WSDOT Maintenance Performance Measure Algorithms

WA-RD 932.1

Kishor Shrestha

August 2023

WSDOT photos

Washington State Department of Transportation
Office of Research & Library Services

WSDOT Research Report

Research Report
WA-RD 932.1

WSDOT MAINTENANCE PERFORMANCE MEASURE ALGORITHMS

By
Kishor Shrestha, Ph.D., P.E., M. ASCE
Assistant Professor

School of Design and Construction
Washington State University, Box 641060
Pullman, Washington 99164

Washington State Transportation Center (TRAC)
Washington State University, Box 641060
Pullman, Washington 99164

Washington State Department of Transportation
Technical Monitor
Kelly Shields/ Bruce Castillo
Performance Measurement Team
HQ Maintenance Office

Prepared for

The State of Washington
Department of Transportation
Roger Millar, Secretary

August 2023

TECHNICAL REPORT DOCUMENTATION PAGE

REPORT NO. WA-RD 932.1	2. GOVERNMENT ACCESSION NO.	3. RECIPIENTS CATALOG NO.
4. TITLE AND SUBTITLE WSDOT MAINTENANCE PERFORMANCE MEASURE ALGORITHMS		5. REPORT DATE August 2023 6. PERFORMING ORGANIZATION CODE
7. AUTHOR(S) Kishor Shrestha		8. PERFORMING ORGANIZATION REPORT NO.
9. PERFORMING ORGANIZATION NAME AND ADDRESS Washington State Transportation Center (TRAC) Washington State University, Box 641060 Pullman, Washington 99164		10. WORK UNIT NO. 11. CONTRACT OR GRANT NO. T1462-34
12. SPONSORING AGENCY NAME AND ADDRESS Research Office Washington State Department of Transportation Transportation Building, MS 47372 Olympia, Washington 98504-7372 Project Manager: Doug Brodin, 360-705-7972		13. TYPE OR REPORT AND PERIOD COVERED Final Report 14. SPONSORING AGENCY CODE WSDOT
15. SUPPLEMENTARY NOTES		

16. ABSTRACT

This research project focuses on deteriorating roadway asset conditions, emphasizing the challenges encountered by the roadway maintenance division of the Washington State Department of Transportation (WSDOT). The project goal is to develop algorithms for prediction models that will forecast the levels of service (LOS) performance conditions of six important highway assets: culvert maintenance, barrier maintenance, traffic signal systems, ditches, slope repairs, and shoulder maintenance. These algorithms are based on a data-driven approach. The algorithms provide a step-by-step process to develop prediction models. The models can be used to forecast LOS performance conditions and trends under various funding levels, allowing them to set performance targets that align with available funds and asset maintenance priorities, potentially preventing expensive reactive maintenance. Data collection included direct collection from WSDOT and two-phase questionnaire surveys to document factors impacting LOS performance conditions. Statistical analyses such as the Relative Importance Index (RII), Kolmogorov-Smirnov and Shapiro-Wilk normality tests, and Mann-Whitney U tests were employed to determine critical factors for each of the six assets. The project identifies the top five highly ranked factors for each asset, which are utilized during model development. Based on the dataset collected, a future study employing Machine Learning approach is recommended to develop prediction models for the assets. Prediction models serve as a tool for forecasting asset conditions, calculating base funds required for each asset, and optimizing resource allocation. Through the project outcomes, states will be able to improve asset management decision-making, resulting in safer and more environmentally friendly roads.

17. KEY WORDS Culvert Maintenance, Barrier Maintenance, Traffic Signal Systems, Ditches, Slope Repairs, Washington State.	18. DISTRIBUTION STATEMENT No restrictions. This document is available to the public through the National Technical Information Service, Springfield, VA 22616

19. SECURITY CLASSIF. (of this REPORT) None	20. SECURITY CLASSIF. (OF THIS PAGE) None	21. NO. OF PAGES 82	22. PRICE

DISCLAIMER

The contents of this report reflect the views of the author, who is responsible for the facts and accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the Washington State Department of Transportation, Federal Highway Administration, or U.S. Department of Transportation. This report does not constitute a standard, specification, or regulation.

Contents

LIST OF FIGURES

LIST OF TABLES

EXECUTIVE SUMMARY

This executive summary provides an overview of this WSDOT research project to address the issue of roadway asset conditions. The primary objective of the project was to develop algorithms that predict the performance conditions of six important highway assets: culvert maintenance, barrier/guardrail maintenance, traffic signal systems, ditches, slope repairs, and shoulder maintenance. The algorithms use a data-driven approach and predict levels of service (LOS) performance conditions and trends under various funding levels. The algorithms developed in this project are the first step to developing prediction models.

For data collection, two major strategies were used to achieve the project objectives. The first step was acquiring direct WSDOT data on asset LOS condition and expenditure. Second, two-phase questionnaire surveys were conducted with WSDOT professionals to collect their insights regarding the factors influencing the LOS conditions of the six assets. The Relative Importance Index (RII) analysis approach was used to assess the survey results, the Kolmogorov-Smirnov and Shapiro-Wilk normality tests were utilized to assess if the dataset was distributed normally, and the Mann-Whitney U test was used to identify differences between the group of variables.

The factors affecting the LOS condition of an asset were ranked, and then highly ranked factors were identified for each of the six roadway assets. For example, the five highly ranked factors for culvert maintenance are hydrological/weather conditions, previous maintenance dates, current LOS, scoured around culvert/pipe, and material type.

Similarly, the highly ranked factors for the other five assets have also been determined. The data analysis results indicated that each asset has more than ten highly ranked factors.

Once the data was analyzed, the project developed prediction model algorithms for each of the six assets. The key steps involved in developing the algorithm for predicting the LOS condition of assets were identified and explained. The key steps of culvert maintenance algorithm are

Step 1: Identify, collect and understand the significant factors of culvert maintenance and clean the data

Step 2: Visualize the data

Step 3: Split the data into training and test datasets

Step 4: Develop a regression model

Step 5: Validate the model

Step 6: Test the model

Step 7: Make predictions using the model

Once the model is validated and tested, it can be used to predict culvert LOS condition. To advance the project in developing prediction models, the author recommends applying Machine Learning (ML) techniques for a future study. High-dimensional datasets and non-linear variables can be processed by ML models, producing more accurate results. The accuracy of prediction models will be improved by training the models with historical and real-time data. The ML technique especially helps in developing more dependable prediction models, while saving time in developing the models and training, validating and testing the models.

Findings and results from this project have great promise for enhancing the overall condition of roadway assets, assuring greater mobility, and fostering economic growth for millions of Americans. WSDOT and other states may use the algorithms in developing the prediction models. The prediction models assist in predicting asset conditions, calculating base funds required for individual assets, and efficiently allocating resources. The project outcomes provide WSDOT with a robust platform to improve asset management decision-making, eventually resulting in safer and more environmentally friendly roads for the general public.

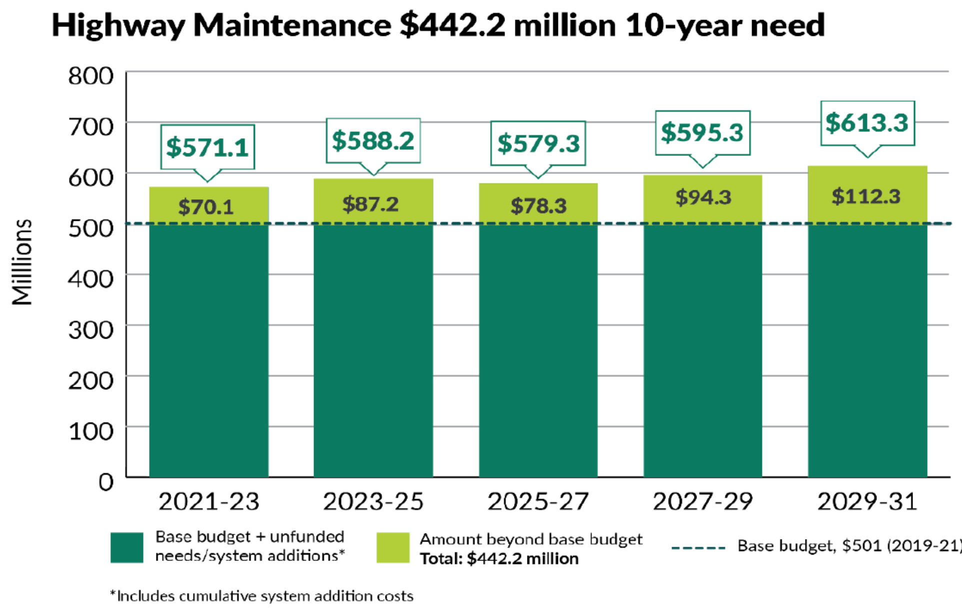
1. INTRODUCTION

Highways are the lifeline of mobility for millions of Americans, and they are essential for economic growth. Vehicle mile travel (VMT) is increasing in the U.S. per Federal Reserve Economic Data (FRED 2022); however, the performance of highway assets is not satisfactory. According to the American Society of Civil Engineers (ASCE) report card, over 40% of public roadways were in poor or mediocre condition in 2021, and that number was consistent for several years (ASCE 2021). With the poor conditions of highway assets, challenges for state departments of transportation (DOTs) are increasing.

