capacity(Hendrickson and Au 1989). However, if the project continues beyond one season, likely, efficiencies due to such economies of scale may not be significantly realized (Kishore and Abraham 2009).

3.5. Effect of Competition on Bid Unit Prices

The number of potential competitors in the market reflects the supply capacity utilization in the industry. Therefore, the degree of competition can be measured in terms of the likely number of potential competitors for projects in the market, and the degree of competition depends on the market conditions (Ngai et al. 2002). It is also typical for contractors to trim their estimated costs when competing against a large number of competitors(Carr 1983). The number of bidders is negatively correlated to construction cost, suggesting that the completed cost decreases when the number of bidders increases in the bidding process(Carr 2005; Baek and Ashuri 2018). In practice, more bidders mean more competition; thus, contractors are forced to lower their bid prices to win the jobs (Zhang et al. 2017).

Regardless of whether the reduction of bid unit price is due to material limitations, bid timing, overall contractor disinterest, or an imposed limitation based on labor policy; the fewer bid offers received will, on average, result in a higher cost of an award to the low, responsible, responsive bidder(Carr 2005). The dynamics of the bidding process include not only the prime contractors bidding the work but also the various subcontractors and suppliers who provide services and goods on the project. During the bid period, active competitive pricing from all of these entities impact bid prices: contractors, subcontractors, and suppliers. One might suggest that with increased competition, through a wider field of prime bidders, there would be greater interaction within and among the contractors, subcontractors, and suppliers; resulting in a lowering of the average bid price (Carr 2005).

3.6. Methodology

Exploratory data analysis methods are general-purpose instruments that illustrate the essential features of a data set and determine relationships between datasets (Kaski and Kohonen 1996) through the application of resistant and robust descriptive statistical and graphical tools that are qualitatively distinct from the classical statistical tools (Carranza 2009). A reliable method of tracking construction costs is to observe the variability in the average unit price of individual highway construction bid items that occur in several contracts, which enables them to be compared yearly (Cheng and Wilmot 2009). The frequency of the bid items of each project in the database was determined to identify the top five common bid items between 2013 to 2018. Bid items whose units were not precisely defined for instance each, lump sum, were discarded and those with consistent and specific characteristics that allowed a price comparison over time were retained for the analyses. The dataset was visually screened to check for completeness, consistency, and to ensure the location of each bid item corresponded to the precise project location. Bid data were then subjected to exploratory data and statistical analyses. The descriptive statistics consisted of the total count, mean, mode, median, standard mean error, standard deviation, coefficient of variation, skewness, and kurtosis. These outputs helped to understand and make logical choices and conclusions for further modeling procedures. Statistical plots were used to display the distribution of the bid items, detect, and remove outliers, ascertain trends, and make inferences about the bid data. Although graphical methods are useful in checking the normality of sample data, they are unable to provide formal conclusive evidence that the normality assumption holds because the graphical method is generally subjective (Yap and Sim 2011). Therefore, two statistical (Anderson–Darling, and Kolmogorov-Smirnov) tests were conducted to confirm the results from graphical methods. Also, research hypotheses were developed to further ascertain the impact of competition and project size on unit prices submitted by contractors for the top five common bid items identified in the database. The output of the exploratory and statistical data analyses for each year will be analyzed, interpreted, and discussed.

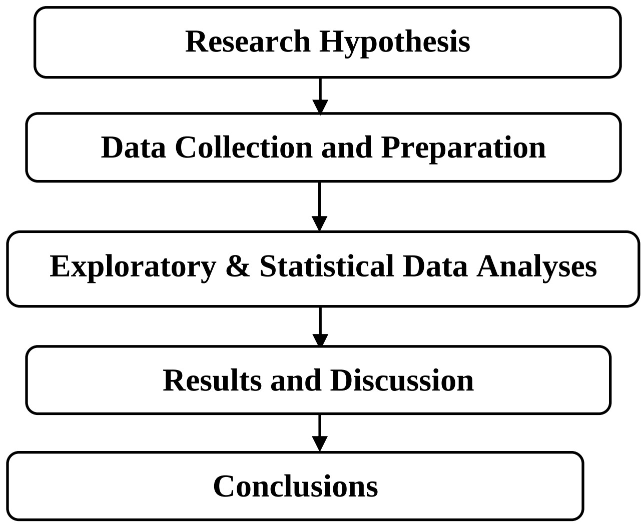


Figure 11. Research methodology

3.6.1. Research Hypotheses

Two research hypotheses were formulated to determine the relationship between unit prices and the number of bidders and between project size as well as unit prices of the highway construction bid items used for the study.

Table 3. Research hypotheses

Hypothesis No.	Research Hypothesis
I	H_a1: There is a relationship between the number of bidders and bid unit prices
II	H_a2: There is a relationship between Project sizes and unit prices of the Highway Bid Items

Hypothesis No.	Research Hypothesis
I	H_o1: There is no relationship between the number of bidders and bid unit prices
II	$H_0$2: There is no relationship between project size and Unit prices of the Bid Items

3.6.2. Data Description

The data used in this study were obtained in Excel format from the contract division of the Wisconsin Department of Transportation (WisDOT). Table 4 provides a sample of the bid unit data used in this study. The database contained 1,670 projects that were let between 2013 to 2018. Details of the contract type, proposal Improvement type and concept, work rating, region, county, project size, the lowest bidder, total bid amount, longitude and latitude of each project, and other project attributes were provided in the dataset. A detailed database for each of 1, 670 projects, and each project consisted of individual pay items with attributes such as item number, description, quantity, unit, unit price, and the bid amount. Unit prices of the top five bid items from the responsible and responsive bids were extracted and used for the study. The detailed database comprising of all the bid items for each of the 1,670 transportation projects was categorized quarterly from 2013 to 2018. This data was cross-referenced with the main database to check the correctness and ensure the integrity of the data set. The transportation historical cost data consisted of highway projects, bridge projects, and cofferdams. For this study, 380 highway projects were extracted from the original database for further analyses.

3.6.3. Data Preparation

This section summarizes the data collection and cleaning procedures implemented in this study. Many decisions about data preparation are made during the data processing Stage (Dasu and Johnson 2003). The frequency of the bid items of each project in the database was determined to identify the top 5 common bid items between 2013 to 2018; (1) Base Aggregate Dense 1 ¼”; (2) Base Aggregate Dense ¾”; (3) Common Excavation; (4) Tack Coat; and (5) Asphaltic Surface as shown in Figure 3.

Table 4. Sample of 2013 highway bid data for Wisconsin state

Project	Year	County	Bid Total	Item Description	Units	Quantity	Unit Price	Amount	Longitude	Latitude
Mosinee - Elderon	2013	Marathon	1,615,976.43	Excavation Common	CY	1135	7	7945	-89.64	44.79
Westboro - Rib Lake	2013	Taylor	2,377,424.87	Excavation Common	CY	9020	4.65	41943	-90.25	45.35
Stockton - Amherst	2013	Portage	3,675,286.82	Excavation Common	CY	12250	2.74	33565	-89.40	44.45
City Wausau, Grand Ave	2013	Marathon	2,856,082.09	Excavation Common	CY	245	17	4165	-89.62	44.95
City Superior, Tower Ave	2013	Douglas	13,372,078.96	Excavation Common	CY	68430	6	410580	-92.10	46.73
Eau Claire - Osseo	2013	Eau Claire	25,335,293.58	Excavation Common	CY	364950	7.03	2565599	-91.47	44.77
Lake Delton - I 90	2013	Sauk	2,723,412.57	Excavation Common	CY	13920	8.8	122496	-89.79	43.59
Eau Claire, C.A	2013	Eau Claire	1,047,731.02	Excavation Common	CY	3252	14.5	47154	-91.54	44.83
Wisconsin Dells E.	2013	Marquette	1,192,671.85	Excavation Common	CY	1119	11.25	12588.8	-89.54	43.67
Mount Horeb - Madison	2013	Dane	26,108,864.59	Excavation Common	CY	117000	8	936000	-89.46	43.03
Park Falls - Springstead	2013	Price	618,268.00	Excavation Common	CY	1300	16	20800	-90.30	45.95
Mineral Point - Spring	2013	Iowa	1,614,935.78	Excavation Common	CY	17101	7.99	136637	-90.13	43.09
USH 18 - Woodman	2013	Grant	2,290,665.88	Excavation Common	CY	1300	8	10400	-90.85	43.03
N-S Freeway, CTH K INTER	2013	Racine	17,075,835.83	Excavation Common	CY	407949	3.78	1542047	-87.95	42.78
Clam Lake - STH 13	2013	Ashland	713,823.53	Excavation Common	CY	940	11.5	10810	-90.90	46.16

Missing data are a constant feature of massive data, where individual cells, columns, rows, or entire sections of the data can be missing (Dasu and Johnson 2003).There are three broad categories of data cleaning: (1) missing data, (2) incomplete data, and (3) outliers. Missing data are unobserved values that would be meaningful for analysis if observed. In other words, a missing value hides a meaningful value. Missing attributes relevant to predict highway unit prices were cross-referenced with the main data and were corrected, respectively. In other instances where attributes especially geographic coordinates were missing, the entire bid item was deleted and not considered for the analyses.Table 1 shows a sample of 2013 common excavation bid data for Wisconsin state.

3.6.4. Outlier Detection and Removal

In unit price, competitive bidding, awarding a contract to an unbalanced bid may cause the owner’s project cost to increase during the project development process (Arditi and Chotibhongs 2009). Unit price contracts require the engineer’s estimated quantities to be as accurate as possible to ensure the profitability of a balanced bid. A quantity underrun occurs when bid quantities are altered to build an additional project contingency to guard against construction price volatility (Gransberg and Riemer 2009). This forces contractors to unbalance their unit prices to protect their fixed costs and target profit (Gransberg and Riemer 2009). When actual quantities are less than the bid quantities, the contractor does not recover the fixed costs, overhead, and profit that were allocated to the actual quantities of work that were not performed and therefore cannot claim payment. Therefore, as most contractors have limited ability to pick and choose which projects they bid and remain in business, inaccurate bid quantities lead to unbalancing unit prices to recover all the costs associated with the project and to protect the contractor’s target profit on the bid (Moon et al. 2007; Gransberg and Riemer 2009).

Polat et al. (2018) drew the attention of project owners to consider not only the total bid price but also the unit prices offered for each item when selecting the most appropriate contractor for a project. According to Le et al.(2019), when dealing with bid items with small quantities, bidders tend to give extremely high unit prices because those bid items do not necessarily have significant effects on the total bidding amount and ensure a higher profit in case the quantities increase during the construction phase. Those circumstances are extreme and not of interest in this research and therefore were excluded from the dataset. For instance, the common excavation dataset for 2013 consists of 111 bid items. However, 8 outliers were identified with high values ranging between $ 20 to $200 as shown in the violin plot in Figure 12.

To substantiate the results obtained from the visual outlier detection approach, Grubbs (1969) outlier detection approach value was used to determine whether all data values for 2013 excavation common come from the same normal distribution at a significance level of 5%. Grubbs (1969) detects outliers by calculating the Z value as the difference between the mean value for the attribute and the query value divided by the standard deviation for the attribute where the mean and standard deviation are calculated from all attribute values including the query. Figure 13 shows the number of data points for the top 5 bid items after removing outliers.

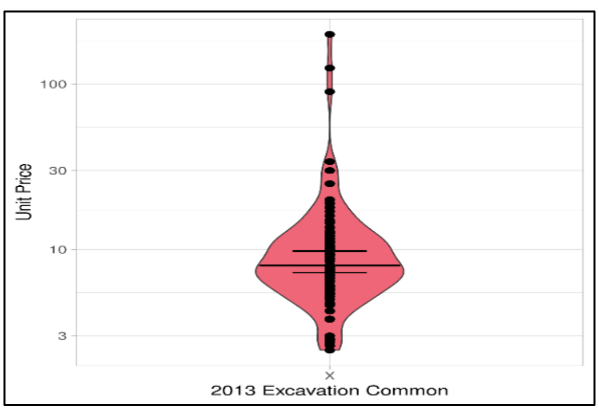


Figure 12. Outlier detection for common excavation 2013

To account for variations due to cost escalation and inflation over time, the bid unit prices were converted to a march 2020 base cost using the Wisconsin Department of transportation Construction Cost Index and Equation 12.

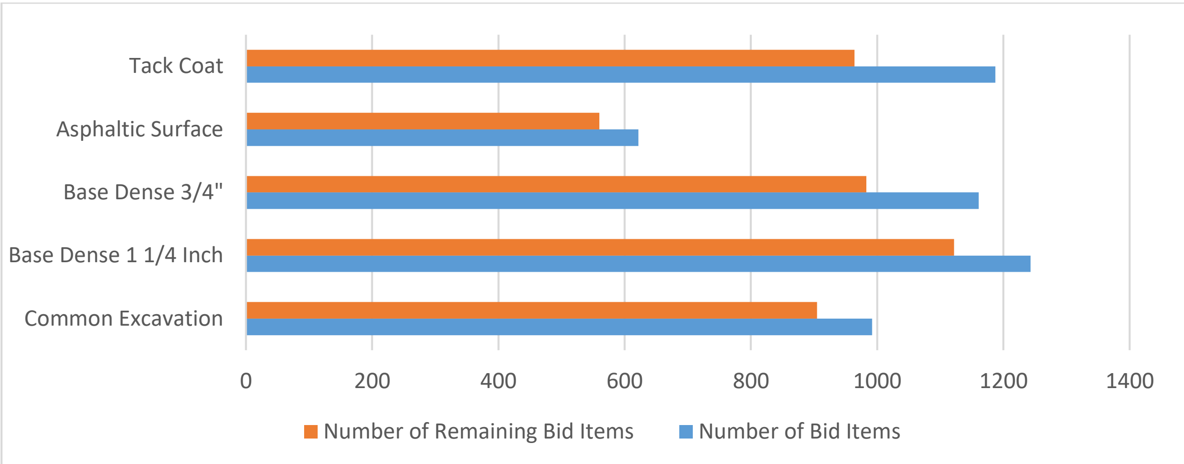


Figure 13. Sizes of the datasets for top 5 bid items

The WisDOT Chained Fisher Construction Cost Index (WisDOT CCI) uses the same methodology as the Federal Highway Administration's National Highway Construction Cost Index (NHCCI). The WisDOT CCI shown in Figure 3, shows the trend of construction cost escalation over time and provides inflation rates to convert past bid history into current year dollars.

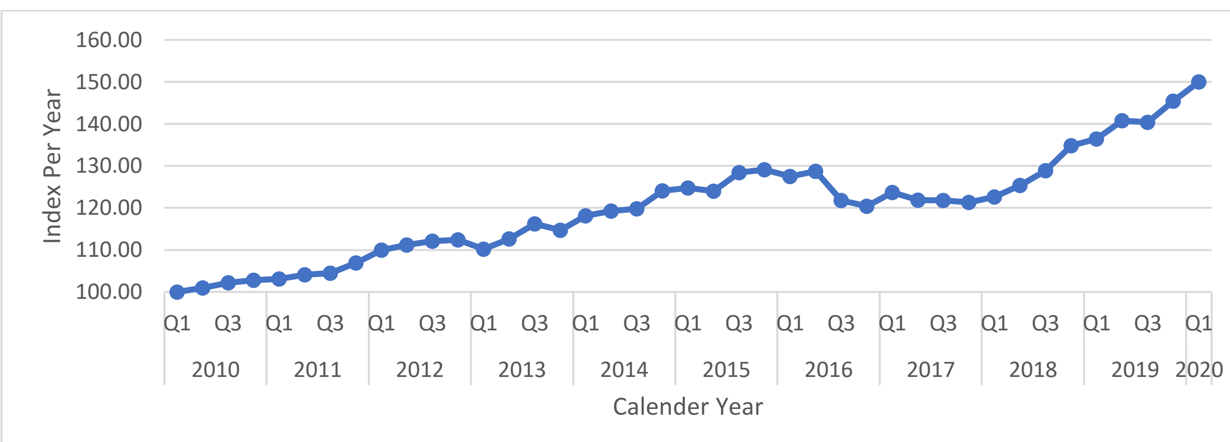


Figure 14. Wisconsin department of transportation chained fischer construction cost index.

The WisDOT CCI accounts for changes in the basket and weight of bid items and performs better than fixed weight indices when prices and quantities are volatile (WisDOT 2010).

$$Current\ Bid\ Price = \frac{Current\ Index\ Value}{Past\ Index\ Value} \times Past\ Bid\ Price \quad (12)$$

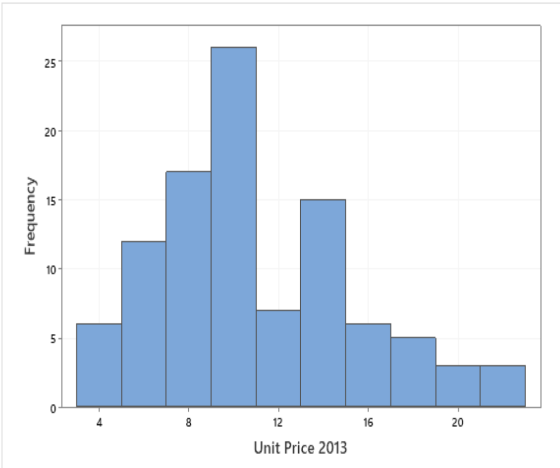
3.7. Results and Discussion

The descriptive statistics of the unit price of the top 5 bid items for each year were analyzed as shown in Table 5. The analysis shows that the mean and median are close indicating a nearly normally distributed for excavation common, base aggregate 1 ¼", base aggregate ¾", asphaltic surface, and tack coat. However, the distribution for the tack coat is negatively skewed from 2013 to 2018 as shown in Figures 15 and 16. Therefore, the bid unit price data may need to be transformed before cost modeling to meet the normality assumption and optimize the modeling results. The high standard deviation of the asphaltic surface and tack coat bid unit prices indicates a considerable variation in the pricing between 2013 to 2018. The volatility associated with tack coat and asphaltic bid items results in complexities and uncertainties for accurate cost modeling in highway transportation projects. The mean unit prices for the common excavation bid item followed a general upward trend from $10.95/CY to $14.87/CY between 2013 and 2017. However, this trend was interrupted by a leveling off in prices in 2018. For the base dense aggregate 1 ¼", the average bid price increased steadily from 2013 to 2015. However, the mean unit price decreased in 2016 and increased in 2017 and finally declined in 2018. Unit prices for base aggregate ¾" increased gradually from $20.58/CY to $23.26/CY from 2013 to 2015. However, the unit price in 2016 decreased by 3%($22.60) from the previous year and subsequently increased in 2018 by 4.42%($26.45/CY). For the asphaltic surface, the bid unit prices increased from 2013 to 2014 by 19.54% and decreased in 2015 by 17.97%.

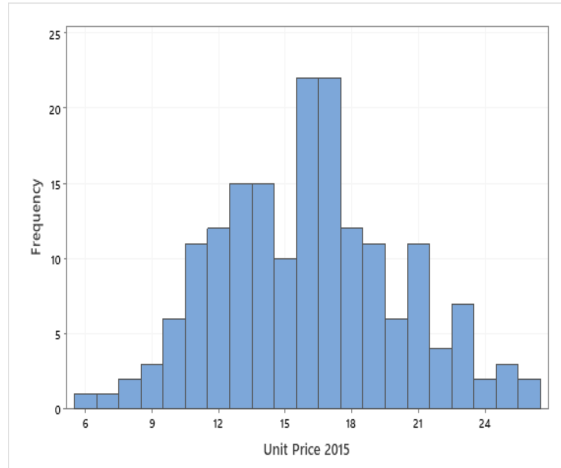
Table 5. Descriptive statistics of highway bid unit prices

Bid Item	N	Unit	Mean	SD	Minimum	Q1	Median	Q3	Maximum
Excavation Common									
2013	100	CY	10.95	4.45	3.28	7.74	10.27	14	22.65
2014	144	CY	11.21	4.45	1.40	7.9	10.56	14	22.6
2015	179	CY	11.73	5.75	0.01	7.73	11.00	16	27.16
2016	170	CY	12.84	6.72	0.01	7.6	11.62	17	29.46
2017	116	CY	14.87	6.19	4.99	10.2	13.57	19	30.92
2018	190	CY	12.30	4.55	0.01	9.79	11.96	15	22.26
Base Aggregate 1 1/4"									
2013	163	TON	14.69	3.82	6.41	11.6	14.19	17	24.50
2014	160	TON	15.59	3.87	5.27	12.6	15.75	18	26.40
2015	178	TON	16.07	4.05	5.80	13.2	16.03	19	26.08
2016	214	TON	15.54	4.12	6.57	12.5	15.21	18	25.29
2017	217	TON	17.98	5.76	3.89	13.6	17.11	21	31.69
2018	185	TON	17.61	4.73	5.56	14	17.80	20	29.92
Base Aggregate 3/4"									
2013	161	TON	20.58	5.55	6.45	16.7	19.98	24	35.39
2014	151	TON	21.76	5.54	10.80	18	21.25	25	35.56
2015	159	TON	23.26	7.17	3.63	18.5	21.77	28	43.10
2016	180	TON	22.60	6.64	11.19	17.7	21.18	26	41.11
2017	159	TON	25.33	7.64	11.32	19.4	22.77	30	45.75
2018	173	TON	26.45	8.53	5.56	19.9	24.52	33	48.94
Asphaltic Surface									
2013	65	TON	125.63	33.11	69.84	101	122.50	147	218.79
2014	96	TON	150.17	50.28	62.87	114	144.79	186	279.42
2015	85	TON	123.18	33.3	63.46	95.6	118.81	145	209.14
2016	102	TON	133.08	48.05	18.47	100	118.44	171	241.18
2017	106	TON	131.09	36.16	65.16	107	127.26	157	219.65
2018	105	TON	127.67	31.79	61.13	105	125.98	146	206.77
Tack Coat									
2013	142	GAL	4.25	1.40	2.49	3.07	3.93	5.2	7.66
2014	176	GAL	6.56	4.48	0.13	3.22	4.71	9.8	19.17
2015	92	GAL	3.39	1.16	0.61	2.61	2.98	3.9	6.05
2016	151	GAL	3.15	0.84	1.25	2.51	2.87	3.7	5.29
2017	195	GAL	4.52	2.58	0.01	2.52	3.38	6.2	11.39
2018	202	GAL	4.92	2.78	1.87	2.75	3.63	6.5	12.56

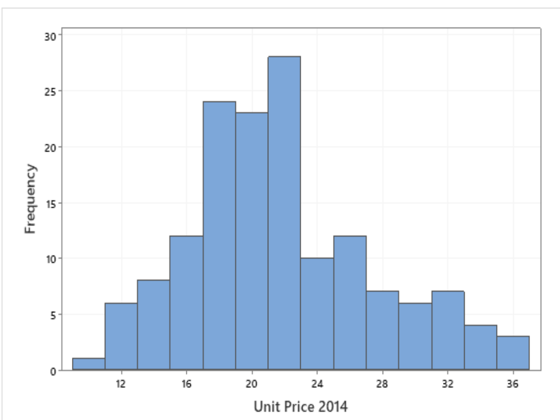
Note: CY= Cubic Yards, TON= Tons, GAL= Gallons , SD= Standard Deviation



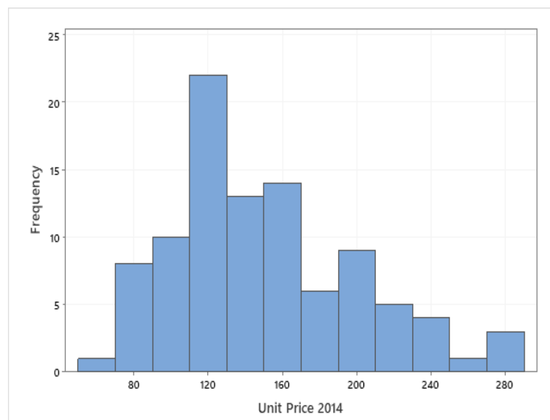
Excavation Common 2013



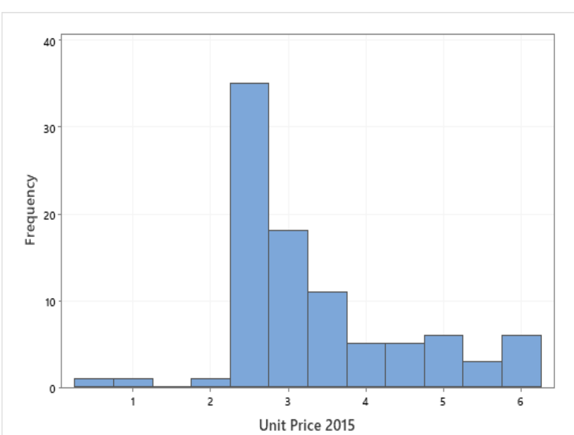
Base Aggregate 1 ¼” 2015



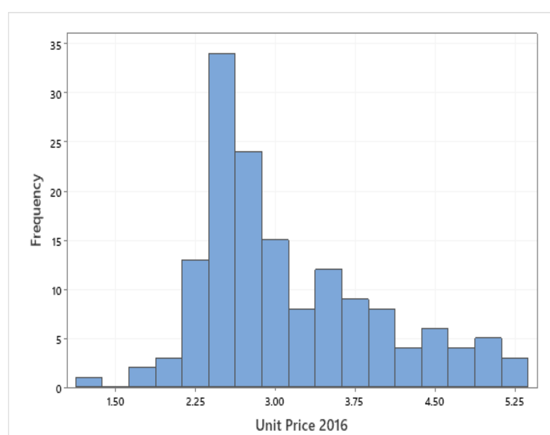
Base Aggregate ¾” 2014



Asphaltic Surface 2014

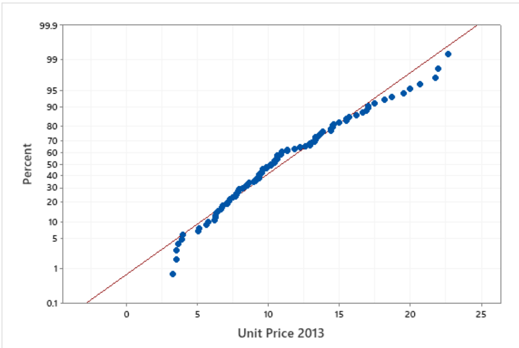


Tack Coat 2015

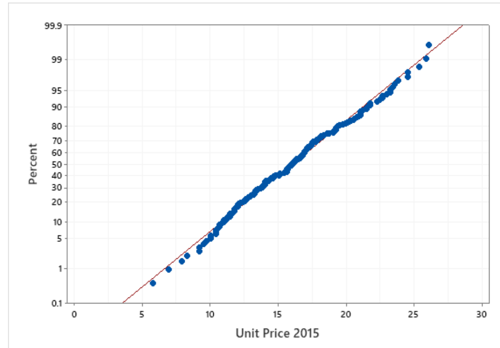


Tack Coat 2016

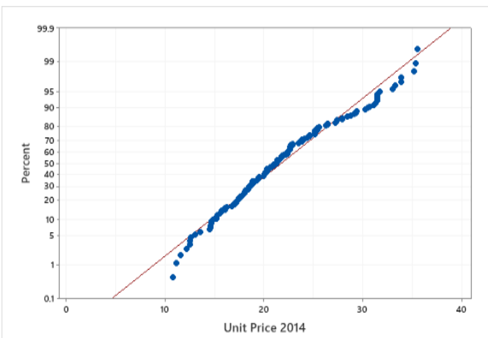
Figure 15. Histogram plots of unit prices for top 5 highway bid items



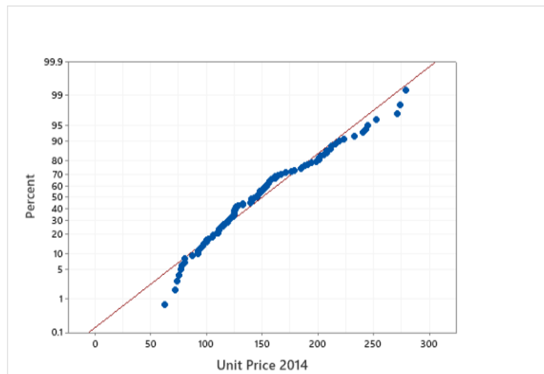
Anderson-Darling Test p-value =0.018
Kolmogorov-Smirnov p-value<0.010
Excavation Common 2013



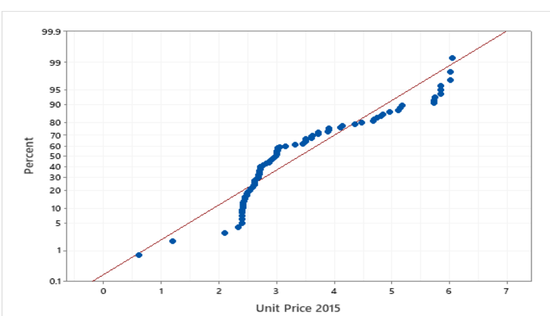
Anderson-Darling Test p-value =0.330
Kolmogorov-Smirnov p-value>0.150
Base Aggregate 1 ¼" 2015



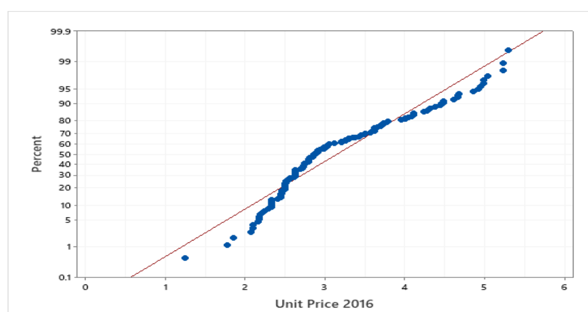
Anderson-Darling Test p-value <0.005
Kolmogorov-Smirnov p-value<0.010
Base Aggregate ¾" 2014



Anderson-Darling Test p-value =0.06
Kolmogorov-Smirnov p-value=0.03
Asphaltic Surface 2014



Anderson-Darling Test p-value <0.005
Kolmogorov-Smirnov p-value<0.010
Tack Coat 2015



Anderson-Darling Test p-value <0.05
Kolmogorov-Smirnov p-value<0.010
Tack Coat 2016

Figure 16. Normality tests for top 5 highway bid items

However, in 2016, the unit price increased by 8.04% from the previous year. In 2017 and 2018, the unit prices decreased by 1.52% and 4.24% from the 2016-unit price. The mean unit price for tack coat bid items increased from $4.25/Ton to $6.56/Ton which indicates a 54% increase between 2013 to 2014. However, the bid unit price decreased in 2015 and 2016 by 48% and 52% respectively from 2014. Subsequently, the bid unit price increased in 2017 and 2018 by 43% and 51% respectively from 2016.

