Evaluation and Development of Cost Prediction Models for Resurfacing Projects to Improve M&R Analysis and Project Development

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16. Abstract

Accurate preliminary cost estimates for resurfacing projects are essential to conduct a reliable Maintenance & Rehabilitation (M&R) analysis, prioritize projects, and optimize the use of available budget. However, TDOT is currently using an outdated cost per lane mile data for such analysis, and hence the results of such analysis can be less reliable. To address the issue, this study develops a framework and a tangible tool entitled "Resurfacing Cost Prediction (RCP)." This framework and tool require limited project characteristics, such as, project length and location, that are available at the early phase of project development. The validation of the tool achieved 100% compliance for accuracy based on AASHTO Practical Guide for Cost Estimation for three treatment types for planning phase. The study also addresses another issue related to project bundling. TDOT creates bundles of resurfacing projects to attract more contractors, achieve lower cost per lane mile, and reduce administrative burden. However, TDOT lacks a systematic methodology to create project bundles. As such, it relies on manual identification of projects suitable for bundling. This manual approach can be very time-consuming and cumbersome, and it can create inconsistent bundles. To address this issue, an Automated Maintenance Project Bundling (AMPB) tool is developed. The tool was able to achieve up to 92% accuracy in correctly identifying if a project should be bundled or not. These frameworks and tools are expected to aid TDOT in improving the planning and execution of resurfacing projects while optimizing the use of available budget.

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Executive Summary

Accurate preliminary cost estimates for resurfacing projects are essential to conduct a reliable Maintenance and Rehabilitation (M&R) analysis. The M&R analysis aids the Tennessee Department of Transportation (TDOT) in identifying and prioritizing projects. However, there is a lack of a robust methodology to update this cost information in the M&R analysis. As a result, the project recommendations provided by the pavement management system are subject to change, which leads to a significant amount of extra work in project development. Thus, there is a need to develop a robust methodology for predicting resurfacing project cost using project characteristics that are available at the early phase of project development.

Project size is one of the main factors that affects the construction costs for two reasons: a) larger project naturally means more work and hence higher total project cost and b) similarly complex larger projects tend to have lower cost per lane mile because of the economy of scale. However, if a project is too large, some contractors may not be able to bid on the project. If a project is too small, contractors may not be very interested in bidding on the project. Thus, to attract sufficient contractors to create competition, many state DOTs including the TDOT bundles smaller projects to create a larger contract. While this approach can be effective, TDOT does not have a consistent and systematic methodology to create bundles of projects. Thus, there is a need to create a systematic methodology to create project bundles using various project characteristics.

To address these two challenges, this study collected and analyzed 11 years of resurfacing project dataset from 2013 to 2024. The dataset contained various project characteristics, such as, project cost, location, lane mile, and treatment type. The impact of various project characteristics on the resurfacing project costs are evaluated, and various models are developed using data from 201 to 2023 to predict resurfacing project costs. Based on these models, a theoretical framework and a tangible tool for Resurfacing Cost Prediction (RCP) are developed. The framework and tool are validated using the project data from 2024.

The analysis of the dataset was also used to develop a new theoretical framework and tool for Automated Maintenance Project Bundling (AMPB). This framework introduces a new concept of an overall compatibility score to quantify suitability of projects for bundling. All resurfacing projects are evaluated using the framework to identify projects that are most suitable for bundling. Then, bundles that exceeds a minimum similarly threshold are recommended for bundling. The framework and tool are validated using entire dataset from 2013 to 2024.

Key Findings

The key findings of the study are listed below.

- TDOT has practice of creating new treatment types by combining various components on as required basis. This creates a less systematic dataset that are more challenging to compile and analyze.
- Seventy three percent of bundled contracts contained two projects.
- Mill & 411D is the most common asphalt (ASPH) treatment type used at TDOT that accounted for $1.57 billion worth of projects (inflation adjusted). Micro-surfacing @22

lbs/sy was the most common type of surface treatment (SRFT) type that accounted for over $45 million worth of projects.

- The Cost Per Lane Mile (CPLM) varied notably for various treatment types and various locations. For example, “Mill, C & OGFC” costs $351,096.21 per lane mile on average while Micro-surfacing @ 22 lbs/sy costs $40,102.98. Neighboring counties can also have notably different CPLM experience. These findings highlight the importance of developing separate cost estimating models for various treatment types and locations.
- Impact of inflation must be considered when estimating resurfacing project costs. However, TDOT does not have an in-house highway construction cost index that represents TDOT-specific construction inflation.
- New metrices to measure the performance of bundling algorithms are developed: a) exact result rate, b) successful result rate, and c) successful bundling rate.

RCP Tool

The RCP tool is developed as a parametric cost estimating tool for resurfacing projects. The tool includes cost prediction models for ASPH and SRFT types. The models for the tool are developed at county, region, and state levels, and the final estimate is calculated as a weighted average of the three models. The models that consider smaller geographical are more reflective of localized market conditions, but they can be biased if a few unique projects exist in the area. The models that consider larger geographical area are more consistent as they are based on larger number of projects, and hence are less affected by a few unique projects. By integrating the models that covers different levels of geographical coverage, it provides more robust estimates. The tool automatically accounts for inflation from the model year to the planned construction year using National Highway Construction Cost Index (NHCCI). Overall, the RCP tool achieved 100% compliance for accuracy based on “AASHTO Practical Guide for Cost Estimation” for three treatment types for planning phase. It also showed compliance for two treatment types for scoping level and one treatment type for design phase.

AMPB Tool

The AMPB tools is a powerful tool developed to mimic TDOT engineers’ approach for creating bundles of projects based on various project characteristics. The tool introduces a new concept of compatibility scores that is based on five components: geographical, treatment type, project cost, project length, and asphalt mix plant compatibility scores. Criteria for various scores are developed based on the analysis of historical data. Interpolation is performed as relevant when the compatibility scores are based on continuous project characteristics such as project cost. The tool was validated using entire resurfacing project dataset from 2013 to 2024 as the algorithm for AMPB tool does not rely on the dataset. The AMPB tool achieved up to 92% accuracy in correctly identifying if a project should and should not be bundled. Further, the tool had up to 91% accuracy in identifying projects that should not be bundled.

Key Recommendations

The key recommendations of the study are listed below.

- TDOT should standardize the resurfacing treatment types across the state to ease the analysis of resurfacing project cost data in the future.
- TDOT should develop TDOT-specific highway construction cost indexes to adjust estimates for inflation. Currently, National Highway Construction Cost Index (NHCCI) is used for inflation adjustment. However, NHCCI reflects the national trend in the construction market and may not accurately reflect Tennessee highway construction market.
- The cost prediction models should be regularly updated so that the predictions from the model are more reflective of the up-to-date market conditions.
- Currently TDOT utilizes an outdated software for performing benefit cost analysis for project prioritization. This tool requires cost per lane mile for computing the benefit cost. However, the cost per lane mile is not the most reliable method for predicting cost. As such, a modern tool capable of accepting modern models for calculating cost should be developed for performing benefit cost analysis.

The RCP tool and AMPB tools are expected to increase consistency and reliability of cost prediction and project bundling while saving time and effort required to produce the results. The tools should not be considered as replacements for engineering judgment. Cost prediction models predict costs assuming that historical trend will be followed in future projects. If the new projects have similar project characteristics as historical projects, the tool is likely to produce more accurate results. However, if the new projects are significantly different than historical projects, the tool will likely produce less accurate results.

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Glossary of Key Terms and Acronyms

AASHTO	American Association of State Highway and Transportation Officials
AMPB	Automated Maintenance Project Bundling
ASPH	Asphalt
DOT	Department of Transportation
FHWA	Federal Highway Administration
HCCI	Highway Construction Cost Index
MAPE	Mean Absolute Percentage Error
MPE	Mean Percentage Error
NHCCI	National Highway Construction Cost Index
OLS	Ordinary Least Squares
PIN	Project Identification Number
RCP	Resurfacing Cost Prediction
SRFT	Surface Treatment
STP	Surface Transportation Program
TDOT	Tennessee Department of Transportation

Chapter 1 Introduction

The Tennessee Department of Transportation (TDOT) uses Pavement Management System (PMS) for identifying potential resurfacing projects as a part of Maintenance and Rehabilitation (M&R) analysis. This M&R analysis requires estimated construction costs for the resurfacing projects, and TDOT has relied on average cost per lane mile to estimate the cost. However, the current cost per lane mile data has not been updated for many years, which decreases the reliability of the results from such M&R analysis. Further, current inputs used for the M&R analysis does not sufficiently reflect the impact of the project location and size. Project location can significantly affect the cost of the project because of various factors, such as, site conditions, traffic, competition, and local labor rates. If a project is too small, it may not be attractive to many contractors. If the project is too big, many contractors may not be able to bid on the project. Many state DOTs including TDOT attempts to address this issue of project size by bundling smaller projects together to make it more attractive to more contractors. Further, when multiple projects are bundled into a single contract, it can reduce the mobilization cost for contractor and administrative burden for TDOT. However, TDOT currently does not have a systematic method to bundle projects in a single contract. Instead, TDOT engineers have to manually evaluate various projects for their suitability for bundling. This manual process of evaluating hundreds of projects for bundling can be very time-consuming, and it can produce inconsistent results. Thus, TDOT has two major challenges related to M&R analysis of resurfacing projects: a) there is a lack of modern cost prediction models and b) there is a lack of systematic method for project bundling.

1.1 Research Objectives

The overall goal of this study is to develop theoretical frameworks and tangible tools that can be used to aid TDOT in performing M&R analysis. The specific objectives of the study are to:

- Identify, analyze, and quantify the impact of various factors – such as inflation, local competition, supplier's location, aggregate requirements, total contract size, project bundling, and resurfacing treatment type – on the resurfacing project cost using data from historical resurfacing projects such as project characteristics and bidding information.
- Develop, test, and validate a TDOT-specific accurate cost prediction models for resurfacing projects that accounts for relevant factors, such as project characteristics, that are available during the early phases of the project development.
- Develop a project bundling strategy and associated tool for resurfacing projects that has potential to increase the competition and decrease the construction cost.
- Prepare a guideline to integrate the methodologies and tools with project prioritization process.
- Disseminate the results of the study to TDOT engineers and to other state DOTs via meetings and conferences such as Transportation Research Board (TRB) Annual Meeting.

1.2 Significance of the Research

This study develops theoretical frameworks and tangible tools to predict costs of resurfacing projects and identify projects that are suitable for bundling. The cost prediction tool will enable TDOT to predict the costs of resurfacing projects quickly and accurately at early phase of project development. This will result in more reliable M&R analysis and hence better project prioritization. Further, more reliable cost predictions during the planning and budgeting phase will enable TDOT to better utilize the available funding.

The tool to automate project bundling will enable TDOT to develop more consistent and unbiased project bundles, which will increase the transparency among stakeholders. The automated nature of the tool will ensure a significant reduction in the time and effort required to identify projects that are suitable for bundling. This time-saving tool will free up time for TDOT engineers to focus on other more important tasks and responsibilities.

1.3 Organization of the Report

The remaining part of the report is organized into six chapters. Chapter 2 Literature Review summarizes current practices of cost estimating and project bundling across various DOTs. Chapter 3 Methodology provides an overview of various tasks completed to achieve the objectives of the study. Chapter 4 Framework for Resurfacing Cost Prediction (RCP) develops a theoretical framework developed for reliable and consistent cost estimating at the early phase of project development. Chapter 5 Framework for Automated Maintenance Project Bundling (AMPB) develops another theoretical framework to automate the process of identifying projects suitable for bundling. Chapter 6 Results implements the theoretical frameworks as tangible tools and validates the tools using historical data. Finally, Chapter 7 Conclusion concludes the report by highlighting major findings and recommendations.

Chapter 2 Literature Review

The literature review is divided into two sections: a) parametric cost estimation, b) bundling of the projects.

2.1 Parametric Cost Estimation

Parametric cost estimation has been utilized as a powerful tool for predicting transportation infrastructure costs, particularly during early project development phases when detailed design data is unavailable. This method utilizes relationships between cost and project attributes, such as location, length, width, pavement type, to generate early-stage cost estimates. In resurfacing projects, where quick yet reasonably accurate estimates are often necessary for budgeting and scoping, parametric models offer a practical alternative to resource-intensive bottom-up methods (Piratla et al., 2024).

The American Association of State Highway and Transportation Officials (AASHTO) notes that conceptual estimates at the early planning stage can deviate significantly, with potential cost errors ranging from -50% to +200% (AASHTO, 2013a). These uncertainties arise from factors such as evolving project scope, inflation, local material availability, and labor market variability. Nevertheless, parametric methods remain valuable because they deliver consistent estimates using minimal project information.

Early studies established the foundation for parametric estimation in transportation projects. Duverlie & Castelain (1999) compared parametric models with case-based reasoning (CBR), finding that parametric approaches outperformed CBR when data were well-structured. Similarly, Saito et al. (1991) demonstrated the importance of structural and classification variables in bridge cost estimates. Trost and Oberlender (2003) further highlighted the influence of complexity, contract type, and location on estimation accuracy, emphasizing the importance of including contextual drivers in cost models.

Other efforts have expanded parametric methodologies to incorporate statistical enhancements. For example, Liu et al. (2011) applied hierarchical linear modeling and multilevel Bayesian approaches to account for multilevel data structures and enhance predictive performance in highway project estimates. This methodology allowed models to incorporate categorical and continuous data and perform effectively even with limited input variables.

Machine learning techniques have also gained traction in cost estimation studies. Lowe et al. (2006) developed both linear regression and neural network models, with neural networks demonstrating superior accuracy (MAPE of 16.6% vs. 19.3%) but reduced interpretability. Similarly, Dominic & Smith (2014) and Adel et al. (2016) applied artificial neural networks and genetic algorithms to highway projects, producing high predictive accuracies. However, such models' complexity and “black box” nature have raised concerns about usability among estimators.

Recognizing this trade-off, Piratla et al. (2024) developed a preliminary cost estimation tool using linear regression, support vector machines, and neural networks for the South Carolina DOT. Despite exploring advanced models, they emphasized institutional feasibility, concluding that regression-based models remain most practical for public agency adoption. The study reported accuracy levels between 61% and 84% across different project types, reinforcing the utility of regression models for early-stage forecasting.