The challenges facing the Washington State DOT (WSDOT) Highway Maintenance Program are continually increasing, which weakens its ability to provide a State of Good Repair for highway assets. For example, in 2020, WSDOT met 68% of its highway maintenance asset condition targets, which was down from 77% in 2019 (Shields and Andrea 2021). WSDOT Maintenance has been evaluating the effectiveness of its Maintenance Program through outcome-based performance measures, referred to as level of service (LOS) since 1996 (WSDOT 2018). As it has become known, the Maintenance Accountability Process (MAP) is a comprehensive planning, measuring, and managing process that provides a means for communicating the impacts of policy and budget decisions on program service delivery to key customers, including WSDOT Executive Leadership, the Legislature, and the public.

The challenges come in many forms, including aging equipment, personnel shortages, aging assets, and system additions, as well as underfunding in both preservation and maintenance. Figure 1 illustrates the growing needs of WSDOT's Maintenance Division budget to maintain highway assets in acceptable condition. Studies have shown that for several highway assets, 'due,' 'past due,' and 'far past due' for maintaining assets increased to 46% in 2020 from 37% in 2019 (Weston 2021). The current budget limitations have led to an inability to maintain and

Maintenance Needs



preserve all highway infrastructure assets as needed at acceptable levels, or keep annualized investments within a reasonable range of lowest life-cycle cost. In most cases, a lack of available funding delayed maintenance activities; additionally, the consequences of delayed maintenance are usually underestimated or not fully considered (NCHRP 2017). Often, WSDOT personnel are faced with making data-driven, trade-off decisions.

When assets are not maintained at the right time, it may result in the need for reactive maintenance activities, which cost significantly more. For example, the chip seal cost could be $50,000 to $60,000 per lane mile (Weston 2021). If chip sealing is not done on time and paving is past due, because of backlog and poor condition, major rehabilitation may be required; major rehabilitation is $400,000 to $500,000 per lane mile (Weston 2021), which is considerably more expensive than chip seal.

Thus, predicting future conditions of highway assets using advanced technologies has become necessary today. Machine learning (ML), Artificial Intelligence (AI), and other similar advanced technologies have been utilized in various sectors to address such challenges. Tsai and Wang (2015) developed an algorithm to detect pavement raveling. In that 2015 study, the authors used a data-driven texture analysis techniques approach to classify whether pavement is raveled. In another study, vehicle travel time on a highway was predicted using an algorithm development (Saleh et al. 2023). To predict the travel time, the algorithm evaluated the traffic flow for congestion, slow movement, or free-flow using an eight-step algorithm. In other studies conducted by various authors, predicted friction on roadway pavements and predicted road accidents using ML technologies (Karimzadeh and Shoghli 2020; RAI 2022).

The ability to predict asset performance would help the WSDOT Maintenance Division to set performance targets that balance available funds, acceptable performance expectations, and maintenance division priorities (Adams et al. 2014), which could potentially prevent the need for expensive reactive maintenance actions.

The principal objective of this project is to develop algorithms that will be used as a basis to develop prediction models later. The prediction models can be used to forecast the performance condition of highway assets. This project focused on six highway assets to develop algorithms, which use a data-driven approach, utilizing historical data. Developing the algorithms gives WSDOT Maintenance Division the ability to predict LOS performance data in order to predict trends under differing funding conditions. The six highway assets are listed below.

1. MAP Activity 2A2- Culvert Maintenance
2. MAP Activity 6A7- Barrier /Guardrail Maintenance
3. MAP Activity 6B1- Traffic Signal Systems
4. MAP Activity 2A1- Ditches
5. MAP Activity 2A5- Slope Repair
6. MAP Activity 1A3- Shoulder Maintenance

2. REVIEW OF PREVIOUS WORK

The literature related to highway asset management was collected and reviewed. The main sources of the existing literature were ResearchGate, ASCE Libraries, and WSU Libraries. The review of existing studies is presented in three sub-sections as below. They are i) roadway condition, vehicle mile travel, and consequences of delayed maintenance, ii) performance measurement of roadway assets, and iii) studies on specific assets.

2.1 Roadway Condition, VMT, and Consequences of Delayed Maintenance

In the United States, there are over four million miles of public roadways (ASCE 2021). As the backlog of road maintenance and rehabilitation grows annually, in 2021, 43% of roadways were in poor or mediocre condition. While most interstate highways are in good condition, most non-interstate highways and collector roads are in poor condition. One of the principal reasons for the poor road conditions in Washington State is a result of funding specific to preservation.

The consequences of continued deterioration of road conditions are increased costs to highway maintenance and safety issues resulting from lowered Level of Service (LOS), as well as additional expenses on fuel and repair and increased congestion and delays on travel. It is necessary to prioritize strategic investment in roadway preservation and improvement (NCHRP 2017). The scorecard also provided recommendations, including increasing maintenance budgets to address the roadway system's LOS; developing an asset management plan and incorporate life-cycle cost analysis, building resilient infrastructure, and integrating resilience planning into asset management plans.

Vehicle Mile Travel (VMT) is a direct indicator of most roadway asset conditions, and it is increasing across the United States including Washington state (PSRC 2018; FRED 2022). According to the Federal Highway Administration (FHWA), VMT in 2019 was over 18% more than in 2000 (USDOT 2022; ASCE 2021).

The National Cooperative Highway Research Program (NCHRP 2017) studied the consequences of delayed highway asset maintenance. In many states, agencies have employed various maintenance treatments to slow down deterioration and restore asset conditions; however, in many cases, the treatments employed were delayed due to budget limitations. Study results show that delayed maintenance leads to lower LOS and early deterioration, as well as the need for expensive maintenance actions. Results also show that tools are available to quantify the effects of employing maintenance activities for highway pavements and bridge assets; however, assessing the dollar savings and asset performance enhancement of employing the maintenance activities on time is simply not possible. Therefore, this NCHRP study developed a framework with a procedure to quantify the evaluation of delayed maintenance for seven highway assets: pavements, bridges, culverts, guardrails, lighting, pavement marking, and signs. Many pavement management systems incorporate deterministic models or probabilistic models, and the bridge management system incorporates probabilistic models. This study recommends the following maintenance scenarios to assess the consequences of delayed maintenance: address all needs, do nothing, and delayed maintenance, as well as budget-driven with limited maintenance funds.

2.2 Performance Measurement of Roadway Assets

In Washington state, highway assets have been evaluated using outcome-based performance measures since 1996 (WSDOT 2018). The maintenance program measures the performance of highway maintenance assets that can be categorized into three types, which are i) condition assessment, ii) operational assessment, iii) task completion. Condition assessment is done through the Maintenance Accountability Process (MAP). The MAP is a mechanism for monitoring and communicating the results of maintenance activities, such as conducting field surveys. WSDOT's MAP determines the number of deficient culverts out of all culverts that fall within the 0.10-mile sample site. Currently, WSDOT samples 756 different locations across the state that contain a wide variety of inventory. Operational assessment features inventory against the number of repairs against the number of systems. Finally, task completion is measured based on the number of tasks that can be completed against the planned task amount, or the total number of tasks that should have been completed against a known inventory.

The WSDOT Maintenance Division reports statewide highway asset LOS conditions. In 2020, WSDOT met 68% of its highway maintenance asset condition targets and missed 32% of asset condition targets. The eight missed target highway assets were: i) sweeping and cleaning, ii) catch basin and inlet maintenance, iii) stormwater facility maintenance, iv) slope repair, v) roadside cleanup, vi) noxious weed control, vii) bridge cleaning, and viii) pavement striping maintenance. Out of these eight maintenance assets, four missed the target with LOS rating of 'F', which means the assets are in poor or failing conditions, and system failures are likely.