3.7.1. Multiple Comparisons between Project Size and Bid Unit Price

This section examines the significance of the difference of the average bid unit prices associated with the different sizes of highway projects for the five bid items used in the study. The unit prices for the bid items submitted by the lowest responsive and responsible bidder was proposed to be different. These differences reflect the influence of project size on the pricing mechanisms implemented by different contractors between 2013 to 2018. Multiple comparisons analysis was used to examine whether the bid data provide support for the null hypothesis related to the average bid unit prices and project sizes.

Two sample t-tests were applied to determine the level of significance between the mean unit prices of the bid items and their associated project sizes. Table 6 shows the difference of the mean bid unit prices of excavation common for each pair of project size between 2013 to 2018. The results of the analysis show that there are significant differences between the means of $0.5 million or less versus $1 million to 2 million, $0.5 million or less versus $10 million to 20 million, $0.5 million to $1 million versus $10 million to 20 million, and $2 million to 10 million versus $10 million to 20 million at a significance level of 95%. The largest mean value of bid unit prices related to each pair of project sizes can be determined by the difference of the mean values. The average bid unit prices for ($0.5 million or less) projects were higher compared to $1 million to 2 million and $10 million to 20 million project sizes. This showed that, for common excavation, bidders tended to decrease their unit prices with an increase in the size of projects $1 million to 2 million versus $10 million to 20 million as shown in Table 6. For projects within the $0.5 million to $1 million threshold, bidders tended to increase their bid prices for common excavation compared to projects within $10 million to 20 million. There was a significant difference between unit prices for projects within $2m to $10m versus $10 million to 20 million.

Table 6. Multiple comparisons for the excavation common bid unit price mean differences per project size category

Project Size (In millions of $) (A)	Project Size (In millions of $) (B)	Mean difference (A-B)	*P*-Value	95% Confidence Interval	
				Lower bound	Upper bound
0.5m or less	0.5m-1m	0.342	0.569	-1.521	0.838
	1m-2m	1.263*	0.027	0.148	2.379
	2m-10m	0.261	0.596	-0.707	1.229
	10m-20m	2.757*	0.000	1.256	4.258
	20m-More	1.464	0.123	-0.408	3.337
0.5m-1m	1m-2m	0.922	0.156	-0.352	2.196
	2m-10m	-0.081	0.890	-1.228	1.067
	10m-20m	2.415*	0.004	0.795	4.035
	20m-More	1.123	0.259	-0.843	3.089
1m-2m	2m-10m	-1.002	0.069	-2.084	0.08
	10m-20m	1.493	0.063	-3.068	0.081
	20m-More	0.201	0.836	-1.729	2.131
2m-10m	10m-20m	2.496*	0.001	-3.792	-1.019
	20m-More	-1.203	0.199	-3.506	0.65
10m-20m	20m or More	-1.290	0.239	-3.46	0.87

However, for project size(10m- 20m), the unit price stopped decreasing and might have increased, and therefore there were insignificant differences in the average bid prices.

Table 7 shows the mean differences of base dense aggregate 1 ¼” bid unit price per project size category from 2013 to 2018. The results of the analysis showed that there are significant differences between the mean unit prices of $0.5 million or less versus $1 million to 2 million, $0.5 million or less versus $10 million to 20 million, and $0.5 million or less versus $20 million or more. At a significance level of 95%, the average bid unit prices for project size $0.5 million to $1 million and $1 million to 2 million, $0.5 million to $1 million and $2 million to 10 million, $0.5 million to $1 million and $10 million to 20 million, and $0.5 million to $1 million and $20 million or more were significant for 1¼" base dense aggregate between 2013 to 2018 and therefore the null hypothesis should be rejected. However, a comparison between bid unit price for $0.5 million or less versus $1 million to 2 million and $10 million to 20 million versus $20m or More diminished marginally with an increase in the project size.

Table 7. Multiple comparisons for the base dense aggregate 1 ¼" bid unit price mean differences per project size category

Project Size (In millions of $) (A)	Project Size (In millions of $) (B)	Mean difference (A-B)	*P*-Value	95% Confidence Interval Lower bound	Upper bound
0.5m or less	0.5m-1m	0.463	0.274	-1.293	0.368
	1m-2m	1.844	0.000*	1.003	2.684
	2m-10m	2.680	0.000	1.951	3.408
	10m-20m	4.884	0.000*	3.977	5.790
	20m-More	4.187	0.000*	2.676	5.698
0.5m-1m	1m-2m	1.381	0.002*	0.499	2.263
	2m-10m	2.217	0.000*	1.441	2.993
	10m-20m	4.421	0.000*	0.795	4.035
	20m-More	3.724	0.000*	2.191	5.258
1m-2m	2m-10m	0.836	0.037*	0.049	1.623
	10m-20m	-3.040	0.000*	-3.994	-2.086
	20m-More	2.343	0.003*	0.805	3.882
2m-10m	10m-20m	2.215	0.000*	-3.073	-1.357
	20m-More	1.518	0.045*	-3.002	-0.035
10m-20m	20m or More	-0.696	0.380	-2.269	0.876

Table 8 shows the results of the multiple comparisons of the effect of economies of scale on the unit price of base aggregate ¾-inch. A comparison between project size 0.5m or less versus 0.5 to 1m, 1m to 2m, 2m to 10m, 10m to 20m, and 20m or more revealed significant differences between the mean prices between the respective project sizes as shown in Table 8.

Also, a comparison between the mean unit prices for project size (0.5m to 1m) versus (1m to 2m, 2m to 10m, 10m to 20m, and 20m or more) showed that contractors tend to price lower as the size of the project increases. This result was also evident in the subsequent analysis between project sizes (1m to 2m) versus (2m to 10m, 10m to 20m, and 20m or more) with a positive increase in the difference between the average bid unit prices for the respective project sizes.

Table 8. Multiple comparisons for the base dense aggregate ¾-inch bid unit price mean differences per project size category

Project Size (In millions of $) (A)	Project Size (In millions of $) (B)	Mean difference (A-B)	*P*-Value	95% Confidence Interval Lower bound	Upper bound
0.5m or less	0.5m-1m	-2.242	0.003	-3.731	-0.754
	1m-2m	3.049	0.000	1.541	4.558
	2m-10m	4.680	0.000	3.413	5.948
	10m-20m	5.051	0.000	3.275	6.828
	20m-More	4.83	0.000	2.49	7.17
0.5m-1m	1m-2m	0.807	0.302	-0.730	2.344
	2m-10m	2.438	0.000	1.137	3.739
	10m-20m	2.809	0.002	1.009	4.609
	20m-More	2.590	0.032	0.230	4.950
1m-2m	2m-10m	1.631	0.016	0.307	2.955
	10m-20m	2.002	0.031	-3.819	-0.186
	20m-More	1.780	0.138	-0.590	4.150
2m-10m	10m-20m	0.371	0.652	-1.996	-1.254
	20m-More	0.150	0.892	-2.380	2.080
10m-20m	20m or More	-0.220	0.864	-2.760	2.320

Table 9 shows the results of the multiple comparisons of the mean differences of the bid unit prices for each pair of the size of projects for asphaltic surface bid item. There are significant means differences between each pair of project sizes (0.5m or less, 2m to 10m, 10m to 20m) at a 0.05 significance level (all $P<0.05$). The mean differences of the asphaltic bid unit prices increased according to the increase in project value, which means that contractors tend to decrease the per-unit price of asphaltic surface within these project size thresholds. There are significant means differences between each pair of project sizes (0.5m to 1m, 2m to 10m, 10m to 20m) at a 95% significance level (all $P<0.05$) for asphaltic bid items.

Table 9. Multiple comparisons for the asphaltic surface bid unit price mean differences per project size category

Project Size (In millions of $) (A)	Project Size (In millions of $) (B)	Mean difference (A-B)	*P*-Value	95% Confidence Interval Lower bound	Upper bound
0.5m or less	0.5m-1m	-0.04	0.969	-9.84	9.46
	1m-2m	10.84	0.058	-0.39	22.07
	2m-10m	11.49	0.007	3.15	19.83
	10m-20m	20.78	0.002	8.17	33.39
	20m-More	11.4	0.287	-10.1	32.90
0.5m-1m	1m-2m	10.65	0.102	-2.14	23.44
	2m-10m	11.30	0.033	0.92	21.68
	10m-20m	20.59	0.004	6.61	34.56
	20m-More	11.20	0.313	-11.0	33.40
1m-2m	2m-10m	0.65	0.914	-11.21	12.51
	10m-20m	-9.63	0.215	-24.96	5.70
	20m-More	0.6	0.961	-22.40	23.50
2m-10m	10m-20m	-8.98	0.187	-22.44	4.48
	20m-More	0.10	0.993	-21.70	21.90
10m-20m	20m or More	-9.40	0.425	-32.90	14.10

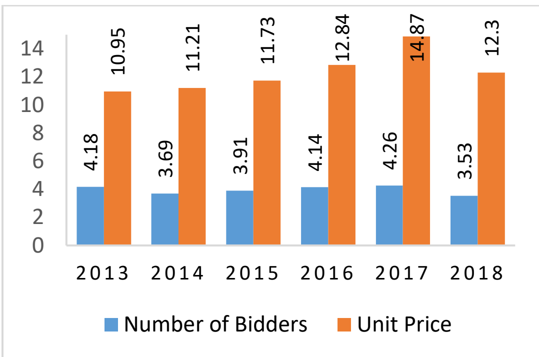
For the tack coat bid item, there was a significant mean difference between each pair of project sizes(0.5m or less, 0.5m to 1m, 1m to 2m, 2m to 10m, 10m to 20m, and 20m or more) at 0.05 significance level as shown in Table 10.

Table 10. Multiple comparisons for the tack coat bid unit price mean differences per project size category

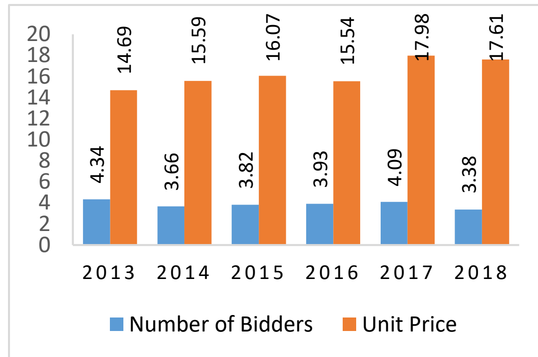
Project Size (In millions of $) (A)	Project Size (In millions of $) (B)	Mean difference (A-B)	*P*-Value	95% Confidence Interval Lower bound	Upper bound
0.5m or less	0.5m-1m	-1.684	0.000	-2.549	-0.818
	1m-2m	3.139	0.000	2.394	3.885
	2m-10m	3.329	0.000	2.644	4.013
	10m-20m	3.309	0.000	2.500	4.118
	20m-More	3.270	0.000	2.353	4.187
0.5m-1m	1m-2m	1.156	0.010	0.285	2.027
	2m-10m	1.345	0.002	0.526	2.165
	10m-20m	1.325	0.005	0.401	2.250
	20m-More	1.287	0.014	0.267	2.306
1m-2m	2m-10m	0.189	0.367	-0.223	0.602
	10m-20m	0.169	0.578	-0.769	0.430
	20m-More	0.131	0.727	-0.611	0.872
2m-10m	10m-20m	0.371	0.652	-1.996	-1.254
	20m-More	0.059	0.864	-0.623	0.741
10m-20m	20m or More	-0.039	0.924	-0.843	0.766

3.7.2. Effect of Competition on Bid Unit Prices

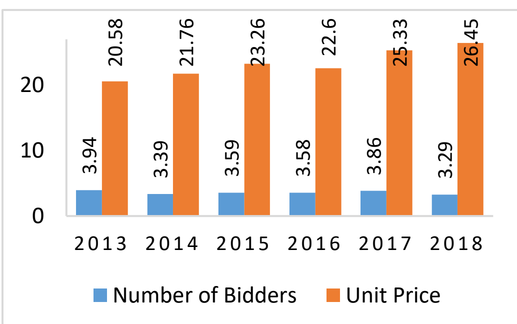
To assess the influence of the number of bidders on the unit price of the top 5 bid items, statistical analyses were performed to compare the level of significance between the average number of bidders and the mean unit prices per each year as shown in Figure 17



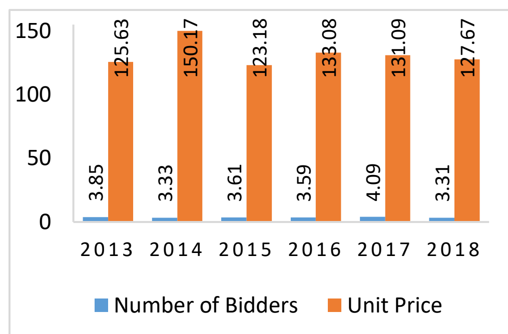
Excavation Common



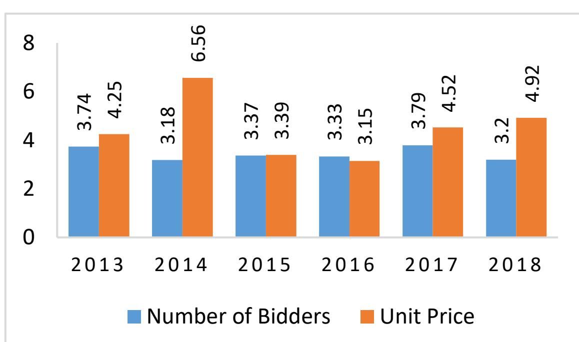
Base Aggregate 1 ¼”



Base Aggregate ¾ ”



Asphaltic Surface



Tack Coat

Figure 17. Number of bidders vs. unit prices for top 5 highway bid items

For the common excavation bid item, between 2013 to 2014 as the average number of bidders increased the average bid unit price reduced. However, the subsequent increase in the average number of bidders did not result in a lower mean unit price from 2014 to 2018. A t-test was performed to compare the significance of the difference in the number of bidders for each bid item from 2013 to 2018. There was significant difference in the number of bidders for 2013 common excavation (M= 4.18, SD= 2.07) and 2014 common excavation (M= 3.69, SD= 2.12).

Parametric and non-parametric correlation analyses were performed to assess the relationship between the number of bidders and the unit price for the top 5 bid items used for the study from 2013 to 2018. The results from the correlation analysis between the number of bidders and unit price for 2013 and 2014 common excavation, indicated a significant moderate negative correlation between the two variables. That is, as the unit prices decreased with an increase in the number of bidders. However, between 2014 to 2018, there was an insignificant correlation between the number of bidders and unit prices for common excavation bid items. The results translate the minimal effect of competition on the pricing of common excavation. In pricing excavation works, contractors may weight other factors about ground conditions such as soil and geological factors more than other factors that might influence the probable cost.

A comparison between the number of bidders and unit price for base aggregate 1 ¼" revealed a moderate negative correlation between the two variables from 2013 to 2017, indicating a statistically significant association between the two variables. However, the findings for the 2018 base aggregate 1 ¼" the negative association between the number of bidders and unit price was not statistically significant. For the asphaltic surface bid items, the number of bidders is not a statistically significant explanatory variable with a weak positive association in 2013, 2014, 2016, and 2018 and a weak negative relationship was recorded in 2015 and 2017.

Table 11. Correlation analysis of the effect of the number of bidders on bid unit prices

Bid Item		Mean Unit Prices	Mean Number of Bidders	Pearson Correlation	P-Value	Spearman Correlation	P-Value
Excavation Common							
	2013	10.95	4.18	-0.378	0.000	-0.436	0.000
	2014	11.21	3.69	-0.399	0.000	-0.399	0.000
	2015	11.73	3.91	0.079	0.293	0.077	0.308
	2016	12.84	4.14	0.052	0.499	0.065	0.396
	2017	14.87	4.26	-0.112	0.233	-0.146	0.117
	2018	12.30	3.53	-0.160	0.027	-0.096	0.188
Base Aggregate 1 ¼”							
	2013	14.69	4.34	-0.325	0.000	-0.338	0.000
	2014	15.59	3.66	-0.503	0.000	-0.507	0.000
	2015	16.07	3.82	-0.363	0.000	-0.336	0.000
	2016	15.54	3.93	-0.409	0.000	-0.373	0.000
	2017	17.98	4.09	-0.314	0.000	-0.280	0.000
	2018	17.61	3.38	-0.116	0.116	-0.102	0.165
Base Aggregate 3/4"							
	2013	20.58	3.94	-0.138	0.082	-0.125	0.114
	2014	21.76	3.39	-0.165	0.042	-0.161	0.048
	2015	23.26	3.59	-0.177	0.000	-0.179	0.024
	2016	22.60	3.58	-0.256	0.001	-0.224	0.002
	2017	25.33	3.86	-0.112	0.161	-0.069	0.391
	2018	26.45	3.29	0.090	0.238	0.128	0.093
Asphaltic Surface							
	2013	125.63	3.85	0.009	0.946	0.045	0.724
	2014	150.17	3.33	0.040	0.699	0.089	0.390
	2015	123.18	3.61	-0.172	0.116	-0.128	0.245
	2016	133.08	3.59	0.065	0.518	0.084	0.403
	2017	131.09	4.09	-0.100	0.310	-0.066	0.503
	2018	127.67	3.31	0.116	0.240	0.175	0.074
Tack Coat							
	2013	4.25	3.74	0.261	0.002	0.239	0.004
	2014	6.56	3.18	-0.006	0.932	0.144	0.057
	2015	3.39	3.37	-0.108	0.307	-0.046	0.664
	2016	3.15	3.33	0.219	0.007	0.171	0.036
	2017	4.52	3.79	0.229	0.001	0.214	0.003
	2018	4.92	3.20	0.305	0.000	0.349	0.000

These findings are consistent with results from Wang and Liu (2012) and Ilbeigi et al. (2016). Their study accentuated that even though there is an inverse relationship between the number of bidders on the unit price of asphaltic bid items, most contractors own and operate their plants which require intensive capital to build, operate, and manage. Therefore, contractors need to secure enough asphalt projects in the geographical area adjacent to the plant to recover the capital investment and support the plant operation. The results of the correlation analyses between the number of bidders and unit price for tack coat bid items showed a significant moderate positive relationship between the two variables in 2013 and between 2016 to 2018. This means that the number of bidders increased in these years, the unit price of the tack coat also increased. However, in 2014 and 2015, there was a negative association between the number of bidders and the unit price even though they were insignificant.

3.8. Conclusions

State highway transportation agencies are increasingly storing vast amounts of data generated during their operations. Therefore, conducting proper analyses to track highway construction costs and detect patterns is essential for ensuring the accuracy of cost estimation models.

This study explored and ascertained trends in historical highway construction bid data from the Wisconsin department of transportation from 2013 to 2018 to generate forward-looking insights. In addition, statistical analyses were performed to determine the impact of economies of scale and competition on the unit prices of the top 5 bid items. The results of the data exploration revealed that among the top 5 bid items identified, asphaltic surface and tack coat bid items recorded severe price volatility. The trend analysis showed high variability in the pricing of bid items for the study. This reflects the need for data transformation and normalization for the bid unit prices to meet the assumption of normality to enhance the performance of cost estimation models.

This study confirmed that larger highway construction contracts yield leads to economies of scale. However, findings suggest that there is a threshold beyond which the unit cost of the top 5 bid items starts increasing with an increase in project size. In addition, larger projects due to inherent complexity and uncertainty will limit the number of potential bidders because not all construction firms have the required financial and technical capacities to deliver larger transportation projects.

For common excavation, due to inherent complexities in-ground and geotechnical conditions, contractors tend to allocate high variable cost to cater for uncertainties associated with delivering large project sizes. Consequently, the unit price for the base aggregate 1 ¼” and ¾” bid items were predominately significantly influenced by the size of the projects. The results of the correlational analysis showed that the number of bidders significantly affects the unit price of base aggregate 1 ¼” and ¾” bid items from 2013 to 2017. However, for common excavation, asphaltic surface, and tack coat bid items, the number of bidders does not significantly influence the probable cost. This empirical evidence is the result of extensive exploratory data analysis and pattern-seeking visualizations of highway historical cost data.

To optimize the accuracy of highway cost predictions, preference must be given to cost drivers that have a high association of influencing the probable price of such a bid item. To ascertain the optimal cost drivers influencing asphaltic surface and tack coat bid items, future research could focus on assessing the effect of macroeconomic factors such as crude oil prices, the spatial proximity of asphaltic plants, on the unit price of asphalt bid items to improve estimation results.

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CHAPTER 4. CONCEPTUAL COST ESTIMATION OF HIGHWAY BID UNIT PRICES USING ORDINARY KRIGING [2]

4.1. Abstract

State highway agencies (SHAs) adopt state average historical bid unit prices to estimate the cost of highway bid items and use location factors to adjust estimates to reflect the appropriate geographical location at the conceptual phase. However, these location factors are not readily available for all projects or work types for all geographic locations. Practical, technical, and economic constraints make it difficult for SHAs to store and process historical cost data of highway projects for every desired point over space and time. In this paper, ordinary kriging (OK) was combined with three commonly used semivariograms (spherical, exponential, and Gaussian) models one at a time to interpolate six years of the top five common highway bid items: common excavation, base aggregate dense 1 ¼- inch, base aggregate dense ¾-inch, tack coat, and asphaltic surface obtained from Wisconsin Department of Transportation (WisDOT). For the common excavation, base aggregate dense 1 ¼ inch, and tack coat bid items, a combination of OK and exponential semivariogram yielded a better prediction accuracy compared to spherical and Gaussian models. A combination of OK and Gaussian model performed better in minimizing the mean absolute percentage error for the base aggregate dense ¾ inch, compared to spherical and exponential models. The unique contribution of this paper to the state-of-practice is an in-depth application of linear geostatistical models (ordinary kriging) to interpolate bid data that would enable estimators to develop unit price maps of highway

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construction bid items. The geovisualized bid price maps would enable SHAs to generate forward-thinking insights by considering the effects of spatial variations and time of highway bid unit prices across multiple geographic locations.

4.2. Introduction

Developing accurate cost estimates is important to the successful delivery of capital projects. SHAs must estimate the cost of highway projects at several stages in the project development process, from initial planning through the design phase to bidding and award of a construction project (Cao et al. 2018). Preliminary project estimates represent a key ingredient in business unit decisions and often become the basis for the ultimate funding of a project (Trost and Oberlender 2003) and are conceived as a significant starting process that influences the fate of new transportation projects (Chou 2009). Despite the recent developments in cost estimating methodologies and the increase in cost estimation research, the accuracy of highway cost estimates has not significantly improved over the last few decades (Hassanein 2006).

Inaccurate estimation of highway construction costs could lead to two unintended consequences- overestimation and underestimation (Hassanein 2006; Chou 2009). An overestimated cost could cause a misjudgment of the feasibility of a project, which could limit the number of business opportunities an owner can pursue at a time (Chou and O’Connor 2007; Liu and Zhu 2007; Migliaccio et al. 2015). In contrast, an underestimated cost could later force the owner to secure additional funding, reduce project scope to satisfy budgetary constraints, which could subsequently disrupt the successful delivery of SHAs construction program (Chou and O’Connor 2007; Liu and Zhu 2007; Migliaccio et al. 2015). Developing a reliable and accurate total project estimate is a challenge for SHAs (Chou 2009; Asmar et al. 2011) especially at the conceptual stage because very little project information is available to perform the estimation (Sodikov 2005; Hassanein 2006).

Using historical bid prices is a relatively straightforward and common method of estimating highway costs, which could yield good results if applied properly (Chou 2009). However, cost escalation associated with this method can be attributed to project location, project size, environmental conditions, market conditions, bidding volume, time inflation, political risk, geological conditions, and uncertainty (Tarek Hegazy 1998; Hassanein 2006; Chou 2009).

Project costs vary by location, thus an essential process in cost estimation is the accurate cost adjustment to reflect the appropriate geographical variation (Zhang et al. 2017) and ensure the accuracy of conceptual cost estimates. The geographic location of a highway transportation project is a larger cost driver in asphalt pavement bid unit prices than mix design. Therefore, bid prices for other asphalt bid items in a similarly priced geographical area should be investigated (WisDOT 2020). A cost estimating procedure for accounting for the spatial variability of highway project costs is to automatically derive the cost-driving characteristics of road components for any specific location and to analyze cost per unit of road length based on their unit cost data (Stückelberger et al. 2006). However, these location adjustment factors are not readily available for every type of highway project across all locations in the United States (Migliaccio et al. 2013; Zhang et al. 2014; Zhang et al. 2017). Furthermore, practical, technical, and economical constraints make it difficult to collect, store, and process historical cost data for every desired point over space and time.

Construction cost models reflect experiences that are unique to a construction organization for a certain project or work type (Sonmez 2011). The inherent heterogeneity

associated with historical cost data from multiple highway transportation projects affects the accuracy of conceptual cost estimation modeling (Neill 1984; Oberlender and Trost 2001). Therefore, the inclusion of estimation variability is crucial for management decisions as cost estimates of highway bid items are characterized by a high amount of uncertainty at the conceptual phase
(Sonmez 2011).

Over the past few decades, geographic information systems(GIS) has proven to be a versatile and effective tool for decision making in several fields including geoscience, civil, and environmental engineering (Hassanein 2006; Mendes and Lorandi 2006; Asa et al. 2012, Le et al. 2019). GIS provides a robust platform that could be employed in estimating construction costs and aid in visualization and analyses of several spatial parameters, such as location, topography, right-of-way acquisition costs, and haul distances (Hassanein 2006; Le et al. 2019). Despite the widespread applications of GIS to the construction industry, GIS-based visualization has not been extensively employed in construction planning. The construction industry uses different tools other than the GIS for visualization, which are not capable of storing large amounts of spatial and non-spatial project data (Bansal and Pal 2007). By accurately visualizing infrastructure prices on a map, total project resources can be optimized using geospatial analytics (RSMeans 2020).