Regression-based parametric models are particularly advantageous in resurfacing projects, typically characterized by repeatable scopes and well-defined cost components. These projects benefit from consistent datasets (e.g., historical bid prices, pavement condition, location), which are ideal for developing predictive models. Karaca et al. (2020) demonstrated that top-down estimation using high-impact cost drivers can outperform detailed bottom-up methods for such projects, especially when rapid decisions are required.

Despite the importance and usability of various parametric cost estimating techniques, TDOT currently lacks a robust parametric cost estimation tool for resurfacing projects. This study will fill this gap by developing a framework and tool for parametric cost estimation of resurfacing projects.

2.2 Project Bundling

Project bundling has gained prominence as an effective strategy to enhance cost-efficiency and streamline project delivery in transportation infrastructure, particularly in bridge rehabilitation and replacement efforts. The Federal Highway Administration (FHWA, 2020) and several state Departments of Transportation (DOTs), including PennDOT, INDOT, and MoDOT, have actively promoted and implemented bundling approaches with positive outcomes. Shrestha et al. (2024) emphasize that bundling multiple projects under a single contract can reduce administrative workload, improve coordination, and expedite delivery timelines. These efficiencies are especially important in agencies facing staffing limitations or managing large-scale infrastructure programs.

Among the most frequently cited benefits of bundling are economies of scale, administrative efficiency, faster project completion, and uniform quality control. D'Angelo & Minchin (2021) explain that bundling enables bulk procurement of materials and more efficient allocation of labor and equipment, thereby reducing per-unit costs. Contractors also benefit from minimizing idle time and repetitive mobilization. On the agency side, fewer contracts translate to less paperwork, simplified procurement, and improved oversight capacity (Qiao et al., 2018; J. Shrestha et al., 2023)

Geographic proximity and project similarity are key to realizing these benefits. Projects located near one another allow smoother logistics, reduced travel time, and easier contractor mobilization (FHWA, 2020). When bundled projects involve similar work types, contractors can apply standardized workflows, reduce subcontracting, and benefit from learning curve efficiencies. Mid-sized bundles, those that are large enough to capture efficiencies but small enough to attract a diverse pool of bidders, tend to strike the most effective balance.

Despite these advantages, bundling is not without challenges. Large bundle sizes may deter small and medium-sized contractors from participating, reducing competition and potentially increasing bid prices (Xiong et al., 2017). In addition, managing complex, multi-project contracts requires higher levels of coordination and project control. Misaligned schedules, stakeholder conflicts, or dispersed project locations can introduce delays and public inconvenience (Miralinaghi et al., 2022). Furthermore, D'Angelo et al. (2019) emphasize that bundling does not always guarantee savings—benefits can vary widely depending on project scope, location, and market conditions.

While a growing body of literature supports the strategic use of bundling, most existing studies focus on bridge projects and case-specific successes. Assaf & Assaad (2023) highlight important decision-making factors like scope compatibility and contract size but also point out the absence of comprehensive frameworks that integrate these variables. Most of the studies have developed some high-level guidelines about creating project bundles, but they do not create systematic framework that can be used to develop an automated tool for creating project bundles. This study addresses this issue by developing a framework and a tool that uses quantitative measures to automatically recommend project bundles based on various project characteristics.

Chapter 3 Methodology

The overall methodology of the research consists of five major tasks: 1) collection and processing of datasets, 2) inflation adjustment, 3) preliminary analysis of historical data, 4) development of theoretical frameworks for Resurfacing Cost Prediction (RCP) and Automated Maintenance Project Bundling (AMPB), and 5) development of RCP and AMPB tools.

3.1 Collection and Processing of Datasets

This study utilized a comprehensive dataset obtained from the Tennessee Department of Transportation (TDOT). The dataset encompasses 2,027 resurfacing projects completed from 2013 to 2024 across all 95 counties in Tennessee. The dataset includes detailed project-level information, such as, contract number, Project Identification Number (PIN), treatment type, project length, location, and cost. If multiple PINs were included in the same contract number, those projects are identified as bundled. Seventy-three percent of the contracts with bundled projects included two projects and 24% included three projects (Table 3-1). A few contracts included four or five projects.

Table 3-1 Historical Bundle Size

Project Count in Bundles	*Number of Contracts*	*Percentage*
2	260	73%
3	85	24%
4	10	3%
5	2	1%
Total	*357*	*100%*

TDOT’s treatment methods are categorized into two groups a) ASPH and b) SRFT. The ASPH (Asphalt-based Treatments) group focuses on durable and cost-effective methods like overlays, milling, and full-depth reclamation, aimed at restoring structural integrity and extending roadway service life. The SRFT (Surface Treatments) treatment focuses on preventative methods, such as, chip seals, scrub seals, and micro-surfacing. They emphasize on enhancing surface durability, friction, and protection against minor wear, often used on rural or low-traffic roads.

To ensure analytical reliability, the dataset underwent rigorous preprocessing. Any projects with missing information on essential parameters, such as, project location (e.g., region, county, etc.), lane miles, project cost, or resurfacing treatment type, were removed from the dataset. This step ensured that the analysis would be based only on records with consistent and comparable information for all key variables. The second step focused on evaluating potential outliers. Box plots were used to identify unusually high or low project costs relative to lane miles and treatment type. Examples of the box plots are provided in the Appendix. These potential outliers identified from the box plots were reviewed in consultation with TDOT personnel, who confirmed that the values reflected real project conditions rather than data entry errors. Accordingly, such data were retained for the analysis. Finally, the treatment types were standardized to streamline the analysis. For instance, the same treatment type may be referred as “CS” in one region and “Chip Seal” in another region. After removing the incomplete records, the size of the dataset was reduced from 2,027 original records to 2,004 valid records, which was used for further analysis. The list of records removed from the analysis are presented in the Appendix.

3.2 Inflation Adjustment

To account for the impact of inflation on the resurfacing project costs, the resurfacing project costs must be adjusted using an inflation rate. As TDOT does not have Tennessee-specific inflation rate, National Highway Construction Cost Index (NHCCI) was used as the best available substitute. The NHCCI reflects national construction cost trend instead of Tennessee-specific cost trend, and the researchers recommend that TDOT develop its own Highway Construction Cost Index (HCCI) in the future. The annual inflation rate was calculated using the following equation (1):

$$\text{Inflation rate (i)} = \left(\left(\sqrt[N]{\frac{HCCI_d}{HCCI_e}}\right) - 1\right) \times 100\% \tag{1}$$

Where,

$HCCI_d$ = HCCI for the Desired Year

$HCCI_e$ = HCCI for the Estimate Year

N = Number of Years Between the Desired Year and Estimate Year

The average NHCCI value for 2003 was 1.013813 and for 2023, the value was 2.859906. From these two values, an average inflation rate was determined to be 5.32% per year. With this inflation rate, each estimate can be adjusted from the estimate year to the desired base year for model development using Equation (2).

$$E_d = E_e * (1+i)^N \tag{2}$$

Where,

E_d = Estimated Cost of the Project in the Desired Year

E_e = Estimated Cost of the Project in the Estimate Year

I = Inflation Rate

N = Number of Years Between the Desired Year and Estimate Year

Once all estimates are converted to the desired base year, the data can be used for model development.

3.3 Preliminary Analysis of Historical Data

TDOT employed 86 ASPH and 37 SRFT resurfacing treatment types across 95 counties, adapting the treatment types based on road conditions, traffic levels, and specific regional needs. The expenses for these treatment types were over $3 billion for ASPH and over $169 million for SRFT (inflation adjusted to year 2023). Data from these projects were analyzed to get a better understanding of the distribution of costs across various project types, project location, and current bundling practices. The preliminary analysis of historical data includes a) identification of the top treatment types by total project cost, b) identification of the most frequently used treatment types, c) average resurfacing cost per lane mile by location, and d) the impact of bundling on CPLM.

3.4 Development of Theoretical Frameworks for RCP and AMPB

Two separate theoretical frameworks for RCP and AMPB were developed. The theoretical framework for RCP is based on parametric modeling. The models were developed at county, regional, and state levels to account for geographic variability. Separate models are also developed for various treatment types. The outputs from relevant models are used to compute final aggregated estimate for new resurfacing project. For AMPB, a new concept of compatibility scores was developed. The compatibility score indicates the suitability of maintenance projects for bundling based on historical pattern. The overall compatibility score was calculated from five compatibility score components: geographical, treatment type, project length, project cost, and asphalt mix plant compatibility scores.

3.5 Development of RCP and AMPB Tools

The theoretical frameworks for RCP and AMPB were implemented as two separate spreadsheet-based tools. The RCP tool was validated using the dataset that was not used in model development. The AMPB tool was validated using the entire dataset as it utilizes custom algorithm to mimic past bundling practices.

Chapter 4 Framework for Resurfacing Cost Prediction (RCP)

The theoretical framework for RCP consists of four major components: 1) Data Preparation, 2) Model Development, 3) Estimate Aggregation, and 4) Inflation Adjustment.

4.1 Data Preparation

In parametric cost estimating models, project characteristics are used to predict the project cost. For this framework, the relevant resurfacing project characteristics include treatment type, location, lane mile, and construction year. These parameters quantify the three essential components of cost estimating: project size, location, and type. These historical project characteristics and corresponding project costs are collected in this phase. As historical project costs are from various years, they are adjusted for inflation for the model year to normalize the cost data for model development.

4.2 Model Development

To ensure the ease of implementation of the framework as a tangible tool, regression models are developed using Ordinary Least Squares. In a regression model, the project characteristics is used as independent variables (inputs), and the cost is predicted as a dependent variable (output). One option to build such model is to utilize the entire dataset from the state covering all treatment type in a single model. However, such “one size fits all” models may not be able to account for the variation in the project cost because of the location and treatment types with sufficient granularity. As such, separate models are developed for various treatment types in various geographical areas. State-, region-, and county-level models are developed for each treatment type. Mathematically, a linear regression can be expressed by Equation (3).

$$y = \beta_0 + \beta_1 x \tag{3}$$

Where,

y	=	dependent variable (cost)
X	=	independent variable (project characteristic)
β_0	=	y-intercept of the regression line
β_1	=	slope of the regression line

4.3 Estimate Aggregation

The state-, region-, and county-level models have their advantages and disadvantages. The county-level models can indirectly account for the county-specific market conditions, such as local competition, distance from asphalt mix plants, and labor rates. However, each county may not have a large number of historical resurfacing projects, and hence a few peculiar projects may result in biased models. The state-level models will generally have significantly more projects, and hence such models are less prone to creating biased models because of a few peculiar models. But the state-level models will not account for local market conditions. The advantages and disadvantages of the region-level models lies somewhere in between the state-level and county-level models. In this framework, instead of relying on a single "one size fits all" model, it utilizes the outputs from all models to benefit from the strengths of all the models. These outputs are aggregated using weighted average method to compute the final score as shown in Equation (4).

$$Aggregated\ Final\ Estimate = \frac{\sum_{i=1}^{n} w_i * e_i}{\sum_{i=1}^{n} w_i} \tag{4}$$

In this equation, w_i are weights corresponding to the estimates e_i.

4.4 Inflation Adjustment

The models produce estimates for the model year. As the planned construction year is likely to be different than the model year, the outputs from the model need to be adjusted for inflation. This inflation adjustment made while using the model is different than the inflation adjustment made during the model development. This adjusted estimate will be the final estimate for the new project. Equation (2) is used for this inflation adjustment.

Chapter 5 Framework for Automated Maintenance Project Bundling (AMPB)

The theoretical framework for AMPB is developed to mimic TDOT engineers' historical bundling practices. The framework consists of three components: a) data collection and preprocessing, b) compatibility scores, c) framework design, and d) framework implementation. The implementation details of the framework are provided in section 6.3 AMPB Tool.

5.1 Data Collection and Preprocessing

This framework requires a list of bundled and unbundled projects with their resurfacing project characteristics. Specifically, the location, treatment types, cost, and lengths are required. Further, an asphalt mix plant location dataset is required to compute the number of asphalt mix plants that are easily accessible for the projects. The project costs are adjusted for inflation before further analysis. The dataset needs to be cleaned to remove projects with incomplete information. Further, the project characteristics should include a data attribute to indicate its bundling status.

5.2 Compatibility Score Calculation

This framework introduces a new concept of compatibility score. A compatibility score indicates suitability of projects for potential bundling. Based on the literature review, four factors were identified for evaluating the suitability of projects for bundling: a) project location, b) project type, c) project length, and d) project cost. Another factor highlighted by TDOT engineers was the proximity of the bundled projects to asphalt mix plants for making the contract more competitive. Based on these factors, five components of compatibility scores are introduced for bundling resurfacing projects: a) geographical, b) treatment type, c) project length, d) project cost, and e) asphalt mix plant presence compatibility scores. Scoring matrixes that maps the project characteristics with the scores are developed for computing each of the compatibility scores. These matrixes are based on the analysis of historical bundling practices. When relevant, interpolation is performed using Equation (5) to compute compatibility scores for scenarios that are not directly available in the scoring matrix.

$$s = s_1 + \frac{s_2 - s_1}{x_2 - x_1} * (x - x_1) \tag{5}$$

In the equation, s represents the required score corresponding to an input project characteristic x. The s_1 and s_2 are scores corresponding to x_1 and x_2. Once these scores are calculated, an overall compatibility score is computed as a weighted average of five components using Equation (6).

$$Overall\ Compatibility\ Score = \frac{\sum_{i=1}^{n} w_i * s_i}{\sum_{i=1}^{n} w_i} \tag{6}$$

In the equation, w_i are weights of various components of compatibility scores s_i.

Geographical Compatibility Score

Literature review and communication with TDOT and other state DOT engineers indicated that geographical proximity of the projects is one of the most important factors in deciding project bundles. The proximity of projects enables contractors to reduce their mobilization cost and stay within their service area, which could result in lower bids. Mathematically, the geographical compatibility score is inversely proportional to the distance between two projects. However, in practices, up to certain distance (e.g., 25 miles), the compatibility of two projects would not change much. To accomplish this, scores at various distances can be assigned, and value for any intermediate distance can be interpolated from the scores. Further, to reduce the data requirements for creating bundles, centroid of an area (e.g., county) can be used as the location of the project. A matrix of distances between every area (e.g., county) can be prepared using Haversine formula that accounts for Earth's curvature.