A study was conducted to evaluate the performance of pavements, forecast its condition, and determine the effects of maintenance and rehabilitation strategies (Baladi et al. 2017). The authors established new pavement performance measures and rating systems, which were applied using pavement condition data. The inventory and pavement condition data, as well as distress data were obtained from long-term pavement performance (LTPP) data from three state agencies: Washington State Department of Transportation, Colorado Department of Transportation, and Louisiana Department of Transportation.

The new systems developed were utilized to compute the benefits of maintenance treatment used, identify the impact of weather, and evaluate the design variables on pavement durability. The study made several conclusions, including that thin overlay treatment was not the viable solution to improve pavement performance of cracks (alligator, longitudinal, and transverse cracking) in all regions. After the overlay, the cracks were hidden, but resurfaced again through the overlay after a few years. Slurry seal and crack sealing may improve the International Roughness Index (IRI) and/or rutting but does not improve the pavement performance in terms of cracks. However, aggregate seal coats improve the IRI, rutting, and cracking in all climatic regions.

2.3 Studies on Specific Assets

2.3.1 Culvert Maintenance

Culvert maintenance is an important task of the roadway system as it directly impacts the roadway and local hydrology (Pajouh et al. 2020). Culverts reduce the risk of hydroplaning, vehicle tires being affected by hydrodynamic drag, and a reduction of weather-related crash potential, and the culverts may in many storm events potentially prevent flooding on the roadways during rainfall. A study conducted by Pajouh et al. (2020) shows that the type of culvert material impacts the frequency of culvert maintenance; the size of the culvert and type of inlet/ outlet also impact the culvert maintenance (Jensen et al. 2001; Albuquerque et al 2011). Lack of maintenance for culverts can result in damage not only to the roads on an urban, suburban, and rural level but can also be a detriment to ecosystem (Gharaibeh and Lindholm 2013). Table 1 presents factors affecting the LOS condition of culverts.

Figure 2. A Culvert at US 195 Washington State

Table 1. Factors Affecting the LOS Condition of Culverts

S.N.	Factors Affecting the LOS Condition of Culverts	Sources
1.	Previous date of maintenance	Based on PI's experience
2.	Material type: concrete vs. galvanized steel vs. PVC vs. HDPE	Pajouh et al. (2020)
3.	Length of culvert or serving for Interstate, US, or SR roadways	Albuquerque et al. (2011), Okafor et al. (2023)
4.	Height or diameter of the culvert	Albuquerque et al. (2011)
5.	Orientation of the culvert (cross or approach)	Pajouh et al. (2020)
6.	Inlet / outlet end type	Jensen et al. (2001)
7.	Current LOS	Based on PI's experience
8.	Funding allocated for the current year	Albuquerque et al. (2011)

9.	Hydrological/weather condition in the area - Precipitation	Pajouh et al. (2020)
10.	Location: urban, suburban, rural area, alluvial fan, upstream land use	Gharaibeh and Lindholm (2013)
11.	Age of culvert	Gassman et al. (2016)
12.	Culvert that pass fish life (Yes/No)	Jensen et al. (2001)
13.	Water/soil related - PH, saltwater exposure, bed loading	Pajouh et al. (2020)
14.	Record of repair - repaired and functional (Yes/No)	Gassman et al. (2016)
15.	Depth of fill or depth buried	Okafor et al. (2023)
16.	Scoured around culvert pipe and headwalls	Gassman et al. (2016)

2.3.2 Barrier Maintenance

According to a study conducted by Karim et al., barrier maintenance is directly influenced by the local factors including weather, average annual daily traffic (AADT) of the road, and what specific type of highway the road is (divided, two-lane, or multi-lane) (Karim et al. 2011). These factors affect the performance of barriers and thus imply the ways that they must be maintained. Supporting this idea, Karim et al.'s study also implies that the age of the barriers has an impact on their need to be maintained. This especially is true as Washington state has such a wide variety of annual weather types which leads to a greater attention towards barrier age as they are impacted

by the local weather factors. Figure 3 presents concrete barrier and Table 2 presents the factors affecting the LOS condition of barrier maintenance with their sources.

Table 2. Factors Affecting the LOS Condition of Barriers

S.N.	Factors Affecting the LOS Condition of Barrier Maintenance	Sources
1.	Average Daily Traffic	Karim et al. (2011)
2.	Type of Barrier - Beam; Jersey; Cable	Karim et al. (2011)
3.	Location - Ramp; Corner, illuminated intersection/corridor	Liu (2013)
4.	Type of Highways - divided, two lane, multi-lane	Karim et al. (2011)
5.	Pavement Type - Portland Cement Concrete Pavement, Hot Mix Asphalt, Bituminous Surface Treatment	Based on PI's experience
6.	Shoulder Build-up	Based on PI's experience
7.	Weather	Karim et al. (2011)
8.	Last year's Outcome Threshold	Based on PI's experience
9.	Previous date of repair or replace (after repaving or third-party damage)	Hawzheen (2008)
10.	Funding allocated current year for potential repairs	Hawzheen (2008)
11.	Record of repair - Repaired and functional (Yes/No)	Hawzheen (2008)
12.	Age of the Barrier elements (guardrail posts)	Karim et al. (2011)

2.3.3 Traffic Signal Systems

Traffic signal systems (TSS) is a vital component of roadway safety. Figure 4 presents a TSS system. Traffic congestion is a significant cause of vehicle accidents, incremental delays, fuel consumption, and operational costs. Thus, paying attention to TSS has a direct impact on the economy and the safety of public. With this in mind, the LOS condition of TSS correlates accordingly with the location of the TSS and their presence in high accident areas (Atewi, 2022). On the topic of safety, storms may affect the performance of TSS. It is important that TSS bear minimal impact from storms, wind gusts, and other varying factors as the impacts of these can result in unsafe traffic conditions both during and after the storm (Irwin et al, 2016).

Westbrook attributes the age of the bulbs in a TSS to the LOS as well (Westbrook and Rasdorf 2023). As modern technology has advanced, it is important to consider that newer light emitting diode (LED) bulbs have become significantly more effective than where they were 20 years ago. Thus, the age and type of bulb impacts the overall LOS condition (Westbrook and Rasdorf 2023). From experience in the field, it is also important to consider not only the age of the bulbs in a TSS, but also the age of the wiring system including connections, the pole itself, and the control system. Table 3 presents the factors affecting the LOS condition of TSS.

Table 3. Factors Affecting the LOS Condition of TSS

S.N.	Factors Affecting the LOS Condition of TSS	Sources
1.	Types of signal system	Based on PI's experience
2.	Location: Corrosion vs non-corrosion areas	Based on PI's experience
3.	High accident area	Nuri et al. (2022)
4.	High storm/hurricane location	Irwin et al. (2016)
5.	Last year's LOS	Based on PI's experience
6.	Previous date of repair (wiring and connections)	Westbrook and Rasdorf (2023)
7.	Funding allocated current year for potential repairs	Chen et al. (2009)
8.	Record of repair - Repaired and functional	Westbrook and Rasdorf (2023)
9.	Age of the bulbs	Westbrook and Rasdorf (2023)
10.	Age of wiring system including connections	Based on PI's experience
11.	Age of the pole	Based on PI's experience
12	Age of the control system	Based on PI's experience
13.	Method of operating the system	Based on PI's experience

2.3.4 Ditch Maintenance

Roadside ditches are a significant source of sediment runoff which directly impacts local water sources. The US Environmental Protection Agency (EPA) has listed nonpoint source pollutants from ditches as the third main source of contamination in rivers and lakes (Shuangcheng, et. al, 2018). In a study, many respondents across New York state claimed that insufficient critical resources (labor, funding, and equipment) were the largest challenge to maintaining their roadside ditches (Schneider et. al, 2019). Lack of proper maintenance may also result in roadside erosion and ditch failure, which corresponds to the lifespan of pavement, safety of travelers, and costs of upkeep (Schneider et al. 2019). Thus, it is important for state DOTs to maintain roadside ditches, particularly, as they directly impact local hydrology in a compounding effect. Practical ways of doing this include proper maintenance strategies, implementation of appropriate vegetation, and well designed construction for maximized drainage efficiency.