Spatial interpolation methods differ from classical modeling approaches in that they incorporate information on the geographic coordinates of the sample data points to predict spatial phenomena (Setianto and Triandini 2015). The choice of an appropriate kriging method is dependent on how well the variogram model used fits the data set (Shamo et al. 2012). In this paper, OK will be combined with three commonly used semivariograms (spherical, exponential, and Gaussian) one at a time to predict highway construction unit prices from the WisDOT from 2013 to 2018. This study seeks to ascertain which combination of ordinary kriging and variogram models yields the best results in estimating unit prices for highway construction bid items and quantify the level of variability included in the estimated unit prices. The remaining parts of the paper are organized as follows. The literature review section examines previous related research in accounting for spatial variation of estimating highway bid unit prices. A detailed description of the data, the data exploration, and the geostatistical algorithms used in the study are presented in the methodology section. The final part of the paper discusses the results and conclusions derived from the study.

4.3. Literature Review

Zhang et al. (2017) proposed a new method of using nighttime light satellite imagery (NLSI) to estimate location adjustment factors at unmeasured locations. The NLSI method for estimating location adjustment factors was evaluated against an established cost index database, and the results showed that NLSI can be used to effectively estimate location adjustment factors. One key advantage of the NLSI-based method over purely proximity-based interpolation methods is that it indirectly incorporates local economic conditions. When compared with the nearest neighbor(NN) and other proximity-based location adjustment methods, the proposed NLSI method led to a 25–40% reduction of the median absolute error.

Martinez et al. (2009) used GIS tools to conduct spatial and statistical analyses to confirm the validity of the nearest available method. An assessment of alternative interpolation methods was also conducted, including an evaluation of the state average and the nearest available method. A comparison among conditional nearest neighbor method, unconditional nearest neighbor method, and state average method demonstrated that the conditional nearest neighbor method produced the least amount of error between actual and estimated values and therefore, should produce the most accurate location adjustment estimate among the methods evaluated.

Migliaccio et al. (2013) deployed commonly used set of LCAFs, the city cost indexes (CCI) by RSmeans, and the socioeconomic variables included in the ESRI Community Sourcebook, to assess the accuracy of various spatial prediction methods in estimating LCAF values for unsampled locations. Two regression-based prediction models, global regression analysis and geographical weighted regression analysis (GWR) were employed to model the spatial variation of LCAF values at unsampled locations. A comparison of the methods showed that GWR produced a better prediction accuracy in modeling CCI as a function of multiple covariates.

Le et al. (2019) applied GIS-based interpolation methods (Inverse distance weighted, ordinary kriging, and ordinary cokriging) and location cost-adjustment factors to adjust the total costs of two similar projects in two different cities. The GIS-based framework proposed by Le et al. (2019) leveraged historical bid data for unit-price estimation and visualization with consideration of the effects of project-specific location on different bid items. Additionally, various strategies such as the use of quantity in interpolation models were employed to improve the accuracy of the preliminary estimates. Temporal changes in unit prices and relationships between quantities and unit prices were also explored. A comparison of the spatial interpolation algorithms indicated that ordinary cokriging (OCK) performed better than the OK and inverse distance weighted (IDW) models.

4.4. Methodology

Finding an appropriate GIS-based interpolation method to model spatial phenomena poses several challenges. Additionally, the modeled fields are usually very complex, data are spatially heterogeneous and often based on sub-optimal sampling, and significant noise (Caruso and Quarta 1998; Mitas and Mitasova 1999; Apaydin et al. 2004). Kriging often known as the best linear unbiased estimator (BLUE) is an optimal spatial regression technique that requires a spatial statistical model and a semivariogram which represents the internal spatial structure of the data. In this paper, the OK model will be combined with three common semivariograms (spherical, exponential, and Gaussian) one at a time to predict highway construction unit prices from the WisDOT from 2013 to 2018. Ordinary kriging is evaluated in this study because it is one of the most commonly used geostatistical interpolation techniques across multiple disciplines (Eldeiry and Garcia 2012).

Exploratory spatial data analysis was used to study the statistical properties of the data followed by variogram modeling and kriging. Cross-validation was then used as a diagnostic to assess the variability and validity of the modeling results and formed the basis of comparison and selection of the optimal results (Figure 18). The same process was repeated for all the combinations of the kriging and variogram algorithms.

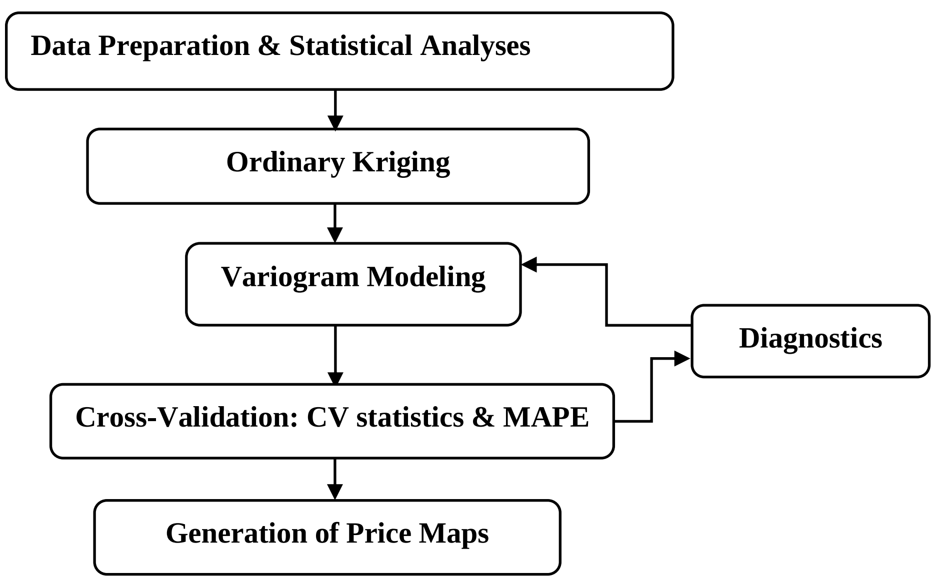


Figure 18. Research methodology

4.4.1. Variogram Modeling

A variogram model is an important statistical tool in the geostatistical analysis used to assess the spatial variability between data points (Asa et al. 2012). The variogram is a fitted function used to express the relationship between the known and unknown data points. A theoretical semivariogram model, which is a mathematical function, is selected to fit the empirical semivariogram. The theoretical function reflects the relationships between distance *h* and differences in values at two locations separated by distance *h* (Le et al. 2019). The variogram approach to developing kriging weights is similar to inverse distance weighting except that in the case of kriging weights, the weights are modeled by the best-fitted variogram (Shamo et al. 2015). Accurate semivariogram modeling is not an easy task, and some experience is required to find models and parameters close to the optimal ones (Krivoruchko 2011).

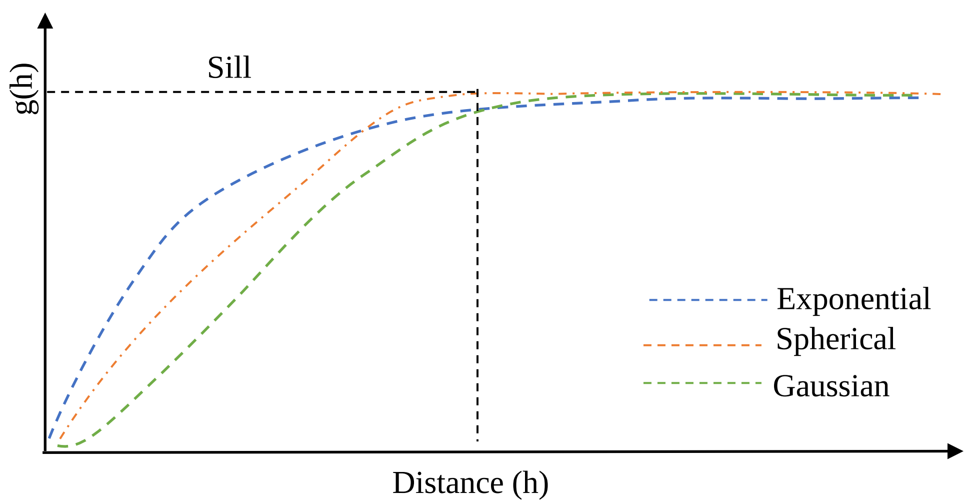


Figure 19. Graphical representation of theoretical semivariogram

This study employed three commonly used variogram models (Pang et al. 2012; Mälicke et al. 2018), namely (1) spherical (Eq.13), (2) exponential (Eq. 14), and (3) Gaussian (Eq. 15) to assess the spatial variability of unit price data from 2013 to 2018.

$$\text{Spherical Model} = Sph\left(\frac{h}{a}\right)\left\{\frac{1.5h}{1} - 0.5\left(\frac{h}{a}\right)^3\right\} \tag{13}$$

$$\text{Exponential model} = 1 - exp\left(\frac{-3h}{a^2}\right) \tag{14}$$

$$\text{Gaussian model} = 1 - exp\left(\frac{-3h^2}{a}\right) \tag{15}$$

were h and a are referred to as distance and range, respectively.

4.4.2. Ordinary Kriging

Ordinary kriging (OK), a linear weighted-average technique is the most widely used interpolation method in geostatistics and is unbiased to the expected value of errors (Adhikary and Dash 2017). It is a nonstationary algorithm that involves estimating the mean value at each location and can be generally applied in moving search neighborhoods. However, the covariance function is stationary (Asa et al. 2012). OK assumes that variation is random and spatially dependent and that the underlying random process is intrinsically stationary with constant mean and a variance that depends only on separation in distance and direction between data points and not on absolute position (Oliver and Webster 2015). Although other nonlinear geostatistical algorithms are now utilized, the relative transparency and straightforwardness of the OK algorithm, combined with its good performances in the past, has ensured its continued popularity (Van Groenigen 2000). The equation for ordinary kriging is given by (Shamo et al. 2015):

$$Z*(b) = \sum_{a=1}^{n(b)} \lambda_a(b) Z(b_a) + \left[1 - \sum_{a=1}^{n(b)} \lambda_a\,(b)\right]\mu(b) \tag{16}$$

The sill, range, and nugget obtained from the variogram used in combination with this estimator is then employed to compute the kriging weight (λ_α); for which the sum is 1. To ensure that the estimate is unbiased, the mean is obtained by requiring the kriging weights sum to 1 (Shamo et al. 2015):

$$\sum_{a=1}^{n(b)} \lambda_a \,(b) \;= 1 \tag{17}$$

Therefore, the estimator in OK becomes (Shamo et al. 2015):

$$Z * (b) = \sum_{\alpha=1}^{n(b)} \lambda_\alpha \,(b) Z(b_\alpha) \tag{18}$$

4.4.3. Cross-Validation and Validation

The generation of spatially distributed maps and interpolated values through the geostatistical modeling approach is accompanied by uncertainty and thus, requires the accuracy of the estimated values to be assessed (Mirzaei and Sakizadeh 2016; Gupta et al. 2017). The cross-validation technique is generally adopted to validate the generated spatial maps by evaluating the accuracy of the critical parameters that could affect the interpolation process of the variable under study (Gupta et al. 2017). The true prediction error of the estimates obtained from each of the kriging techniques is then measured by comparing the estimated values with the actual sample data at the data validation points (Asa et al. 2012; Le et al. 2019). The calculated statistics serve as diagnostics that indicate whether the model and its associated parameter values are reasonable (ESRI 2020).

To assess the accuracy of the interpolation methods, this study employed the output of cross-validation statistics (Eqns 19 through 21), mean standardized error (MSE), root mean square error (RMSE), and average standard errors (ASE). For a model that provides accurate predictions, the MSE should be close to zero (Gupta et al. 2017). To ensure an accurate and unbiased geostatistical model, then the RMSE should equal the kriging variance, so the RMSE should equal 1. If the average standard errors are close to the root mean squared prediction errors, then the variability in the prediction is correctly assessed. However, if the RMSE is greater than 1, then the variability in the predictions is being underestimated, and vice versa. Likewise, if the average standard errors (ASE) are greater than the root mean square errors (RMSE), then the variability is overestimated, and vice versa (Robinson and Metternicht 2006; Asa et al. 2012; Eldeiry and Garcia 2012; ESRI 2020). The equations of the cross-validation statistics employed in this study are (Asa et al. 2012; Eldeiry and Garcia 2012; ESRI 2020):

$$\text{Mean Standardized Error} = \frac{1}{N}\sum_{i=1}^{N}[Z_1(y_1) - Z_2(y_2)] \tag{19}$$

$$\text{Root Mean Square Error} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[Z_1(y_1) - Z_2(y_2)]^2} \tag{20}$$

$$\text{Average Standard Error} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[Z_1(y_1) - \left(\sum_{i=1}^{N} Z_2(y_2)\right)/N\right]^2} \tag{21}$$

where $Z_1(y_1)$ and $Z_2(y_2)$ are the measured and estimated bid unit price, respectively, of the *ith* unit-price data point N, is the total number of cost data points.

Mean absolute percentage error (MAPE) is a performance metric that is a common measure used for assessing the level of accuracy of the algorithms used to estimate the cost of highway bid items. This method of validation is traditionally used by authors of data-driven conceptual estimating models (Gardner et al. 2017). The equation for computing MAPE is furnished in equation 10 (Choi et al. 2014; Gardner et al. 2017):

$$MAPE = \left(\frac{100\%}{n}\right)\sum_{i=1}^{n}\left|\frac{P_i - A_i}{A_i}\right| \tag{22}$$

where n= number of data points; P_i = predicted bid unit price A_i = actual bid unit price for the *ith* project.

4.5. Results and Discussion

4.5.1. Exploratory Spatial and Statistical Data Analysis

Unit price data were subjected to exploratory and spatial data analyses to ascertain descriptive statistics and to detect spatial trends in the observed data. Table 12 provides an assessment of univariate descriptive statistical indexes such as total count, mean, mode, median, and standard deviation for a sample of the bid unit price data. These outputs help to understand and make logical choices about the data and conclusions for further modeling procedures. The analysis shows that the mean and median are close indicating approximately normally distributed for excavation common.

The high standard deviation of the bid unit prices indicates a considerable variation in the pricing from 2013 to 2018. Statistical plots were used to display the distribution of the bid items, detect trends, and make inferences about the bid data. Kolmogorov-Smirnov (K-S) and Anderson–Darling(AD) statistical tests were conducted to check the normality condition. The results show that the distribution of the bid items is not of a normal distribution from 2013 to 2018. As shown in Figure 5, the data points are not closely positioned along a 45-degree inclined line and therefore the assumption of normality is rejected by the Anderson-Darling test or the Kolmogorov-Smirnov test or both at a *95%* significance level. Optimal geostatistical models assume that the data is generated from a normal distribution. Data not meeting the normality assumption is transformed before variogram and geostatistical modeling to improve the prediction accuracy of interpolation results. Therefore, to test the significance of this claim, this paper compared the kriging results using non-transformed data and the case where the data was transformed to determine the best kriging results. The results of the exploratory spatial analysis showed trends in the bid dataset. Therefore, prior to performing the structural analysis and kriging, the dataset was detrended to satisfy the stationarity assumption and model short-range variation.

4.5.2. Comparison of Spatial Interpolation Methods

This section highlights the structural analysis performed to generate interpolation surfaces for the five top bid items from 2013 to 2018. Three semivariogram models (spherical, exponential, and Gaussian) were fitted to the data before interpolation with ordinary kriging. This paper used the cross-validation leave-one-out approach as a diagnostic to assess the variability and validity of the modeling results for each of the five bid items from 2013 to 2018.

Table 13 shows the cross-validation results for common excavation bid data sets evaluated from 2013 to 2018. The MSE show values close to zero for the three semivariograms used for the study from 2013 to 2018, which indicates that the models are unbiased for all combinations of the variogram and kriging models. A comparison of the cross-validation results showed the RMSE is closer to the ASE for the 2013, 2014, and 2016 data set when ordinary kriging is combined with a spherical semivariogram model.

Table 12. Sample descriptive statistics of the top five highway bid unit prices

Bid Item	N	Unit	Mean	Median	SD	Minimum	Q1	Q3	Maximum
Excavation Common									
2013	100	CY	10.95	10.27	4.45	3.28	7.74	14	22.65
2014	144	CY	11.21	10.56	4.45	1.4	7.9	14	22.6
2015	179	CY	11.73	11	5.75	0.01	7.73	16	27.16
2016	170	CY	12.84	11.62	6.72	0.01	7.6	17	29.46
2017	116	CY	14.87	13.57	6.19	4.99	10.2	19	30.92
2018	190	CY	12.3	11.96	4.55	0.01	9.79	15	22.26

Note: CY= Cubic Yards, SD= standard deviation, N= Number of Data Points

This indicates a more valid model because it captures the variability in the interpolated values accurately (Asa et al. 2012). Even though the variability of the interpolated values for the

2013 and 2018 data set is overestimated, this estimation is comparably small. In 2016 and 2018, a combination of OK and Gaussian models performed best and in 2013, 2015, and 2017, a combination of OK and exponential semivariogram models performed best with lower MSE, RMSE, ASE, and, MAPE values. This indicates that a combination of kriging and variogram models with the lowest aggregate value for all the cross-validation statistics was considered to assess the accuracy of the unit price prediction of the bid items at unsampled locations. The closeness of the ASE to the RMSE values, which indicates a good assessment of variability of the interpolation results, does not translate to the best interpolation result. Subsequently, in 2014, OK combined with spherical semivariogram performed best with lower cross-validation error metrics and MAPE values (Table 2). However, the MAPE differences between the distinctive semivariograms used to interpolate unit prices are not significant.

Table 13. Cross-validation results for common excavation bid item from 2013 to 2018

Prediction Error	2013			2014			2015		
	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
RMSE	4.23475	**4.17656**	4.2104	**3.8613**	3.882656	3.85564	4.26602	**4.267902**	4.26398
ASE	4.32358	**4.36161**	4.33333	**3.80002**	3.735279	3.80955	4.82113	**4.748584**	4.90977
MSE	0.00607	**-0.00204**	0.0062	**0.00133**	0.000335	0.00111	0.00778	**0.007106**	0.0064
MAPE %	32.84	**32.31**	32.64	**28.33**	29.09	28.90	27.72	**27.51**	27.49
Prediction Error	2016			2017			2018		
	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
RMSE	5.74757	5.75058	**5.7326**	5.81696	**5.809145**	5.82931	3.75662	3.75369	**3.74598**
ASE	5.80413	5.87961	**5.8944**	5.43479	**5.499458**	5.39412	3.72517	3.715106	**3.74359**
MSE	0.00294	0.00448	**0.0056**	0.00502	**-0.00099**	0.00578	0.02757	0.028647	**0.02751**
MAPE %	32.60	32.61	**32.45**	33.51	**33.08**	33.76	24.10	24.10	**24.01**

Table 14 summarizes the cross-validation results obtained from combining three semivariograms and ordinary kriging to model base aggregate dense 1 ¼-inch from 2013 to 2018. A combination of OK and spherical semivariogram performed better than spherical and exponential models in 2013, 2015, 2016, and 2018 with lower MSE, RMSE, ASE, and MAPE values. Subsequently, OK based on the Gaussian semivariogram model performed best in 2014 and 2017 (Table 3).

Table 14. Cross-validation results for base aggregate dense 1 ¼-inch bid item from 2013 to 2018

Prediction Error	2013			2014			2015		
	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
RMSE	**3.72577**	3.80222	3.74460	3.46286	3.47245	**3.452**	**3.62921**	3.677102	3.7147
ASE	**3.60047**	3.92973	3.77358	3.45636	3.421763	**3.46448**	**3.38857**	3.570687	3.65977
MSE	**0.00085**	-0.00511	0.00125	-0.0079	-0.00736	**-0.0093**	**-0.0015**	0.003517	0.00467
MAPE %	**21.26**	21.82	21.56	17.92	17.95	**17.83**	**18.93**	19.32	19.48

Prediction Error	2016			2017			2018		
	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
RMSE	**3.91946**	3.92197	3.91946	5.46175	5.447715	**5.43554**	**4.66265**	4.632346	4.67302
ASE	**3.85537**	3.83422	3.85076	5.27707	5.324651	**5.32909**	**4.68242**	4.678923	4.67757
MSE	**0.02015**	0.02037	0.02018	0.00907	-0.00834	**0.00718**	**0.01207**	0.009666	0.01295
MAPE %	**21.26**	21.29	21.63	25.87	25.81	**25.72**	**22.40**	22.51	22.73

The performance of the combination of OK and three semivariogram models used to interpolate historical unit prices for base aggregate sense ¾” are evaluated in Table 15. A combination of OK and exponential semivariogram model outperformed Gaussian and exponential models in 2013 to 2015 as shown in the cross-validated statistics in Table 15. In the 2016 to 2018 base aggregate ¾-inch bid dataset, a combination of the OK and Gaussian semivariogram model performed better when compared to other models.

Table 16 summarizes the cross-validation results obtained from combining three semivariograms and ordinary kriging for tack coat from 2013 to 2018. In 2013, 2014, and 2018 a combination of OK and Gaussian semivariogram model performed best whereas a combination of OK and exponential semivariogram model is the best fitted experimental semivariogram in the 2015 and 2016 data set. Subsequently, in 2017, a combination of OK and spherical semivariogram performed best with lower MSE, RMSE, and MAPE (Table 16).

Table 15. Cross-validation results for base aggregate dense ¾-inch bid item from 2013 to 2018

	2013			2014			2015		
Prediction Error	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
RMSE	5.50239	**5.50023**	5.53593	5.85645	**5.842782**	5.84622	6.97804	**6.963859**	6.94882
ASE	5.43462	**5.40693**	5.39724	5.86083	**5.857025**	5.85951	6.93759	**6.88751**	6.94563
MSE	-0.0162	**-0.0136**	-0.0127	0.00361	**0.000388**	0.00194	0.00437	**-0.00262**	0.01299
MAPE %	22.63	**22.58**	22.66	22.92	**22.94**	22.84	24.61	**24.50**	24.69
	2016			2017			2018		
Prediction Error	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
RMSE	6.7149	6.72541	**6.67774**	7.6912	7.686483	**7.72022**	7.71038	7.647754	**7.57644**
ASE	6.70981	6.71884	**6.69079**	7.28263	7.28481	**7.37465**	7.29505	7.413284	**7.45695**
MSE	0.0094	0.01078	**0.00898**	-0.01944	-0.01991	**-0.01802**	-0.0221	-0.01584	**-0.0088**
MAPE %	25.73	25.79	**25.50**	26.34	26.34	**26.32**	24.61	24.69	**24.47**

Table 16. Cross-validation results for tack coat bid item from 2013 to 2018

	2013			2014			2015		
Prediction Error	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
RMSE	1.33747	1.3404	**1.33999**	1.55031	1.553394	**1.54862**	1.26152	**1.142544**	1.15129
ASE	1.39979	1.30247	**1.30871**	1.51385	1.50524	**1.52013**	1.29857	**1.254809**	1.23866
MSE	-0.0323	-0.0378	**-0.0376**	-0.0062	-0.00645	**-0.0064**	0	**-0.00874**	-0.0049
MAPE %	25.74	25.55	**25.5**	29.76	29.72	**29.56**	26.15	**25.73**	26.05
	2016			2017			2018		
Prediction Error	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
RMSE	0.79563	**0.79007**	0.801	**1.48662**	1.493959	1.49371	1.40199	1.433607	**1.41586**
ASE	0.77203	**0.77307**	0.77204	**1.45922**	1.472317	1.46617	1.42175	1.292284	**1.29737**
MSE	-0.00816	**-0.00482**	-0.01211	**-0.00222**	0.000573	-0.0002	-0.0028	0.012417	**-0.0112**
MAPE %	20.37	**20.26**	20.49	**31.49**	31.77	31.64	28.99	28.99	**28.82**

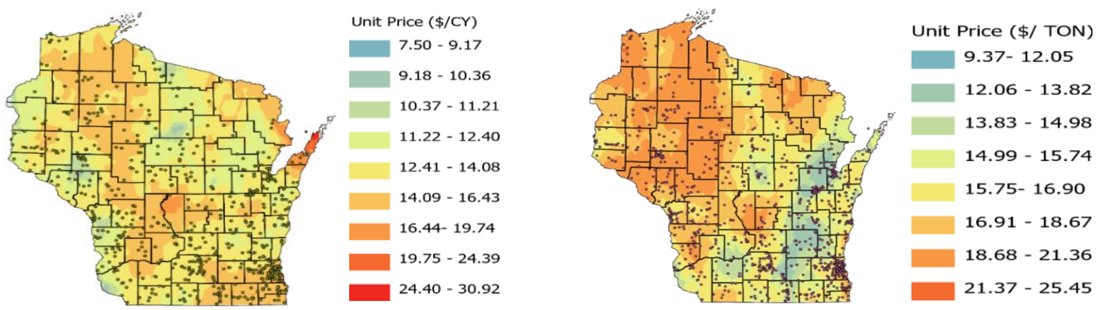
Table 17 provides an assessment of the quality of the models used to interpolate unit prices of the asphaltic surface bid items based on cross-validation results. The results indicate that several combinations of OK and semivariograms assessed the variability of the interpolated surfaces accurately. The MSE values approached zero, which indicates that the model is unbiased. A combination of OK and Gaussian semivariogram performed best in 2013, 2016, 2017. However, in the 2013 dataset, the MAPE value of the OK and Gaussian model versus the OK and spherical model revealed an insignificant difference (0.01%). The high MAPE value obtained from combining OK and exponential semivariogram could be attributed to the high

ASE obtained from the cross-validation results. These results suggest that an appropriate prediction performance could be accomplished using a combination of OK and spherical semivariogram based on MAPE values and the cross-validation statistics. In 2014 and 2018, the prediction performance metrics results suggest that a combination of the OK and exponential semivariogram model was able to predict unit prices of the asphaltic surface with greater precision than Gaussian and spherical semivariogram. Subsequently, a combination of OK and spherical semivariogram performed best in 2015 as shown in Table 17.

Table 17. Cross-validation results for asphaltic surface bid item from 2013 to 2018

Prediction Error	2013			2014			2015		
	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
RMSE	24.6742	24.6655	**24.6842**	29.76504	**29.23062**	30.15866	**28.2085**	28.33452	28.2185
ASE	23.8760	23.9605	**23.7163**	28.42308	**28.3221**	28.4515	**28.1814**	28.12884	28.259
MSE	0.0166	0.0168	**0.0165**	-0.00594	**-0.00361**	-0.00961	**0**	0.003513	0.01362
MAPE %	19.43	19.44	**19.43**	20.78	**20.26**	21.18	**20.80**	23.12	21.75
Prediction Error	2016			2017			2018		
	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
RMSE	33.5461	33.4785	**33.0403**	27.256	27.27187	**26.9529**	23.8368	**23.68897**	23.84
ASE	33.8486	34.4532	**34.6437**	25.7551	25.52324	**25.6753**	23.9264	**23.25351**	23.4793
MSE	-0.00199	0.00651	**0.00511**	-0.00596	-0.00057	**-0.00752**	0.01779	**0.008974**	0.01569
MAPE %	23.41	23.43	**23.07**	19.76	19.74	**19.18**	16.38	**16.12**	16.29

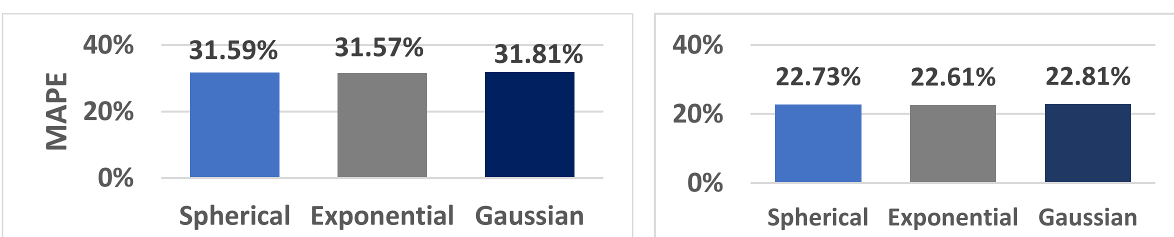
Highway construction unit price bids undergo significant variations because of inflation and deflation over time. This study combined historical cost data of the same bid item in different years (2013 to 2018) and accounted for variation because of inflation and deflation to generate current bid unit price maps. The maps for bid items common excavation and base dense aggregate 1 ¼-inch bid items are shown in Figures 20a and b, respectively. For each of the bid unit price maps, the point shapefile represents the actual bid unit prices for each project location.The unit price maps would enable SHAs to accurately visualize, query, and retrieve unit prices infrastructure unit prices of disparate highway bid items on a map and improve the prediction performance using geospatial analytics. Additionally, cost estimators can ascertain the impact of geographical differences in pricing highway bid items to make better-informed funding decisions at the conceptual phase. To enhance inference from the price maps, SHAs can zoom into a specific county or region and accurately visualize the bid price using the legend provided for each map.