Treatment Type Compatibility Score

Various treatment types can be used for resurfacing projects. If the treatment types are similar, then same pieces of equipment can be used for all projects. But, if the treatment types of two projects are significantly different, then the contractor may need to bring additional types of equipment. Thus, bundling of projects with similar treatment types would increase efficiency for the contractors. A matrix indicating similarities in treatment types can be developed, and higher compatibility scores can be assigned for the projects with similar treatment types. If a treatment type consists of multiple components, then compatibility scores for the components can be developed.

Project Cost Compatibility Score

If a resurfacing project is too small, contractors may not be attracted enough to bid on the project. Project cost is one of the measures of project size. The historical distribution of individual project cost for unbundled project and combined project cost for bundled projects would indicate the engineers' preference on the overall project cost for competitive contract. This historical distribution can be used as a measure to assign project cost compatibility score. For future projects to be bundled, these scores can be interpolated for the new combined project cost.

Project Length Compatibility Score

Project length is another of the measures that represents the project size. The historical distribution of individual project length for unbundled project and combined project length for bundled projects would indicate the engineers' preference on the overall project length for competitive contracts. This historical distribution can be used as a measure to assign project length compatibility score. For future projects to be bundled, these scores can be interpolated for the new combined project length.

Asphalt Mix Plant Compatibility Score

The availability of asphalt mix plant near the project location can play a significant role in the contractors' interest to bid on a project. If asphalt mix plant is not available near a project, bundling it with another project which has asphalt mix plant(s) nearly would increase contractors' interest in bidding on the project. If higher number of asphalt mix plants are available near the bundled projects, it will likely increase the competition. However, if the framework is developed to encourage the highest number of nearby asphalt plants, it will focus on bundling projects that already has higher number of asphalt mix plants nearby. Once bundles are created, the projects with lowest number of plants (or no plants) nearby will remain unbundled. This will create very high competition for some projects but will create very low competition for others. As such, this implementation focuses on creating bundles where optimal (not highest) number of asphalt mix plants are available near each bundle.

5.3 Bundle Recommendation

Once the overall compatibility scores are computed for all potential bundles, a bundle with the highest score (say, "Project A + Project B") is selected first. Subsequently, another bundle that does not contain previously bundled project ("Project A" or "Project B") is selected. This process is continued for all projects. However, the bundles with lower overall compatibility scores may not be similar enough to obtain the potential benefits of bundling. As such, certain threshold can be set to recommend better bundles only. This "Minimum Similarity Threshold" should be customizable.

5.4 Bundling Performance Metrices

The performance of the algorithm can be defined as the correctness of the bundling results produced by the algorithm compared to the historical bundling. For a validation dataset with multiple projects, the performance will be based on the correctness of bundling of all projects. Thus, to calculate the overall performance, the correctness of bundling for each project must be computed first. For that, the correctness of bundling needs to be defined first.

The comparison of the algorithmic bundling and actual/historical bundling can result in one of the five scenarios: a) exactly bundled, b) correctly unbundled, c) correctly bundled with incorrect partner, d) incorrectly unbundled (should be bundled), and e) incorrectly bundled (should be unbundled). These results can be expressed as a percentage of total number of projects.

Exactly Bundled: If "Project A" and "Project B" were bundled historically, the algorithm also recommends the same bundle ("Project A" + "Project B"). This represents a correct result.

Correctly Unbundled: If a project was not bundled in the historical data, the algorithm also recommends not to bundle the project. This represents a correct result.

Correctly Bundled with Incorrect Partner: If "Project A" and "Project B" was bundled historically, the "Project A" is still bunded but with a different partner ("Project A" + "Project C"). This can be considered as a partially correct result.

Incorrectly Unbundled (Should be Bundled): If "Project A" and "Project B" were bundled historically, the "Project A" is not recommended for bundling by the algorithm. This represents an incorrect result.

Incorrectly Bundled (Should be Unbundled): If "Project A" was not bundled historically, the algorithm recommended to bundle it ("Project A" + "Project B"). This represents an incorrect result. With these five scenarios defined, the performance of the algorithm can be computed. This study defines four performance metrices based on the above scenarios: a) Exact Result Rate, b) Successful Result Rate, c) Successful Bundling Rate, and d) Successful Unbundling Rate. The Exact and Successful Result Rates are computed as percentages of all projects irrespective of whether they are bundled.

The Exact Result Rate considers perfect results only and can be defined mathematically by Equation (7).

$$Exact\ Result\ Rate = \frac{\text{Exactly Bundled} + \text{Correctly Unbundled}}{\text{Total Number of Projects}} * 100\% \quad (7)$$

The Successful Result Rate includes partial success case as well and can be defined mathematically by Equation (8).

$$Successful\ Result\ Rate = \frac{\text{Exactly Bundled} + \text{Correctly Unbundled} + \text{Correctly Bundled with Incorrect Partner}}{\text{Total Number of Projects}} * 100\% \quad (8)$$

The Successful Bundling and Unbundling Rates are computed as percentages of bundled or unbundled projects, respectively. The Successful Bundling Rate can be defined mathematically by Equation (9).

$$Successful\ Bundling\ Rate = \frac{\text{Exactly Bundled} + \text{Correctly Bundled with Incorrect Partner}}{\text{Total Number of Bundled Projects}} * 100\% \quad (9)$$

The Successful Unbundling Rate can be defined mathematically by Equation (10).

$$Successful\ Unbundling\ Rate = \frac{\text{Correctly Unbundled}}{\text{Total Number of Unbundled Projects}} * 100\% \quad (10)$$

Chapter 6 Results

This chapter presents the results of the data analysis followed by the implementation of the two theoretical frameworks. The frameworks for the Resurfacing Cost Prediction and Maintenance Project Bundling were implemented as spreadsheet-based tools to enable TDOT to implement and integrate the findings of this study in existing cost estimating practices.

6.1 Data Analysis

The results of the data analysis are presented in four sections: a) top treatment types by total cost, b) most frequently used treatment types, c) average CPLM by location, and d) impact of bundling on CPLM.

Top treatment Types by Total Cost

The top treatment types under ASPH and SRFT by total cost are provided below.

Top ASPH Treatment Types by Total Cost

Figure 1 shows that TDOT spent approximately \$1.57 billion on the resurfacing treatment type "Mill &411D," which accounts for the largest fraction of the total expenditure on the ASPH resurfacing projects. Four other top treatment types accounted for approximately \$260 million expenditure each: "Mill, CS & OGFC"; "Mill, C & OGFC"', "411D Overlay", and "411TLD Overlay @85 lb/sy". The remaining treatment types accounted for smaller expenses, which indicates either a limited use or lower cost per project within the ASPH resurfacing category.

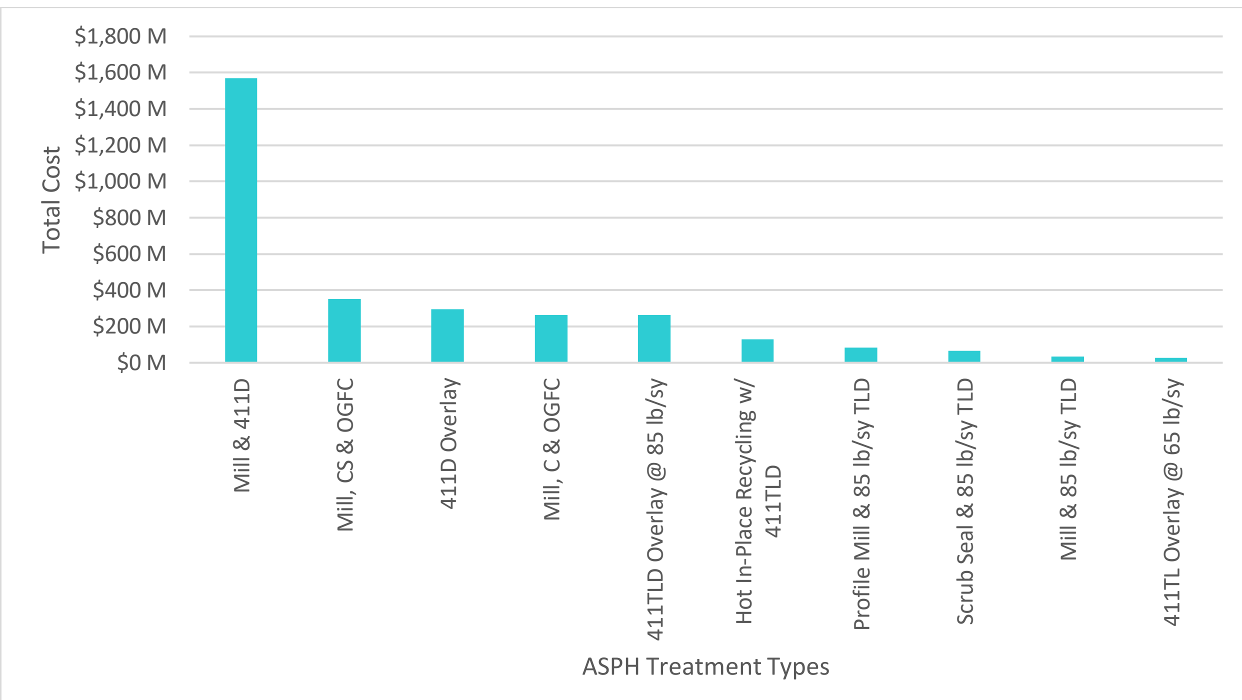


Figure 1: Total Cost of 10 Major ASPH Road Resurfacing Treatment Types

Top SRFT Treatment Types by Total Cost

Figure 2 shows that various types of Micro-surfacing is the most popular choice. For example, "Micro-surfacing @22 lbs/sy" accounted for more than $76 million in expenses. "Cape Seal" was the largest treatment type after two Micro-surfacing types.

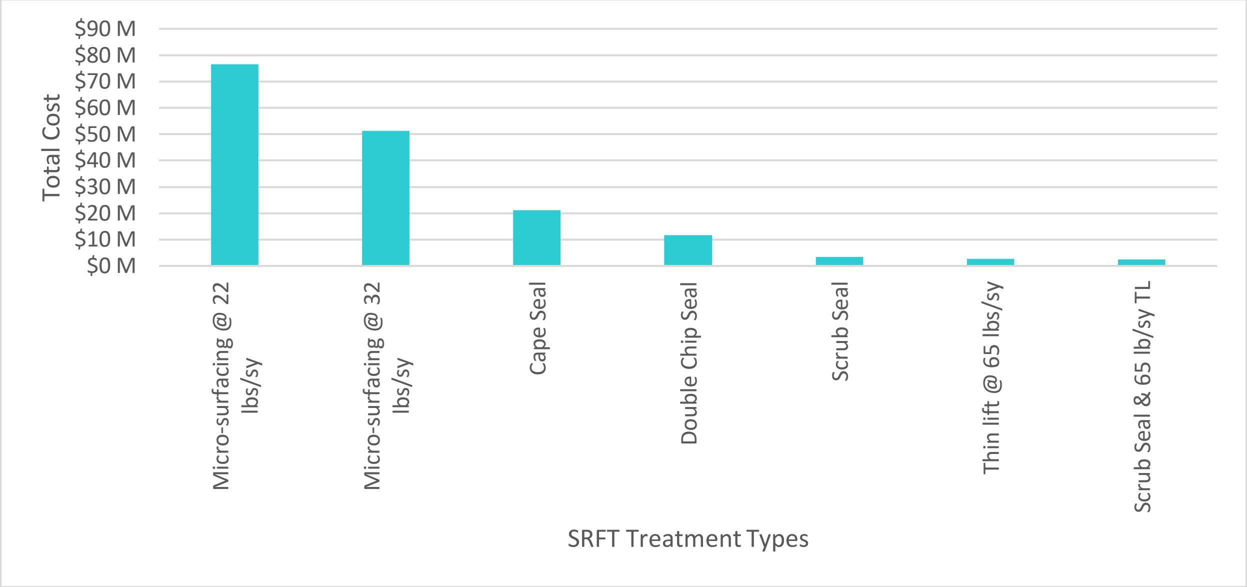


Figure 2: Total Cost of 7 Major SRFT Road Resurfacing Treatment Types

Most Frequently Used Treatment Types

The most frequently used treatment types under ASPH and SRFT are identified below.

Most Frequently Used ASPH Treatment Types

Table 6-1 shows the most frequently used ASPH treatment types. "Mill & 411D" is the most frequently used ASPH treatment types followed by "411TLD Overlay @ 85 lb/sy" and "411D Overlay."

Most Frequently Used SRFT Treatment Types

Table 6-2 shows the most frequently used SRFT treatment types. Two variants of Micro-surfacing are the most used type of SRFT treatment type.

Table 6-1 Ten Most Frequently Used ASPH Treatment Types

ASPH Resurfacing Treatment Type	*No of Projects*	*Average Lane-Mile*	*Inflation Adjusted CPLM ($)*		
			Min	*Max*	*Average*
Mill & 411D	*729*	*12.22*	*43,314.46*	*982,071.99*	*183,306.77*
411TLD Overlay @ 85 lb/sy	*226*	*12.59*	*46,694.13*	*401,547.72*	*95,997.22*
411D Overlay	*165*	*13.25*	*33,063.66*	*425,469.12*	*137,212.38*
Profile Mill & 85 lb/sy TLD	*74*	*12.36*	*22,649.72*	*708,398.58*	*105,401.32*
Mill, CS & OGFC	*51*	*26.54*	*58,525.38*	*434,206.44*	*268,570.53*
Mill & 85 lb/sy TLD	*34*	*9.63*	*6,640.51*	*219,953.76*	*110,846.82*
Mill, C & OGFC	*32*	*24.79*	*153,776.39*	*628,392.94*	*351,096.21*
411TL Overlay @ 65 lb/sy	*31*	*12.43*	*38,022.96*	*151,525.56*	*70,363.56*
Scrub Seal & 85 lb/sy TLD	*30*	*14.46*	*106,035.30*	*269,001.38*	*154,689.98*
Hot In-Place Recycling w/ 411TLD	*29*	*20.58*	*145,236.75*	*422,446.44*	*216,624.96*

Table 6-2 Top Seven Most Frequently Used SRFT Treatment Types

SRFT Resurfacing Treatment Type	*No of Projects*	*Average Lane-Mile*	*Inflation Adjusted CPLM ($)*		
			Min	*Max*	*Average*
Micro-surfacing @ 22 lbs/sy	*129*	*15.22*	*23,972.94*	*85,495.50*	*40,102.98*
Micro-surfacing @ 32 lbs/sy	*59*	*14.78*	*36,272.73*	*107,401.37*	*52,206.30*
Cape Seal	*23*	*12.39*	*40,288.09*	*121,542.48*	*78,291.81*
Double Chip Seal	*8*	*11.57*	*61,472.37*	*100,689.60*	*76,228.81*
Scrub Seal	*6*	*12.57*	*29,886.98*	*56,948.08*	*46,357.12*
Scrub Seal & 65 lb/sy TL	*4*	*8.97*	*60,422.71*	*74,288.67*	*70,089.17*
Thin lift @ 65 lbs/sy	*3*	*10.67*	*83,402.31*	*89,958.86*	*87,415.50*

Average CPLM by Location

A Power BI dashboard was developed to visualize the average CPLM by location. Figure 3 shows an example of CPLM distribution across various counties for "Mill & 411D." Various shades of green color indicate lower CPLM while various shades of red color indicate higher CPLM. The gray color indicates a lack of data for the county.