Scraping of ditches must be done carefully to avoid reducing existing sediment, and is most effective in the late spring/early summer months (STAC 2014). A study indicates that increasing the presence of both sediment and herbaceous plants in roadside ditches can decrease the amount of runoff pollution from roads, especially small particles (<2 mm) in road runoff (Shuangcheng et al. 2018). Strategies for use of technologies such as ecological ditch, grass planting ditch, and a kind of freeway drainage ditch based on the combination of percolation and drainage are all proposed ways to improve the overall LOS for ditches (Shuangcheng et al. 2018). Other studies revealed that the slope adjacent to the roadside ditch may impact the LOS condition as waterflow may be redirected depending on the high points of the ditch (Davis and Shakoor 2005). Figure 5 presents a highway ditch and Table 4 shows the factors affecting the LOS condition of ditches with their sources.

Table 4. Factors Affecting the LOS Condition of Ditches

S.N.	Factors Affecting the LOS Condition of Ditches	Sources
1.	Slope (steepness) of ditches	Davis and Shakoor (2005)
2.	Width and depth of ditch	Davis and Shakoor (2005)
3.	Proximity to falling rocks nearby	Davis and Shakoor (2005)
4.	Type of road (paved or unpaved)	Schneider et al. (2019); Schneider and Orr (2019)
5.	Sediment type	Buchana et al. (2013)
6.	Previous date of cleaning	STAC (2014)
7.	Type and density of vegetation (local to area or not)	Schneider et al. (2019)

8. Connection to local stream system		Schneider et al. (2019)
9. Drainage outlets nearby		Carlson and Sands (2018)
10. Timely drainage, no pooling		FAO (1998)
11. Local weather patterns, rainfall, snowfall, etc.		FAO (1998)
12. Upstream land use (forestry/ agricultural)		Based on PI's experience

2.3.5 Slope Repairs

The slope of a highway embankment is critical to the stability of various transportation infrastructures (Cheng et al. 2021; Hearn and Massey 2009). Effective embankment fill slope construction and maintenance can reduce the risks associated with slope failure, lowering the possibility of single vehicle crashes, and damage to the roadway network.

Similar to other highway assets, slope repair is also influenced by the amount of annual precipitation in the region. Dahal et al. (2006) revealed that excessive amount of precipitation causes roadway slope failure and even landslides. Along with precipitation, other natural factors play a role in the LOS condition of a roadway embankment slopes. A study revealed that slope failure is common in the state of Texas due to extreme weather conditions. (Shahandashti et al. 2022; Baral and Shahandashti 2022). Similarly, Washington has weather patterns that may cause damage to roadside slopes. Multiple studies showed that the height of the slope plays a large part

Figure 6. Highway Slope

in its LOS condition as well as upkeep (Neranjan et al. 2018; Dahal 2015). Figure 6 present a highway embankment slope and Table 5 presents 22 factors that affect the LOS condition of slopes.

Table 5. Factors Affecting the LOS Condition of Slopes

S.N.	Factors Affecting the LOS Condition of Ditches	Sources
1.	Slope steepness	Dahal et. al (2006)
2.	Slope height	Dahal (2015)
3.	Local weather patterns (rainfall, snowfall, etc.)	Dahal (2015); Dahal et al. (2006)
4.	Local hydrology & connection to drainage system	Dahal (2015); Wemple and Jones (2003); Liu et al. (2014)
5.	Wind rates in area	Jankauskas et al. (2008)
6.	Slope material type (earth, gravel, other)	Dahal, et al. (2006); Parsakhoo et al. (2019)
7.	Vegetation present on slope	Jankauskas et al. (2008); Liu et al. (2014); Yin et al. (2014)
8.	Type of vegetation present on slope (grass, other)	Liu et al. (2014)
9.	Adjacent topography	Baral et al. (2022); Sheikh et al. (2010)
10.	Adjacent land use	Dahal (2015)
11.	Frequency of maintenance	Jankauskas et al. (2008)
12.	Current state of slope	Kim et al. (2013); Akhmudiyantoet al. (2021)
13.	History of collapse	Kim et al. (2013)
14.	Amount of accumulated debris on the shoulder contributing to water flow	Kim et al. (2013)
15.	Existing signs of erosion	Liu et al. (2014)
16.	Traffic flow	Baral et al. (2022)

2.3.6 Shoulder Maintenance

Highway shoulders provide a space for parking in case of emergency or breakdown. Figure 7 presents a snapshot of a highway shoulder. This is especially crucial on high-speed and high-traffic routes. Existing studies revealed that many factors affect the LOS condition of highway shoulders. The width and types of shoulders used may affect the LOS condition. Depending on the type of roadway, three most common shoulder types are paved, unpaved and composite. Shoulder paving and maintenance is a positive countermeasure that reduces crash potential (Li and Kepaptsoglou 2013). Paved shoulders protect pavement structural integrity and provide space for highway maintenance works.

A study conducted by Barman (2020) revealed that the LOS condition of paved shoulders depends on the existence of cracking, potholes, and raveling. Unpaved shoulders may collect debris, which may damage water flow as debris accumulates. Gharaibeh (2013) revealed that paved shoulders should remain free of weeds, sediment, and vegetation for maximum effectiveness. According to Dafalla et al. (2022) annual precipitation, annual temperature, local hydrology, adjacent topography, and the slope of the shoulder affects the LOS condition of a shoulder. Table 6 presents other factors that affect the LOS condition of a highway shoulder.

Figure 7. Highway Shoulder at US 12

Table 6. Factors Affecting the LOS Condition of Shoulders

S.N.	Factors Affecting the LOS Condition of Shoulders	Sources
1.	Total shoulder width	Fitzpatrick et al. (2016); Schrock et al. (2011)
2.	Type of shoulder: paved, unpaved, or composite	Bisht and Tiwari (2022); Zeng and Schrock (2012)
3.	Unpaved shoulder types (gravel, earth, or mixed)	Hallmark et al. (2013); Huber et al. (2020)
4.	Width of paved and/or unpaved shoulder	Bisht and Tiwari (2022)
5.	Porosity of pavement & water infiltration	Barrett et al. (2006); Huber et al. (2020)
6.	Cracks, type and width of cracks present	Barman and Bandyopadhyaya (2020)
7.	Potholes	Barman and Bandyopadhyaya (2020)
8.	Raveling	Barman and Bandyopadhyaya (2020)
9.	Presence of rumble strips	Park and Abdel-Aty (2016)
10.	Presence of guardrail	Fitzpatrick et al. (2016)
11.	Age of shoulder	Intharasombat et al. (2007)
12.	AADT (general)	Park and Abdel-Aty (2016)
13.	AADT (truck)	Park and Abdel-Aty (2016)
14.	Condition/type of topography adjacent to shoulder	Dafalla et al. (2022)
15.	Soil type below pavement	Intharasombat et al. (2007)
16.	Presence of vegetation on unpaved shoulder	Slaughter et al. (1999)
17.	Presence of vegetation beyond shoulder	Slaughter et al. (1999)
18.	Grade of road/ shoulder	Gross and Jovanis (2007)
19.	Lateral slope of shoulder	Dafalla et al. (2022)
20.	Annual rainfall intensity in area	Dafalla et al. (2022)
21.	Local hydrology & connection to drainage system	Dafalla et al. (2022)
22.	Presence of shoulder liner	Dafalla et al. (2022)
23.	Average annual temperature, temperature variation	Intharasombat et al. (2007)
24.	Frequency of shoulder maintenance	Intharasombat et al. (2007)
25.	Current state of shoulder	Based on PI’s experience

2.4 Use of Algorithms for Highway Assets

Using extensive 3D pavement data, Tsai and Wang (2015) have created flexible algorithms to identify and categorize pavement raveling. Data pre-processing, pavement texture feature computation, subsection-level raveling classification, post-processing for section raveling data smoothing, and aggregation of detection to segment-level measurement of raveling are the five main stages of the algorithms. The initial step, data pre-processing, entails getting the 2D intensity data and 3D pavement data ready for further analysis. To guarantee accuracy and consistency, the data may need to be cleaned, have noise removed, and normalized. The pavement texture feature calculation step involves calculating the pavement's texture characteristics.

These parameters aid in capturing pavement features that may be suggestive of raveling. In the third stage, subsections of the pavement are classified as either raveled or unraveled. This classification uses machine learning or statistical techniques to evaluate the existence and degree of raveling in each part. The last stage of the algorithm entails merging the data from the previous subsections and thoroughly evaluating raveling across broader stretches of pavement. The proposed algorithms can automatically identify, categorize, and measure raveling in asphalt pavement.