(a) (b)

Figure 20. Interpolation map for combined bid data (2013 to 2018) for (a) common excavation and (b) base aggregate dense 1 ¼" bid data

The performance of the interpolation results for the combined data of the common excavation bid data ranged from 31.57% to 31.87% (Figure 21a), as measured by the MAPE, which is consistent with the year-wise interpolation results from 2013 to 2018. Compared with spherical and Gaussian semivariograms, a combination of OK and exponential variogram provides a more accurate unit price forecast. Similarly, for the base dense aggregate 1 ¼" bid item, a combination of the OK and exponential semivariogram model yielded greater precision than spherical and Gaussian semivariogram models (Figure 21b).



(a) (b)

Figure 21. Comparison of kriging results for combined data (2013 to 2018) for (a) common excavation and (b) base aggregate dense 1 ¼" bid data

Figures 22a and b show the interpolated map for base dense ¾" and tack coat bid items. These maps provide a granular indication of the spatial variation of base dense ¾" and tack coat unit prices across Wisconsin state.

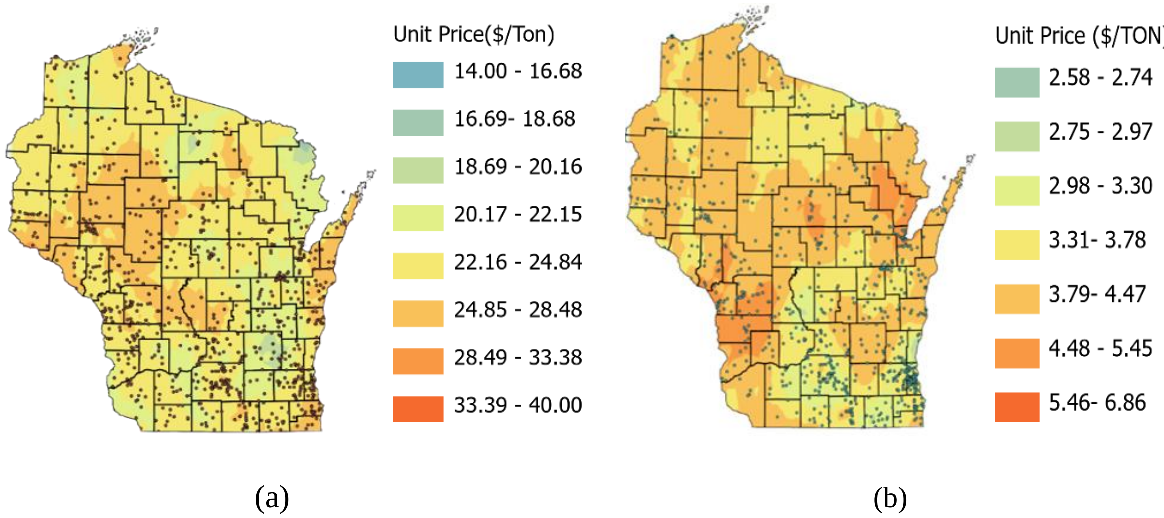
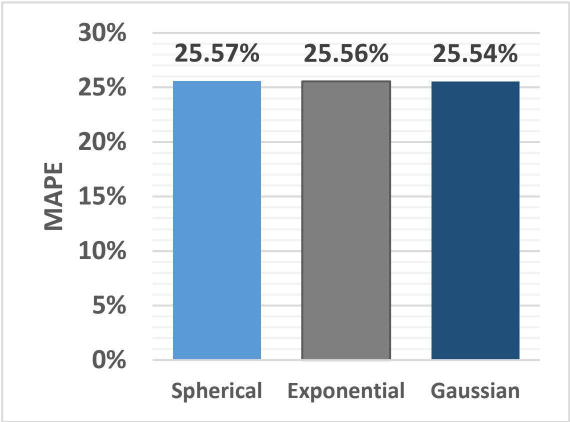
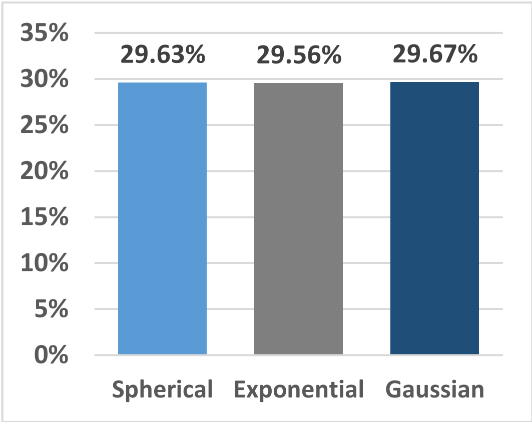


Figure 22. Interpolation map for combined bid data (2013 to 2018) for (a) base aggregate dense ¾" bid unit price and (b) tack coat bid unit price

For the base aggregate dense ¾" bid item, kriging based on the Gaussian semivariogram model performed best with a MAPE value of 25.54% as shown in Figure 23a. The superior performance in Figure 9a is in accordance with the results of the year-wise base dense ¾" bid unit price interpolation models. In Figure 23b, it is evident that a combination of OK and exponential semivariogram model prediction performance (MAPE=22.56%) was superior to spherical and Gaussian variogram models. The results of the disparate combination of OK and semivariogram models are within the range suggested by the AASHTO practical guide to cost estimating (AASHTO 2013) at the conceptual stage of transportation projects.





(a) (b)

Figure 23. Comparison of kriging results for combined data (2013 to 2018) for (a) base aggregate dense ¾" and (b) tack coat bid item

The map for the asphaltic surface bid item were developed and are shown in Figure 24. Figure 25 shows the prediction performance for the combined bid data of the asphaltic surface. The results of the MAPE values ranged from 19.31% to 19.32%. A combination of OK and two semivariograms (spherical and exponential) models performed better compared to ordinary kriging based on the Gaussian semivariogram model. Nevertheless, the results obtained from combining OK and the Gaussian semivariogram model produced acceptable results as the difference between the MAPEs is insignificant. This indicates that the Gaussian model could be used to interpolate tack coat unit prices at unmeasured locations within acceptable prediction accuracy.

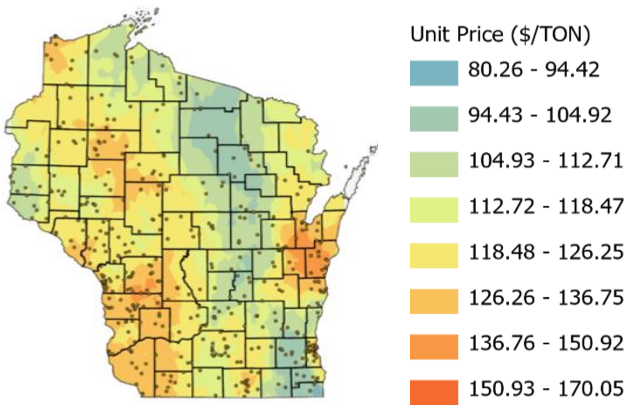


Figure 24. Interpolation map for asphaltic surface bid unit price

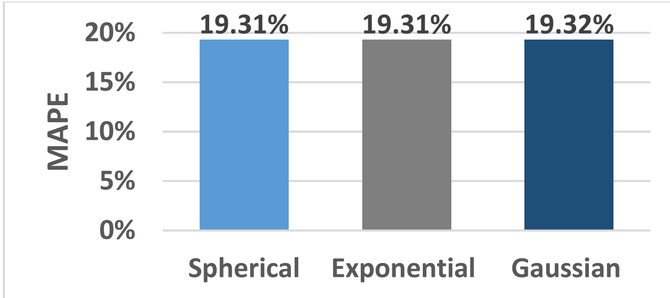


Figure 25. Comparison of asphaltic kriging results for combined data (2013 to 2018)

4.6. Conclusion and Future Works

Challenges associated with ensuring the efficacy and reliability of cost estimation of highway construction bid items, especially during the conceptual phase of a project, are of significant interest to state highway transportation agencies. Even with the existing research undertaken on the subject, the problem of inaccurate estimation of highway bid items still exists. Highway construction costs are subject to significant spatial variations that could disrupt transportation agencies in making the right funding decisions at the conceptual phase. In this study, ordinary kriging was combined with three commonly used semivariogram (spherical, exponential, and Gaussian) to model and interpolate six years (2013 to 2018) of the top five highway bid data; common excavation, base aggregate dense 1 ¼”, base dense aggregate ¾”, tack coat, and asphaltic surface obtained from WisDOT.

For the common excavation, base aggregate dense 1 ¼”, and tack coat bid items, a combination of OK and exponential semivariogram provided an improved prediction accuracy compared to spherical and Gaussian models. Regarding the base aggregate dense ¾”, a combination of ordinary kriging and Gaussian model performed better in minimizing the mean absolute percentage error compared to spherical and exponential models. A combination of OK and two semivariograms (spherical and exponential) models performed best for the unit prices of the asphaltic surface bid item. Nonetheless, a combination of the OK and Gaussian semivariogram model produced acceptable results as the difference between the MAPEs of the three distinct combinations of OK and variograms is insignificant.

This chapter's unique contribution to the start-of-practice is its in-depth application of linear geostatistical (OK) models to interpolate bid data that would enable estimators to easily develop unit price maps of highway construction bid items. Additionally, the geovisualized price maps enable state highway agencies to generate forward-thinking insights about the effect of spatial variations and time of highway bid unit prices across multiple geographic locations.

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CHAPTER 5. COMPARISON OF ORDINARY AND DISJUNCTIVE KRIGING METHODS FOR CONCEPTUAL COST ESTIMATION OF HIGHWAY BID ITEMS[3]

5.1. Abstract

In developing highway construction cost estimates, state highway agencies (SHAs) use location factors to account for uncertainty associated with the spatial variation of highway bid prices across multiple geographic locations. The state-of-the-art has been the application of deterministic and linear geostatistical algorithms that consider only a linear combination of historical cost data to assess the spatial variation on highway unit-price estimates. However, for non-Gaussian data, deterministic and linear predictions are not optimal. This study seeks to compare the prediction performance of ordinary kriging (OK) and disjunctive kriging(DK) methods when used to model and interpolate six years (2013 to 2018) of the top five common highway bid data: common excavation, base aggregate dense 1 ¼-inch, base dense aggregate ¾-inch, tack coat, and asphaltic surface obtained from WisDOT. The findings indicate that for the common excavation, base aggregate dense 1 ¼-inch, base aggregate dense ¾-inch, and tack bid items, the DK algorithms provided a better prediction accuracy over the OK models. Conversely, for the asphaltic surface bid item, the OK model yielded superior prediction accuracy compared to the performance obtained from employing the DK methods. The contribution to the body of knowledge of this paper is the empirical comparison and assessment of the predictive performance of OK and DK algorithms to model and quantify the effect of spatial variation and time on different highway bid unit prices. The price maps developed from this study would

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enable SHAs to visualize and evaluate the temporal changes in prices due to the effect of spatial variability and time on bid unit prices in different geographical areas to make better-informed funding decisions at the conceptual phase of highway projects.

5.2. Introduction

Transportation infrastructure is pivotal for the economic and social development of the world, especially the United States. Many governmental agencies commit significant portions of their budgetary allocations to plan, construct, and maintain their set of highway transportation projects (Love et al. 2019). Cost estimates evolve through conceptual phases into detailed estimates, depending on the amount of information known at the time the estimate is prepared (Al-Tabtabai et al.1999). SHAs require accurate cost estimates for planning future highway construction programs (Wilmot and Mei 2005). Conceptual cost estimates are important to owners, who need to examine the financial viability of a proposed project before committing their resources. While future funding is fraught with uncertainty, incorrect estimation of transportation costs leads to significant overestimation or underestimation of highway construction costs (Walton and Stevens 1997; Baek and Ashuri 2019) and often presents challenges in the successful completion of construction projects (Wilmot and Cheng 2003; Molenaar 2005).

The actual cost of a project is subject to many variables including scope, location, time, size, capacity, human judgmental factors, random market fluctuations, and weather, and complexity, which could significantly influence the range of probable projected costs (AASHTO 2013; Zhang et al. 2016; Baek and Ashuri 2019). Transportation agencies face significant uncertainties in price volatility across different geographical locations due to the changes in the availability of local contractors, materials, equipment, and labor (Baek and Ashuri 2017). A fundamental process in conceptual construction cost estimation is the appropriate adjustment of costs to reflect project location (Zhang et al. 2017). Location adjustment is made using the location factor to convert a base project cost from one geographic location to another by reflecting the relative difference in cost between the two locations (Woo et al. 2017; Parameswaran et al. 2019). There must be a methodology for localizing the cost data, either through a robust and granular localization factor or through deep local research that incorporates local requirements and conditions (Gordian 2020).

The costs of construction materials, equipment, and labor depend on numerous factors, with no explicit mathematical model for price prediction (Adeli and Wu 1998). In construction cost modeling, beta and log-normal distributions are commonly used distribution functions for modeling construction costs. However, selecting an appropriate distribution function for a specific data set may depend on the characteristics of the project data and thus, other distribution functions may provide better fits (Sonmez 2005). The relationship in linear regression imposes a functional relationship that may not always be appropriate for every project or work type (Wilmot and Mei 200; Cao et al. 2018). While this may be partially addressed through the transformation of cost data, the assumption of a specific mathematical formulation limits the ability of the model to fit the data on which it is estimated (Wilmot and Mei 2005). Furthermore, depending on the highway project type and cost data being deployed, the use of nonlinear models could be necessary to capture the nonlinearity inherent in the cost data (Sonmez 2005).

Visualization techniques hold significant potential to represent large data sets of construction information that provide valuable insight into various construction domains (Leite et al. 2016). Geographic information systems (GIS) is a robust technology and can be used to fulfill various requirements of projects including, the integration of diverse datasets to facilitate the development of interactive databases for various construction applications and collective decision making by a single repository within GIS (Bansal 2011). Although GIS has been successfully implemented in many fields for construction engineering management, which includes planning, scheduling, and construction material management, its application in construction cost estimation, especially at the conceptual level, is not prominent (Zhang 2010).

The state-of-the-art has applied deterministic and linear geostatistical models to assess the spatial variation of unit prices on highway cost estimates. However, deterministic and linear approaches assume that the data form a realization of a Gaussian or nearly Gaussian random field, an assumption that produces linear predictors (Rivoirard et al. 2014). Therefore, these algorithms are not capable of accurately modeling the nonlinear relationships and also cannot handle non-Gaussian distributions associated with construction cost data and the cost drivers influencing highway unit prices. Nonlinear kriging methods have a further advantage over linear kriging: their predictions should be more accurate when a Gaussian random process is inappropriate to model the observations (Moyeed and Papritz 2002). Therefore, in assessing the spatial variability of construction costs, there is a need to employ stochastic models that can provide a range of probable costs and account for nonlinear unit price functions to accurately model the cost of highway projects. Unlike linear spatial interpolation, where there is evidence about the predictive performance of various methods, there is a lack of empirical validation studies that compare nonlinear with linear interpolation methods to predict highway construction unit prices at unsampled locations.

In this paper, ordinary kriging, a linear interpolation algorithm is compared to disjunctive kriging, a non-linear geostatistical interpolation method to predict highway construction unit prices from the Wisconsin Department of Transportation (WisDOT) from 2013 to 2018. This study seeks to ascertain the predictive performance of the disjunctive and ordinary kriging models in forecasting the top five highway bid unit prices and quantify the level of variability included in the estimated bid unit price. The remaining parts of the paper are organized as follows. A detailed description of the data, the data preprocessing and exploration, and the geostatistical models used in the study are described in the methodology section. The results and discussion section offer an in-depth assessment of the study's findings and compare the prediction accuracy of the disjunctive kriging and ordinary kriging algorithms. The final part of the paper presents the conclusions derived from the study.

5.3. Methodology

Spatial and spatio-temporal distributions of both physical and socioeconomic phenomena can be approximated by functions depending on location in a multi-dimensional space (Mitas and Mitasova 1999). In this paper, ordinary kriging is compared to the disjunctive kriging technique to estimate highway construction unit prices from the Wisconsin Department of Transportation (WisDOT) from 2013 to 2018. This study combined each kriging technique with the three commonly used variogram models (spherical, exponential, and Gaussian) one at a time to model the top five bid items.

Exploratory spatial data analysis was used to determine the statistical properties of the data. Geostatistical inferences using kriging techniques are more efficient when data for variables are distributed normally (Wu et al. 2006). Transformation of data may be desirable before kriging to satisfy the normality assumption, suppress outliers, and improve data stationarity (Varouchakis et al. 2012). Disjunctive kriging requires that the data follow a bivariate normal distribution (Eldeiry and Garcia 2012), using the normal score transformation (NST). NST ranks the dataset from lowest to highest values and matches these ranks to equivalent ranks from a standard normal distribution (Gribov and Krivoruchko 2012; Cecinati et al. 2017). The exploratory spatial and statistical data analysis was followed by variogram analysis and kriging. Cross-validation and statistical error metrics were then used to evaluate the validity and correctness of the results. The same process was repeated for all the combinations of the kriging and variogram algorithms and formed the basis of comparison and selection of the best results (Figure 26).

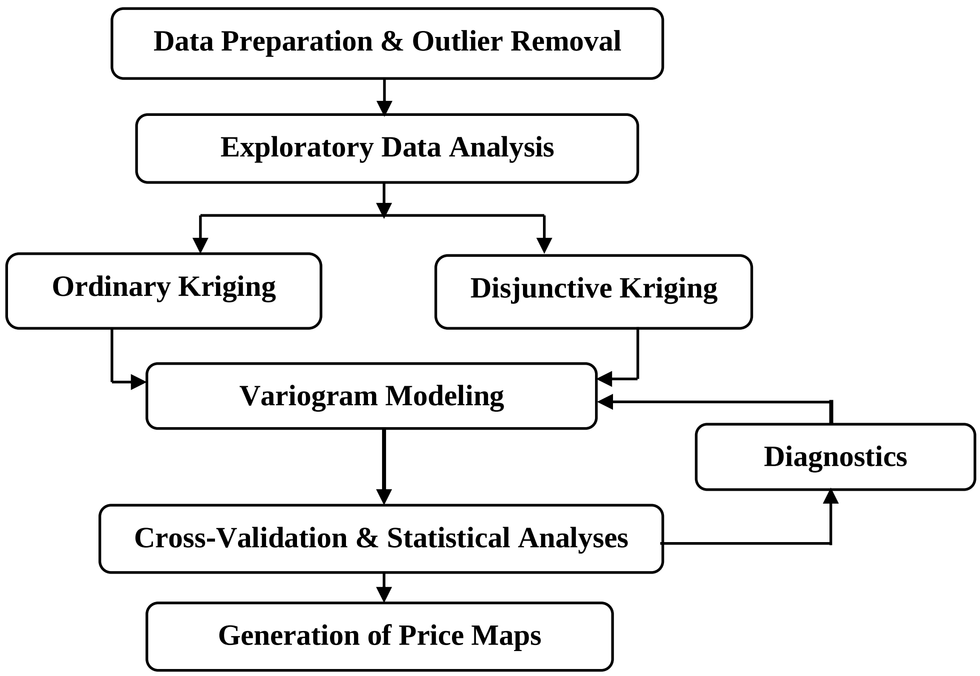


Figure 26. Research methodology

5.3.1. Geostatistical Interpolation Methods

Spatial interpolation models are employed to predict the value of a variable of interest at unmeasured locations using available measurements at sampled locations (Meng et al. 2013). Kriging, a variant of spatial interpolation is one of the commonly used geographic techniques for spatial data visualization, the spatial query of properties, and decision-making (Hassanein 2006; Asa et al. 2012; Meng et al. 2013). Linear kriging algorithms are distribution-free linear interpolation techniques, which are similar to linear regression (Asa et al. 2012).

In contrast, nonlinear estimation methods like disjunctive kriging perform better, have lower estimation variance, and allow less risky economic decision-making (Daya and Zaremotlagh 2013). The steps in applying these techniques include developing theoretical semivariogram models that describe the spatial variation between pairs of spatially related samples and then using these models to estimate sample parameters and their error variances at unknown locations (Gupta et al. 2017).

5.3.2. Variogram Modeling

The experimental variogram represents the spatial variability in the data and is used to determine the optimal weights during kriging. Accurate estimates of variograms are needed for efficient and reliable prediction by kriging, for optimizing sampling schemes and subsequent mapping (Armstrong 1984; Oliver and Webster 2015). Different variogram models may lead to different predictions (Li and Heap, 2008) thus, selecting an appropriate model to capture the features of the data is critical (Li et al. 2011). In this study, three commonly used variogram models, namely (1) spherical (Eq. 23), (2) exponential (Eq. 24), and (3) Gaussian (Eq. 25) were employed to assess the spatial variability of unit price data from 2013 to 2018.

$$\gamma(h) = Sph\left(\frac{h}{a}\right)\left\{\frac{1.5h}{1} - 0.5\left(\frac{h}{a}\right)^3\right\} \tag{23}$$

$$\gamma(h) = 1 - exp\left(\frac{-3h}{a}\right) \tag{24}$$

$$\gamma(h) = 1 - exp\left(\frac{-3h^2}{a}\right) \tag{25}$$

were h and a are referred to as distance and range, respectively.

5.3.3. Ordinary Kriging (OK)

In the OK algorithm, unknown values are obtained from linear combinations of observed data (Adhikary et al. 2016) where the weights are determined by a stochastic model of the spatial dependence quantified by the semivariogram (Shiode and Shiode 2011). The ordinary kriging estimator is furnished in Eq. (26) (Asa et al. 2012):

$$Z_{OK}^{*}(\chi) = \sum_{i=1}^{n} \omega_i(\chi).Z(\chi_i) + \left[1 - \sum_{i=1}^{n} \omega_i(\chi)\right] m(\chi) \tag{26}$$

where $Z(\chi_i)$= random variable at the location χ; χ_i = *n* data locations; $\omega_i(\chi)$= weights; and $m(\chi)$= mean.

5.3.4. Disjunctive Kriging

The disjunctive kriging (DK) method is a nonlinear estimator that is suitable for interpolating a spatially variable property. Generally, the DK has several advantages over linear estimation methods in that it reduces kriging variance compared to linear kriging estimators (Yates et al. 1986; Samui and Sitharam 2010). DK provides a solution space larger than the conventional kriging techniques that only rely on linear combinations of the data (Yates and Warrick 1986; Asa et al. 2012). The disjunctive kriging estimator is given by Eq. (27) (Asa et al. 2012; Daya and Zaremotlagh 2013):

$$Z_{DK}^{*}(y) = \sum_{i=1}^{N} \lambda_i \left(Z(y_i)\right) \tag{27}$$

where $Z(\mathrm{y})$ = measured values, $Z(y_i)$ = predicted value, and λ_i = nonlinear functions of the data.

5.3.5. Cross-Validation

To evaluate the performance of the ordinary and disjunctive kriging algorithm, cross-validation statistics were computed and used as a diagnostic to indicate whether the performance of the models are acceptable and to compare the two methods. Cross-validation removes each data location one at a time and predicts the associated data value and compares the measured and predicted values. Cross-validation prediction errors (Eqns 28 through 32) were used to guarantee that the prediction was unbiased, as close as possible to the measured values, and that the variability of the prediction was correctly assessed (Eldeiry and Garcia 2012; Wackemagel 2013; Oliver and Webster 2014).

The mean standardized error (MSE) was used to check if the models were unbiased, the closer the MSE values to zero, the better the performance of the model. The root-mean-square error (RMSE) (Eqn 30) was used to check whether the prediction is close to the measured values. The smaller the RMSE value, the closer the predictions were to the measured values.

The variability of the predicted data was assessed in two ways; first, by comparing the average standard error (ASE) with the RMSE. If the values are similar, then the variability in the prediction is correctly assessed. If the ASE value is greater than the RMSE value, then the variability of the predictions is overestimated; otherwise, the variability of the predictions is underestimated. Second, the variability of the data was assessed by evaluating the root-mean-square standardized error (RMSSE). If the RMSSE is close to one, then the variability of the prediction is correctly assessed; if greater than one, then it is underestimated; and otherwise, it is overestimated (Robinson and Metternicht 2006; Asa et al. 2012; Eldeiry and Garcia 2012; ESRI 2020).

$$\text{Mean Error} = \frac{1}{n}\sum_{i=1}^{n}\{(y_i) - (y_o)\} \tag{28}$$

$$Mean\ Squared\ Error = \frac{1}{n}\sum_{i=1}^{n}\left\{\left(\frac{y_i - y_o}{\sigma^2(y_i)}\right)\right\} \tag{29}$$

$$Root\ Mean\ Square\ Error = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_o)^2} \tag{30}$$

$$Root\ Mean\ Square\ Standardized\ Error = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n}\left[\frac{(y_i - y_o)}{\sigma^2(y_i)}\right]^2\right)} \quad (31)$$

$$Average\ Standard\ Error = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\sigma^2(y_i)} \quad (32)$$

where (y_i) and y_o are measured and predicted bid unit price, respectively, of the *ith* data point, n is the total number of data points, and σ^2= kriging variance for location y_i.

5.3.6. Statistical Analyses

Examining residuals is a key part of all statistical modeling, and a careful look at residuals can determine if the selected algorithm and its underlying assumptions are reasonable and appropriate to model the phenomena. To evaluate which spatial prediction method provided the most accurate estimates of unit prices for each bid item, the following statistical analyses were computed to compare the OK and DK model residuals:

Mean absolute percentage error (MAPE) is a common measure used for assessing the level of accuracy of the algorithms used to estimate the cost of highway bid items (Gardner et al. 2017). The equation for computing MAPE is furnished in equation 33 (Choi et al. 2014; Gardner et al. 2017):

$$MAPE = \left(\frac{100\%}{n}\right)\sum_{i=1}^{n}\left|\frac{S_i - M_i}{M_i}\right| \quad (33)$$

The RMSE-observations standard deviation ratio (RSR) is the ratio of the RMSE to the standard deviation (Eldeiry and Garcia 2012a). RSR varies from the optimal value of zero, which indicates zero residual variation and therefore a better model prediction to a large positive value (Moriasi et al. 2007). RSR is calculated using equation 34 (Moriasi et al. 2007):

$$RSR = \frac{\sqrt{\sum_{i=1}^{n} (M_i - S_i)^2}}{\sqrt{\sum_{i=1}^{n} \left(M_i - \overline{M}\right)^2}} \tag{34}$$

Percent bias (PBIAS) is a measure of the deviation of the evaluated data expressed as a percentage. It measures the tendency of the predicted data to be higher or lower than the observed data, indicating the model performance (Jung et al. 2020). The optimal value of PBIAS is zero with low magnitude values indicating accurate model simulations (Gupta et al. 1999)**.** PBIAS is computed using equation 35 (Gupta et al. 1999):

$$PBIAS = \frac{\sum_{i=1}^{n} (M_i - S_i) \times 100}{\sum_{i=1}^{n} (S_i)} \tag{35}$$

Mean Absolute Error (MAE) measures the average magnitude of absolute differences between actual and predicted values. MAE is calculated using equation 36 (Ashuri and Lu 2010):

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |S_i - M_i| \tag{36}$$

In equations (11)-(14), n= number of data points; S_i = predicted bid unit price M_i = actual bid unit price for the *ith* project, and $\overline{M}$=average of actual bid unit prices

To ascertain the benefit of introducing the DK model, this paper quantified the performance of the advanced approach (DK) compared to the reference (OK). The relative improvement in the RMSE and MAE values due to the disjunctive kriging algorithm are measured using equation 37:

$$RI = \frac{100 \times (RMSE_{OK} - RMSE_{DK})}{RMSE_{OK}} \tag{37}$$

To account for variations due to cost escalation and inflation over time in the unit prices of the highway bid items, the unit prices were converted to a march 2020 base cost using the Wisconsin Department of transportation Construction Cost Index and Equation 38. The WisDOT CCI uses the same methodology as the Federal Highway Administration's National Highway Construction Cost Index (NHCCI). The WisDOT Chained Fisher Construction Cost Index (WisDOT CCI) provides an indication of construction cost escalation over time and inflation rates to convert past bid history into current year dollars (WisDOT 2010).

$$Current\ Bid\ Price = \frac{Current\ \ Index\ Value}{Past\ Index\ Value} \times Past\ Bid\ Price \tag{38}$$

5.4. Results and Discussion

5.4.1. Exploratory and Statistical Data Analysis

The descriptive statistics of the unit price of a sample bid unit price, tack coat for each year was computed to characterize and describe the data (Table 18). The coefficient of variation (SD/Mean) and median absolute deviation(MAD), a measure of heterogeneity indicates high variability in the pricing of the bid unit prices from 2013 to 2018. This heterogeneity could be attributed to the uniqueness of each construction project selected for the study (Ballesteros-Pérez et al. 2020). The heterogeneity associated with these bid items presents complexity due to the need to meet stationarity assumptions for accurate cost modeling using linear geostatistical algorithms.