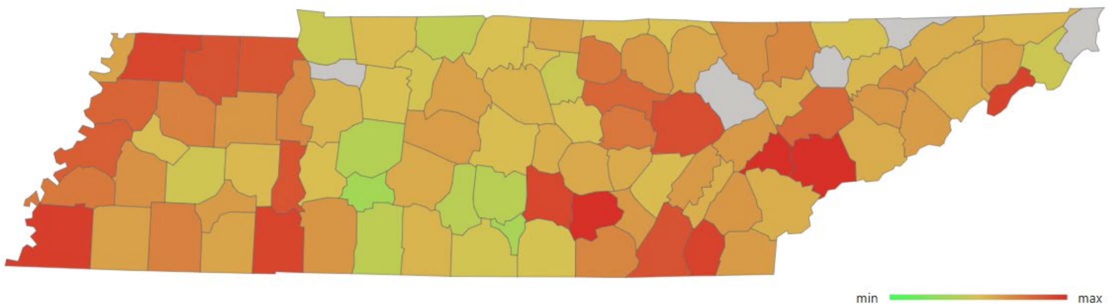


Figure 3: Average CPLM by County for Mill & 411D

The top five counties with the highest CPLM for Mill & 411D are Grundy ($476,440.85), Loudon ($350,646.59), Blount ($288,643.20), Shelby ($266,424.51), and Bradley ($263,280.00). The top five counties with the lowest CPLM for "Mill & 411D" are Lewis ($91,622.07), Moore ($95,849.30), Hickman ($107,410.19), Bedford ($110,457.56), and Marshall ($112,987.90). It also shows that neighboring counties, such as Coffee ($259,414.18) and Moore ($95,849.30), could experience notable different CPLM values. From the regional perspective, the most expensive to least expensive CPLM for "Mill & 411D" are Region 4 ($223,128.84), Region 2 ($210,843.42), Region 1 ($198,514.88), and Region 3 ($149,416.01). Region 4 consistently experienced higher CPLM for various treatment types while Region 3 consistently experienced lower CPLM. These variations highlight the importance of developing cost estimating models that focus on specific county and region. Two tables that represents the CPLM for statewide dataset and region level dataset are provided in the Appendix for updating M&R analysis tool used by TDOT. The updated values are notably different than the original values provided by TDOT. As such, the M&R analysis performed with the updated data would be more representative of the current market condition.

Impact of Bundling on CPLM

Two sets of statistical tests were conducted to evaluate if bundling of projects had statistically significant impact on the CPLM: a) t-tests for statewide and region-level data and b) Mann-Whitney U test for treatment-type-level data.

One-tailed t-tests were conducted with the statewide and region-level datasets to evaluate whether bundling significantly reduced CPLM. The null and alternative hypothesis for the tests were:

1. Null Hypothesis (H_0): There is no significant difference in CPLM between all bundled and unbundled projects at the statewide and regional levels when treatment types are not considered.

2. Alternative Hypothesis (H_1): The CPLM for bundled projects is lower than the CPLM for all unbundled projects at the statewide and regional levels when treatment types are not considered.

The significance level was set at 0.05, with p-values below this threshold indicating a statistically significant difference between bundled and unbundled CPLM values for specific treatment types (Table 6-3). The results show that when all statewide projects are considered, bundled projects cost less per lane mile than unbundled projects. The result is also valid for three out of four regions.

Table 6-3: T-Tests for all contracts statewide and regionally

Location	*Degree of Freedom (DF)*	*T Statistic*	*P Value*
Statewide	*738*	*-4.30*	*0.00001*
Region 1	*197*	*-1.94*	*0.027*
Region 2	*286*	*-3.33*	*0.0005*
Region 3	*194*	*-1.93*	*0.028*
Region 4	*99*	*-1.18*	*0.121*

As the differences in CPLM may be a result of various treatment types, another set of tests were conducted for various treatment types. When the data is segregated using treatment types, a limited number of projects were available. As such, one tailed Mann-Whitney U tests were conducted instead of t-test. The Mann-Whitney U test is a non-parametric statistical test used to compare two independent groups when the assumption of normality is violated or when sample sizes are small. Further, only statewide tests are performed because of the smaller data size when the data is segregated by treatment types. The null and alternative hypothesis for Mann-Whitney U tests were:

1. Null Hypothesis (H_0): There is no difference in the distribution of CPLM between bundled and unbundled contracts within a given treatment type.
2. Alternative Hypothesis (H_1): There is a significant difference in the distribution of CPLM between bundled and unbundled contracts within a given treatment type.

Table 6-4 shows that CPLM of bundled projects are lower than that of unbundled projects for majority of the treatment types. The results of Mann-Whitney U test show fewer statistically significant differences, which indicates that the CPLM of bundled projects are not statistically significantly lower than that of unbundled projects. This does not necessarily mean that bundling does not reduce cost. The statistical insignificance could be the result of the difference in other factors, such as, location and size of the projects (e.g., more bundled projects in more expensive location or in locations that are farther from asphalt mix plants). Further, even if bundling does not reduce project cost directly, it can reduce the administrative burden to TDOT and it can encourage sufficient contractors to bid on the project.

Table 6-4: Mann-Whitney U test results

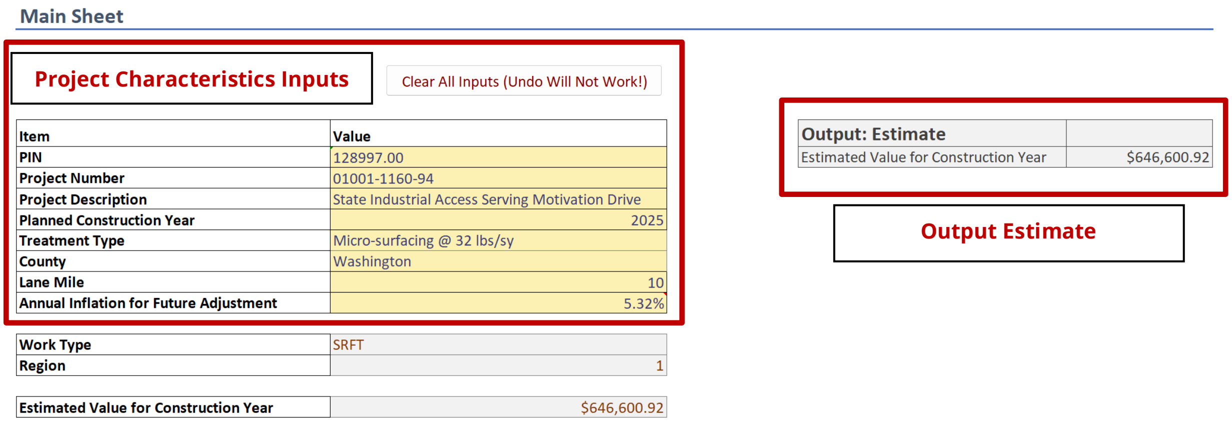
Treatment Type	*Bundling*	*Mean*	*Median*	*St. Dev*	*Count*	*p-value*
411D	*Bundled*	*$129,534.11*	*$126,636.72*	*$31,431.49*	*45*	*0.501*
	Unbundled	*$132,003.73*	*$124,243.13*	*$38,846.87*	*104*	
411TLD @85lb/sy	*Bundled*	*$104,848.72*	*$93,117.38*	*$38,962.53*	*48*	*0.974*
	Unbundled	*$92,738.69*	*$85,910.57*	*$37,807.14*	*134*	
411TLD @65lb/sy	*Bundled*	*$75,084.89*	*$66,344.73*	*$23,343.43*	*11*	*0.452*
	Unbundled	*$76,192.40*	*$78,856.74*	*$26,327.44*	*22*	
Microsurfacing @22lb/sy	*Bundled*	*$39,238.42*	*$38,757.09*	*$9345.70*	*37*	*0.319*
	Unbundled	*$43,396.50*	*$38,970.18*	*$16,040.60*	*33*	
Hot-in-place recycling with 411TLD	*Bundled*	*$202,695.82*	*$178,436.64*	*$77,410.02*	*7*	*0.037*
	Unbundled	*$219,570.37*	*$211,135.46*	*$34,391.85*	*19*	
Profile Mill & 411TLD @85lb/sy	*Bundled*	*$70,508.75*	*$73,641.53*	*$12,015.17*	*8*	*0.0013*
	Unbundled	*$96,309.24*	*$91,735.37*	*$29,435.38*	*51*	
Mill & 411D	*Bundled*	*$184,651.46*	*$170,864.81*	*$88,607.14*	*113*	*0.807*
	Unbundled	*$178,383.87*	*$155,624.62*	*$88,126.08*	*463*	

6.2 RCP Tool

This section presents the a) user interface of RCP tool, b) model overview, and c) validation of the RCP tool.

User Interface of RCP Tool

The tool is implemented as a spreadsheet-based tool to enable TDOT engineers to benefit from it without any in-depth training. The main screen of the RCP Tool includes all the required inputs for cost estimation based on historical trend (Figure 4). The main screen consists of two sections: a) Project Level Input b) Output Estimate.


Main Sheet

Project Characteristics Inputs

Clear All Inputs (Undo Will Not Work!)

Item	Value
PIN	128997.00
Project Number	01001-1160-94
Project Description	State Industrial Access Serving Motivation Drive
Planned Construction Year	2025
Treatment Type	Micro-surfacing @ 32 lbs/sy
County	Washington
Lane Mile	10
Annual Inflation for Future Adjustment	5.32%

Work Type	SRFT
Region	1

Estimated Value for Construction Year	$646,600.92

Output: Estimate	
Estimated Value for Construction Year	$646,600.92

Output Estimate

Figure 4: Overview of RCP Tool

Project Characteristics Inputs

The required project-level inputs include the planned construction year, treatment type, county, and lane-mile. The tool uses county, region, and state-level weights of 50%, 30%, and 20%, respectively. The state- and region-level weights ensure that the reliability from larger state and regional level datasets are utilized while calculating the final estimate. The county-level weight ensures that the specific geographic and localized market conditions from the county level dataset are also represented. The planned construction year refers to the year when the contract is expected to be awarded. A default annual inflation rate is provided based on historical data. This inflation year should represent the average inflation from the model year (2023) to the planned construction year. For example, if the planned construction year is 2030, then the inflation should be representative of the average inflation from 2023 to 2030. If inflation rates for later years are not available, average inflation from the model year to the current year (2025) can be used. Further, the inflation rate should be specific to the highway construction industry in Tennessee. If such an inflation rate is not available, the national inflation rate for the highway construction industry can be used, but it will be less reliable. The National Highway Construction Cost Index (NHCCI) is currently available for this purpose. TDOT currently does not have Tennessee-specific highway construction cost index. As such, TDOT should strongly consider developing a TDOT-specific Highway Construction Cost Index to compute the inflation rate specific to the Tennessee highway construction industry.

Output Estimate

The tool determines the region and work type of the project using the county and treatment type. The tool utilizes the input project characteristics and the derived project characteristics to calculate cost estimates at the county, region, and state levels for the intended resurfacing project. Weighted factors are applied to each level's estimate, and the tool provides the user with the final project estimate.

Model Overview

The tool includes cost prediction capability for most frequently used ASPH and SRFT projects. The state-, region-, and county-level models were aggregated using the 20%, 30%, and 50% weights respectively. In total 11 county level models, 36 region level models, and 346 county level models were developed.

The R^2 values for the models at county, region, and state levels are presented in Table 6-5. Higher R^2 represents higher accuracy. Four models have accuracy exceeding 90% while one model has accuracy below 10%.

Table 6-5 R^2 Values of the Models for Various Treatment Types at the County, Region, and State Levels

Treatment Type	*Work Type*	*R^2 Values (%)*		
		County	*Region*	*State*
411D Overlay	*ASPH*	*41.20*	*78.54*	*74.26*
411TLD Overlay @ 85 lb/sy	*ASPH*	*38.99*	*78.28*	*73.61*
Cape Seal – Chip Seal plus Micro-surfacing	*SRFT*	*72.99*	*66.73*	*66.00*
Cape Seal – Scrub Seal plus Micro-surfacing	*SRFT*	*97.58*	*91.58*	*87.93*
Micro-surfacing @ 22 lbs/sy	*SRFT*	*80.18*	*71.40*	*69.16*
Micro-surfacing @ 32 lbs/sy	*SRFT*	*99.04*	*90.06*	*87.78*
Mill & 411D	*ASPH*	*27.78*	*65.24*	*62.36*
Mill, CS & OGFC	*ASPH*	*43.05*	*57.45*	*57.45*
Profile Mill & 85 lb/sy TLD	*ASPH*	*58.94*	*66.29*	*57.60*

Validation of the RCP Tool

The RCP tool is validated in two phases: a) Statistical Validation and b) Compliance with AASHTO Practical Guide to Cost Estimating. For this study, the data set provided by TDOT covering resurfacing projects from 2013 through 2023 was used as the training set. These records formed the historical basis for developing and calibrating the models. The validation set consisted of newly available resurfacing project data from 2024, which was not part of the training set. Using the 2024 projects for validation allowed us to assess the model's performance on data outside of the training period. Project information of 81 projects was used for the validation.