Saleh et al. (2023) developed an algorithm of vehicle travel time calculation on a highway based on traffic data. There are eight steps in the algorithm for prediction. It is started with a specific control, for example, the route they want to take. The algorithm then determines the traffic flow while considering variables like congestion, slowly moving, or free-flowing traffic. The method moves directly to step 8 if it is determined that calculating the scheduled travel time is unnecessary. The method further evaluates the flow type if the estimated travel time is essential. The program forecasts using initial values if the traffic flow is labeled as congested. The approach incorporates current values linearly to estimate travel time, on the other hand, whether the flow type is identified as slow-moving or free-flowing. The algorithm moves on to step 8 to determine the travel time for the full route if none of the aforementioned circumstances hold. Users may get an estimate for the travel time associated with a specific route by following this computational procedure.

3. RESEARCH APPROACH

Figure 8 demonstrates the overall research methodology of this project. The scope and objectives were defined, and related literature on the topic of highway asset management in general and on the topic of six assets were administered to gather data of factors affecting the LOS condition of assets. Questionnaire surveys were conducted with WSDOT professionals to collect data and then analyzed. Finally, this project developed six algorithms to predict LOS condition of assets.

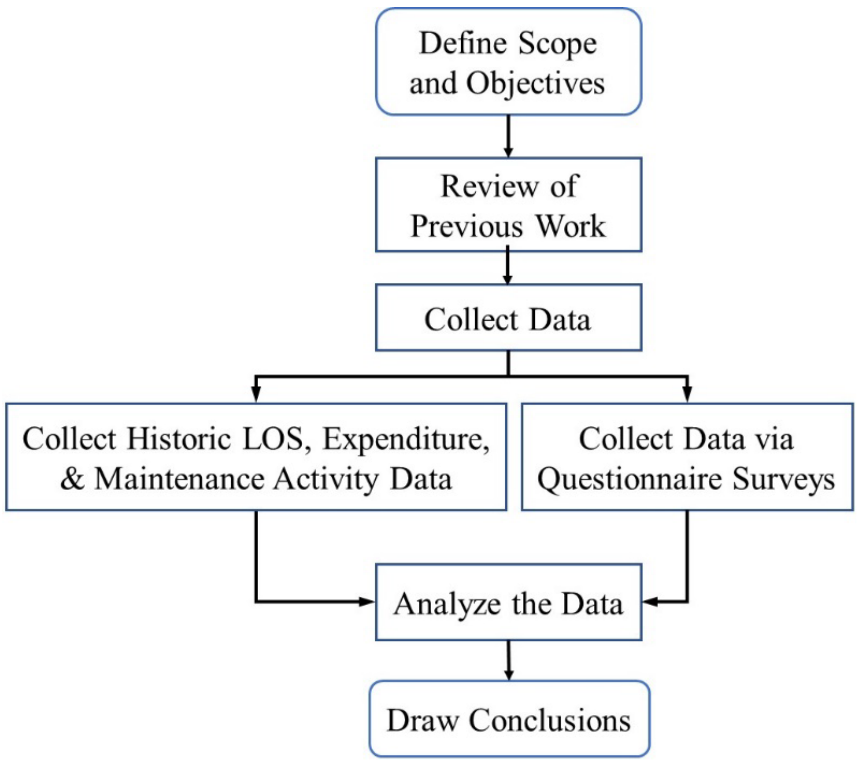


Figure 8. Overall Research Approach

3.1 Data Collection

This research project gathered data in two ways: through direct data collection from WSDOT and via surveys. The direct data collection involves collecting historic LOS data, expenditure records, and maintenance activities records completed for the six assets. The provided data detailed the work in the Maintenance Management System (MMS) for each asset. These data were collected in the Excel files. Moreover, this research project collected ranking data via questionnaire surveys administered to with WSDOT professionals. These surveys were regarding the factors affecting the LOS condition of six assets. The following sub-sections explain the data collection process via the questionnaire surveys.

3.1.1 Phase 1 Survey Development:

The research project team developed the Phase 1 survey to identify and document factors affecting LOS condition of six assets. Factors were collected through the existing literature and the experiences of the project team, and a list of factors for each of the six assets were prepared. The surveys also included a description that stated how asset conditions are assessed (A through F), which was taken from WSDOT Maintenance Manual. The contents of the Phase 1 survey of six assets are presented in Appendix A. That survey was distributed to related senior asset managers for their review, and they were also asked to add additional factors that they suspect might affect the LOS condition of assets. The WSDOT managers provided their feedback either in the survey or through email. The additional factors provided by the WSDOT managers/ professionals were included in the Phase 2 survey. These additional factors were presented in the results and discussion section in Table 12 (TSS), Table 14 (Ditches), Table 16 (Shoulders), and Table 18 (Slopes).

3.1.2 Phase 2 Survey Development:

The Phase 2 survey was developed based on the Phase 1 survey and feedback received from WSDOT asset managers. For the six assets, six phase 2 survey questionnaires were developed. For the Phase 2 surveys, participants were given 10 days to complete the survey. If a significant number of professionals had not completed the survey, a follow up email was sent to increase the response rate. In the Phase 2 survey, the list of factors that affects the LOS condition of assets were distributed to the relevant WSDOT professionals, and the respondents were asked to rank the provided factors on the Likert scale from 1-to-X, where 1 refers to the most important factor and X refers to the least important factor. (X is the variable, and is different for different assets, for example, there are 16 factors in culvert maintenance, so the respondents were asked to rank the factors from 1-to-16.)

Specific surveys were distributed only to those professionals working with that specific asset for an extensive period. The surveys were conducted on word files and respondents provided numbers ranking the provided factors. These surveys were collected through email conversation, and their responses were stored digitally on a Spreadsheet separately for each asset for data analysis.

3.2 Data Analysis

3.2.1 Relative Importance Index (RII) Method

After data was collected from survey respondents, data analysis was performed. First, data regarding crucial factors that affect the LOS condition of each asset were analyzed using a descriptive analysis. Then, for each asset, the Relative Importance Index (RII) method was used to rank the factors. The equation (1) given below was used to find out the RII values. This method is similar to the one adopted by Shrestha (2016).

$$\text{RII} = \frac{\sum_{i=1}^{N} W_i}{A \ x \ N} \qquad (1)$$

Where, Wi = Rank assigned by i^{th} responder; A = Highest rank; N = Total number of respondents.

3.2.2 Kolmogorov-Smirnov and Shapiro-Wilk Test

Following descriptive analysis, the gathered responses were analyzed to determine if the collected dataset were normally distributed. The Kolmogorov-Smirnov and Shapiro-Wilk normality tests in Statistical Package for Social Sciences (SPSS) were utilized. If the dataset were normally distributed, parametric tests are conducted. Conversely, if the dataset were not normally distributed, non-parametric tests are conducted.

3.2.3 Mann Whitney U tests

As explained in the result section, the datasets in this project were not normally distributed; therefore, the project team conducted a non-parametric test, the Mann Whitney U tests, to compare two groups. If the p-value of the test statistics were less than 0.05, the test result is significant. Using these test results, the project team determined critical factors affecting the LOS condition of the each of the six assets.

4. RESULTS AND DISCUSSION

In the Round 2 surveys, WSDOT professionals were asked to rank the listed factors based on how important they are comparatively. The number of factors listed in the surveys were different for different assets. The summary of the responses received is presented in Table 7 below. The following sub-sections present details about the data analysis of the six assets.

Table 7. Phase 2 Survey Responses

Roadway Assets	No. of Factors in Phase 2 Survey	No. of Responses Received
1. Culvert Maintenance	16	29
2. Barrier Maintenance	12	31
3. Traffic Signal System	14	23
4. Ditch Maintenance	18	30
5. Slope Repair	22	8
6. Shoulder Maintenance	29	8

4.1 Ranking of Factors Affecting the LOS of Culvert Maintenance

In the Phase 2 survey of Culvert Maintenance, the respondents were asked to rank the factors that affect the LOS of culverts. Participants were asked to rank sixteen factors. The top five highly ranked factors based on RII analysis were as follows: "Hydrological/ weather condition in the area – Precipitation," "Previous date of maintenance," "Current LOS," "Scoured around culvert/pipe and headwalls," and "Material Type: Concrete vs. Galvanized Steel vs. PVC vs. HDPE." Table 8 presents the summary of the results. The "Hydrological/ weather condition in the area – Precipitation," factor received the highest rating from responders.