The normality assumption was assessed using two numerical measures of shape-skewness and kurtosis indexes. From Table 1, the results indicate that the data is skewed and have kurtosis that is fairly different from that of the normal distribution. If a variable of interest has a positive skewness, the confidence limits on the variogram are wider than they would otherwise be and consequently, the kriging variances are less accurate (Reza et al. 2010).

The results of the exploratory spatial analysis indicated the presence of trends in the bid dataset. Therefore, to satisfy the stationarity assumption and model short-range variation, these datasets were detrended prior to modeling the semivariograms to improve the model's prediction performance.

The global Moran's I test results for the top 5 bid items from 2013 to 2018 are summarized in Table 2. The Moran's I index for common excavation, base aggregate 1 ¼-inch, tack coat, and asphaltic surface bid items are positive, and the Z score and p-value are significant, which indicates that the null hypothesis of no spatial autocorrelation is rejected. For the base aggregate dense ¾-inch bid item, the Moran's I index was positive. However, there was insufficient evidence to reject the null hypothesis of no spatial autocorrelation as indicated in Table 19.

Table 18. Descriptive statistics of top five highway bid unit prices

Bid Item	N	Unit	Mean	COV	Skewness	Kurtosis	MAD	SD
Tack Coat								
2013	142	GAL	4.25	32.96	0.74	-0.52	0.97	1.4
2014	176	GAL	6.56	68.25	1.19	0.43	1.88	4.48
2015	92	GAL	3.39	34.31	0.84	0.14	0.53	1.16
2016	151	GAL	3.15	26.51	0.78	-0.09	0.41	0.84
2017	195	GAL	4.52	57.18	1.11	0.3	0.99	2.58
2018	202	GAL	4.92	56.5	1.15	0.22	1.14	2.78

Table 19. Spatial autocorrelation for the combined data of the top five highway bid unit prices

Bid Data	Moran's, I Index	Z-score	P-value	Clustered	Significance
Excavation Common	0.053	2.904	0.004	Yes	Yes
Base Aggregate 1 1/4"	0.148	8.636	0	Yes	Yes
Base Aggregate 3/4"	0.031	1.618	0.1057	Yes	No
Asphaltic Surface	0.104	4.992	0	Yes	Yes
Tack Coat	0.096	4.84	0	Yes	Yes

5.4.2. Performance Evaluation of Spatial Interpolation Algorithms

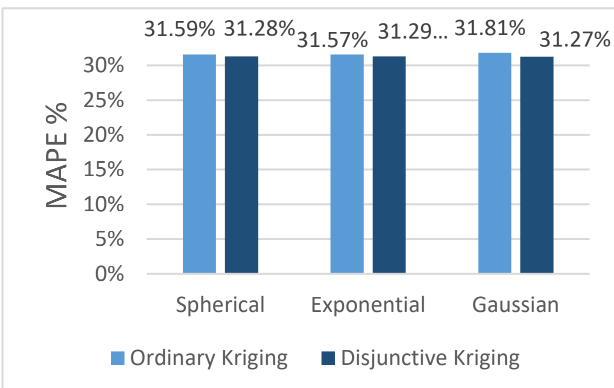
Highway construction costs are subject to significant variations from project to project and over time which results in dynamic changes in prices for different bid items. Different datasets of the same bid item converging toward one value provide a high degree of confidence in the data (GAO 2020). This study combined historical cost data of the same bid item in different years and accounted for spatial variations and variation due to inflation and deflation to generate current price maps for the top five bid items. To establish which spatial prediction method provided the most accurate estimates of unit prices for each bid item, cross-validation, and statistical analyses were used to compare the interpolation results with their actual values.

The results of different combinations of common excavation models indicate robust performance with insignificant differences. For each kriging technique, the ME and MSE generally approach zero which indicates an unbiased for the two kriging algorithms. The RMSSE and the difference between the RMSE and ASE values for all combinations of DK and semivariogram models overestimated the variability of the interpolated unit prices. In contrast, the OK algorithms underestimated the variability of the interpolated unit prices as measured by RMSSE. However, the DK models used to interpolate unit prices yielded the least error as measured by cross-validation statistics, ME, MSE, ASE, RMSE, and thus was considered as the best predictive geostatistical algorithm (Table 20).

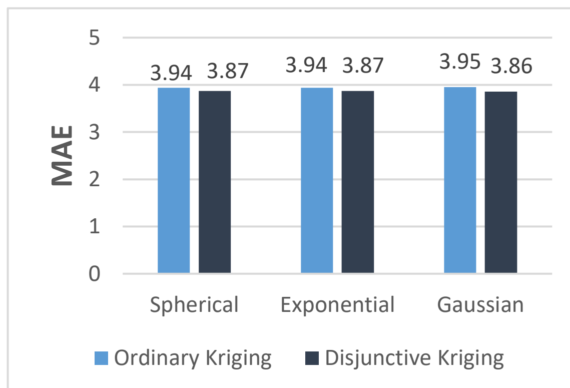
Table 20. Cross-validation results for the combined data of common excavation bid item

	OK	DK	OK	DK	OK	DK
Prediction Error	Spherical	Spherical	Exponential	Exponential	Gaussian	Gaussian
ME	0.00939515	**-0.007228**	-0.0092713	**0.00065027**	0.0242742	**-0.0147**
RMSE	4.93730573	**4.8451894**	4.93295446	**4.84318872**	4.9390726	**4.84706**
ASE	4.94197071	**4.7834449**	4.9617995	**4.78723897**	4.8781986	**4.77851**
MSE	0.00201683	**-0.001539**	-0.0019845	**0.000074**	0.0049455	**-0.0031**
RMSSE	0.9982792	**1.0129245**	0.99343504	**1.01177257**	1.0124009	**1.01432**

To substantiate the cross-validation results, residual assessment statistics: MAPE, MAE, RSR, and PBIAS values were computed to assess the performance of the several combinations of OK and DK geostatistical models. From Figure 27, the DK models have smaller MAPE, RSR, and MAE values, which indicate better prediction performance compared to the OK models. Subsequently, the PBIAS values of both kriging models based on the spherical and exponential semivariogram models indicate 0.10% model underestimation bias. However, OK incorporating Gaussian semivariogram model indicates an overestimation bias whereas, DK based on Gaussian semivariogram indicates 0.10% model underestimation bias (Figure 27d).



(a)



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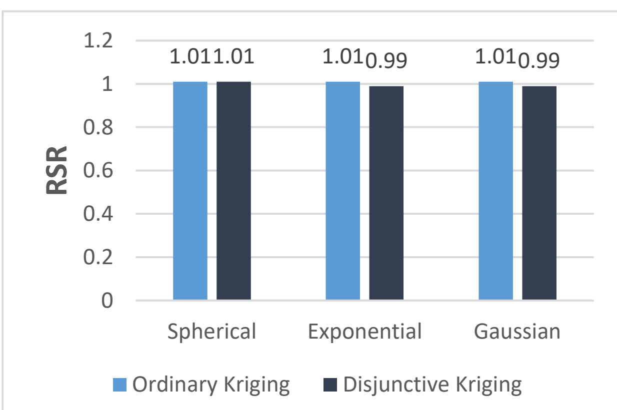

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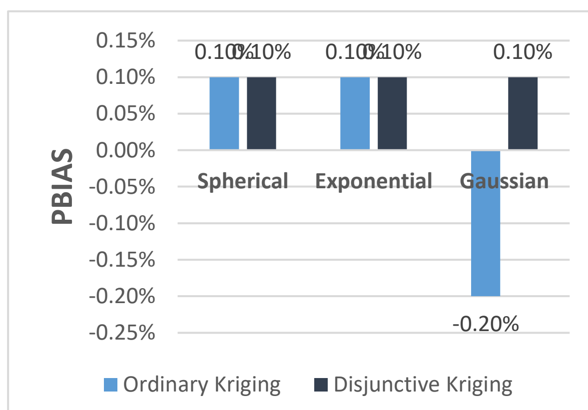


(d)

Figure 27. Model residual assessment parameters evaluated for combined data of common excavation bid item: (a) MAPE; (b) MAE; (c) RSR; (d) PBIAS

Table 21 presents the relative improvement performance of the DK technique over the OK models used to interpolate the common excavation bid unit prices. A comparison of OK and DK models shows that a reduction in prediction error of 2% for RMSE and MAE was obtained with the DK algorithms. However, this improvement obtained from combining the DK and semivariograms are relatively small. Therefore, the computational complexity associated with the DK model does not compensate for the 2% accuracy over the OK interpolation model.

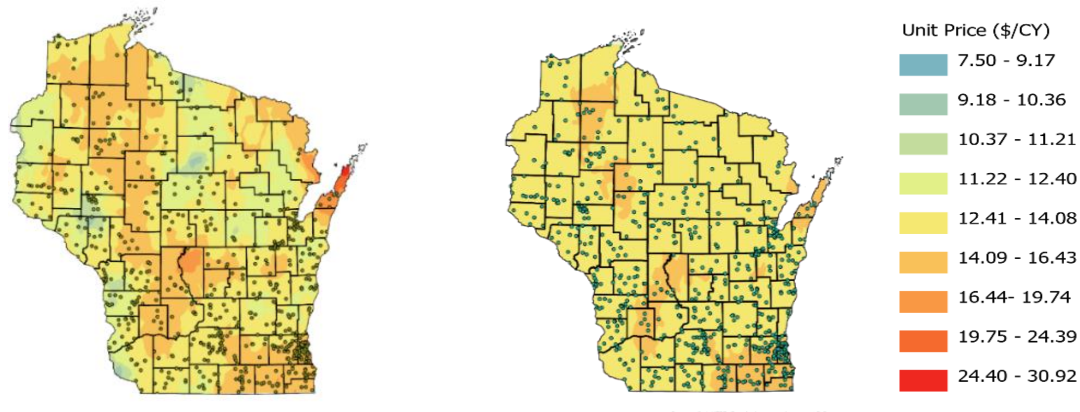
Table 21. Performance of interpolation methods in terms of improvement over ordinary kriging models for prediction of common excavation bid unit prices

	Improvement in RMSE by DK			Improvement in MAE by DK		
Models	OK	DK	RI (%)	OK	DK	RI(%)
Spherical	4.94	4.85	1.82	3.94	3.87	1.78
Exponential	4.93	4.84	1.83	3.94	3.87	1.78
Gaussian	4.94	4.85	1.82	3.95	3.86	2.28

Figures 28a and b show the interpolated surfaces for common excavation based on ordinary kriging and disjunctive kriging in a 2D visualization environment. The closer the surface is to the sample points, the better the performance of the interpolation technique for that dataset (Eldeiry and Garcia 2012).

The price map (Figure 28b) shows that OK captures the spatial variation of unit prices accurately; and therefore, the interpolated surfaces are close to the actual bid unit prices. However, the price map generated using the DK model appears to have a smoother surface with higher unit prices across multiple geographical locations.

The performance of the OK and DK algorithms used to predict unit prices for aggregate dense 1 ¼-inch bid items are evaluated in Table 22.



(a) (b)

Figure 28. Excavation common price maps for (a) ordinary kriging and (b) disjunctive kriging

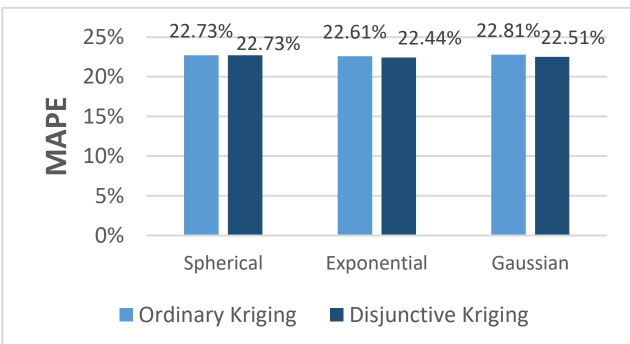
The ME and MSE were near zero and suggest that the unit price predictions for the base aggregate dense 1 ¼-inch are fairly unbiased for both DK and OK algorithms. Additionally, in both algorithms, the ASE values were greater than the RMSE, therefore, the models are overestimating the variability of the predictions. This observation was substantiated by the results of the RMSSE values which are greater than one, hence the variability is being overpredicted to a small magnitude. However, for the OK techniques based on the Gaussian semivariogram model, the RMSE was greater than the ASE values which indicates that the model underestimated the variability of the interpolated unit prices.

Table 22. Cross-validation results for base aggregate dense 1 ¼" bid item

	OK	DK	OK	DK	OK	DK
Prediction Error	Spherical	Spherical	Exponential	Exponential	Gaussian	Gaussian
ME	0.00916436	**0.0072187**	0.00087855	**-0.0260082**	0.0098973	**-0.06076**
RMSE	4.36959142	**4.3496413**	4.36152288	**4.33708869**	4.378139	**4.343115**
ASE	4.22583781	**4.3054413**	4.16118353	**4.15268018**	4.3886204	**4.1742973**
MSE	0.0025144	**0.0020808**	0.00086513	**-0.0057416**	0.0024396	**0.0133894**
RMSSE	1.0332604	**1.0097129**	1.04690019	**1.04390098**	0.9971108	**1.039385**

The individual cross-validation statistics were ranked for each combination of the OK and DK models. The results indicate that for each combination of kriging and semivariogram algorithm, the DK model yielded a better prediction accuracy compared to OK algorithms.

Figure 29 shows the plots of various error statistics used to evaluate the residuals of DK and OK models for the base aggregate 1 ¼-inch bid item. OK, and DK algorithms based on spherical semivariogram yielded a similar performance as measured by MAPE values (Figure 29a). However, the performance of the base aggregate dense 1 ¼-inch cost models measured by the mean absolute percentage error indicates that for the exponential and Gaussian semivariogram,the DK algorithm yielded better predictive accuracy than the OK algorithm.



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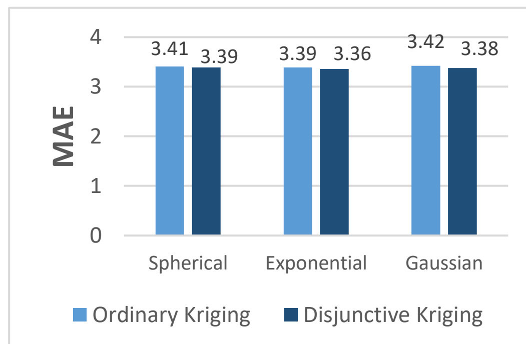

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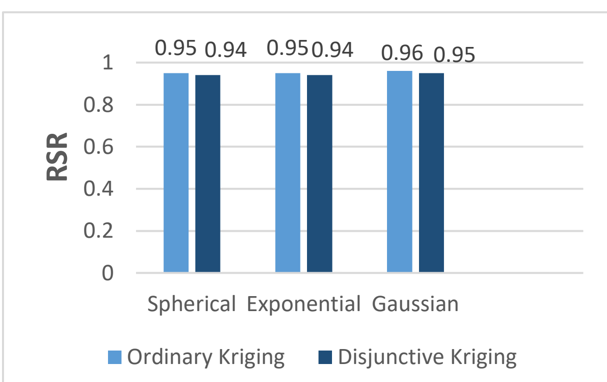

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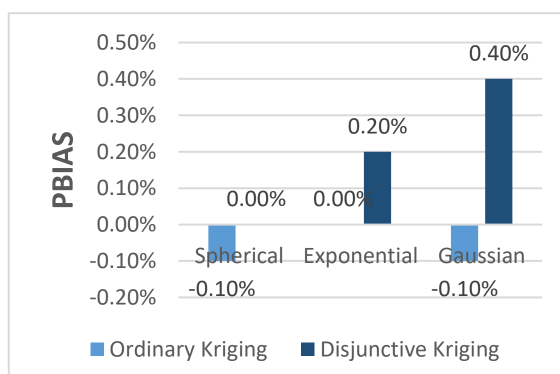


(d)

Figure 29. The model residual assessment parameters evaluated for combined data of base dense aggregate 1 ¼-inch bid item: (a) MAPE; (b) MAE; (c) RSR; (d) PBIAS

Similarly, the DK algorithm yielded lower RSR and MAE error analysis values, which indicate a better model performance compared to the OK algorithms. The PBIAS values for the DK based on exponential and Gaussian semivariograms indicate model underestimation bias, whereas the OK algorithms incorporating spherical, and Gaussian overestimated the bias compared to the actual base aggregate 1 ¼-inch bid unit prices.

The relative performance of the DK models over the OK was quantified and is presented in Table 23. The results show that the DK models yielded an RMSE between 0.5% to 5% lower than the OK geostatistical models. Similarly, the reduction of MAE for the DK over the OK algorithm was between 0.5% to 1.5%.

Table 23. Performance of interpolation methods in terms of improvement over ordinary kriging models for prediction of base dense aggregate 1 ¼-inch bid unit prices

	Improvement in RMSE by DK			Improvement in MAE by DK		
Models	OK	DK	RI (%)	OK	DK	RI(%)
Spherical	4.37	4.34	0.69	3.41	3.39	0.59
Exponential	4.36	4.33	0.69	3.39	3.36	0.88
Gaussian	4.38	4.17	4.79	3.42	3.38	1.17

Figure 30 shows a set of 2D price maps for the base aggregate 1 ¼-inch bid items. The actual bid unit prices of the base dense 1 ¼-inch bid item were superimposed onto the interpolation surfaces generated from the respective kriging algorithms.

Comparison between the two price maps shows that both kriging algorithms captured most of the spatial variation of the base aggregate dense 1 ¼-inch bid unit prices accurately across multiple geographical locations.

Leave-one-out cross-validation was performed to evaluate the prediction performance of the OK and DK models used to interpolate base aggregate dense ¾-inch (Table 24). The results indicate that the ME and MSE for the OK and DK algorithm yielded nearly unbiased estimates of the accuracy, but with relatively high variability, particularly the RMSE values were greater than the ASE, which indicates that the OK models underestimated the variability of the predictions than the Dk models.

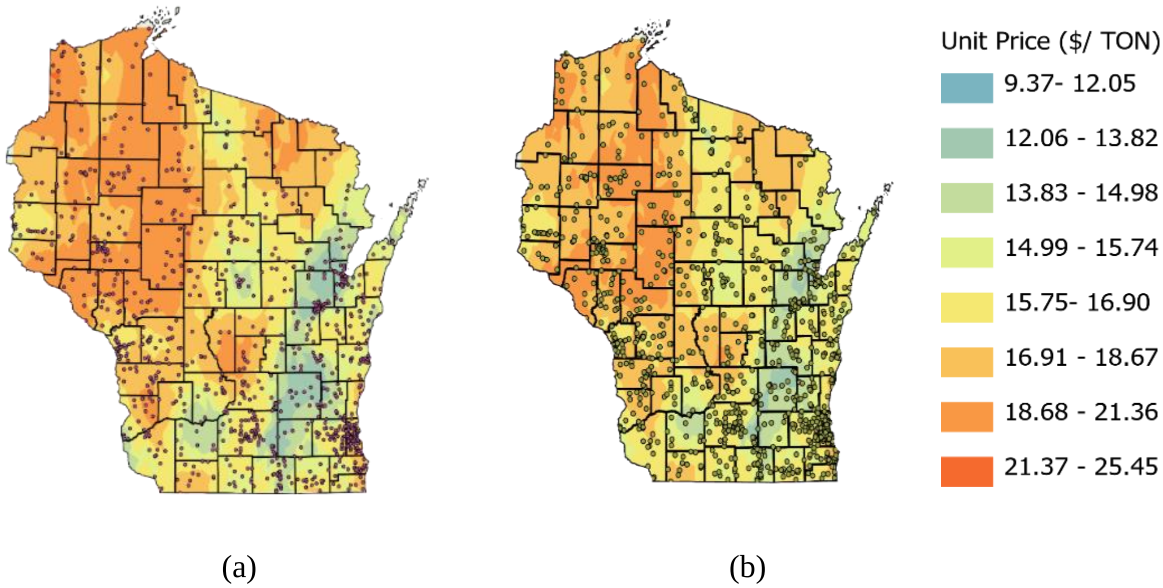


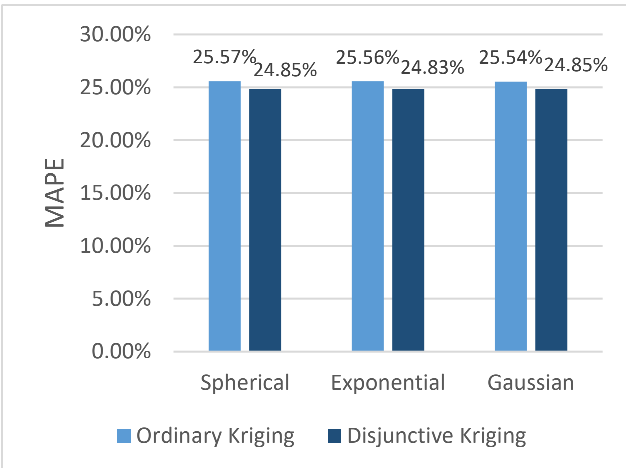
Figure 30. Base aggregate dense 1 ¼-inch price maps for (a) ordinary kriging and (b) disjunctive kriging

Table 24. Cross-validation results for base aggregate dense 3/4" bid item

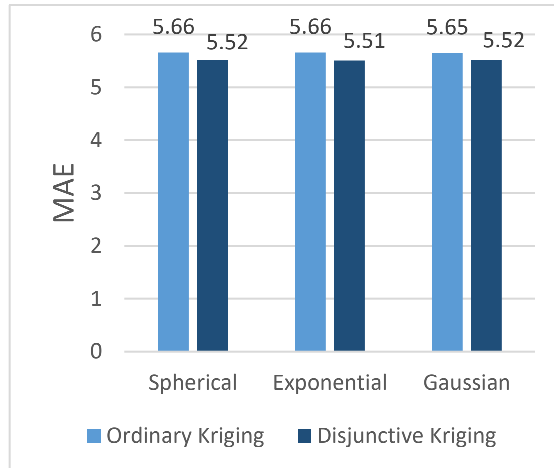
	OK	DK	OK	DK	OK	DK
Prediction Error	Spherical	Spherical	Exponential	Exponential	Gaussian	Gaussian
ME	0.00567673	**-0.053297**	-0.0044389	**-0.027157**	-0.007233	**-0.0299963**
RMSE	7.1754479	**6.9930364**	7.1709925	**6.98808169**	7.1684188	**6.98672918**
ASE	6.95601444	**6.8979323**	6.91080837	**6.86271188**	7.0234152	**6.868496177**
MSE	0.00082514	**-0.007734**	-0.0006649	**-0.0039762**	-0.001032	**0.004386019**
RMSSE	1.03099305	**1.0135867**	1.0368697	**1.01796667**	1.0201503	**1.01697952**

A comparison between the results of the different combinations of DK and the OK models indicates that DK algorithms produce an enhanced prediction performance (lower ME, MSE, RMSE, and RMSSE) for the combined base dense aggregate ¾-inch bid data (Table 24). To further assess and corroborate the comparative performance of the different combinations of OK and DK models used to interpolate base aggregate dense ¾-inch bid unit prices, MAPE, MAE, RSR, and PBIAS values were computed and formed the basis of comparison (Figure 31).

The results of the MAPE, MAE, and RSR values were low for the DK models, which indicate a superior performance that is consistent with the results obtained from the cross-validation statistics from Table 24. The PBIAS values show that the overestimation bias of the DK models' is higher compared to the OK algorithms (Figure 31)



(a)



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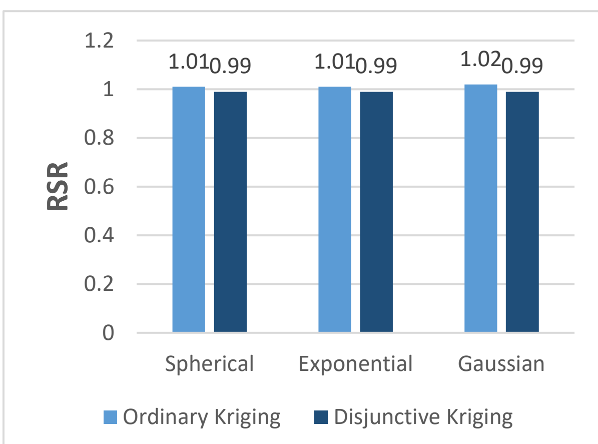
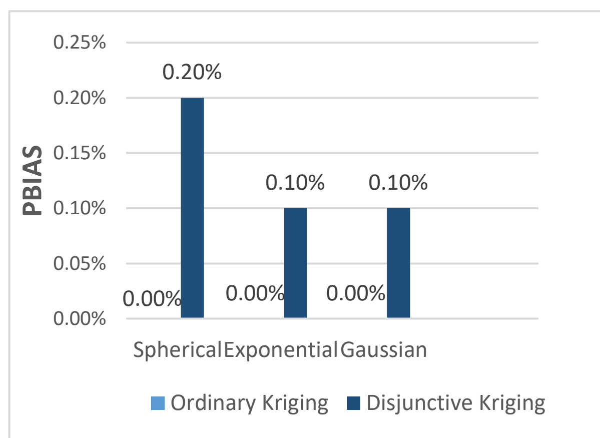


(c)



(d)

Figure 31. Model residual assessment parameters evaluated for combined data of base dense aggregate 3/4-inch bid item: (a) MAPE; (b) MAE; (c) RSR; (d) PBIAS

To test the performance of DK over the OK algorithm, Table 25 presents the results of relative improvement analysis of the OK and DK and the three semivariogram models employed to model the base aggregate dense ¾-inch bid item. The reduction of the RMSE of DK over OK ranged from 2.51% to 2.65%. Subsequently, the MAE value of the DK algorithm showed a moderate reduction from 2.30% to 2.65% as shown in Table 25.

Table 25. Performance of interpolation methods in terms of improvement of DK over OK models for prediction of base dense aggregate ¾-inch bid unit prices

	Improvement in RMSE by DK			Improvement in MAE by DK		
Models	OK	DK	RI (%)	OK	DK	RI(%)
Spherical	7.18	6.99	2.65	5.66	5.52	2.47
Exponential	7.17	6.99	2.51	5.66	5.51	2.65
Gaussian	7.17	6.98	2.65	5.65	5.52	2.30

Figure 32 shows the interpolated surfaces for base aggregate ¾-inch bid unit prices generated using ordinary kriging and disjunctive kriging in a 2D visualization environment. From Figure 32 (a), the OK price map is closer to the actual price data whereas the DK interpolation map for the base aggregate dense ¾-inch appears smoother with more values between ($22.16 to $24.84). This indicates that the OK model offers a more accurate price map compared to the maps obtained from the DK algorithm, which provides a misleading picture of the variation in a region.