Statistical Validation

Mean Percentage Error (MPE) and Mean Absolute Percentage Error (MAPE) were calculated for the available validation dataset. The MPE indicates the average directional error, while MAPE measures the average magnitude of error (without direction). Table 6-6 summarizes the results of the validation.

Table 6-6 Statistical Validation of the RCP Tool Performance

Project Type	*MAPE*	*MPE*
Mill & 411D	*33.39%*	*2.55%*
411 D Overlay	*39.78%*	*-29.97%*
411TLD Overlay @ 85 lb/sy	*20.03%*	*10.75%*
Mill, CS & OGFC	*5.78%*	*0.52%*
Micro-surfacing @ 22 lbs/sy	*31.42%*	*-31.42%*
Overall	*32.45%*	*-1%*

* Bold values indicate the lowest absolute value for any row while underlined values indicate the highest absolute value for any row.

The cost estimation accuracy varied significantly across resurfacing project types. Among the treatments, *Mill, CS & OGFC* exhibited the highest accuracy with a MAPE of just 5.78% and a near-zero MPE of 0.52%, indicating strong predictive performance. In contrast, *Longitudinal Joint Stabilization* showed the relatively lower performance, with both MAPE and MPE at 88.78%. Overall, the model's average MAPE was 32.45% with an MPE of -1%, indicating an acceptable level of accuracy for early phases of project development.

Compliance with AASHTO Practical Guide.

The expected cost estimation accuracies for different phases of project development – as prescribed by AASHTO – is used as the basis for the second phase of validation (AASHTO, 2013b). The range of values for estimates stated in the AASHTO guideline is presented in Table 6-7. As expected, the range of estimates narrows down from planning phase to final design phase, which indicates that the expected accuracy of the estimates should increase as the project development continues.

Table 6-7 Expected Cost Estimation Accuracies by Project Development Phases – AASHTO Practical Guide for Cost Estimation (Source: AASHTO (2013b))

Phase	*Project Maturity*	*Purpose of the Estimate*	*Estimation Methodology*	*Error Range*
Planning	*0% - 2%*	*Conceptual Estimating – Estimate Potential Funds Needed*	*Parametric (Stochastic or Judgement)*	*-50% to 200%*
	1% - 15%	*Conceptual Estimating – Prioritize Needs for Long-Range Plan*	*Parametric or Historical Bid-based (Primarily Stochastic)*	*-40% to 100%*
Scoping	*10% - 30%*	*Design Estimating – Establish a Baseline Cost for Project and Program Projects*	*Historical Bid-Based or Cost-based (Mixed but Primarily Stochastic)*	*-30% to 50%*
Design	*30% - 90%*	*Design Estimating – Manage Project Budgets against Baseline*	*Historical Bid-Based or Cost-Based (Primarily Deterministic)*	*-10% to 25%*
Final Design	*90% - 100%*	*PS&E Estimating – Compare with Bid and Obligate Funds for Construction*	*Cost-based or Historical-Bid Based Using Cost Estimate System (Deterministic)*	*-5% to 10%*

Table 6-8 presents the overall compliance of the costs estimated by the models. The RCP tool is a parametric-model-based tool developed for computing estimates for early phases of project development. As such, the compliance of the estimates is higher for planning phases than the later phases. Three project types had 100% compliance rate for 1% – 15% planning phase while two had 100% compliance for 10% – 30% project scoping phase. Moreover, one project type had 100% compliance at the 30% - 90% of design phase.

Table 6-8 Compliance of the Cost Estimates in Reference to the AASHTO Guideline

Project Type	*Project Count*	*Percentage of Compliance (%)*				
		Planning (0% - 2%)	*Planning (1% - 15%)*	*Scoping (10% - 30%)*	*Design (30% - 90%)*	*Final Design (90% - 100%)*
		-50% to 200%	*-40% to 100%*	*-30% to 50%*	*-10% to 25%*	*-5% to 10%*
Mill & 411D	*63*	*88.89*	*80.95*	*73.02*	*31.75*	*17.46*
411 D Overlay	*4*	*75.00*	*50.00*	*50.00*	*25.00*	*0.00*
411TLD Overlay @ 85 lb/sy	*7*	*100.00*	*100.00*	*100.00*	*42.86*	*0.00*
Mill, CS & OGFC	*2*	*100.00*	*100.00*	*100.00*	*100.00*	*50.00*
Micro-surfacing @ 22 lbs/sy	*4*	*100.00*	*100.00*	*25.00*	*0.00*	*0.00*

The compliance analysis across different resurfacing project types reveals varied levels of alignment with acceptable cost variance ranges at different project development stages. These results indicate a consistent trend of higher compliance during early planning and scoping, with significantly lower alignment in the Design and Final Design phases across most project types.

6.3 AMPB Tool

The AMPB framework is implemented as a macro-enabled spreadsheet tool. The tool was developed and validated by analyzing historical resurfacing project dataset from 2013 to 2024. The contracts containing multiple Project Identification Numbers (PINs) are used as an indicator of bundled projects. The dataset included 123 resurfacing project types from across all 95 counties of Tennessee. This section presents a) user interface of AMPB tool, b) compatibility scores, c) validation of AMPB tool, and d) limitations of AMB tool. An example demonstrating the calculations performed automatically by the tool for recommending bundles is provided in the Appendix.

User Interface of AMPB Tool

An overview of the AMPB tool is shown in Figure 5. The only required input is a list of projects with their project characteristics. The a) project list inputs and b) recommended bundles are discussed below.

Main Sheet

Enter project-level data including treatment types, locations, lane miles, and estimated costs. This information will be used to calculate compatibility scores and identify optimal bundling opportunities across similar projects.

Clear Project List | Recommend Bundles

SN	Project ID	Treatment Type	County	Lane Miles	Cost
1	PIN1	Mill & 411D	Robertson	8.00	$747,478.00
2	PIN2	411TL Overlay @ 85 lb/sy	Lawrence	11.01	$1,082,445.00
3	PIN4	Mill, CS & 411D	Coffee	9.40	$2,150,192.00
4	PIN6	Mill & 411D	Bradley	3.04	$1,891,522.00
5	PIN7	Scrub Seal	Lauderdale	9.70	$407,200.00
6	PIN8	Scrub Seal & 85 lb/sy TLD or Scrub Seal & Micr	Henry	12.42	$886,000.00
7	PIN12	Mill & 411D	Lincoln	25.28	$3,947,724.00
8	PIN13	Mill, CS & OGFC	Hickman	13.84	$3,820,789.00
9	PIN18	Mill, B-M2 & 411D	Decatur	11.44	$2,774,800.00
10	PIN20	Mill & 411D	Meigs	15.13	$3,092,732.00
11	PIN21	Mill & 411D	Shelby	20.94	$5,339,800.00
12	PIN22	411 D Overlay	Sullivan	5.10	$853,015.00
13	PIN24	Mill & 411D	Montgomery	14.18	$1,869,576.00
14	PIN25	Mill & 411D	Washington	13.78	$3,345,515.00
15	PIN26	Micro-surfacing @ 22 lbs/sy	Cumberland	23.42	$1,342,829.00
16	PIN27	Micro-surfacing @ 22 lbs/sy	White	16.17	$1,129,700.00
17	PIN28	Mill & 411D	Davidson	3.70	$593,441.00
18	PIN31	Mill & 411D	Lewis	0.94	$368,648.00
19	PIN32	Mill & 411D	Rutherford	4.69	$898,881.32
20	PIN37	Mill & 411D	Jefferson	13.51	$2,555,155.00

Figure 5: Overview of AMPB Tool

Project List Input

The required project characteristics for the tool are project ID, treatment type, lane miles, and cost. The tool allows users to customize various options, such as, compatibility matrices, score weights, and minimum threshold.

Recommended Bundles

The tool identifies the best project bundles that meets or exceeds the minimum compatibility score threshold (Figure 6). The bundled projects are grouped together in the output to enable visual comparison of the project characteristics. Further, the output provides individual compatibility scores as well as aggregated compatibility scores. The individual scores are based on the highest score of 10 while the aggregated compatibility score is based on the highest score of 100.

Recommended Bundles

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These are the bundles recommended and sorted based on the weighted total compatibility scores.

Bundle ID	Project ID	Treatment Type	Primary Treatment Type	Secondary Treatment Type	Overlay Treatment Type	Location	Region Multiplier	Asphalt Mix Plant	Lane Mile	Cost
Bundle01 (Overall Score: 89.70)										
	PIN55	Chip Seal & TLD		Chip Seal	411TLD	Bledsoe			1.80	$238,578.00
	PIN157	Chip Seal & TLD		Chip Seal	411TLD	Bledsoe			6.30	$727,429.00
	Total								8.10	$966,007.00
	Score		0.00	10.00	10.00	10.00	1.00	4.50	9.27	9.62
Bundle02 (Overall Score: 84.24)										
	PIN132	Mill & 411D	Milling		411D	Jackson			4.76	$884,381.00
	PIN158	Mill & 411D	Milling		411D	Jackson			3.02	$259,444.00
	Total								7.79	$1,143,825.00
	Score		10.00	0.00	10.00	10.00	1.00	0.00	9.22	9.31
Bundle03 (Overall Score: 84.21)										
	PIN135	Mill, Scrub Seal & 411D	Milling	Scrub Seal	411D	Hardin			14.89	$2,209,800.00
	PIN159	Mill, Scrub Seal & 411D	Milling	Scrub Seal	411D	Hardin			5.36	$873,900.00
	Total								20.25	$3,083,700.00
	Score		10.00	10.00	10.00	10.00	1.00	9.00	5.10	2.00
Bundle04 (Overall Score: 83.38)										
	PIN1	Mill & 411D	Milling		411D	Robertson			8.00	$747,478.00
	PIN129	Mill & 411D	Milling		411D	Robertson			5.92	$587,007.00
	Total								13.92	$1,334,485.00
	Score		10.00	0.00	10.00	10.00	1.00	9.50	9.14	8.71

Figure 6: Sample Bundles Recommended by AMPB Tool

Compatibility Scores

In this implementation, the overall compatibility score is computed with 100 as the full score. The overall compatibility score is computed as a weighted average of individual compatibility score components. These components are a) geographical, b) treatment type, c) project cost, d) project length, and e) asphalt mix plant compatibility scores. Each component of the compatibility scores is assigned with 10 as the full score.

Table 6-9 presents the weights assigned for various components of the compatibility score. Higher values are assigned for more important components. Assigning 0% weight for the asphalt mix plant compatibility score (instead of 7%) increased the accuracy of the model. However, instead of seeking for higher statistical accuracy, the research team focused on utilizing the factors that are relevant. As such, 7% weight was assigned to the asphalt mix plant score.

Table 6-9 Score Weights

Components	*Weight (%)*
Geographical	*38*
Lane Miles	*11*
Project Cost	*13*
Asphalt Mix Plant	*7*
Primary Treatment	*9*
Surface Treatment	*14*
Overlay Treatment	*8*
Total	*100*

Geographical Compatibility Score

The tool utilizes the county associated with the project as the basis for computing geographical compatibility score. Table 6-10 shows the scores assigned for various distances between the counties.

Table 6-10 Geographical Compatibility Score Matrix

County Distance (Miles)	*Score*
0	*10*
25	*10*
25	*8*
120	*0*

Treatment Type Compatibility Score

Table 6-11 shows the basic criteria for assigning treatment type compatibility scores. However, these criteria cannot be applied directly in TDOTs resurfacing projects as TDOT does not have a standardized set of treatment types. Instead, new treatment types are created as required and are generally a combination of various components. This practice creates complication with comparing the similarities of various treatment types. The research team recommends that TDOT develop and utilize a consistent method of assigning the treatment types for resurfacing projects.

Table 6-11 Treatment Type Compatibility Score Criteria

Condition	*Score*
High Compatibility	*9 – 10*
Moderate Compatibility	*5 – 8*
Low Compatibility	*3 – 4*
No Compatibility	*0 – 2*

To address this issue, currently used treatment types are divided into three components each: a) primary treatment type, b) secondary treatment type, and c) overlay. A mapping was created for dividing the treatment types into its components, and it covered 91% of the treatment types used by TDOT. The compatibility between various components were determined through qualitative analysis of treatment definitions and practical considerations.

The primary treatments focus on pavement removal, recycling, or structural improvements. Some examples of primary treatment include Milling, Full Depth Reclamation (FDR), Hot In-Place Recycling (HIR), Cold In-Place Recycling (CIR), Cement Asphalt Mixture (CAM), and Spot Repairs. Table 6-12 provides the compatibility scores between these treatment types.

Table 6-12 Primary Treatment Compatibility Matrix

	Mill	*FDR*	*HIR*	*CIR*	*CAM*	*Spot*
Mill	*10*	*8*	*3*	*8*	*7*	*7*
FDR	*8*	*10*	*3*	*8*	*7*	*7*
HIR	*3*	*3*	*10*	*3*	*4*	*4*
CIR	*8*	*8*	*3*	*10*	*8*	*7*
CAM	*7*	*7*	*4*	*8*	*10*	*9*
Spot	*7*	*7*	*4*	*4*	*9*	*10*

Secondary treatments involve sealing and protecting the surfacing without adding structural layers. Some examples of secondary treatment include Chip Seal, Scrub Seal, Crack Seal, Fog Seal, Micro-Surfacing, and Cape Seal. Table 6-13 shows the compatibility scores for various combinations of secondary treatment types.

Table 6-13 Secondary Treatment Compatibility Matrix

	Chip Seal	*Scrub Seal*	*Micro Surfacing*	*Cape Seal*	*Fog Seal*	*Crack Seal*
Chip Seal	*10*	*8*	*9*	*9*	*7*	*7*
Scrub Seal	*8*	*10*	*8*	*8*	*8*	*7*
Micro-surfacing	*9*	*8*	*10*	*10*	*8*	*7*
Cape Seal	*9*	*8*	*10*	*10*	*8*	*7*
Fog Seal	*7*	*8*	*8*	*8*	*10*	*7*
Crack Seal	*7*	*7*	*7*	*7*	*7*	*10*

Overlay treatments include new structural or surface layer using asphalt mixes. Some examples of an overlay treatment include 411D, 411TLD, Open Grade Friction Course (OGFC), 307CW. A treatment type may include one, two, or three components. Table 6-14 shows compatibility scores for various combinations of the overlay treatment types.