Table 8. Ranking of Factors Affecting the LOS of Culverts

Factors	Sample Size (N)	RII Values	Ranking
Hydrological/ weather condition in the area – Precipitation	29	0.63	1*
Previous date of maintenance	29	0.58	2*
Current LOS	29	0.57	3*
Scoured around culvert/pipe and headwalls	29	0.55	4*
Material Type: Concrete vs. Galvanized Steel vs. PVC vs. HDPE	29	0.51	5*
Age of Culverts	29	0.50	6*
Location: Urban, Suburban, Rural area, Alluvial fan, Upstream land use	29	0.49	7*
Record of repair – Repaired and functional (Yes/No)	29	0.48	8*
Height or Diameter of the Culvert	29	0.46	9*
Culverts that pass fish life (Yes/No)	29	0.46	10*
Water/soil related – PH, saltwater exposure, bed loading	29	0.45	11*
Length of Culvert or serving for Inter State, US, or SR roadways	29	0.44	12*
Depth of fill or depth of buried	29	0.38	13*
Inlet / Outlet End Type	29	0.38	14*
Orientation of the Culvert (Cross or Approach)	29	0.34	15*
Funding allocated for the current year	29	0.28	16

Note: Significant at α level 0.05
* Significant at α level 0.05

After the factors were ranked from 1-16 based on the RII analysis, statistical analysis was conducted to determine the critical factors affecting the Culvert Maintenance. When Mann-Whitney U tests were administered to determine the group differences, the test results show that the group of top fifteen factors are statistically significantly higher rated than 16th factor (Table 9).

Table 9. Results of Mann-Whitney U Tests of the Factors Affecting the LOS of Culverts

Geotechnical-related Change Orders on Cost Overrun	N	Mean Rank	Sig.
Factors ranked 1 through 15	435	226.80	0.01*
Factors ranked 16	29	318.00	

Note: Significant at α level 0.05
* Significant at α level 0.05

4.2 Ranking of Factors Affecting the LOS of Barrier Maintenance

Responders ranked the factors affecting the LOS condition of barriers to the Barrier Maintenance Phase 2 survey. They were asked to rank each of the twelve stated factors. The five highly ranked factors based on RII study are "Type of Highways - divided, two lane, multi-lane," "Location - Ramp; Corner, Illuminated Intersection/Corridor," "Average Annual Daily Traffic," "Types of

Barrier - Beam; Jersey; Cable," and "Previous Date of Repair or Replacement." The results are summarized in Table 10. The factor "Type of Highways - divided, two lane, multi-lane," obtained the highest rating from respondents.

Table 10. Ranking of Factors Affecting the LOS of Barriers

Factors	N	RII Values	Ranking
Type of highways – divided, two lane, multi-lane	31	0.69	1*
Location – ramp; corner, illuminated intersection/corridor	31	0.66	2*
Average annual daily traffic (AADT)	31	0.65	3*
Types of barrier – beam; jersey; cable	31	0.64	4*
Previous date of repair/ replacement	31	0.45	5*
Record of repair – repaired and functional (Yes/No)	31	0.42	6*
Age of the barrier elements	31	0.40	7*
Weather	31	0.40	8*
Shoulder build-up	31	0.38	9*
Funding allocated towards current year for potential repairs	31	0.30	10*
Pavement type – Portland cement concrete pavement, hot mix Asphalt, bituminous surface treatment	31	0.28	11*
Last year's outcome threshold	31	0.23	12

Note: Significant at α level 0.05
* Significant at α level 0.05

The critical factors impacting the barrier condition were identified after the factors were ranked from 1 to 12 based on the RII analysis. The group of the top 11 factors is statistically substantially higher rated than factor 12 when Mann-Whitney U tests were used to evaluate the group differences. The summary of the Mann-Whitney U tests is presented in Table 11.

Table 11. Results of Mann-Whitney U Tests of the Factors Affecting the LOS of Barriers

Geotechnical-related Change Orders on Cost Overrun	N	Mean Rank	Sig.
Factors ranked 1 through 11	341	179.08	0.01*
Factors ranked 12	31	268.11	

Note: Significant at α level 0.05
* Significant at α level 0.05

4.3 Ranking of Factors Affecting the LOS of Traffic Signal Systems (TSS)

The factors affecting the LOS of TSS were ranked by respondents to the Phase 2 TSS Survey. Participants were asked to rank fifteen factors. The five highly ranked factors based on RII analysis are "Age of wiring system including connections," "Age of the control system," "Inability to complete preventive maintenance due to lack of FTEs," "Age of the bulbs," and "Previous date of repair (wiring and connections"). Table 12 presents the summary of test. The factor that respondents rated highest was "Age of wiring system including connections."

Table 12. Ranking of Factors Affecting the LOS of TSS

Factors	N	RII Values	Ranking
Age of wiring system including connections	23	0.76	1*
Age of the control system	23	0.74	2*
Inability to complete preventive maintenance due to lack of FTEs#	23	0.71	3*
Age of the bulbs	23	0.61	4*
Previous date of repair (wiring and connections)	23	0.58	5*
aCrash Analysis Locations	23	0.56	6*
Record of repair - Repaired and functional (Yes/No)	23	0.52	7*
Funding allocated current year for potential repairs	23	0.46	8*
Theft/ vandalism location#	23	0.42	9*
Types of signal system (regular traffic signal vs dynamic message single vs reversible lane signal vs emergency vehicle signal vs data accumulator stations vs ramp meter signal, etc.)	23	0.34	10*
Last year's Outcome Threshold	23	0.30	11*
Location: Corrosion vs non-corrosion areas	23	0.28	12*
Age of the pole	23	0.22	13*
Method of operating the system	23	0.18	14*
High storm/ hurricane location	23	0.14	15

Note: Significant at α level 0.05
* Significant at α level 0.05
\# Factors identified from a meeting with WSDOT professionals

A statistical analysis was performed to identify the critical factors impacting the TSS after the factors were ranked from 1 to 15 based on the RII analysis. The top 14 variables ranked statistically higher than factor 15 when Mann-Whitney U tests were used to identify group differences. Table 13 below presents the test summary.

Table 13. Results of Mann-Whitney U Tests of the Factors Affecting the LOS of TSS

Geotechnical-related Change Orders on Cost Overrun	N	Mean Rank	Sig.
Factors ranked 1 through 14	322	165.51	0.01*
Factors ranked 15	31	277.85	

Note: Significant at α level 0.05
* Significant at α level 0.05

4.4 Ranking of Factors Affecting the LOS of Ditches

Similarly, in Phase 2 survey of ditches, the respondents were asked to rank the factors that impact the LOS of ditches. Participants were asked to rank eighteen factors. Based on RII analysis, the five highly rated factors are as follows: “slope (steepness) of ditch,” “width and depth of ditch,” “local weather patterns, rainfall, snowfall,” “unstable slopes / slide area,” and “proximity to falling rocks nearby”. The test results are summarized in Table 14. Survey respondents rated the "slope (steepness) of ditch," factor as the most critical.

Table 14. Ranking of Factors Affecting the LOS of Ditches

Factors	N	RII Values	Ranking
Slope (steepness) of ditch	30	0.69	1*
Width and depth of ditch	30	0.68	2*
Local weather patterns, rainfall, snowfall	30	0.66	3*
Unstable slopes / Slide area # (as defined in MAP Guide)	30	0.66	4*
Proximity to falling rocks nearby	30	0.60	5*
Sediment type	30	0.60	6*
Type and density of vegetation	30	0.56	7*
Timely drainage, no pooling	30	0.56	8*
Drainage outlets nearby	30	0.56	9*
Connection to local stream system	30	0.50	10*
Geographical location (coastal vs mountain passes) #	30	0.44	11*
Upstream land use (forestry and agricultural)	30	0.43	12*
Previous date of cleaning	30	0.41	13*
Access connections / man made barriers #	30	0.39	14*
Applying sand or other abrasives for snow and ice control #	30	0.25	15*
Type of the road (paved or unpaved)	30	0.21	16*
Frequency of sweeping #	30	0.16	17*
Wind erosion from farmers' fields #	30	0.14	18

Note: Significant at α level 0.05
* significant at α level 0.05
# Factors identified with a meeting with WSDOT professionals

After the factors were ranked from 1-18 based on the RII analysis, statistical analysis was conducted to identify the critical factors affecting the LOS condition of ditches. When Mann-Whitney U tests were conducted to determine the group differences, the test results show that the group of top 17 factors are rated statistically significantly higher than the factor 18. The Mann-Whitney U test results are summarized in Table 15 below.