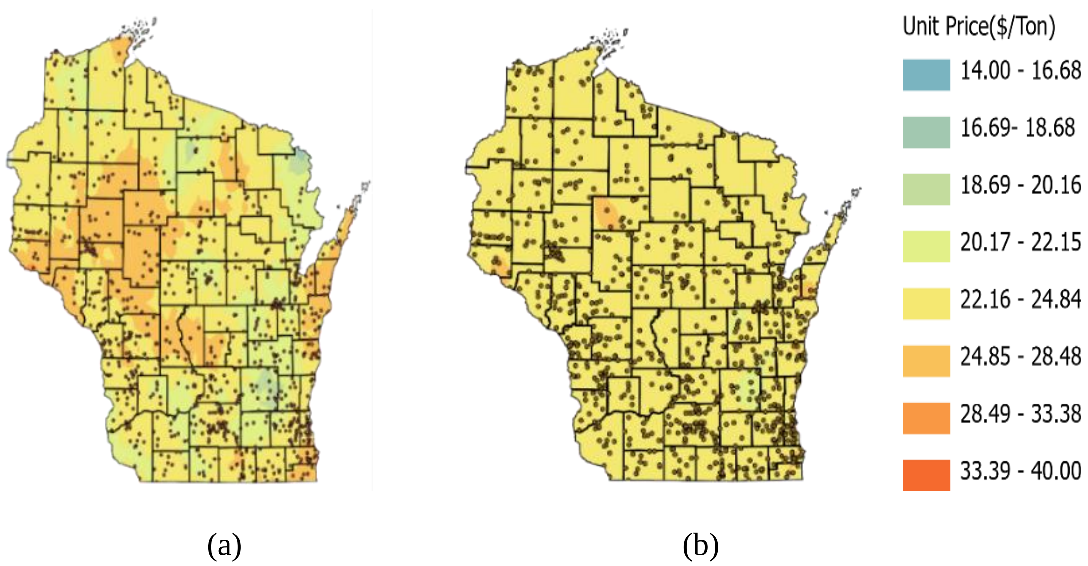


Figure 32. Base aggregate dense ¾-inch price maps for (a) ordinary kriging and (b) disjunctive kriging

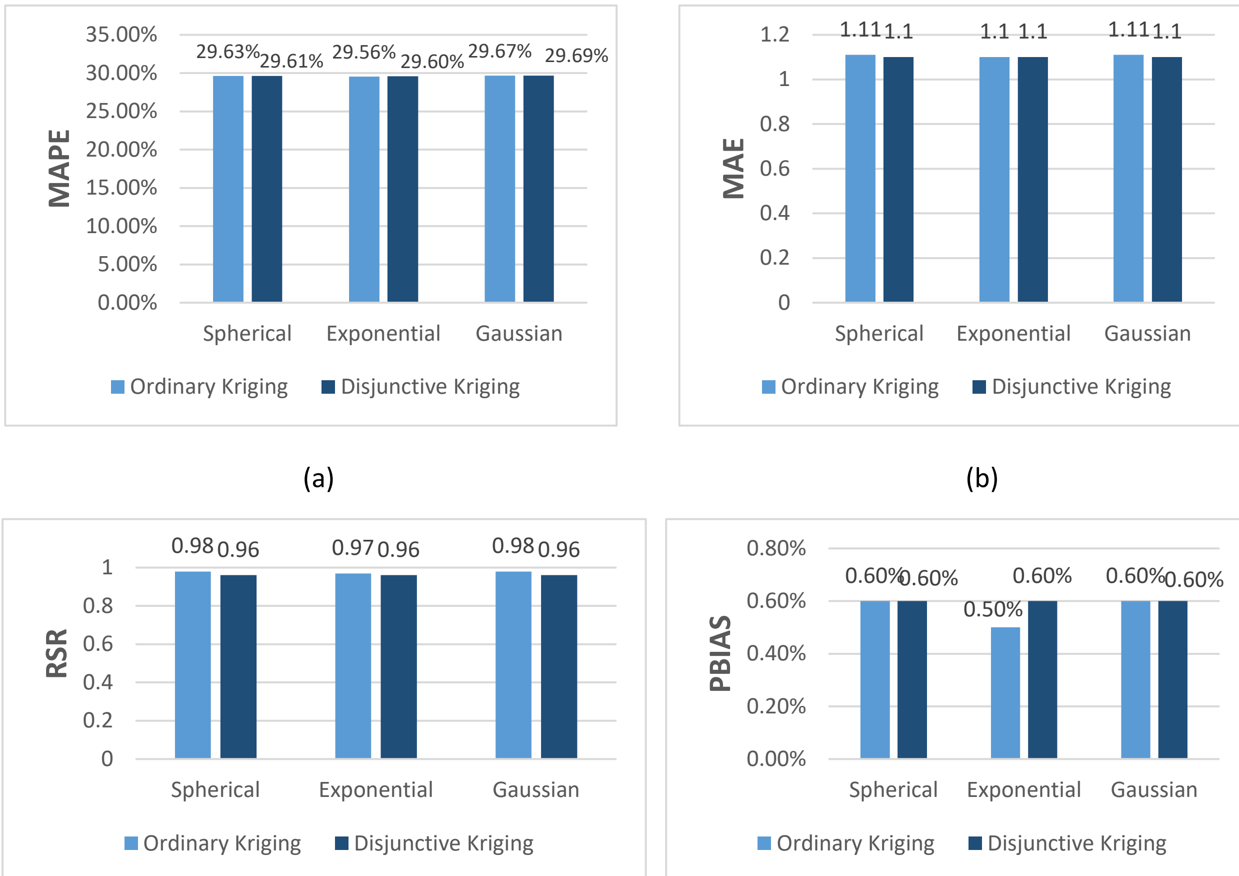
The cross-validation comparison of the OK and DK algorithms for the tack coat bid unit prices is presented in Table 26. In terms of accuracy, DK models yielded slightly better results than the OK algorithms with lower prediction errors. However, a comparison of the kriging models shows that both algorithms overestimated the variability of the interpolated values with the OK models generating an accurate variability of the predicted values.

Table 26. Cross-validation results for tack coat bid item

	OK	DK	OK	DK	OK	DK
Prediction Error	Spherical	Spherical	Exponential	Exponential	Gaussian	Gaussian
ME	0.02110056	**-0.024284**	-0.0185729	**-0.0237875**	-0.024472	**-0.0215281**
RMSE	1.41421655	**1.3890988**	1.40893847	**1.38873187**	1.4187475	**1.38833357**
ASE	1.37745318	**1.2870931**	1.3790302	**1.2750683**	1.3773384	**1.276243049**
MSE	0.01549432	**-0.019442**	-0.0140277	**-0.0192094**	-0.017656	**0.017738371**
RMSSE	1.02674021	**1.0794925**	1.02212203	**1.08925282**	1.0299017	**1.08815301**

Mean absolute percentage error (MAPE) values were used to rank the predictive performance of the different interpolation algorithms to interpolate tack coat bid unit prices. The DK model incorporating spherical semivariogram produced the least MAPE value (Figure 33a). However, a combination of OK and the two semivariograms (exponential and Gaussian) one at a time yielded a lower MAPE value than when DK was combined with these two semivariograms. The MAE and RSR values obtained from the distinct combination of DK and the three semivariograms were lower compared to OK algorithms. Subsequently, the PBIAS values for both kriging models were similar for the spherical and Gaussian semivariograms. However, for the kriging based on exponential semivariogram, OK algorithms resulted in a lower PBIAS compared to the DK model.

The relative performance of the DK models over the OK for the tack coat bid item was quantified and are presented in Table 27. The results suggest that the superior predictive power of the DK does not offer significant improvement relative to the other OK models.



(a) (b)

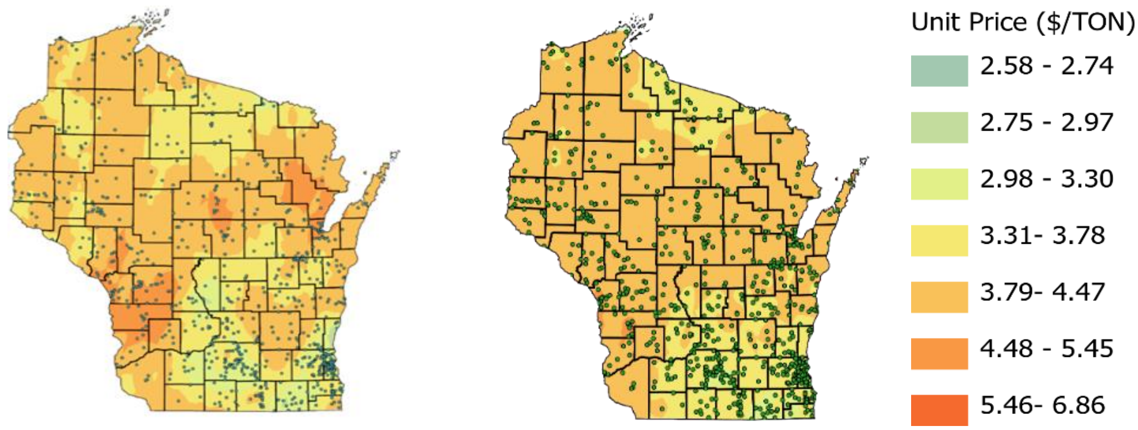
(c) (d)

Figure 33. Model residual assessment parameters evaluated for combined data of tack coat bid item: (a) MAPE; (b) MAE; (c) RSR; (d) PBIAS

Table 27. Performance of interpolation methods in terms of improvement of DK over OK models for prediction of tack coat bid unit prices

	Improvement in RMSE by DK			Improvement in MAE by DK		
Models	OK	DK	RI (%)	OK	DK	RI(%)
Spherical	1.41	1.39	1.42	1.11	1.10	0.90
Exponential	1.41	1.39	1.42	1.10	1.10	0
Gaussian	1.42	1.39	2.11	1.11	1.10	0.90

Figure 34 shows a set of 2D maps for the base aggregate 1 ¼-inch bid items. The geovizualized map for the tack coat bid unit price shows predominantly clusters of high unit prices ($4.48 to $ 5.45) in the north-east, central, and north-west part of the study area for both kriging methods. However, a comparison between the two maps shows that the OK algorithm captured most of the spatial variation of the tack coat bid unit prices accurately across multiple locations.



(a) (b)

Figure 34. Tack coat price maps for (a) ordinary kriging and (b) disjunctive kriging

The cross-validation prediction errors of the asphaltic surface bid item are presented in Table 28. For the kriging based on the spherical semivariogram model, the DK model provides an enhanced prediction accuracy (lower ME, MSE, RMSE, and RMSSE near 1) than the OK model.

Table 28. Cross-validation results for asphaltic surface bid item

	OK	DK	OK	DK	OK	DK
Prediction Error	Spherical	Spherical	Exponential	Exponential	Gaussian	Gaussian
ME	0.371838	**0.13321**	**-0.34268**	0.23843687	**0.38389**	-0.1164
RMSE	27.46524	**27.34483**	**27.44861**	27.5497558	**27.49583**	27.35395
ASE	28.96443	**27.956**	**28.8869**	26.1247848	**28.90665**	28.35201
MSE	0.01286	**0.00513**	**-0.01204**	0.00912685	**0.01322**	0.00487
RMSSE	0.948591	**0.978632**	**0.950627**	1.05454479	**0.951452**	0.966094

However, a comparison of the kriging incorporating the other two semivariograms (exponential and Gaussian) semivariograms one at a time showed that OK models yielded a better prediction performance than the DK models. These results indicate that different dataset characteristics may favor different prediction models.

Figure 35 presents a comparison of the prediction accuracies of the OK and DK models employed to interpolate the asphaltic surface bid item. The OK algorithms outperformed the DK algorithms with lower MAPE, MAE, and RSR values. The PBIAS values show that OK models underestimated the bias to a higher magnitude compared to the DK algorithms. However, the DK based on spherical semivariogram overestimated the prediction bias (Figure 35b). The findings of the MAPE analysis reinforce the conclusions of the cross-validation results in Table 28.

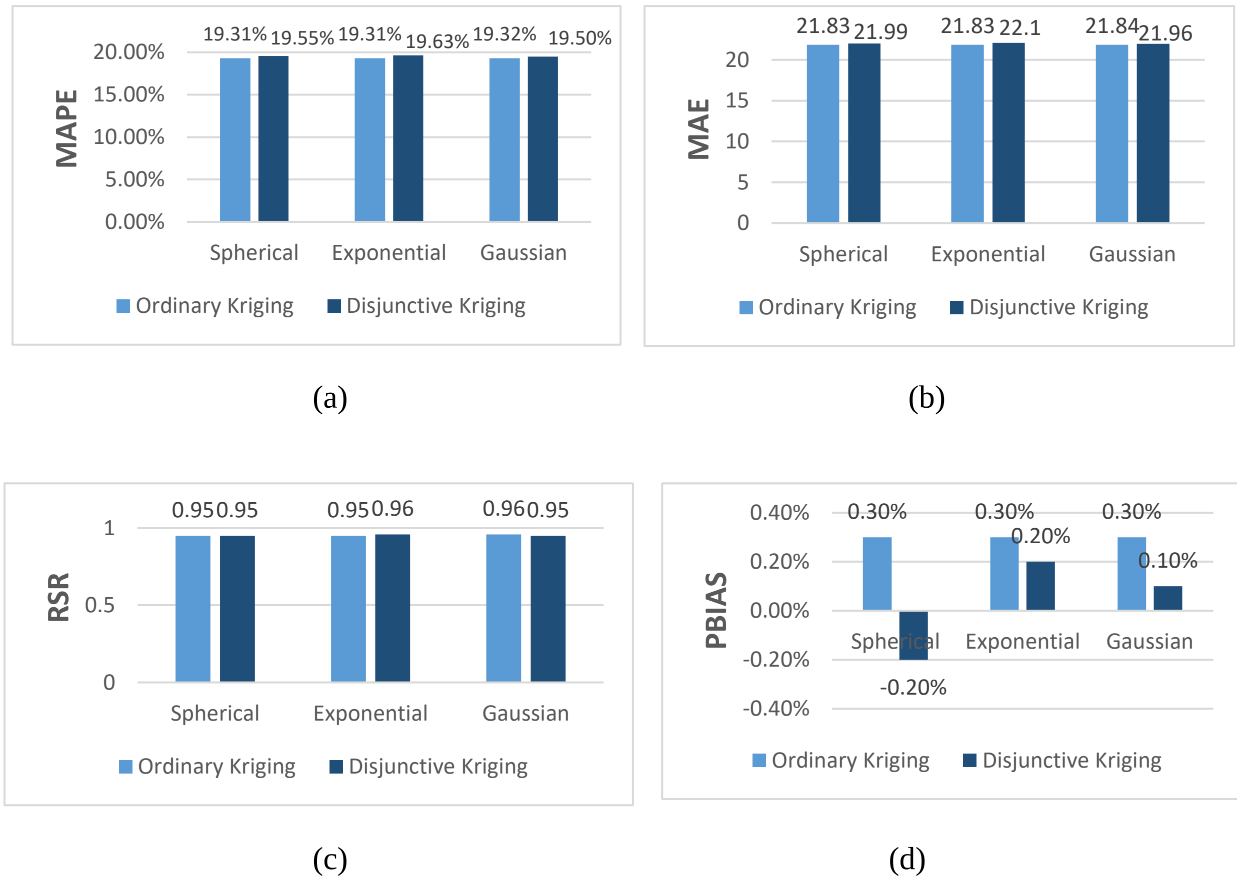


Figure 35. Model residual assessment parameters evaluated for combined data of asphaltic surface bid item: (a) MAPE; (b) MAE; (c) RSR; (d) PBIAS

The relative improvement performance of the DK over the OK models used to interpolate the asphaltic surface bid unit prices were assessed and are presented in Table 29. Apart from the improvement in RMSE by the DK over the OK algorithm, the OK models outperformed DK algorithms when each kriging model was combined with the other two semivariograms (exponential and Gaussian).

Table 29. Performance of interpolation methods in terms of improvement of DK over OK models for prediction of asphaltic surface bid unit prices.

	Improvement in RMSE by DK			Improvement in MAE by DK		
Models	OK	DK	RI (%)	OK	DK	RI(%)
Spherical	27.47	27.34	0.47	21.83	21.99	-0.73
Exponential	27.44	27.54	-0.36	21.83	22.10	-1.24
Gaussian	27.50	27.35	0.55	21.84	21.96	-0.55

Figure 36 shows the maps generated by the two kriging methods to model and interpolate the asphaltic surface bid item. A comparison between the two models indicates similar performance in describing the spatial variation of asphaltic bid unit prices across the study region. However, the DK model shows a fairly smoother surface, with higher unit prices of the asphaltic surface bid item.

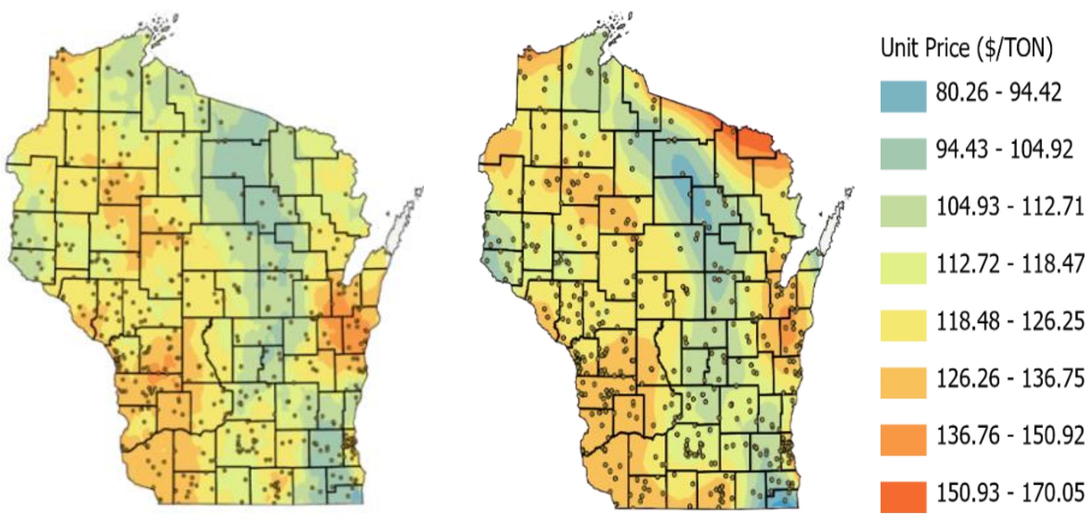


Figure 36. Asphaltic surface price maps for (a) ordinary kriging and (b) disjunctive kriging

5.5. Conclusion

Developing an accurate forecast of highway construction cost estimates poses considerable challenges for state highway transportation agencies due to the uncertainty associated with the variability in construction prices across multiple geographic locations. The state-of-the-art has applied deterministic and linear geostatistical models to assess the spatial variation on highway cost estimates. However, deterministic and linear approaches do not accurately model the nonlinear relationship and also handle non-Gaussian distributions associated with construction cost data. Unlike linear spatial interpolation, where there is some evidence about the predictive performance of various methods, there is a lack of empirical studies that compare nonlinear kriging algorithms with linear interpolation methods when used to predict highway construction unit prices.

To this end, this study evaluated the prediction capabilities of ordinary and disjunctive kriging algorithms to model and interpolate six years (2013 to 2018) of the top five highway bid data: common excavation, base aggregate dense 1 ¼-inch, base dense aggregate ¾-inch, tack coat, and asphaltic surface obtained from WisDOT. The findings of the study show that for the common excavation, base aggregate dense 1 ¼-inch, and base aggregate dense ¾-inch, disjunctive kriging algorithms provide a better prediction accuracy over the ordinary kriging models. However, the prediction power of the disjunctive kriging models was shown to not offer significant improvement over the performance of the ordinary kriging models. Regarding the tack coat bid item, the disjunctive kriging algorithm yielded superior prediction accuracy compared to the performance obtained from the ordinary kriging method. The computational cost associated with the disjunctive kriging could pose a challenge to SHAs who require quick cost estimates of highway projects at the conceptual phase. In contrast, ordinary kriging yielded a better prediction performance accuracy compared to the disjunctive kriging method for the asphaltic surface bid item.

This paper contributes to the growing literature on cost estimation of highway transportation projects by comparing the prediction accuracy of ordinary kriging to the disjunctive kriging algorithm to predict unit prices of the top five common highway bid items and quantify the effect of spatial variation and time on construction costs. The price maps developed from this study would enable SHAs to visualize and evaluate the temporal changes due to the effect of spatial variability and time on bid unit prices in different geographical areas to make better-informed funding decisions at the conceptual phase of highway projects.

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CHAPTER 6. CONCEPTUAL COST ESTIMATION OF HIGHWAY UNIT PRICES: AN EMPIRICAL BAYESIAN KRIGING APPROACH[4]

6.1. Abstract

Challenges associated with ensuring the accuracy and reliability of cost estimation of highway construction bid items are of significant interest to state highway agencies (SHAs). Highway construction unit prices are subject to spatial variation, which causes significant uncertainty in developing accurate cost estimates. The state-of-the-art encompasses the application of deterministic and linear geostatistical interpolation methods to assess the uncertainty associated with the spatial variation of highway bid prices. However, these interpolation methods assume that the estimated semivariogram is the true semivariogram for the interpolation region and does not assess the uncertainty introduced by estimating the underlying semivariogram. To address this shortcoming, this paper employed a combination of empirical Bayesian kriging (EBK) with three semivariograms (exponential detrended, whittle detrended, and K-Bessel detrended) to interpolate six years (2013 to 2018) of the top five highway bid data: common excavation, base aggregate dense 1 ¼-inch, base dense aggregate ¾-inch, tack coat, and asphaltic surface obtained from WisDOT. The findings show that EBK based on exponential detrended semivariogram yields superior prediction accuracy for the common excavation and tack coat bid items whereas a combination of EBK and K-Bessel detrended variogram provides better predictive performance for the base aggregate dense 1 ¼-inch, base aggregate dense ¾-inch, asphaltic surface bid items. This study contributes to the body of knowledge by applying

[4] Awuku, B., and Asa E., (2021). To be submitted to ASCE Journal of Construction Engineering and Management. The material in this chapter was co-authored by Awuku, and Dr. Eric Asa. Bright Awuku had primary responsibility for conceptualization and design, literature search, analysis, writing and revising the manuscript . Bright Awuku was the primary developer of the conclusions, drafted and revised all versions of this chapter that are advanced here. Dr. Eric Asa helped in the conceptualization and served as proofreader, checked and approved the methodology and analysis conducted by Bright Awuku.

EBK algorithms to accurately assess the standard prediction error introduced by estimating the underlying semivariogram in quantifying the effect of project-specific location and time on highway bid unit-price estimation.

6.2. Introduction

Completing transportation projects under their budgeted cost remains a challenge for many transportation agencies in the United States (Love et al. 2019). SHAs require accurate estimates of future funding and project costs to prepare reliable highway construction programs (Wilmot and Cheng 2003) under minimal scope definition and time constraints (Kim and Kim 2010), which presents challenges in developing an accurate and reliable conceptual estimate (Gardner et al. 2017). Inaccurate estimation of highway construction costs could lead to two unintended consequences-overestimation and underestimation (Hassanein 2006; Chou 2009). An overestimated cost could result in a misjudgment of the feasibility of a project or loss of a contract to competitors. On the other hand, the contractor could incur significant losses from an underestimated cost (Liu and Zhu 2007) or it could present challenges in the successful completion of a construction project (Wilmot and Cheng 2003). While inaccurate estimates may be more tolerable during periods of stable economic growth, most governmental agencies currently struggle to meet capital requirements for new construction and renovation of infrastructures while being subjected to continuous budget cuts (Zhang et al. 2017).

Conceptual cost estimates are developed based on historical cost data and adjustment factors, which include project location, time, size, and complexity, and thus the accuracy of those adjustment factors directly influence the accuracy of cost estimates (Wilmot and Mei 2005; Elbeltagi et al. 2014; Zhang et al. 2016). These estimates are crucial to the success of construction projects, and knowledge of project location is fundamental to developing them.

Construction projects are typically planned and executed at the local level and therefore, significant variation could exist in construction costs across locations (Choi et al. 2021). It is essential to incorporate local economic conditions when estimating location adjustment factors at unsampled locations (Zhang et al. 2017). Price volatility in labor rates, materials, and equipment has a significant effect on highway construction costs. This volatility may irregularly be distributed across different geographical locations due to the changes in the availability of local contractors, materials, equipment, and labor (Baek and Ashuri 2017). Thus, there is a need for SHAs to assess the uncertainty associated with the influence of spatial variation on construction costs (Baek and Ashuri 2018).

Location-cost adjustment factors (LCAF) are commercially available to account for spatial variation in construction cost but, they do not include all geographic locations. Therefore, LCAFs for unsampled locations need to be inferred through spatial interpolation or prediction methods (Migliaccio et al. 2013). Construction cost models reflect experiences that are unique to a construction organization for a particular project or work type (Sonmez 2011). The inherent heterogeneity associated with historical cost data from multiple highway transportation projects affects the accuracy of conceptual cost estimates (Neill 1984; Oberlender and Trost 2001). The inclusion of estimation variability is crucial for management decisions as cost estimates of highway bid items are characterized by a high amount of uncertainty at the conceptual phase (Sonmez 2011).

The state-of-the-art has employed classical kriging algorithms, deterministic and linear geostatistical approaches to assess the spatial variability of unit prices on construction cost. However, these geostatistical models assume that there is one process that generates the data, and that process is usually Gaussian (Gribov and Krivoruchko 2020). Beyond Gaussianity, lognormal kriging, disjunctive kriging, generalized linear model-based kriging, and trans-Gaussian kriging have been proposed in the literature. However, these kriging variants do not take into account the uncertainty concerning the distribution and the estimated covariance function of the data (Pilz and Spöck 2008). Furthermore, the spatial process is usually described by a single covariance model. Some interpolation models allow a spatially varying covariance model, but the covariance structure can only change slowly and smoothly. The number of data-generating processes can be large, and information about these processes is typically incomplete or absent. Therefore, there is a need for statistical models that produce reasonably accurate predictions given spatial data that does not change smoothly and when the sources of this change are at least partially unknown.

To account for uncertainty in estimating the underlying semivariogram models, empirical Bayesian kriging (EBK) predicts values at unsampled locations using the weighted sum of the models from the possibly overlapping or disjoint nearby subsets has been proposed in the literature (Gribov and Krivoruchko 2020). EBK models do not require specification of the prior distributions for the model parameters; allow moderate local and large global data non-stationarity; locally transform data to Gaussian distribution, if required; allow for varying measurement error; produce reliable outputs with default parameters (Krivoruchko and Gribov 2019). Classical kriging also assumes that the estimated semivariogram is the true semivariogram of the observed data. This means the data was generated from Gaussian distribution with the correlation structure defined by the estimated semivariogram. This is a very strong assumption, and it rarely holds in practice (Krivoruchko 2012).

This study aims to automate the unit-price estimation process and investigate which combination of EBK and the three semivariogram models yields the best results in estimating unit prices for highway construction bid items. The remaining parts of the paper are organized as follows. The literature review section examines previous related research in accounting for spatial variation of estimating highway bid unit prices. A detailed description of the data, the data exploration, and the EBK algorithms used in the study are presented in the methodology section. The final part of the paper discusses the results and conclusions derived from the study.

6.3. Literature Review

Previous studies employed the deterministic and linear geostatistical interpolation methods, nearest neighbor (NN); local averaging method; inverse distance weighted (IDW); linear kriging; global regression analysis (GRA) geographically weighted regression analysis (GWR); and nighttime light satellite imagery (NLSI) to assess the spatial variation of unit prices on highway construction costs, and interpolate LCAFs at unsampled locations (Zhang et al. 2014).

The NN is the simplest method because it relies on the simple equality function that determines values using a linearly weighted combination of a set of sample points (Zhang et al. 2014). The accuracy of this method depends largely on sampling density. Additionally, since the transitions between polygons are often abrupt, this method does not accurately model continuous data. Martinez et al. (2009) and Migliaccio et al. (2009, 2013) assessed the validity of NN interpolation using empirical LCAF data to interpolate LCAF at unsampled locations. Despite the evidence supporting the validity of the NN proximity-based location adjustment method, when compared against alternative geostatistical interpolation methods, the NN method does not yield better prediction accuracy (Zhang et al. 2014).