Table 6-14 Overlay Treatment Compatibility Matrix

	411D	*411TLD*	*307CW*	*OGFC*
411D	*10*	*9*	*3*	*4*
411TLD	*9*	*10*	*3*	*4*
307CW	*3*	*3*	*10*	*8*
OGFC	*4*	*4*	*8*	*10*

Project Cost Compatibility Scores

For project cost compatibility score, the historical distribution of individual project cost for unbundled projects and combined project cost for bundled projects were computed. These project costs are assigned to various buckets of cost ranges for contract frequency distribution. The frequency distribution is converted to a score with 10 as the highest score. The scores are then assigned for the mid-point of the cost range (Table 6-15). For example, the highest frequency for a bucked ($500,000 to $1,000,000) was 401. The mid-point of the bucked is $750,000 (= ($500,000 + $1,000,000)/2). The score for this mid-point cost range is assigned as 10. For other ranges like $0 to $500,000 lane miles, the score was computed based on relative frequency of this range with respect to the highest frequency. In this case, it would be 5.54 (= (10*222/401)). For new bundle of projects under consideration, these compatibility scores are interpolated to get the final compatibility score using the combined the contract cost.

Table 6-15 Project Cost Scoring

Cost	*Count*	*Score*
$0	*0*	*0.00*
$250,000	*222*	*5.54*
$750,000	*401*	*10.00*
$1,250,000	*366*	*9.13*
$1,750,000	*268*	*6.68*
$2,250,000	*171*	*4.26*

Cost	*Count*	*Score*
$2,750,000	*91*	*2.27*
$3,250,000	*75*	*1.87*
$3,750,000	*58*	*1.45*
$5,000,000	*23*	*0.57*

Project Length Compatibility Scores

For project length compatibility score, lane miles of the projects are used. First, the historical distribution of individual project lane miles for unbundled projects and combined project lane mile for bundled projects were computed. These lane miles are assigned to various buckets of lane mile ranges for contract frequency distribution. The frequency distribution is converted to a score with 10 as the highest score. The scores are then assigned for the mid-point of the lane mile range (Table 6-16). For example, the highest frequency for a bucked (10 to 15 lane miles) was 493. The mid-point of the bucked is 12.5 miles (= (10+15)/2). The score for this mid-point lane mile is assigned as 10. For other ranges like 0 to 5 lane miles, the score was computed based on relative frequency of this range with respect to the highest frequency. In this case, it would be 4.42 (= (10*218/493)). For new bundle of projects under consideration, these compatibility scores are interpolated to get the final compatibility score using the combined project lane mile.

Table 6-16 Lane Mile Scoring

Lane Miles (Mid-Point)	*Frequency*	*Score*
0.00	*0*	*0.00*
2.50	*218*	*4.42*
7.50	*452*	*9.17*
12.50	*493*	*10.00*
17.50	*343*	*6.96*
22.50	*176*	*3.57*
27.50	*92*	*1.87*
32.50	*52*	*1.05*
37.50	*21*	*0.43*
55.00	*0*	*0.00*

Asphalt Mix Plant Compatibility Score

The asphalt mix plants located in the same county as the project is easily accessible for the project. When multiple projects are bundled, an equivalent number of asphalt plants can be computed by averaging the distinct asphalt mix plants only in the project counties. Thus, if multiple projects are located in the same county, same plants are not considered multiple times for averaging. On average, each county in Tennessee has 1.33 asphalt mix plants per county. This number is used as an optimal or target number of asphalt mix plant, and it is reflected in the higher scores assigned for equivalent number of asphalt mix plants of 1 to 4 (Table 6-17). Bundles with higher numbers of asphalt mix plants are discouraged by assigning lower scores to reduce the possibility of creating extreme bundles, i.e., bundles with very high competition and bundles with very low competition. If the equivalent number of asphalt mix plants are somewhere in between two rows, interpolation is performed to get the score.

Table 6-17 Asphalt Plant Count Scoring

Equivalent Number of Asphalt Mix Plants	*Score*
0	*0*
1	*9*
2	*10*
4	*10*
10	*4*
15 or more	*0*

Validation of AMPB Tool

The AMPB framework and tool was validated with the dataset of historically bundled and unbundled projects from 2013 – 2024. The historical bundling of the projects and the bundling of the projects from the tool was compared to evaluate the performance of the algorithm and the tool. For each set of validation, projects from the same year were used as inputs to ensure that the projects from different years were not recommended for bundling by the algorithm. In total, 800 simulations were performed across a range of parameter weights and similarity thresholds. After extensive testing, a final set of weights was selected based on the optimal balance of bundling success, error reduction, and year-to-year consistency. These weights are represented in Table 6-18. Location, often the most restrictive constraint in real-world execution, was given the highest weighting (38%), followed by treatment types and cost. Lane miles and cost reflect the size of the project.

Table 6-18 Final Parameter Weights

Parameter	*Final Weight*
Location	*38%*
Primary treatment	*9%*
Secondary treatment	*14%*
Overlay treatment	*8%*
Project Cost	*13%*
Lane Miles	*11%*
Asphalt Mix Count	*7%*
Total	*100%*

The historical distribution of bundled and unbundled projects in validation data is presented in Table 6-19. Except for 2019, more projects were unbundled than bundled.

Table 6-19 Distribution of Bundled and Unbundled Projects

Year	*Bundled Project*	*Unbundled Projects*	*Total Projects*	*Bundled (%)*	*Unbundled (%)*
2013	*68*	*114*	*182*	*37%*	*63%*
2014	*77*	*99*	*176*	*44%*	*56%*
2015	*36*	*114*	*150*	*24%*	*76%*
2016	*36*	*116*	*152*	*24%*	*76%*
2017	*71*	*115*	*186*	*38%*	*62%*
2018	*107*	*117*	*224*	*48%*	*52%*
2019	*72*	*102*	*174*	*41%*	*59%*
2020	*74*	*81*	*155*	*48%*	*52%*
2021	*103*	*92*	*195*	*53%*	*47%*
2022	*84*	*115*	*199*	*42%*	*58%*
2023	*78*	*116*	*194*	*40%*	*60%*
2024	*43*	*62*	*105*	*41%*	*59%*

The similarity threshold from 10% to 90% were tested for its impact on the overall accuracy of the bundling. However, for brevity, only the results for 60% and 70% thresholds are presented below (Table 6-20). For 60% threshold, the exact result ranged from 42% to 67% while the successful results ranged from 56% to 77%. The successful bundling and unbundling ranged from 56% to 92% and 54% to 78%, respectively. When the threshold was increased to 70%, the exact result, successful result, and successful unbundling increased in most of the cases, while the successful bundling rates decreased or stayed stagnant.

Table 6-20 Bundling Performance Results

Year	*Exact Result*		*Successful Result*		*Successful Bundling*		*Successful Unbundling*	
Threshold	*60%*	*70%*	*60%*	*70%*	*60%*	*70%*	*60%*	*70%*
2013	*52.41*	*58.82*	*67.91*	*68.98*	*92.42*	*50.00*	*54.55*	*79.34*
2014	*59.22*	*64.80*	*69.83*	*72.07*	*76.39*	*51.39*	*65.42*	*85.98*
2015	*61.18*	*71.71*	*64.47*	*73.68*	*85.29*	*44.12*	*58.47*	*82.20*
2016	*56.33*	*71.52*	*62.03*	*75.95*	*91.18*	*61.76*	*54.03*	*79.84*
2017	*42.11*	*54.21*	*55.79*	*65.26*	*57.58*	*43.94*	*54.84*	*76.61*
2018	*50.66*	*54.19*	*66.52*	*62.11*	*70.21*	*31.91*	*63.91*	*83.46*
2019	*48.86*	*58.52*	*62.50*	*68.18*	*56.25*	*39.06*	*66.07*	*84.82*
2020	*61.78*	*59.87*	*77.07*	*68.15*	*75.76*	*37.88*	*78.02*	*90.11*
2021	*41.92*	*53.03*	*66.67*	*68.69*	*69.15*	*43.62*	*64.42*	*91.35*
2022	*57.00*	*59.50*	*70.00*	*67.00*	*76.32*	*40.79*	*66.13*	*83.06*
2023	*62.12*	*72.73*	*73.74*	*79.80*	*81.94*	*61.11*	*69.05*	*90.48*
2024	*66.67*	*71.43*	*69.52*	*73.33*	*73.81*	*52.38*	*66.67*	*87.30*
Average	*55.02*	*62.53*	*67.17*	*70.27*	*75.53*	*46.50*	*63.47*	*84.55*
Max	*66.67*	*72.73*	*77.07*	*79.80*	*92.42*	*61.76*	*78.02*	*91.35*

The table shows that the average exact result rate increased when the threshold is increased from 60% to 70%. This may look counterintuitive at first as the higher threshold means the algorithm is more selective while bundling. However, the exact result rate includes projects that are exactly bundled as well as the projects that were not bundled correctly. When the threshold is increased, the successful unbundling increased from 63% to 85% while the successful bundling decreased from 75% to 46%. Thus, the exact result increased because fewer projects are bundled which resulted in higher successful unbundling. In conclusion, the increase or decrease in threshold offers tradeoff between higher successful bundling vs higher successful unbundling.

In either scenario significant portion of the projects were bundled and unbundled correctly. Further, these inaccurate bundling or unbundling by the algorithm does not necessarily indicate incompatible projects. The bundles recommended by the algorithm are likely to be the bundles that TDOT engineers would approve of or even prefers better over the historical bundles. Because of the manual process of identifying the bundles, these better bundles may not have been evaluated or considered. Thus, the actual performance of the algorithm is likely to be better than the statistics presented in the table.

Limitations of AMPB Tool

The tool has a couple of limitations: a) incomplete coverage of treatment type transformation matrix, b) geographic simplifications, and c) Larger Bundles.

Incomplete Coverage of Treatment Type Transformation Matrix: While the current treatment type transformation matrix covers 91% of projects, less commonly used or emerging treatment types are not covered by the current transformation matrix. The matrix can be expanded to fully cover all treatment types. However, this is a challenging task as TDOT does not have a strict rule of creating and limiting standard treatment types.

Geographic Simplifications: Currently, the distance between the centroid of each county is used as the basis for the county compatibility scores. This approach provides the highest score to the projects in the same county, and it may not provide the most accurate result in some cases. For example, two projects located near the common border between two neighboring counties may be closer than the two projects in the opposite corners of the same county.

Larger Bundles: As majority of the bundles consist of only two projects, this tool was developed to recommend bundles with two projects only. If TDOT sees an increased need to create bundles with three or more projects, this study can be extended to develop a more sophisticated tool.

Chapter 7 Conclusions, Recommendations, and Limitations

This chapter presents the major conclusions, recommendations, and limitations of the study.

7.1 *Conclusions*

The study developed a framework and a tool for Resurfacing Cost Prediction (RCP) to improve the current cost estimating practices for resurfacing projects. It also developed a framework and a tool for Automated Maintenance Project Bundling (AMPB) to enable TDOT to quickly and accurately identify projects that can be bundled for more efficient project delivery. To develop the frameworks and tools, the study collected and analyzed resurfacing project characteristics and estimate data. The data covered projects from year 2013 to 2024.

Data Analysis

The cleaning and analysis of data provided some useful insights. First, resurfacing projects at TDOT utilizes a large number of treatment types that combines some fundamental treatment types. These combined treatment types are less standardized and can creates issues with data cleaning and analysis. Out of the existing treatment types, "Mill & 411D" is the most common treatment type in terms of frequency and total cost. It has been used in 729 projects covering approximately $1.57 billion in cost. The average CPLM varied notably between various project types. For example, "Mill, C & OGFC" costs $351,096.21 per lane mile on average while Micro-surfacing @ 22 lbs/sy costs $40,102.98. The CPLM varied notably between various counties as well as the four TDOT regions. These variations highlight the importance of developing separate models for separate treatment types and locations.

Statistical analysis indicated that CPLM tends to be lower when statewide and region-level data from all treatment types were analyzed together. When the data for each treatment type was analyzed separately, bundled projects typically had lower CPLM on average, but it was not statistically significant. Despite this, bundling does offer other potential benefits, such as, reduced administrative burden for TDOT and potential for attracting more contractors.

RCP Framework and Tool

The RCP framework and tool developed in this study offers a practical and data-driven solution to improve the reliability of early-stage cost estimation for resurfacing projects. The models were produced by analyzing historical data from 2013 to 2023. The resulting tool enables TDOT engineers to compute resurfacing project costs using limited project characteristics, such as, treatment type, lane miles, county, and planned construction year. Data from year 2024 was used for validation. The validation showed an overall Mean Percentage Error (MPE) of -1% and Mean Absolute Percentage Error (MAPE) of 32%.

AMPB Framework and Tool

Several new concepts were introduced to develop the AMPB framework. First, the concept of compatibility scores was introduced to quantify the compatibility of projects for bundling. The overall compatibility score was computed by aggregating five compatibility scores: a) geographical, b) treatment type, c) project length, d) project cost, and e) asphalt mix plant presence. The treatment type was further divided into a) primary, b) secondary, and c) overlay treatment types. A new treatment type to component transformation matrix was introduced. In depth analysis was performed to generate appropriate values of compatibility scores for various scenarios (e.g., combination of project lengths, distances between the counties of the two projects, etc.). Hundreds of scenarios were analyzed to identify the optimal weights for the aggregative the compatibility scores. The framework and tool were validated using data of resurfacing projects from 2013 to 2024. The validation result showed up to 92% successful bundling rate and up to 91% successful unbundling rate. Further, up to 73% exact result (exact bundling or correct unbundling) and up to 80% successful result (correct bundling or correct unbundling) were obtained. These results demonstrate the framework and the tool's ability to mimic experienced engineers' bundling practices with significantly less time and effort.

7.2 *Recommendations*

Below are the recommendations to continuously improve TDOT's cost estimating and bundling practices.

Standardization of Treatment Types

TDOT utilizes combinations of various treatments for its resurfacing projects. In some cases, same treatment type was written differently (e.g., Chip Seal vs CS and Micro-surfacing vs Microsurfacing). Further, when multiple treatments are combined, the same combination was sometimes referred differently. Such artificial variation in treatment types creates a data cleaning issue which complicates data analysis. As such, the research team recommends that TDOT creates more standardized treatment types that are used throughout the state.