Table 15. Results of Mann-Whitney U Tests of the Factors Affecting the LOS of Ditches

Geotechnical-related Change Orders on Cost Overrun	N	Mean Rank	Sig.
Factors ranked 1 through 17	510	259.86	0.01*
Factors ranked 18	30	451.38	

Note: Significant at α level 0.05
* Significant at α level 0.05

4.5 Ranking of Factors Affecting the LOS of Shoulders

Similarly, the responders to the shoulder maintenance Phase 2 survey were asked to rank the factors that influence the LOS of the roadway shoulders. There were 29 factors listed, and responders were asked to rank them. The five variables with the highest RII ratings are "edge drop off greater than 2 inches adjacent to paved shoulder," "cracks, type and width of cracks present," "erosion of gravel shoulder," "current state of shoulder," and “type of shoulder: paved, unpaved, or composite (combined)." The results are summarized in Table 16. The factor that respondents ranked highest was "edge drop off adjacent to paved shoulder."

Table 16. Ranking of Factors Affecting the LOS of Shoulders

Factors	N	RII Values	Ranking
Edge drop-off greater than 2” adjacent to paved shoulder #	8	0.83	1*
Cracks, type and width of cracks present	8	0.81	2*
Erosion of gravel shoulder #	8	0.79	3*
Current state of shoulder	8	0.75	4*
Type of shoulder: paved, unpaved, or composite	8	0.75	5*
Potholes	8	0.67	6*
Frequency of shoulder maintenance	8	0.62	7*
Edge build-up adjacent to paved shoulder #	8	0.61	8*
Raveling	8	0.60	9*
Grade of road/ shoulder	8	0.53	10*
Porosity of pavement and water infiltration	8	0.52	11*
Age of shoulder	8	0.51	12*
Unpaved shoulder types: Gravel, earth, or mixed	8	0.50	13*
Lateral slope of shoulder	8	0.48	14*
Total shoulder width	8	0.46	15*
Width of paved and/or unpaved shoulder	8	0.46	16*
Presence of rumble strips	8	0.46	17*
Presence of vegetation on unpaved shoulder	8	0.44	18*
Local hydrology and connection to drainage system	8	0.43	19*
Soil type below the pavement	8	0.37	20*
Presence of guardrail	8	0.35	21*
Curb Presence #	8	0.34	22*
Condition/type of topography adjacent to shoulder	8	0.33	23*
Annual rainfall intensity in the area	8	0.32	24*
Average annual temperature, temperature variation	8	0.30	25*
Presence of shoulder liner	8	0.22	26*
Presence of vegetation beyond shoulder	8	0.19	27*
AADT (general)	8	0.19	28*
AADT (Truck)	8	0.17	29

Note: Significant at α level 0.05
* Significant at α level 0.05
# Factors identified from a meeting with WSDOT professionals

After the factors were ranked from 1 to 29 based on the RII analysis, statistical analysis was conducted to identify the critical factors impacting the LOS condition of the roadway shoulder. The findings of the Mann-Whitney U tests used to analyze group differences reveal that the top 28 factors are statistically substantially high ranked than the 29th factors. Table 17 presents the summary of the test results.

Table 17. Results of Mann-Whitney U Tests of the Factors Affecting the LOS of Shoulders

Geotechnical-related Change Orders on Cost Overrun	N	Mean Rank	Sig.
Factors ranked 1 through 28	224	113.90	0.02*
Factors ranked 29	8	189.31	

Note: Significant at α level 0.05
* Significant at α level 0.05

4.6 Ranking of Factors Affecting the LOS of Roadway Slopes

Similarly, the factors that impact the LOS condition of roadway slopes were ranked by respondents to the roadway slope Phase 2 survey. They were asked to rate twenty-two factors. The five highly ranked criteria according to RII research are "current state of slope," "existing signs of erosion," "slope steepness," "slope material type (earth, gravel, other)," and "slope height." The results are summarized in Table 18. The factor with the highest ranked was "current state of slope."

Table 18. Ranking of Factors Affecting the LOS of Slopes

Factors	Sample size	RII values	Ranking
Current state of slope	8	0.81	1*
Existing signs of erosion	8	0.79	2*
Slope steepness	8	0.74	3*
Slope material type (earth, gravel, or other)	8	0.72	4*
Slope height	8	0.60	5*
Frequency of maintenance	8	0.56	6
Condition of paved/gravel shoulder #	8	0.52	7
Adjacent topography	8	0.51	8
Type of vegetation present on slope (grass, other)	8	0.51	9
Local weather patterns, rainfall, snowfall, etc.	8	0.49	10
Culvert presence #	8	0.49	11
Vegetation present on slope	8	0.47	12
Shoulder build up along paved shoulder #	8	0.44	13
On Geotechnical unstable slope list #	8	0.41	14
Local hydrology & connection to drainage system #	8	0.41	15
History of collapse	8	0.38	16
Amount of accumulated debris on the shoulder contributing to water flow	8	0.36	17
State of assets- signing, curb, paved shoulder, guardrail #	8	0.36	18
Adjacent land use	8	0.34	19
Wind rates in area	8	0.24	20
Curb Presence #	8	0.23	21
Traffic flow	8	0.16	22

Note: Significant at α level 0.05
* Significant at α level 0.05
# Factors identified from a meeting with WSDOT professionals

To identify the critical factors impacting the roadway slopes, statistical analysis was completed after the factors were ranked from 1 to 22 based on the RII study. The Mann-Whitney U tests were conducted to determine the group differences. The test results revealed that the top twentyone factors are statistically substantially high ranked than factor 22. The summary of the test results is presented in Table 19.

Table 19. Results of Mann-Whitney U Tests of the Factors Affecting the LOS of Slopes

Geotechnical-related Change Orders on Cost Overrun	N	Mean Rank	Sig.
Factors ranked 1 through 21	167	85.31	0.01*
Factors ranked 22	8	144.25	

Note: Significant at α level 0.05
* Significant at α level 0.05

For all the six assets (culvert maintenance, barrier maintenance, traffic signal system, ditches, shoulder maintenance, and slope repair), when the Mann-Whitney U tests were carried out to determine the group differences of between one factor to another (for example, factor 1 versus factor 2, factor 1 versus factor 3, etc.), the test result was insignificant (p-value over 0.05) in most of the cases.

However, when groups (for example, group of factors from factor 1 to factor 5 versus factor 6 to factor 12) were compared, the rest results were significant (p-value less than 0.05). With this result, there are more than ten critical factors for each asset that impact the LOS condition of that specific asset. So, during the model development phase, correlation tests can be utilized to determine which factors are to be utilized in the model. The two correlation tests that are commonly utilized are 'Pearson's correlation coefficient' and 'Point biserial correlation.' The 'Pearson's correlation coefficient' is conducted for two continuous variables (factors) and the 'Point biserial correlation' is conducted for determining the correlation between continuous and categorical variables. Usually, a correlation factor (R) higher than 0.50 is considered significant, and such variables are considered critical variables and are included in prediction model development.

4.7 Algorithm Development

4.7.1 Algorithm for Prediction Model Development for Culvert LOS

Step 1: Identify, collect and understand the predictor variables of culvert maintenance

- Collect all predictor variables: The predictor variables are the factors that impact the LOS of culvert maintenance. The project team collected these variables through literature and a two-phase survey completed by WSDOT professionals with extensive experience in this specific field. The following predictor variables were identified in this study.

<u>Predictor Variables of Culverts</u>:

- Hydrological/ weather condition in the area – precipitation
- Previous date of maintenance
- Current LOS
- Scoured around culvert/pipe and headwalls
- Material type: concrete vs. galvanized steel vs. PVC vs. HDPE
- Location: urban, suburban, rural area, alluvial fan, upstream land use
- Age of culvert
- Record of repair – repaired and functional
- Height or diameter of the culvert
- Culverts that pass fish life
- Water/soil related – PH, saltwater exposure, bed loading
- Length of culvert or serving for Interstate, US, or SR roadways
- Depth of fill or depth of buried
- Inlet/ outlet end type
- Orientation of the culvert
- Funding allocated for the current year

- Collect condition data of culverts and predictor variables
- Clean the data so that data is accurate and reliable for use in data analysis: Once the data has been collected, it must be cleaned to eliminate any duplicates, errors, or inconsistencies. This may entail updating missing data, deleting outliers, and ensuring that the data is formatted consistently. Cleaning the data is crucial in ensuring that the prediction model functions correctly. The Power Query tool can be used to automate the data cleaning process.