Migliaccio et al. (2009, 2013) evaluated the state averaging method, which is derived from the local averaging (LA) method by using the state boundary, instead of fixed radius circles, to define the spatial extents of the search. However, the LA interpolation method is a slightly more complex method that uses fixed radius interpolation to produce a raster grid in a specified region of interest. All values within a state were averaged to estimate a collective value used for every potential project location within the state (Zhang et al. 2014).

The IDW interpolation method is one of the most frequently used deterministic models in spatial interpolation (Zhang et al. 2014). IDW assumes that the attribute value of an unsampled point is the weighted average of known values within the neighborhood, and the weights are inversely related to the distances between the prediction and the sampled locations (Le et al. 2019). Le et al. (2019) evaluated the IDW interpolation method and location cost-adjustment factors to adjust the total costs of two similar projects in two different cities. Shrestha and Jeong (2019) developed a unit price visualization tool using IDW to enable estimators to develop unit price maps of desired bid items. Despite the acceptable prediction accuracy, the IDW method, a deterministic approach could lead to a false inference of accuracy because of its inability to account for the uncertainty of the interpolated values making it difficult for transportation agencies to cater for cost growth (Anderson et al. 2007; Gardner et al. 2017).

Baek and Ashuri (2017) employed two statistical techniques, ordinary least square (OLS) regression, and GWR to explain spatial variation in the submitted highway bid unit prices. Compared to the OLS model, the GWR, a local approach of linear regression yielded a higher prediction performance in explaining the spatial variation with key identified factors including the quantity of asphalt line items, total bid price, and the number of asphalt plants within 50 miles of a project. The primary result of this study indicates that the key identified factors are not uniformly distributed across different geographical locations. However, the limitations of GWR include problems of multicollinearity and could present modeling complexities in obtaining accurate interpolation results.

Zhang et al. (2017) proposed a new method of using NLSI to estimate location adjustment factors at unmeasured locations. The NLSI method for estimating location adjustment factors was evaluated against an established cost index database, and the results showed that NLSI can be used to effectively estimate location adjustment factors. One key advantage of the NLSI-based method over purely proximity-based interpolation methods is that it indirectly incorporates local economic conditions. When compared with the nearest neighbor (NN) and other proximity-based location adjustment methods, the proposed NLSI method leads to a 25–40% reduction of the median absolute error. However, this interpolation model does not address uncertainties inherent in highway cost estimates or consider the realized cost of the actual construction project.

Le et al. (2019) applied linear interpolation methods, ordinary kriging, and ordinary cokriging (OCK) to adjust the total costs of two similar projects in two different cities. The GIS-based framework proposed by Le et al. (2019) leveraged historical bid data for unit-price estimation and visualization with consideration of the effects of project-specific location on different bid items. Additionally, various strategies such as the use of quantity in interpolation models were employed to improve the accuracy of the preliminary estimates. Temporal changes in unit prices and relationships between quantities and unit prices were also explored. A comparison of the spatial interpolation algorithms indicated that OCK performed better than the OK which was consistent with the results from year-wise unit price interpolation from 2011 to 2014.

To obtain optimal kriging results, it is essential to select the appropriate parameters for each method and assess the significance of the various combinations of these parameters on the modeling results (Zhang et al. 2014). The selection of an appropriate kriging method is dependent on how well the variogram model used fits the data set (Shamo et al. 2012; Batistella et al. 2014). Classical kriging methods estimate the semivariogram from known data locations and use this single semivariogram to make predictions at unknown locations; this process implicitly assumes that the estimated semivariogram is the true semivariogram for the interpolation region (Zhang et al. 2020). However, in modeling practical applications, these assumptions may not be appropriate. As a result, the true prediction error in kriging is underestimated or overestimated (Krivoruchko 2012; Zhang et al. 2020). Therefore, in assessing the spatial variability of unit prices on highway construction costs, there is a need to account for the error introduced by estimating the underlying semivariogram.

6.4. Methodology

Reliable interpolation algorithms should satisfy several important demands: accuracy and predictive power, robustness and flexibility in modeling the phenomena and smoothing for noisy data applicability to large datasets (Mitas and Mitasova 1999). In this paper, EBK geostatistical technique will be combined with three semivariograms (exponential detrended, whittle detrended, and K-Bessel detrended) to predict highway construction unit prices from the WisDOT from 2013 to 2018.

Geostatistical inferences using kriging techniques are more efficient when data are normally distributed (Wu et al. 2006). Data transformation may be required before kriging to satisfy the normality assumption, suppress outliers, and improve data stationarity (Varouchakis et al. 2012). Therefore, to test the significance of this claim, this paper compared the kriging results using non-transformed data and the case where the data was transformed to determine the best kriging results. The results showed that prediction errors from models using a log-empirical transformation tended to be smaller than models with data that were not transformed. Cross-Validation was then used to evaluate the validity and correctness of the interpolation results. The same process was repeated for all the combinations of the EBK and variogram algorithms and formed the basis of comparison and selection of the best results (Figure 37).

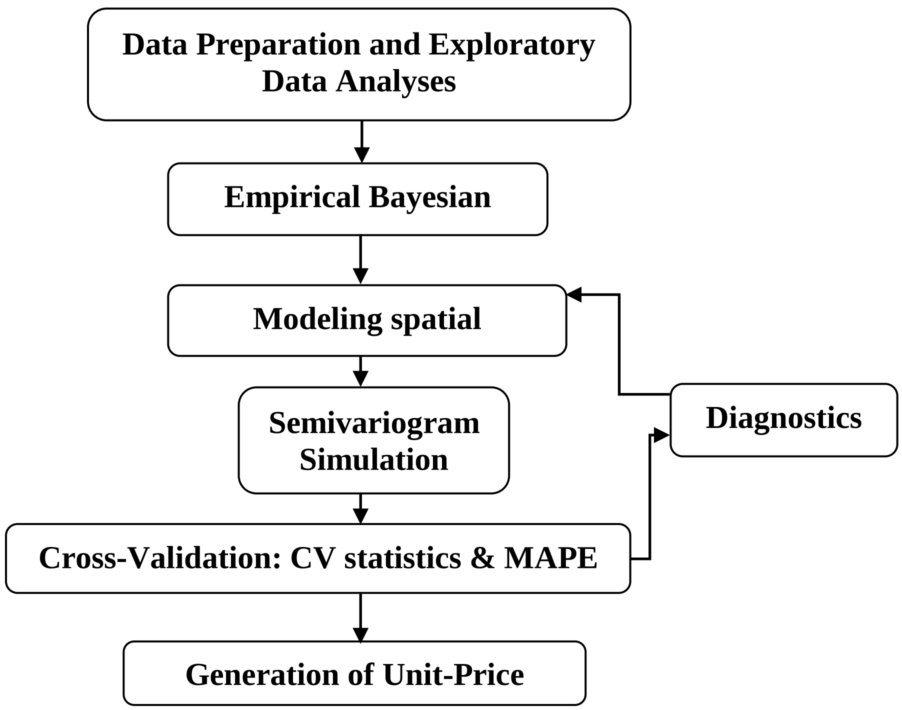


Figure 37. Research methodology

6.4.1. Semivariogram Estimation

EBK, like other kriging variants, uses a semivariogram which is a function of the distance and direction separating two locations to quantify the spatial dependence in the data (Dhakal et al. 2020). A semivariogram is constructed by calculating half the average squared difference of the values of all the pairs of measurements at locations separated by a given distance *h* (Krivoruchko 2012). There are several semivariogram models available in EBK which are based on the choice of data transformation. EBK offers linear, power, and thin-plate spline as the default semivariogram models when data transformation is not required. Linear or thin-plate spline should be selected if faster results and a compromise on some prediction accuracy is desired. If there is no trend or a weak trend is detected from the exploratory spatial data analysis, then a linear semivariogram is a better choice. However, if a balance of accuracy and speed is required, power is a better choice compared to linear and thin-plate spline.

If data transformation is required to satisfy the normality assumption, but the computational expense cannot be compromised, then the exponential or Whittle or their detrended counterparts should be chosen depending on the presence or absence of trends. Equally, K-Bessel or K-Bessel detrended should be chosen, if the problem under investigation requires the most accurate results. Furthermore, the selection of semivariogram in EBK should be based on the theoretical semivariogram that best fits the empirical semivariogram taking into consideration, cross-validation diagnostics (ESRI 2020). This study employed exponential detrended (Eq.39), (2) whittle detrended (Eq. 40), and (3) K-Bessel detrended (Eq. 41) variograms to assess the spatial variability of unit price data from 2013 to 2018 because of the presence of trends detected from the exploratory spatial data analysis. The K-Bessel semivariogram model is given by equation 39 (Johnston et al. 2001; Pasini et al. 2014):

$$\gamma(h;\theta) = \theta_s \left[1 - \frac{\left(\Omega_{\theta_k} \parallel \mathrm{h} \parallel / \theta_r\right)^{\theta_k}}{2^{\theta_k - 1}\Gamma(\theta_k)} \; K_{\theta_k}\left(\Omega_{\theta_k} \parallel \mathrm{h} \parallel / \theta_r\right)\right] \; for\ all\ h, \tag{39}$$

where $\theta_s \geq 0, \theta_r \geq 0, \theta_k \geq 0, \Omega_{\theta_k}$ is a value found numerically so that $\gamma(\theta_r)$= 0.95 θ_s for any θ_k, $\Gamma\ (\theta_k)$ is the gamma function,

$$\Gamma(y) = \int_0^\infty \chi^{y-1} exp(-x)dx \tag{40}$$

and $K_{\theta_k}(\cdot)$ is the modified Bessel function of the second kind of order θ_k.

Exponential semivariogram and whittle semivariogram are given in equation 41 (Johnston et al. 2001; Asa et al. 2012) and equation 3 (Schlather et al. 2015) respectively:

$$\gamma(h) = 1 - exp\left(\frac{-3h}{a}\right) \tag{41}$$

$$\gamma(h) = 2^{1-\nu}\, \Gamma(v)^{-1} \parallel h \parallel^{v}\, K_v(\parallel h \parallel), h \in \mathbb{R}^d \tag{42}$$

where K is a modified Bessel function, Γ is the Gamma function, v > 0 a smoothness parameter, and h and a are referred to as distance and range

6.4.2. Empirical Bayesian Kriging (EBK) Algorithm

Empirical Bayesian kriging differs from classical kriging methods because it accounts for the error introduced by estimating the underlying semivariogram model. The EBK model automates the function of building a valid kriging model, which is considered the most difficult aspect in spatial interpolation through geostatistical modeling (Gupta et al. 2017). EBK modeling technique is an automated simulation-based optimization, which facilitates a quick fitting of several theoretical semivariogram models by estimating their model parameters instead of adjudging the suitability of a single semivariogram. Classical kriging methods use weighted least squares (WLS) approach to estimate valid semivariograms during the interpolation process. However, the semivariogram parameters in EBK are estimated using restricted maximum likelihood (REML). Due to the computational limitations of REML for large datasets, the input data is first divided into overlapping subsets of a specified size (defaulted to 100 points per subset). EBK consists of two geostatistical models: the intrinsic random (IRFK) approach which allows the removal of local nonstationary data and the linear mixed model (LMM) algorithm also known as simple kriging with an external trend in geostatistical modeling (Gribov and Krivoruchko 2020). Therefore, the EBK algorithm can be expressed as a combination of IRFK and LMM processes (equation 43):

$$Z_i = y(S_i) + \varepsilon_i, i = \overline{1 \ldots K}, \tag{43}$$

where Z_i is the measured value at the observed location S_i, $y(S)$ is the Gaussian process understudy at the location S, ε_i is the measurement error, and K is the number of measurements. The following process is followed in EBK modeling: First, parameters of the spatial process Θ, including the semivariogram model, are estimated from the input data. Using Θ, new values are unconditionally simulated at each of the sampled locations K_{sim} *times*. New parameters Θ_i, $i = \overline{1 - K_{sim}}$, are then predicted from the simulated data. A histogram of Θ_i could be used as an approximation of the prior distribution. Where Θ_i, i=1. . . K_{sim}, is referred to as the empirical prior distribution. The model parameters are assumed to take only; Θ_i values, that is $f(\Theta'|z) = 0$ for $\Theta' \neq \Theta_i$. Bayes rule, $\omega_i \propto f(Z|\Theta_i), \omega_i = \frac{f(Z|\Theta_i)}{\sum_{i=1}^{K_{sim}} f(Z|\Theta_i)}$, $\sum_{i=1}^{K_{sim}} \omega_i = 1$ is used to determine a weight for each simulated model. where $f(Z|\Theta_i)$ is the conditional probability of the data Z given the model parameters Θ_i. Prediction and prediction standard errors are produced at unsampled locations using equations 44 and 45 (Tan et al. 2020; Gribov and Krivoruchko 2020).

$$E[y(s)|Z] = \hat{y}(s) = \sum_{i=1}^{ksim} [\omega_i \cdot E[y(s)|Z, \Theta_i|]) \tag{44}$$

$$Var[y(s)|Z] = E\left[\left(y(s)\right)^2|Z\right] = \sum_{i=1}^{K_{sim}} Var[y(s)z, \Theta_i\ ] + \left(E[y(s)|Z, \quad \Theta_i] - \left(\hat{y}(s)\right)^2\right) \tag{45}$$

where $E\left[y(s) - \hat{y}(s)Z, \theta_i\right]$ and Var$[y(s)z, \theta_i]$ are given by the kriging equations.

6.4.3. Comparison of Spatial Interpolation Using Cross-Validation

To evaluate the predictive performance of the several combinations of EBK and the three semivariograms, leave-one-out cross-validation was used. Cross-validation removes each data location one at a time and predicts the associated data value and compares the measured and predicted values. The mean standardized error (MSE) was used to check if the model is unbiased, the closer the MSE values to zero, the better the performance of the model. The root-mean-square error (RMSE) was used to check whether the prediction is close to the measured values (the smaller the RMSE, the closer the prediction is to the measured value).

The variability of the predicted data was assessed by comparing the average standard error (ASE) with the RMSE. If the values are similar, then the variability in the prediction is correctly assessed. If the ASE value is greater than the RMSE value, then the variability of the predictions is overestimated; otherwise, the variability of the predictions is underestimated (Robinson and Metternicht 2006; Asa et al. 2012; Eldeiry and Garcia 2012; Wackemagel 2013; Oliver and Webster 2014; ESRI 2020).

EBK model introduces additional cross-validation diagnostics, the average continuous ranked probability score (CRPS) for model comparison (ESRI 2020). The average CRPS is a diagnostic that measures the deviation from the predictive cumulative distribution function to each observed data value and evaluates both calibration and sharpness of predictive distributions. This value should be as small as possible. This CRPS diagnostic has advantages over other cross-validation diagnostics because it compares the data to a full distribution rather than to single-point predictions (Krivoruchko and Gribov 2019; ESRI 2020).

$$\text{Mean Squared Error} = \frac{1}{n}\sum_{i=1}^{n}[Z(y_i) - Z(y_o)] \tag{46}$$

$$\text{Root Mean Square Error} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[Z(y_i) - Z(y_o)]^2} \tag{47}$$

$$\text{Average Standard Error} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[Z(y_i) - \left(\sum_{i=1}^{n} Z(y_o)\right)/n\right]^2} \tag{48}$$

$$\text{Average CRPS} = \int_{-\infty}^{+\infty}\left(F(y) - \mathbb{1}_{x<y}\right)^2 dy \tag{49}$$

where $Z(y_i)$ and $Z(y_o)$ are the measured and estimated bid unit price, respectively, of the *ith* data point, *n* is the total number of data points, and $F(y)$= is the estimated cumulative distribution function.

Mean absolute percentage error (MAPE) is a common measure used for assessing the level of accuracy of the algorithms used to estimate the cost of highway bid items (Gardner et al. 2017). The equation for computing MAPE is furnished in equation 50 (Choi et al. 2014; Gardner et al. 2017):

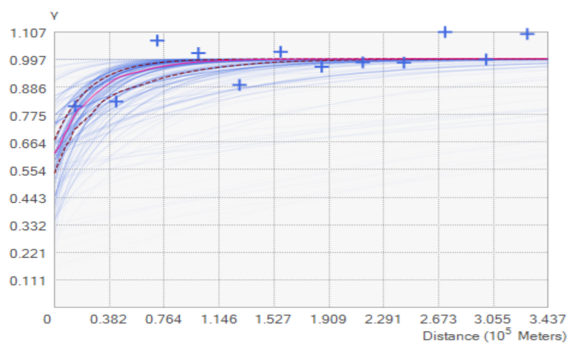
$$MAPE = \left(\frac{100\%}{n}\right)\sum_{i=1}^{n}\left|\frac{b_i - a_i}{a_i}\right| \tag{50}$$

where n= number of data points; b_i = predicted construction cost a_i = Actual construction cost for the *ith* project.

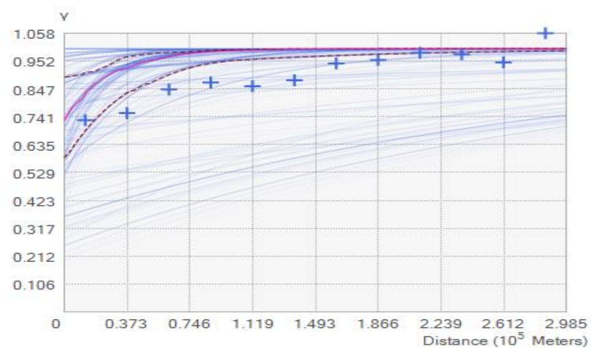
6.5. Performance Evaluation of Spatial Interpolation Algorithms

To establish which spatial prediction method provided the most accurate estimates of unit prices for each bid item, cross-validation was used to compare the interpolation results with their actual values. Figure 38 shows the empirical semivariogram for the top five common bid items. Ideally, the empirical semivariogram should fall in the middle of the semivariogram spectrum. However, from Figure 38, the blue crosses mostly fall toward the top and bottom of the spectrum and do not fall exactly in the middle of the semivariogram spectrum. Table 31 to 35 summarizes the cross-validation results of the top five highway construction bid items from 2013 to 2018.

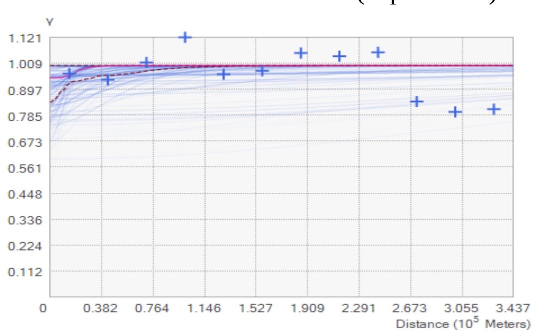
The results of different combinations of EBK and three semivariograms show better predictive performance with minimal differences. For the common excavation bid item, the MSE generally approach zero, which indicates an unbiased geostatistical model. Additionally, the RMSE and ASE values for all year-wise combinations of EBK and semivariogram models are all close and thus indicate that the variability of the interpolated unit prices for the common excavation bid item fairly accurate.



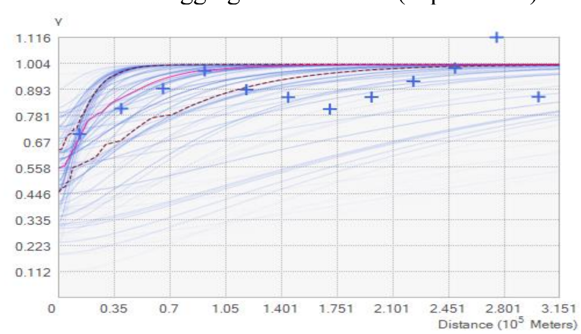
Common excavation 2015 (exponential)



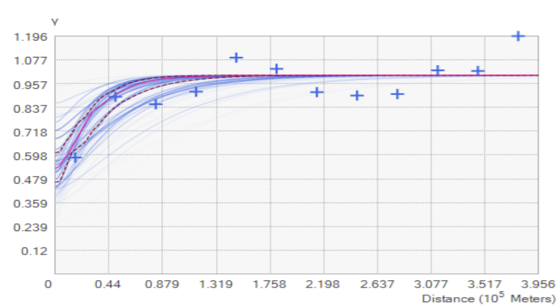
Base aggregate 1 ¼” 2017 (exponential)



Base aggregate ¾”2015 (K-Bessel Detrended)



Tack Coat 2017 (Whittle Detrended)



Asphaltic Surface 2017 (Whittle Detrended)

Figure 38. Empirical semivariogram for the top five common bid items

The variability of the interpolated values for the 2017 data set using K-Bessel detrended semivariogram is overestimated, however, this estimation is comparably small. Subsequently, CRPS and the MAPE values for all the different combinations of EBK and semivariogram models for the common excavation bid item are low, implying better geostatistical interpolation.

From Table 30, a combination of EBK and exponential detrended semivariogram model performed superior in 2013, 2014, and 2018, respectively. Conversely, a combination of EBK and K-Bessel detrended semivariogram performed superior to the other semivariograms in 2015 and 2017. In 2015, a combination of EBK based on whittle detrended semivariogram yielded the least error as measured by cross-validation statistics, average CPRS, MSE, MSE, ASE, and MAPE values thus was considered as the best predictive model.

Table 30. Cross-validation results for common excavation bid item from 2013 to 2018

	2013			2014			2015		
Prediction Error	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.
ACRPS	**2.25476**	2.25451	2.25970	**2.0821890**	2.08868	2.09866	2.30119	2.28957	**2.27409**
RMSE	**4.04617**	4.04554	4.05394	**3.7314644**	3.74070	3.75396	4.08669	4.06539	**4.03700**
ASE	**4.084569**	4.08847	4.08441	**3.7995270**	3.82854	3.74483	4.21373	4.17962	**4.19802**
MSE	**0.018295**	0.01957	0.02545	**0.0052922**	0.01357	0.01596	0.00365	0.00128	**0.00595**
MAPE%	**31.62**	31.64	31.82	**28.15**	28.28	28.38	26.64	26.48	**26.42**
	2016			2017			2018		
Prediction Error	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.
ACRPS	3.1292444	**3.1442654**	3.1407781	3.1159259	3.11463	**3.1201**	**1.92670**	1.9280	1.93218
RMSE	5.509871708	**5.5337156**	5.5331476	5.5202204	5.52612	**5.52517**	**3.45424**	3.4561	3.46246
ASE	5.732946995	**5.6606749**	5.6927906	5.634247	5.5806732	**5.41140**	**3.55697**	3.5656	3.5604388
MSE	0.02752545	**0.0178917**	0.0179434	0.0048586	0.00746	**0.0047**	**0.00164**	0.0083	0.00211
MAPE%	33.28	**33.14**	33.15	31.58	31.62	**31.40**	21.56	21.56	21.62

Table 31 provides an assessment of the performance of the models used to interpolate unit prices of the base aggregate 1 1/4-inch bid items based on cross-validation results and MAPE values. In terms of the prediction accuracy, EBK incorporating the exponential semivariogram model yielded slightly better results than the other variogram models with lower prediction errors from 2014 to 2016. Subsequently, a combination of EBK and K-Bessel detrended semivariogram models outperformed spherical and exponential semivariograms, with lower cross-validated results in 2017 and 2018. However, a comparison of the three semivariogram models in 2013 showed that the kriging variance from the whittle detrended model is slightly lower and more accurate than the exponential and K-Bessel detrended semivariogram models. However, the disparate models underestimated the variability of the interpolated, with RMSE greater than the ASE value.

Table 31. Cross-validation results for base aggregate dense 1 ¼” bid item from 2013 to 2018

	2013			2014			2015		
Prediction Error	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.
ACRPS	1.97995	**1.970191**	1.972187	**1.834849**	1.836913	1.832156	**2.033541**	2.033108	2.037652
RMSE	3.57351	**3.556160**	3.553800	**3.313134**	3.317520	3.309841	**3.596861**	3.599781	3.599923
ASE	3.88755	**3.853009**	3.913463	**3.323764**	3.335436	3.325204	**3.737447**	3.728560	3.783082
MSE	0.006357	**0.008405**	0.020323	**-0.022486**	-0.014917	-0.010865	**-0.006345**	0.007693	0.001590
MAPE %	20.76	**20.6**	20.76	**17.05**	17.09	17.06	**19.25**	19.34	19.28

	2016			2017			2018		
Prediction Error	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.
ACRPS	**2.106963**	2.104046	2.104110	2.985233	2.9996558	**2.970514**	2.379325	2.379333358	**2.373603**
RMSE	**3.758416**	3.747761	3.746893	5.348373	5.377826	**5.318736**	4.245239	4.249506845	**4.237160**
ASE	**3.805041**	3.822127	3.830338	5.669075	5.692221	**5.550225**	4.375789	4.353051612	**4.323981**
MSE	**0.011849**	0.017280	0.037547	0.008307	0.016914	**0.006029**	-0.011821	0.020627096	**0.014977**
MAPE %	**20.2**	20.25	20.41	26.02	26.22	**25.71**	20.81	20.74	**20.73**

Table 32 presents the predictive performance of the different combinations of EBK and the three semivariogram models used to interpolate base aggregate dense ¾-inch from 2013 to 2018. The results indicate that leave-one-out cross-validation gives nearly unbiased estimates of the accuracy, but with relatively high variability, particularly the ASE values were greater than the RMSE. This indicates that the semivariogram models are overestimating the variability of the predictions.

The results of the cross-validated results show that a combination of EBK based on whittle detrended semivariogram yielded lower prediction errors in 2014, 2016, 2018. In 2013 and 2017, EBK based on the K-Bessel semivariogram model shows a better prediction accuracy (lower CRPS, MSE, RMSE, and MAPE) while a combination of EBK incorporating exponential semivariogram performed superior in 2015.

Table 32. Cross-validation results for base aggregate dense 3/4" bid item from 2013 to 2018

	2013			2014			2015		
Prediction Error	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.
ACRPS	2.949622	2.949339	**2.945718**	2.999423	**3.00352**	3.011798	**3.638855**	3.6516679	3.644175
RMSE	5.219923	5.216658	**5.210829**	5.324325	**5.336376**	5.355173	**6.606257**	6.6035264	6.589878
ASE	5.441714	5.380482	**5.400686**	5.284970	**5.303257**	5.279307	**6.926909**	6.7307322	6.8535365
MSE	0.016932	0.008606	**0.007608**	-0.008362	**-0.00873**	-0.00142	**-0.027261**	0.0192964	0.0151897
MAPE %	21.96	21.87	**21.86**	21.04	**21.01**	21.12	**23.13**	23.23	23.21
	2016			2017			2018		
Prediction Error	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.
ACRPS	3.599701	**3.591885**	3.581901	4.231749	4.209527	**4.224931**	4.460718	**4.427902**	4.431696
RMSE	6.433773	**6.421543**	6.407041	7.565323	7.563316	**7.550422**	8.072678	**8.02323**	8.01805
ASE	6.392420	**6.296052**	6.3194	7.523263	7.598777	**7.539387**	8.186884	**8.190953**	8.309138
MSE	-0.001637	**-0.01379**	0.007451	-0.022214	-0.01481	**-0.02268**	-0.006902	**-0.02378**	0.018518
MAPE %	24.74	**24.55**	24.69	25.96	26.06	**25.90**	26.50	**26.18**	26.72

Table 33 summarizes the cross-validation results obtained from combining three semivariograms and ordinary kriging to model the tack coat bid item from 2013 to 2018. In 2013, 2016, and 2017, a combination of OK and Gaussian semivariogram model was the best whereas a combination of OK and exponential semivariogram model is the best fitted experimental semivariogram in the 2015 and 2018 data set. However, in 2014, a combination of EBK and K-Bessel semivariogram yielded the least prediction error values (Table 33).

Table 34 provides an assessment of the performance of the EBK models used to interpolate unit prices of the asphaltic surface bid items based on cross-validation results. From 2013 to 2015, EBK based on K-Bessel detrended semivariogram model shows an enhanced prediction accuracy (lower CRPS, MSE, RMSE) and MAPE values than exponential and whittle detrended semivariogram models. Subsequently, a comparison of the different combinations of EBK and three semivariograms showed that EBK incorporating whittle detrended semivariogram yielded a better prediction performance than the other two semivariogram models from 2016 to

2018. These results corroborate the assertion that different dataset characteristics may favor different prediction models.