TDOT-Specific Highway Construction Cost Indexes

An appropriate inflation rate must be used when developing cost estimating models and utilizing these models for cost estimating. However, TDOT currently lacks a Tennessee-specific highway construction cost index. As such, the current models are based on National Highway Construction Cost Index (NHCCI) that represents the national cost trend. Many state DOTs, including Montana and South Dakota DOT, calculate state-specific Highway Construction Cost Indexes (HCCIs) that represent the inflation trend and the agency's purchasing power (Jeong et al., 2021; K. J. Shrestha et al., 2017). The research team strongly recommends that TDOT develop a comprehensive HCCI for its estimating purposes. The models should be updated once such TDOT-specific HCCI is available.

Continuous Model Improvement

As the construction market changes over time, TDOT should continuously update and evaluated the performance of the cost estimating model. The research team recommends developing the updated models every one to two years by including additional recent year data.

Develop New Project Prioritization Tool

TDOT is currently relying on an outdated software for performing benefit cost analysis for project prioritization. The tool relies on less reliable cost per lane mile method to compute the cost. Further, the tool is not actively developed anymore and future support for the tool may be limited. The research team recommends that TDOT take steps to develop a modern cost benefit analysis and project prioritization tool.

Develop Web-Based Estimating Tools

While the spreadsheet-based tools are quick and easy, they can lack sophisticated features, such as tracking historical estimates, generating insights from multiple projects quickly. A more robust web-based estimating tool will enable TDOT to keep accessible record of historical estimates for various resurfacing projects over time.

Document Positive and Negative Results from Bundling

The positive and negative results from bundling should be recorded systematically. Such project/bundle-specific remarks can help improve the bundling tool in the future.

7.3 Limitations

Due to the lack of relevant data, some analyses were not performed. For example, as the latitude and longitude of the projects were not provided in the dataset, the analysis about the impact of supplier’s location could not be performed. The RCP tool and the CPLM statistics provided with the report were self-explanatory, and hence a separate guideline to integrate them for project prioritization process was not developed.

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Appendix

The appendix consists of a) treatment mapping table, b) box plots for identifying outliers, c) removed data points, d) overall CPLM for various treatment types, e) CPLM by region, and f) AMPB tool example.

Treatment Mapping Table

Table A-1 is used to produce primary, secondary, and overlay treatment types from TDOT's treatment type.

Table A-1 Treatment Mapping Table

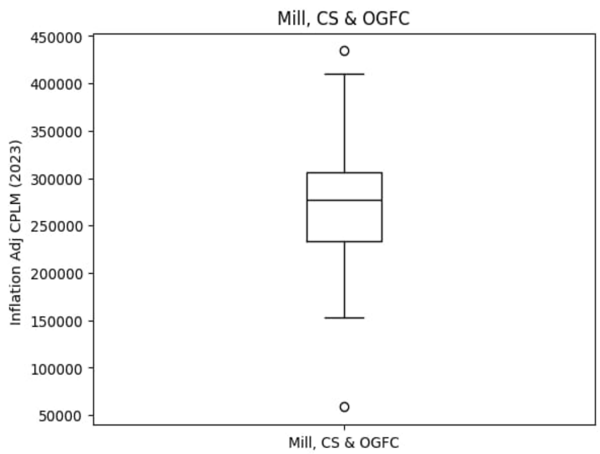
S/N	*Treatment Type*	*Primary*	*Secondary*	*Overlay*
1	*CS*		*Chip Seal*	
2	*Mill*	*Milling*		
3	*411D*			*411D*
4	*85 lb/sy TLD*			*85 lb/sy TLD*
5	*411D Overlay*			*411D*
6	*85TL*			*85 lb/sy TLD*
7	*Profile Mill*	*Profile Mill*		
8	*411TLD Overlay @ 85 lb/sy*			*85 lb/sy TLD*
9	*Hot In-Place Recycling w/ Micro*	*HIR*	*Micro-surfacing @ 22 lbs/sy*	
10	*85 lb/sy TLD*			*85 lb/sy TLD*
11	*65 lb/sy TL*			*65 lb/sy TLD*
12	*411TL Overlay @ 65 lb/sy*			*65 lb/sy TLD*
13	*Cape Seal - Chip Seal plus Micro-surfacing*		*Cape Seal*	
14	*OGFC*			*OGFC*
15	*Crack Seal*		*Crack Seal*	
16	*Micro-surfacing @ 22 lbs/sy*		*Micro-surfacing @ 22 lbs/sy*	
17	*Micro-surfacing @ 32 lbs/sy*		*Micro-surfacing @ 32 lbs/sy*	
18	*HIR*	*HIR*		
19	*Full Depth Reclamation (FDR) with 411D*	*FDR*		*411D*
20	*Full Depth Reclamation (FDR)*	*FDR*		
21	*307CW Overlay*			*307CW*
22	*307CW*			*307CW*
23	*Seal*		*Chip Seal*	
24	*Micro*		*Micro-surfacing @ 22 lbs/sy*	
25	*FDR*	*FDR*		

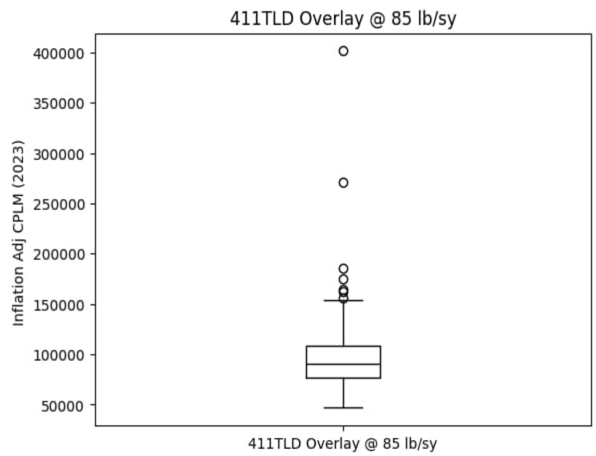
S/N	Treatment Type	Primary	Secondary	Overlay
26	85 lb/sy TL			85 lb/sy TLD
27	85 lb/sy TLD			85 lb/sy TLD
28	411TL @132.5 lb/sy			411TLD
29	411TL Overlay @ 85 lb/sy			85 lb/sy TLD
30	Scrub Seal		Scrub Seal	
31	65 lb/sy TL			65 lb/sy TLD
32	Cape Seal - Scrub Seal plus Micro-surfacing		Cape Seal	
33	Double Chip Seal		Chip Seal	
34	DBST		Chip Seal	
35	411TLD Overlay @ 65 lb/sy			65 lb/sy TLD
36	CIR	CIR		
37	Spot Leveling	Spot		
38	Full depth rehab/replacement	FDR		
39	Microsurface @ 22lbs/sy / Microsurface @ 32 lbs/sy		Micro-surfacing @ 22 lbs/sy	
40	TLD 85 lbs/sy			411TLD
41	411TLD			411TLD
42	85 LB/SY Thin Lift			85 lb/sy TLD
43	CAM	CAM		
44	85 lb/sy 411TLD			85 lb/sy TLD
45	Fog Seal		Fog Seal	
46	D			411D
47	sealing with rejuvenating fog seal		Fog Seal	
48	C-W	CIR		
49	CW	CIR		
50	110Lb/SY OGFC			OGFC
51	1.5 CW			307CW
52	TLD			411TLD
53	Fog Seal		Fog Seal	
54	Crack Sealing		Crack Seal	
55	85 LB/SY			85 lb/sy TLD
56	TLD			411TLD
57	C-W Mix @ 165 lbs/sy			307CW
58	Thin lift @ 65 lbs/sy			65 lb/sy TLD
59	411TL D			411TLD
60	Full-depth PCC repair	FDR		
61	CRS2P DBST		Chip Seal	
62	CW Mix 1.25"			307CW

S/N	Treatment Type	Primary	Secondary	Overlay
63	MILL	Milling		
64	411TLD @ 85 lbs/sy			85 lb/sy TLD
65	411TLD @ 132.5 lbs/sy			411TLD
66	TLD			411TLD
67	Hot In-Place Recycling w/ 411TLD	HIR		411TLD
68	Micro		Micro-surfacing @ 22 lbs/sy	
69	Hot In-Place Recycling	HIR		
70	C		Cape Seal	
71	Spot	Spot		
72	Chip Seal		Chip Seal	
73	Scrub Seal or Crack Seal		Scrub Seal	
74	Hot Recycle in Place w/ 411TLD	HIR		411TLD
75	411D @ 159 lb/sy			411D
76	Micro-surfacing		Micro-surfacing @ 22 lbs/sy	

Box Plots for Data Identifying Outliers

Sample box plots created for identifying outliers are provided below.





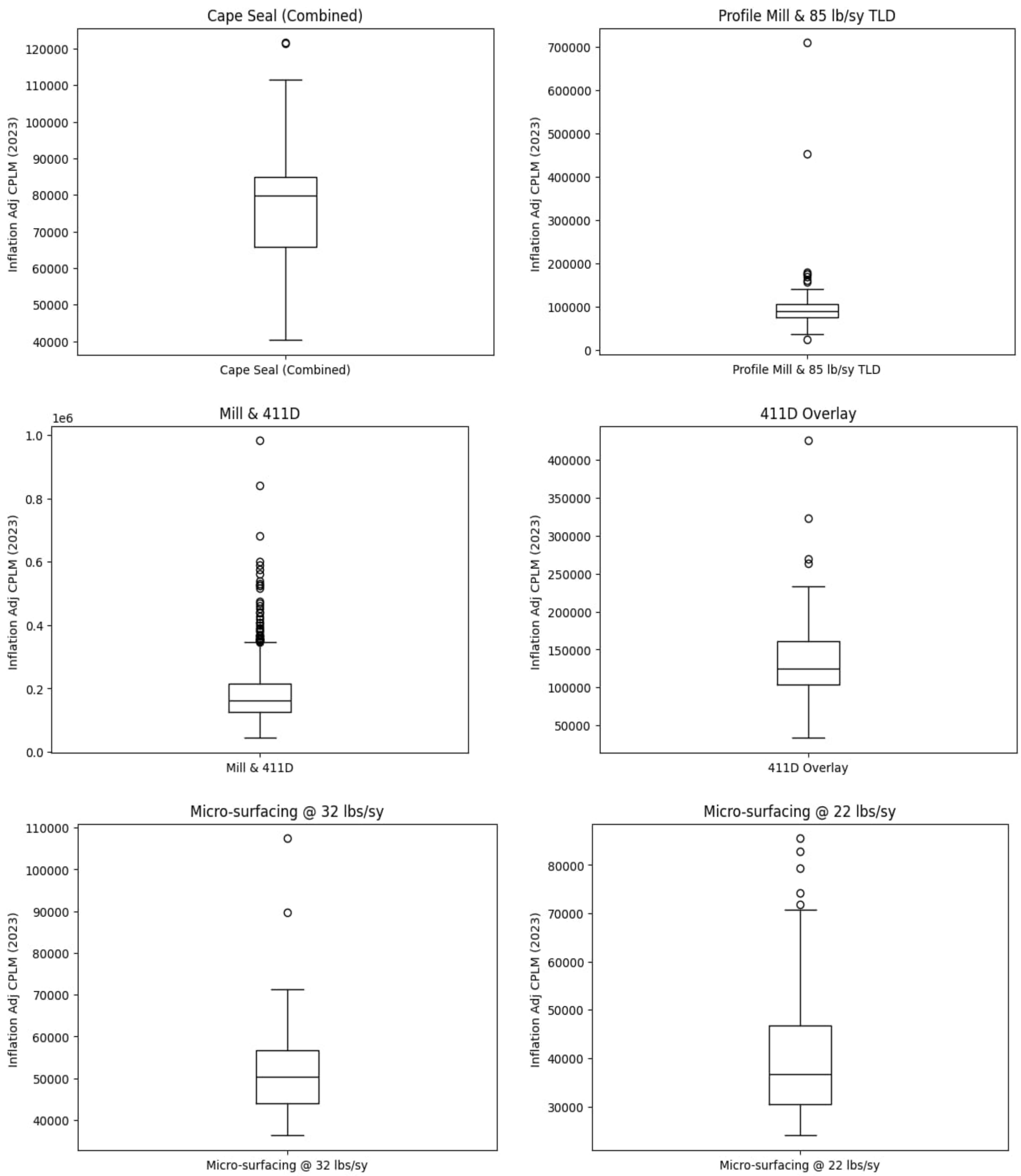


Figure 7: Box Plots for Identifying Outliers

Removed Data Points

Data points that are removed because of the missing project characteristics are presented in Table A-2.

Table A-2 Removed Data Points

Region	*County*	*Contract Number*	*PIN*	*Treatment Type*	*Lane Miles*	*Inflation Adj Cost (2023)*
2		CNM210	117334	Longitudinal Joint Stabilization	0	$457,596.60
3		CNM249	117737	Longitudinal Joint Stabilization	0	$386,390.65
1		CNM295	117692	Crack Seal	0	$975,907.06
4	Benton	CNM323	118140	Mill & 411D	0	$887,995.72
4		CNQ021	122612	Longitudinal Joint Stabilization	0	$305,055.07
3		CNR094	123876	Longitudinal Joint Stabilization	0	$388,418.71
2		CNS023	126111	Longitudinal Joint Stabilization	0	$796,074.98
4	Shelby	CNU912	127340.01	Mill & 411D	0	$313,980.63
4	Madison	CNV138	127341.01	Mill, BM-2 & 411D	0	$344,881.24
2	Putnam	CNV316	127888.01	Mill & 411D	0	$286,581.59
3	Robertson	CNW047	127285.01	Mill & 411D	0	$234,725.84
2	Hamilton	CNW131	127234.01	Mill & 411D	0	$425,984.27
2	Warren	CNW189	127182.01	Mill & 411D	0	$62,020.02
4	Weakley	CNW216	131320	FDR, Chip Seal & 411D	0	$3,057,197.27
2	White	CNW233	127882.01	Mill & 411D	0	$532,212.94
3		CNW253	132730	ADA Curb Ramp Upgrades	0	$1,332,945.80
3		CNW254	132731	ADA Curb Ramp Upgrades	0	$380,842.48
3		CNW255	132732	ADA Curb Ramp Upgrades	0	$615,694.55
4		CNW281	132735	Curb Ramps	0	$706,997.23
1	Sullivan	CNW295	132284.01	ADA Curb Ramps	0	$856,894.14
1	Knox	CNW296	132284.02	ADA Curb Ramps	0	$1,726,483.30
4		CNW297	132734	Curb Ramps	0	$685,516.00
3	Rutherford	CNX144	131740	Concrete Rehabilitation (Ultra-thin PCC)	0	$2,749,170.00

Overall CPLM for Various Treatment Types

The table below provides statewide CPLM that can be used to update information for M&R analysis.

Table A-3: Overall CPLM

Code	*Treatment Type*	*CPLM*
38	*Mill+Interlayer+OGFC*	*N/A*
39	*OGFC Overlay*	*$261,418.87*
40	*Mill and 411D*	*$186,719.73*
41	*Micro @ 22lbpsy*	*$40,845.02*
42	*TLD @85lbpsy*	*$95,590.65*
43	*Micro @ 32lbpsy*	*$54,719.53*
44	*D Overlay*	*$137,252.38*
45	*Prof.Mill+TLD85psy*	*$105,126.47*
46	*Mill+TLD85psy*	*$111,287.25*
47	*CS+D Overlay*	*$138,716.45*
48	*TLD @ 65 lbpsy*	*$74,337.25*
49	*ChipSeal+TLD @85lbpy*	*$114,001.62*
50	*CS+TLD @ 85lbpsy*	*N/A*
51	*Chip Seal plus Micro*	*$71,750.21*
52	*Profile Mill & 411D*	*$132,713.09*
53	*Chip Seal*	*$55,553.01*
54	*Chip Seal & TL65*	*$59,231.72*
55	*Chip Seal &411D*	*$147,986.99*
56	*Scrub Seal*	*$45,731.73*
57	*Mill and BM and 411D*	*$372,230.23*
58	*Scrub Seal & 85 lbs*	*$154,689.98*
59	*Hot Recycle in Placo*	*N/A*
60	*B+D overlay*	*N/A*
61	*Hot Recycle in PlacD*	*$216,624.96*
62	*miscellaneous*	*N/A*
63	*FDR+chip seal+D*	*$286,828.59*
64	*Mill+D on Interstate*	*$293,699.03*
65	*Scrub seal w 1.5 CW*	*$400,122.16*
66	*Scrub Seal w/D*	*$132,785.66*
67	*Double chip seal*	*$76,228.81*
68	*Mill and BM and OGFC*	*$462,626.93*
69	*Cold-in-place and D*	*$315,787.37*
70	*Cold-in-place Mirco*	*N/A*
71	*Saw and Seal Joints*	*$118,539.58*
72	*Ultra-thin PCC*	*$3,472,272.08*
73	*DBST & Fog Seal*	*$56,482.19*
74	*CAM and 85 lb/sy 41D*	*$287,430.00*
75	*Mill, CAM &411D*	*$278,091.83*

76	Mill, CIR, BM2&D	$396,944.14
77	FDR+chip or dbst	$182,182.40

CPLM by Region

The table below provides CPLM by region that can be used to update information for M&R analysis.

Table A-4: CPLM by Region

Region	Code	Treatment Type	CPLM
0	0	N/A	N/A
1	38	Mill+Interlayer+OGFC	N/A
2	38	Mill+Interlayer+OGFC	N/A
3	38	Mill+Interlayer+OGFC	N/A
4	38	Mill+Interlayer+OGFC	N/A
2	39	OGFC Overlay	$261,418.87
1	40	Mill and 411D	$185,205.40
2	40	Mill and 411D	$208,674.76
3	40	Mill and 411D	$151,119.99
4	40	Mill and 411D	$220,052.41
1	41	Micro @ 22lbpsy	$38,319.20
2	41	Micro @ 22lbpsy	$40,492.65
3	41	Micro @ 22lbpsy	$50,765.25
4	41	Micro @ 22lbpsy	$57,962.81
1	42	TLD @85lbpsy	$104,904.19
2	42	TLD @85lbpsy	$82,689.51
3	42	TLD @85lbpsy	$78,587.08
4	42	TLD @85lbpsy	$139,188.76
1	43	Micro @ 32lbpsy	$57,024.25
2	43	Micro @ 32lbpsy	$61,963.68
3	43	Micro @ 32lbpsy	$50,968.21
4	43	Micro @ 32lbpsy	$48,807.73
1	44	D Overlay	$157,582.75
2	44	D Overlay	$115,923.47
3	44	D Overlay	$119,240.02
4	44	D Overlay	$140,483.77
1	45	Prof.Mill+TLD85psy	$100,023.89
2	45	Prof.Mill+TLD85psy	$89,743.59
3	45	Prof.Mill+TLD85psy	$93,397.49
4	45	Prof.Mill+TLD85psy	$248,793.08
1	46	Mill+TLD85psy	N/A
2	46	Mill+TLD85psy	$121,551.94
3	46	Mill+TLD85psy	$83,991.31

4	46	Mill+TLD85psy		$192,486.20
1	47	CS+D Overlay		$156,289.03
2	47	CS+D Overlay	N/A	
3	47	CS+D Overlay		$122,024.21
4	47	CS+D Overlay		$187,912.82
1	48	TLD @ 65 lbpsy		$81,155.03
2	48	TLD @ 65 lbpsy		$66,155.91
3	48	TLD @ 65 lbpsy	N/A	
4	48	TLD @ 65 lbpsy	N/A	
1	49	ChipSeal+TLD @85lbpy	N/A	
2	49	ChipSeal+TLD @85lbpy		$114,817.69
3	49	ChipSeal+TLD @85lbpy		$88,316.08
4	49	ChipSeal+TLD @85lbpy		$164,012.56
1	51	Chip Seal plus Micro	N/A	
2	51	Chip Seal plus Micro		$71,319.03
3	51	Chip Seal plus Micro	N/A	
4	51	Chip Seal plus Micro		$72,756.30
1	52	Profile Mill & 411D	N/A	
2	52	Profile Mill & 411D		$153,627.49
3	52	Profile Mill & 411D		$127,367.85
4	52	Profile Mill & 411D		$186,631.99
1	53	Chip Seal	N/A	
2	53	Chip Seal	N/A	
3	53	Chip Seal		$61,998.42
4	53	Chip Seal		$36,216.78
1	55	Chip Seal &411D		$156,289.03
2	55	Chip Seal &411D	N/A	
3	55	Chip Seal &411D		$123,873.05
4	55	Chip Seal &411D		$187,912.82
1	57	Mill and BM and 411D		$354,220.29
2	57	Mill and BM and 411D		$393,885.97
3	57	Mill and BM and 411D	N/A	
4	57	Mill and BM and 411D		$346,884.87
1	58	Scrub Seal & 85 lbs	N/A	
2	58	Scrub Seal & 85 lbs		$135,426.33
3	58	Scrub Seal & 85 lbs		$163,335.23
4	58	Scrub Seal & 85 lbs		$157,426.36
1	61	Hot Recycle in PlacD	N/A	
2	61	Hot Recycle in PlacD	N/A	
3	61	Hot Recycle in PlacD	N/A	
4	61	Hot Recycle in PlacD		$216,624.96
1	64	Mill+D on Interstate		$330,415.77
2	64	Mill+D on Interstate		$301,226.48
3	64	Mill+D on Interstate		$253,374.52
4	64	Mill+D on Interstate		$305,868.52

1	66	*Scrub Seal w/D*	*N/A*
2	66	*Scrub Seal w/D*	*N/A*
3	66	*Scrub Seal w/D*	*$125,060.72*
4	66	*Scrub Seal w/D*	*$138,579.37*

AMPB Tool Example

The example below demonstrates the internal calculations performed automatically in the AMPB tool. The example assumes a list of six projects. The treatment type used by TDOT (TDOT Treatment Type) is automatically converted to its primary, secondary, and overlay treatment types using a mapping table. Other data attributes, such as location (county), lane miles, and cost are readily available to TDOT engineers.

Table A-5: Sample Project List

Project ID	*TDOT Treatment Type*	*Primary*	*Secondary*	*Overlay*	*Location*	*Lane Miles*	*Cost*
PIN 22	*411 D Overlay*			*411D*	*Sullivan*	*5.10*	*$853,015*
PIN 24	*Mill & 411D*	*Mill*	*-*	*411D*	*Hancock*	*14.18*	*$469,576*
PIN 25	*Mill & 411D*	*Mill*		*411D*	*Washington*	*13.78*	*$645,515*
PIN 26	*Micro-surfacing @ 22 lbs/sy*		*Micro-surfacing @ 22 lbs/sy*		*Cumberland*	*8.42*	*$817,829*
PIN 27	*Micro-surfacing @ 22 lbs/sy*		*Micro-surfacing @ 22 lbs/sy*		*White*	*6.17*	*$733,912*
PIN 28	*Mill & 411D*	*Mill*		*411D*	*Davidson*	*3.70*	*$593,441*

First, five compatibility scores for each pair of projects are computed. An example for the pair of PIN 22 and PIN 24 projects is provided below for illustration. The calculations utilize various tables provided in section 6.3 AMPB Tool.

Geographical Compatibility Score

PIN 22 is located in Sullivan County while PIN 24 is in Hancock. The distance between the centroid of these two counties is approximately 51 miles. Using Table 6-10, 50 miles lie between 25 miles and 120 miles with scores of 8 to 0. Applying the interpolation formula, Equation (5), the location score for 51 miles can be calculated as:

$$Geographical\ Compativility\ Score = 8 + \frac{0-8}{120-25} * (51-25) = 5.81$$

The geographical compatibility score is further multiplied by the region multiplier. If two counties are in the same administrative region, region multiplier is 1, else it is 0. Since Sullivan and Hancock both lie in region 1, final location score is

$$Final\ Geographical\ Compatibility\ Score = 5.81 * 1 = \mathbf{5.81}$$

Primary Treatment Type Compatibility Score

In Table 6-12 Primary Treatment Compatibility Matrix, the combination of "-" and "Mill" does not exist (the primary treatment type for the first project is empty). As such, a score of **0** is assigned.

$$Primary\ Treatment\ Type\ Compatibility\ Score = 0$$

Secondary Treatment Type Compatibility Score

Since we have missing secondary treatment types as well, Table 6-13 Secondary Treatment Compatibility Matrix does not have any value for secondary treatment compatibility scores. As such, a score of **0** is assigned for the secondary treatment type compatibility score.

$$Secondary\ Treatment\ Type\ Compatibility\ Score = 0$$

Overlay Treatment Type Compatibility Score

For the overlay treatment types, both projects have "411D". From Table 6-14 Overlay Treatment Compatibility Matrix, a value of **10** is allocated for this combination.

$$Overlay\ Treatment\ Type\ Compatibility\ Score = 10$$

Project Cost Compatibility Score

For this score, first, the costs of the two projects are added together to get the total contract amount ($1,322,591). In Table 6-15 Project Cost Scoring, this value lies between $1.25M (score of 9.13) and $1.75 (score of 6.68). By interpolating these values, project cost compatibility scores can be calculated:

$$Project\ Cost\ Compatibility\ Score = 9.13 + \frac{6.68 - 9.13}{1.75 - 1.25} * (1.323 - 1.25) = \mathbf{8.77}$$

Project Length Compatibility Score

The lane miles of the two projects are added together to get the total lane mile (19.28 lane miles). This value lies between 17.5 miles (score of 6.96) and 22.5 miles (3.57) in Table 6-16 Lane Mile Scoring.

$$Project\ Length\ Compatibility\ Score = 6.96 + \frac{3.57 - 6.96}{22.5 - 17.5} * (19.28 - 17.5) = 5.75$$

Asphalt Mix Plant Compatibility Score

Sullivan county has a total of 3 asphalt mix plant whereas Hancock has 0. The total number of distinct asphalt plant from the two counties is 3. This value lies between 2 (score of 10) and 4 (score of 10) in Table 6-17 Asphalt Plant Count Scoring. Thus, the interpolation results in the score of 10.

$$Asphalt\ Mix\ Plant\ Compatibility\ Score = 10 + \frac{10 - 10}{4 - 2} * (3 - 2) = 10$$

Overall Compatibility Score

The overall compatibility score is calculated as the weighted average of the six components of the compatibility scores using Equation (6). The weights for various components of the compatibility scores are assigned as 38% for location, 9% for primary treatment type, 14% for secondary treatment type, 8% for overlay treatment type, 13% for project cost, 11% for project length, and 7% for asphalt mix plant count.

$$\begin{aligned} &Overall\ Compatibility\ Score \\ &= \frac{(38 * 5.81) + (9 * 0) + (14 * 0) + (8 * 10) + (13 * 8.77) + (11 * 5.75) + (7 * 10)}{38 + 9 + 14 + 8 + 13 + 11 + 7} \\ &= 5.5 \end{aligned}$$

This initial value is based on the total score of 10, which can be scaled to 100 by multiplying by 10.

$$Final\ Overall\ Compatibility\ Score = 5.5 * 10 = 55\%$$

Similarly, overall compatibility scores for other pairs are calculated and listed in the table below in descending order of the scores.

Table A-6: Sample Overall Compatibility Scores for Various Project Combinations

First Project	***Second Project***	***Overall Compatibility Scores***
PIN 22	*PIN 25*	*70%*
PIN 26	*PIN 27*	*70%*
PIN 24	*PIN 25*	*59%*
PIN 22	*PIN 24*	*55%*
PIN 27	PIN 28	44%
PIN 22	PIN 28	35%
PIN 27	PIN 28	29%
PIN 22	PIN 27	28%
PIN 27	PIN 28	28%
PIN 22	PIN 26	27%
PIN 26	PIN 27	21%
PIN 25	PIN 26	19%

If a minimum threshold of 50% is set for bundling recommendation, only top four combinations are used for recommendation as they exceed the threshold score of 50%. Two combinations receive the highest score of 70%: (PIN 22 + PIN 25) and (PIN 26 + PIN 27). These two combinations will be combined as Bundle 1 (PIN 22 + PIN 25) and Bundle 2 (PIN 26 + PIN 27), respectively. Once these two bundles are prepared, the four projects (PIN 22, PIN 25, PIN 26, and PIN 27) are not available for bundling with other projects. The only remaining pair that exceeds the threshold of 50% is PIN 22 + PIN 24. However, since PIN 22 is already used for another bundle, this bundle is not recommended by the tool. This leaves PIN 24 and PIN 28 as unbundled projects.