Table 33. Cross-validation results for tack coat bid item from 2013 to 2018

	2013			2014			2015		
Prediction Error	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.
ACRPS	0.685873	**0.685002**	0.686742	0.814767	0.812364	**0.808941**	**0.587860**	0.5857961	0.605869
RMSE	1.248700	**1.248334**	1.250008	1.491766	1.490616	**1.487912**	**1.073205**	1.0701654	1.1060108
ASE	1.249037	**1.244459**	1.273939	1.422101	1.428899	**1.416199**	**1.009261**	1.063268	1.008249
MSE	-0.026007	**-0.02887**	0.003945	-0.009218	-0.00502	**-0.02503**	- **0.011486**	0.004853	0.0335231
MAPE %	24.09	**24.08**	24.32	29.65	29.47	**29.03**	**25.09**	25.3	25.49
	2016			2017			2018		
Prediction Error	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.
ACRPS	0.415846	**0.414531742**	0.413950907	0.813740	**0.810527**	0.810984	**0.741280**	0.741029	0.740878
RMSE	0.754450	**0.751998085**	0.74966651	1.488115	**1.483062**	1.483617	**1.374817**	1.373495	1.382028
ASE	0.737434	**0.722339337**	0.715856626	1.469812	**1.452637**	1.452434	**1.350142**	1.369045	1.447502
MSE	-0.014346	**0.014360595**	0.010072458	-0.020680	**-0.03292**	-0.03414	**0.005691**	0.001836	0.018286
MAPE %	19.12	**19.05**	19.17	32.98	**32.53**	32.58	**28.32**	28.37	28.37

Table 34. Cross-validation results for asphaltic surface bid item from 2013 to 2018

	2013			2014			2015		
Prediction Error	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.
ACRPS	13.263128	13.23343	**13.23558**	16.491802	16.45771	**16.44455**	15.124317	15.14003003	**15.08763658**
RMSE	23.052809	23.00329	**23.00636**	28.883460	28.84035	**28.79843**	26.253547	26.26084886	**26.19390634**
ASE	23.619128	23.53562	**23.47082**	29.822310	29.21202	**28.64234**	26.834837	27.00066217	**26.68713285**
MSE	-0.000222	0.006073	**-0.00732**	0.009012	0.021879	**0.030045**	0.034053	0.028040934	**0.029875643**
MAPE %	17.96	17.96	**17.89**	20.19	20.15	**20.11**	21.01	21.1	**20.91**
	2016			2017			2018		
Prediction Error	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.	Exponential D.	Whittle D.	K_Bessel D.
ACRPS	17.918678	**17.57597**	17.97447	14.909204	**14.82092**	14.76038	12.882433	**12.76823**	12.70572
RMSE	31.933367	**31.37994**	31.99071	26.302803	**26.17613**	26.12289	23.002884	**22.77603**	22.60104
ASE	33.295524	**32.37045**	32.71002	26.842677	**26.74857**	26.19466	23.718089	**23.34522**	23.32787
MSE	0.025939	**0.004226**	0.012656	0.010330	**-0.01137**	0.016578	0.004819	**0.000527**	0.009602
MAPE %	22.78	**22.06**	22.77	19.21	**18.96**	19.01	15.64	**15.56**	15.66

Highway construction costs are subject to significant variations from project to project and over time, which results in dynamic changes in prices. To account for variations due to cost escalation over time, this study combined historical cost data of the same bid item in different years and accounted for spatial variations and variation because of inflation and deflation to generate current price maps for the top five bid items. Figures 39a and b show the 2D price maps for common excavation and base dense aggregate 1 ¼-inch bid items. Comparison between the two maps shows that the common excavation map appears smoother with less extreme unit prices than the base aggregate dense 1 ¼-inch which appears to have higher unit prices across the north-western part of the study area.

The performances of the different combinations of the interpolation method and the three semivariogram models have been assessed and compared using MAPE indexes. The results indicate that for the common excavation models, a combination of EBK and exponential detrended semivariogram yielded a better predictive accuracy compared to K-Bessel and whittle detrended semivariograms (Figure 40a).

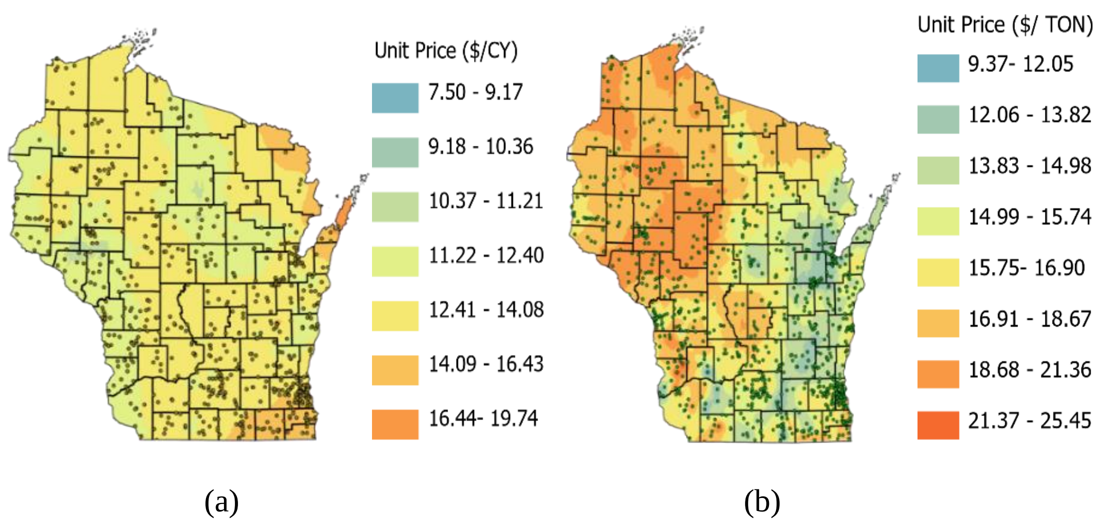
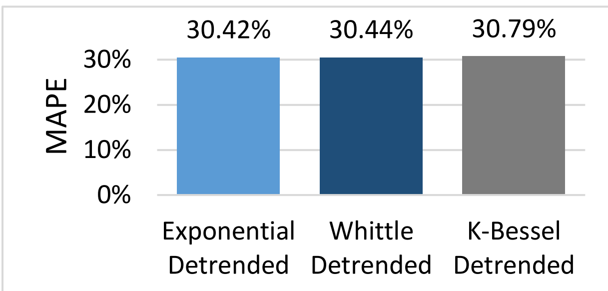
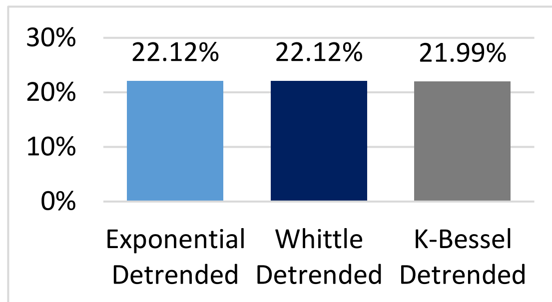


Figure 39. Price map for combined bid data from 2013 to 2018 for (a) common excavation and (b) base aggregate dense 1 ¼-inch bid data

To test the statistical significance of these results, Table 36 presents the results of two-sample t-tests, which assume unequal variances between the different combinations of EBK and the three semivariogram models for the common excavation bid item. The results suggest that the superior predictive power of the EBK based on exponential detrended semivariogram does not provide statistically significant differences over the other semivariogram models.

Regarding the base dense aggregate 1 ¼-inch models, a combination of the EBK and K-Bessel detrended semivariogram model performed better than whittle and exponential detrended semivariogram models (Figure 40b). Despite the different prediction performance from the base aggregate dense 1 ¼-inch models, there is no statistical evidence that the models differ significantly (Table 35).





(a) (b)

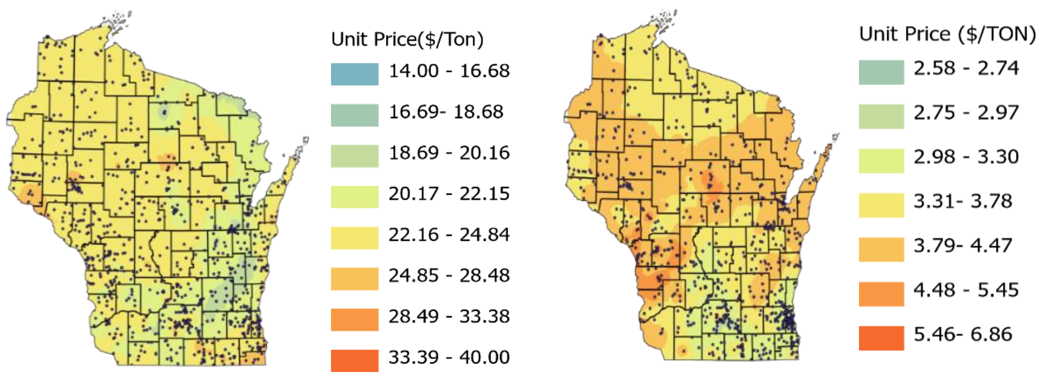
Figure 40. Comparison of kriging results for combined data from 2013 to 2018 for (a) common excavation and (b) base aggregate dense 1 ¼-inch bid data

Table 35. Statistical significance test on the prediction accuracy of the different combinations of EBK and semivariogram models

Bid Item	Exponential detrended versus Whittle detrended		Exponential detrended versus K-Bessel detrended		Whittle detrended versus K-Bessel detrended	
	t-statistic	*p*-value	*t*-statistic	*p*-value	*t*-statistic	*p*-value
Common Excavation	-0.02	0.98	-0.29	0.78	-0.27	0.79
Base Aggregate 1 ¼”	0.01	0.99	0.14	0.88	0.14	0.89
Base Aggregate ¾”	0.04	0.96	0.05	0.96	0.01	0.99
Tack Coat	-0.05	0.96	-0.26	0.79	-0.22	0.83
Asphaltic Surface	-0.01	0.99	0.05	0.96	0.03	0.98

Figures 41a and b show the maps for bid items dense aggregate 1 ¼” and tack coat base bid items. From Figure 9a, the price map of the base aggregate dense ¾-inch bid item appears smoother surface with more values between \$22.16 to \$24.84. In contrast, the geovizualized map for the tack coat bid unit price shows predominantly clusters of high unit prices (\$4.48 to \$ 5.45) and \$5.46 to \$6.86 in the north-east, central, and north-west part of the study area.

In terms of the prediction accuracy of the interpolation models used to predict the combined data of the base aggregate dense ¾-inch, EBK based on K-Bessel semivariogram produced a better prediction accuracy compared to other semivariograms (Figure 42a). Despite the variances of predictive performance among the different base aggregate 1 ¼- inch bid item models, there is no statistical evidence that the predictive performance of the models differs significantly.

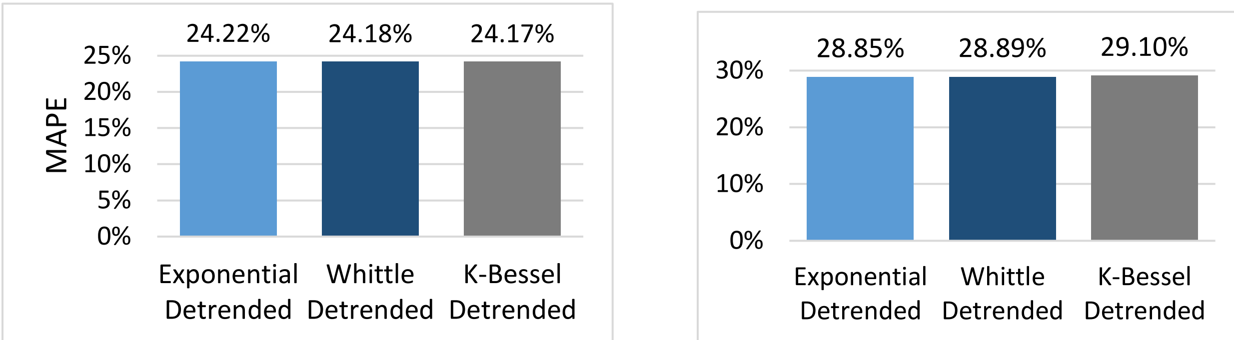


(a) (b)

Figure 41. Price map for combined bid data from 2013 to 2018 for (a) base aggregate dense ¾" bid unit price and (b) tack coat bid unit price

For the tack coat bid item, a combination of EBK and exponential detrended semivariogram performed superior compared to the other two semivariograms. However, Table 36 indicates that there is no evidence of statistically significant differences among the different interpolation methods used to model the tack coat bid item.

Figure 43 shows the interpolated surface for the combined data of the asphaltic surface bid item. From the geovizualized map in Figure 11, the overall trend shows low to medium unit prices at the central part of the study area with sporadic higher unit prices occurs at the south-west and eastern parts of the study area.



(a) (b)

Figure 42. Comparison of kriging results for combined data from 2013 to 2018 for (a) base aggregate dense ¾” and (b) tack coat bid item

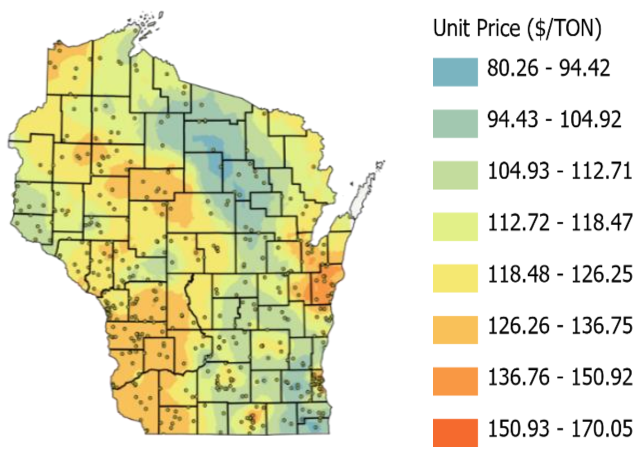


Figure 43. Price map for asphaltic surface bid unit price

The quantitative assessment of the asphaltic surface bid item models reveals that EBK based on K-Bessel detrended semivariogram yields better prediction performance compared to the whittle and exponential detrended semivariograms (Figure 44). However, the predictive power of incorporating K-Bessel detrended semivariogram is not statistically significant compared to the exponential and whittle detrended semivariograms (Table 36).

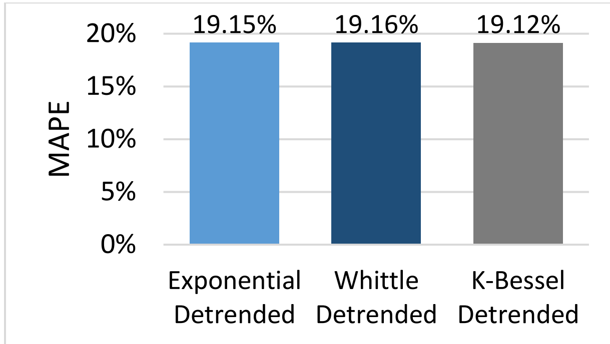


Figure 44. Comparison of asphaltic kriging results for combined data from 2013 to 2018

6.6. Conclusion

Challenges associated with ensuring the accuracy and reliability of cost estimation of highway construction bid items, especially during the conceptual phase of a project, are of significant interest to SHAs. Highway construction unit prices are subject to spatial variation which causes significant uncertainty in developing accurate cost estimates and impedes SHAs capital programming requirements. Therefore, there is a need to accurately account for the uncertainty associated with the spatial variation of highway bid prices across multiple geographic locations. The state-of-the-art encompasses the application of the deterministic and linear geostatistical interpolation methods assumes that the estimated semivariogram is the true semivariogram for the interpolation region and considers only a linear combination of historical cost data to assess the spatial variation on highway unit-price estimates. Additionally, employing classical kriging methods requires manual model parameter configuration to create a valid kriging model which poses several computational difficulties to accurately assess the uncertainty due to spatial variation of highway bid unit prices.

To address this shortcoming, this paper employed a combination of empirical Bayesian kriging with three semivariograms (exponential detrended, whittle detrended, and K-Bessel detrended) to model and interpolate six years (2013 to 2018) of the top five highway bid data:

common excavation, base aggregate dense 1 ¼-inch, base dense aggregate ¾-inch, tack coat, and asphaltic surface obtained from WisDOT. The findings of the study show that EBK based on exponential detrended semivariogram algorithm yields superior prediction accuracy and provides the greater capability of describing variations in common excavation and tack coat bid unit prices. Subsequently, regarding the base aggregate dense 1 ¼-inch, base aggregate dense ¾-inch, asphaltic surface bid items, a combination of EBK and K-Bessel detrended provides enhanced predictive performance compared to the other combinations of EBK and semivariogram models used for the study.

The contribution of this study to the body of knowledge is the application of empirical Bayesian kriging algorithms to accurately assess the standard prediction error introduced by estimating the underlying semivariogram in quantifying the effect of project-specific location and time on highway bid unit-price estimation. The bid unit-price maps generated from this study would enable SHAs to visualize and assess the temporal changes due to the effect of spatial variability and time on bid unit prices in different geographical areas to make better-informed funding decisions at the conceptual phase of highway projects.

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CHAPTER 7. CONCLUSIONS AND RECOMMENDATION

7.1. Introduction

State highway agencies (SHAs) need to deliver capital programs within their planned budgetary and time allocations. SHAs require multiple cost estimates for various purposes throughout the life cycle of highway projects. Therefore, the challenges associated with ensuring the accuracy and reliability of cost estimation of highway construction bid items, especially during the conceptual phase of a project, are of significant interest to SHAs. Even with the existing research undertaken, the problem of inaccurate estimation of highway bid items still exists.

To this end, this research synthesized previous articles on highway bid items to determine research trends, identify the factors affecting highway construction unit prices, and compare the combined performance of the estimation models. A fundamental premise in construction cost estimation is to adjust the estimate to reflect the geographic location of the proposed project. This study employed three geographic information system (GIS)–based methodology for unit-price estimation considering the effects of project-specific location and variations because of cost escalation and inflation on different bid items. This chapter presents a summary and synthesis of the study findings to determine whether the objectives and research questions set out in the introductory section of the thesis have been met. Furthermore, the chapter outlines the theoretical and practical implications of the study findings and presents ideas for future research.

7.1.1. Research Question One to Four (Chapter 2)

From the systematic literature review, this thesis explored the context in which the cost models were used to estimate the cost of highway construction bid items and their associated shortcomings (research question one). Using computational intelligence has enabled the development of several algorithms; namely artificial neural networks (ANNs), genetic algorithms (GA), support vector machines (SVM), regression analysis (RA), and a multitude of tools that are readily available to model construction cost. However, a majority of the existing forecasting models use binary weight values, which are not robust enough to quantify the spatial variation of highway unit prices on construction costs.

To answer research question 2, this study compared the cost estimation methods identified in chapter 2. The findings show that on average, Monte-Carlo simulation models performed superior compared to the Bayesian model, support vector machines, case-based reasoning, artificial neural network, and regression models in that order when weighted by sample size. A comparison amongst artificial neural networks showed that the back-propagation neural network and generalized regression neural network performed better than the multilayer perceptron neural network when weighted by sample size. To ascertain the factors affecting the costs of highway unit prices in the published papers (research question 3), this research employed a qualitative content analysis approach. From the content analysis, 41 factors influencing highway unit prices were identified and classified into three categories, (1) factors relating to project characteristics; (2) organizational factors; and (3) estimate factors based on the common classification used in the selected articles. The results obtained from the mean ranking analysis showed that most of the studies incorporated project-specific factors than the other factors in predicting highway construction costs.

7.1.2. Chapter Three

SHAs are increasingly storing vast amounts of data generated during their operations. To enhance the efficacy of conceptual cost estimates, SHAs need to generate data-driven insights from historical highway cost data. To answer research question 4, this study explored and ascertained trends in historical highway construction bid data from 2013 to 2018 obtained from the Wisconsin Department of Department (WisDOT), determined the relationship between project size and unit prices, and assessed the impact of competition on unit prices of highway construction bid items using exploratory and statistical data analyses. The results of the exploratory data analysis showed tack coat and asphaltic surface to be more volatile than common excavation, base aggregate 1 ¼", and base aggregate ¾" bid items. This volatility could be attributed to the changing instability of crude oil market conditions which could present a challenge to accurately predict the cost of asphaltic surface and tack coat at the conceptual phase. This study confirmed that larger highway construction contracts yielded economies of scale. However, the findings suggest that there is a threshold beyond which the unit cost of the top 5 bid items starts increasing with an increase in project size due to inherent complexity and uncertainty causing contractors to increase their variable cost. The results of the correlational analysis show a trend in which as the number of bidders increased, the unit price decreased from 2013 to 2017. However, for common excavation, asphaltic surface, and tack coat bid items, the number of bidders did not significantly influence the probable bid unit-price estimates.

7.1.3. Chapter Four

State highway agencies (SHAs) employ state average historical bid unit prices and use location adjustment factors to adjust estimates to reflect the appropriate geographical variation at the conceptual phase. Ordinary kriging is one of the most commonly used and straightforward geostatistical interpolation techniques across multiple disciplines. To stimulate the application of GIS-based interpolation techniques that could enable SHAs to account for location-adjustment of highway unit-prices and to address research question 4, this study combined ordinary kriging with three commonly used semivariogram (spherical, exponential, and Gaussian) to model and interpolate six years (2013 to 2018) of the top five highway bid data; common excavation, base aggregate dense 1 ¼", base dense aggregate ¾", tack coat, and asphaltic surface obtained from WisDOT. For the common excavation, base aggregate dense 1 ¼", and tack coat bid items, a combination of OK and exponential semivariogram provided an improved prediction accuracy compared to spherical and Gaussian models.

Regarding the base aggregate dense ¾-inch, a combination of ordinary kriging and Gaussian model performed better compared to spherical and exponential models as measured by the cross-validation and MAPE values. Subsequently, a combination of OK and two semivariograms, spherical and exponential models yielded similar performances, which was superior to the Gaussian model for the unit prices of the asphaltic surface bid item. Nonetheless, a combination of the OK and Gaussian semivariogram model produced acceptable results as the difference between the MAPEs of the three distinct combinations of OK and variograms is insignificant.

7.1.4. Chapter Five

In modeling construction costs, beta and log-normal distributions are commonly used distribution functions for construction cost data. However, the choice of an appropriate distribution function for a specific data set may depend on the characteristics of the project data and therefore, other distribution functions may provide better fits (Sonmez 2005). Depending on the highway project type and cost data being deployed, the use of nonlinear models could be necessary to capture the nonlinearity inherent in the cost data (Sonmez 2005). The state-of-the-art has applied deterministic and linear geostatistical models to assess the spatial variation on highway cost estimates. However, deterministic and linear approaches assume that the data are from a realization of a Gaussian or nearly Gaussian random field, an assumption that produces linear predictors (Rivoirard et al. 2014). Therefore, these algorithms are not capable of accurately modeling the nonlinear relationship and also handling non-Gaussian distributions associated with construction cost data and the cost drivers influencing highway unit prices.

A comparative study was conducted to assess the performance of ordinary and disjunctive kriging methods to model and interpolate six years (2013 to 2018) of the top five common highway bid data: common excavation, base aggregate dense 1 ¼", base dense aggregate ¾", tack coat, and asphaltic surface obtained from WisDOT to answer research question 6. The study's findings for the common excavation, base aggregate dense 1 ¼-inch, base aggregate dense ¾-inch, and tack bid items, the DK algorithms provide a better prediction accuracy over the OK models. However, the prediction power of the DK models was shown to not offer statistically significant differences over the performance of the other two semivariograms. Conversely, for the asphaltic surface bid item, the OK model yielded better prediction performance accuracy compared to the results obtained from employing the DK methods.

7.1.5. Chapter Six

Classical kriging also assumes that the estimated semivariogram is the true semivariogram of the observed data. This means the data was generated from Gaussian distribution with the correlation structure defined by the estimated semivariogram. This is a very strong assumption, and it rarely holds in practice (Krivoruchko 2012). The state-of-the-art has applied deterministic and linear geostatistical interpolation methods to assess the uncertainty associated with the spatial variation of highway bid prices. However, classical interpolation methods assume that the estimated semivariogram is the true semivariogram for the interpolation region and does not assess the uncertainty introduced by estimating the underlying semivariogram.

To address this shortcoming and answer research question 7, this paper employed a combination of empirical Bayesian kriging (EBK) with three semivariograms (exponential detrended, whittle detrended, and K-Bessel detrended) to interpolate six years (2013 to 2018) of the top five highway bid data. The findings show that EBK based on exponential detrended semivariogram yields superior prediction accuracy for the common excavation and tack coat bid items whereas a combination of EBK and K-Bessel detrended variogram provides better predictive performance for the base aggregate dense 1 ¼-inch, base aggregate dense ¾-inch, asphaltic surface bid items.

7.1.6. Research Question Eight

To assess the performance of cost estimation models, several empirical studies employed MAE, MSE, RMSE, and MAPE values. To answer research question 8, this study rigorously evaluated (cross-validation and statistical error metrics) the performance of the different models employed to account for spatial variation and time of highway unit price estimation. The results of the cross-validation statistics corresponded with the assessment of the results obtained from the statistical error assessments.

7.2. Theoretical Contribution

Having achieved the aims and objectives and answered the research questions, it is essential to place the study findings within the wider context of highway construction cost estimation research and practice. The first theoretical contribution is an in-depth statistical data analysis that provides preliminary data-driven insight into the combined accuracy of the cost estimation models identified from the selected literature survey. Chapter 2 identified and categorized a comprehensive set of factors that affect highway construction costs that will serve as a reference for future research in advancing cost estimation modeling at the early stages of highway projects.

This study contributes to the body of knowledge by employing a GIS-based methodology that leverages vast historical bid data for unit-price estimation and the robust GIS capabilities with consideration of the effects of project location and variations because of cost escalation and inflation overtime on different bid items. This study provides evidence supporting the use of advanced geostatistical prediction models (disjunctive and empirical Bayesian kriging) to deal with non-Gaussian data and accurately assesses the standard prediction error introduced by estimating the underlying semivariogram in considering the effect of spatial variation and time on different highway bid unit prices, which is an additional point of departure from the existing body of knowledge.

7.3. Contribution to Practice

SHAs employ state average historical bid unit prices and use location factors to adjust estimates to reflect the appropriate geographical location at the conceptual phase. Ordinary kriging, the most commonly used and straightforward geostatistical interpolation techniques across multiple disciplines, could stimulate the application of GIS-based interpolation techniques that could enable SHAs to account for location-adjustment of highway unit-price estimation.

A comparison of the three different spatial interpolation techniques operationalized in this research, including ordinary kriging for how well they can interpolate cost indexes across space revealed that two alternative methods, the disjunctive and empirical Bayesian kriging, lead to more accurate cost prediction at the conceptual stage than ordinary kriging algorithms. These findings are relevant to industry practitioners, especially SHAs because it enables them to accurately quantify the effect of spatial variation of highway unit prices and ultimately improve the efficacy of highway conceptual cost estimates. Finally, the bid unit-price maps generated from this study would enable SHAs to visualize and assess the effect of spatial variability and time on bid unit prices and make better-informed funding decisions at the conceptual phase of highway projects.

7.4. Recommendations

From the literature review in chapter 2, this paper found areas of potential improvement in the way SHAs report highway construction estimation performance metrics. The studies reviewed in the literature review section used several statistical measures to assess the performance of the cost estimation models. However, the disparate performance metrics reported do not enable an exhaustive comparison of results among empirical highway cost estimation studies.

To monitor the differences between a current cost estimate to previous estimates for highway construction projects, there is a need for standardized estimation performance metrics. Future research could focus on creating a framework for developing and implementing cost-estimating performance metrics and generate additional performance metrics to evaluate the accuracy of highway cost estimation models. Future studies could also provide a longitudinal assessment of how these performance measures improve the estimation accuracy of highway construction projects.

Although this study achieved acceptable prediction accuracy using the proposed models, this further research is recommended to enhance the efficacy of location-adjustment of highway unit prices. For each of the three kriging models employed in this study, further research could employ other semivariogram models which could increase the accuracy of the preliminary cost estimation that has not been experimented within this thesis. For further improvement of the modeling results, the interpolation methods need to be further validated using different highway projects executed in different geographic locations across the country.

7.5. References

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