Step 2: Visualizing the data

This step is also called exploratory data analysis. In this step, the collected data is explored for visualizing the condition of culverts. The researchers will be identifying past trends. For this task, we will conduct descriptive and statistical analyses to uncover patterns and trends in data. To understand the patterns of the numerical variables, scatter plots can be utilized; to understand the patterns of the categorical variables, bar charts or boxplots may be used.

Step 3: Splitting the data into training and test datasets

Regression models must be trained and tested before using. Therefore, it is necessary to prepare a separate dataset for training and a separate dataset for testing the regression model. This step entails separating the collected historical data into a training dataset and a testing dataset. As with most models, approximately 80% of the data will be used to train the models, while 20% of the data will be used to test models.

Step 4: Developing a regression model

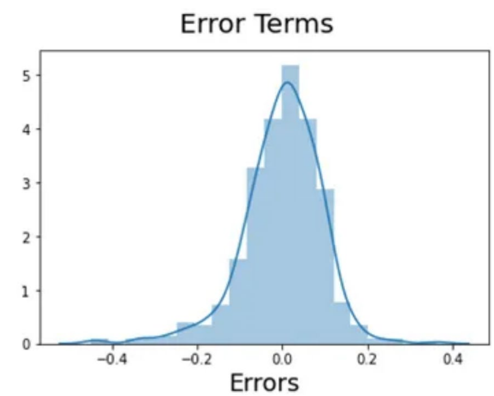
Completing all the steps explained above, the most important task is to develop a regression model for the culvert maintenance asset. While there are three different types of methods in use for the model development, one of the common methods is the 'Backward Selection Method'. In this method, all 16 predictor variables (identified in section 4.1) will be added first; then insignificant variables ($p>0.05$) will be eliminated. After eliminating the insignificant variables, the regression model will look like:

Condition of Culvert = $b_0 + b_1$(critical factor 1) + b_2 (critical factor 2) + …. + b_n (critical factor n)

Where critical factor 1, critical factor 2, critical factor n and b0, b1, b0, bn will be determined during the model development.

Step 5: Validate the model

The developed regression model will be trained using the training dataset. Then, residuals analysis is performed to assess the validity of model by comparing observed values with predicted values of a part of the training dataset. The residual analysis provides information on the distribution of errors (actual outcome of the model versus the predicted outcome of the model) throughout the model. A reliable residual analysis will show that the mean is about centered at zero. Figure 9 shows the residual errors are centered around zero.



Step 6: Test the model

The goal of model testing, in contrast, is to evaluate the model performance with new data (testing data) that was not utilized for training or validation. It gives an estimate of how the model will perform with the new dataset that has not previously been seen by the model.

Step 7: Making predictions using the final model and evaluation

After the model is validated and tested, it is ready to predict the LOS condition of the culverts. The regression model output will be the originally continuous variable (such as 3.86) that can be easily converted into a continuous variable, such as LOS A, LOS B, LOS C.

Now, using the model, the base fund required or fund required to keep the culvert at LOS 'B' or 'A' can be computed using the model.

4.7.2 Algorithm for Prediction Model Development for Barrier LOS

Step 1: Identify, collect and understand the predictor variables of barrier maintenance

- Collect all predictor variables: The predictor variables (factors that impact the condition of barriers) were collected through literature and a two-phase survey with WSDOT professionals, with significant experience in barrier maintenance work. The following predictor variables were identified in this project.

- Collect condition data of Barriers and predictor variables
- Clean the data so that data is accurate and reliable to be used for data analysis: Once the data has been collected, it must be cleaned to eliminate any duplicates, errors, or inconsistencies. This may entail updating missing data, deleting outliers, and ensuring that the data is formatted consistently. Cleaning the data is necessary to ensure that the prediction model functions correctly. The 'Power Query tool' can be utilized to automate the data cleaning process.

<u>Predictor Variables of Barriers</u>:

- Type of highways – divided, two lane, multi-lane
- Location – ramp, corner, illuminated intersection/corridor
- AADT
- Types of barrier – beam, jersey, cable
- Previous date of repair/ replacement
- Record of repair – repaired and functional
- Age of the barrier elements
- Weather
- Shoulder build-up
- Funding allocated towards current year for potential repairs
- Pavement type – Portland cement concrete pavement, hot mix asphalt, or bituminous surface treatment
- Age of the barrier elements

Step 2: Visualizing the data

Visualizing the data is also called exploratory data analysis. In this step, the collected data is explored for visualizing the condition of barriers. The researchers will be identifying past trends. For this task, we will conduct descriptive and statistical analyses to uncover patterns and trends in data. Scatter plots and bar charts or boxplots can be used to understand the patterns of numerical variables and categorical variables, respectively.

Step 3: Splitting the data into training and test datasets

Regression models must be trained, validated, and tested before using. Therefore, it is necessary to prepare a separate dataset for training/ validating and a separate dataset for testing the regression model. This step entails separating the collected historical data into a training dataset and a testing dataset. As with most models, approximately 80% of the data will be used to train the models, while 20% of the data will be used to test models.

Step 4: Developing a regression model

Completing all the steps explained above, the most important task is to develop a regression model for the barriers. While there are three different types of methods in use for the model development, one of the common methods is the 'Backward Selection Method'. In this method, all twelve predictor variables (identified in section 4.1) will be added first then insignificant variables ($p>0.05$) will be eliminated. After eliminating the insignificant variables, the regression model will look like:

Condition of barriers = $b_0 + b_1$(critical factor 1) + b_2 (critical factor 2) + …. + b_n (critical factor n)

Where critical factor 1, critical factor 2, critical factor n and b_0, b_1, b_0, b_n will be determined during the model development.

Step 5: Validate the model

The developed regression model will be trained using the training dataset. Residual analysis is then performed to assess the validity of the model by comparing observed values with predicted values of a part of training dataset. The residual analysis provides information on the distribution of errors (actual outcome of the model versus the predicted outcome of the model) throughout the model. A reliable residual analysis will show that the mean is centered at about zero.

Step 6: Test the model

The goal of model testing, in contrast, is to evaluate the model performance with new data (testing data) that was not utilized for training or validation. It gives an estimate of how the model will perform with the new dataset not previously seen by the model.

Step 7: Making predictions using the final model and evaluation

After the model is validated and tested, it is ready to predict the LOS condition of the barriers. The regression model output will be originally continuous variable (such as 3.86) that can be easily converted into a continuous variable, such as LOS A, LOS B, LOS C. Now, using the model, the base fund required or fund required to keep the barrier at LOS ‘B’ or ‘A’ can be computed using the model.

4.7.3 Algorithm for Prediction Model Development for TSS LOS

Step 1: Identify, collect and understand the predictor variables of TSS

Collect all predictor variables: The predictor variables are the factors that impact the LOS of TSS. The authors collected these variables through literature and a two-phase survey with WSDOT professionals who are in this job for a long time. The following predictor variables were identified in this study.

- Collect condition data of TSS and predictor variables
- Clean the data so that data is accurate and reliable for use in data analysis: Once the data has been collected, it must be cleaned to eliminate any duplicates, errors, or inconsistencies. This may entail updating missing data, deleting outliers, and ensuring that the data is formatted consistently. Cleaning the data is necessary to ensure that the prediction model functions correctly. The ‘Power Query tool’ can be utilized to automate the data cleaning process.

<u>Predictor Variables of TSS</u>:

- Age of wiring system including connections
- Age of the control system
- Inability to complete preventive maintenance due to lack of FTEs
- Age of the bulbs
- Previous date of repair (wiring and connections)
- High accident area
- Record of repair - repaired and functional
- Funding allocated current year for potential repairs
- Theft/ vandalism location
- Types of signal system
- Last year's outcome threshold
- Location: corrosion vs non-corrosion areas
- Age of the pole
- Method of operating the system
- High storm/ hurricane location

Step 2: Visualizing the data

This step is also called exploratory data analysis. In this step, the collected data is explored for visualizing the condition of TSS. The researchers will be identifying past trends. For this task, we will conduct descriptive and statistical analyses to uncover patterns and trends in data. To understand the patterns of the numerical variables, scatter plots can be utilized; to understand the patterns of the categorical variables, bar charts or boxplots could be used.

Step 3: Splitting the data into training and test datasets

Regression models must be trained, validated, and tested before using. Therefore, it is necessary to prepare a separate dataset for training/ validating and a separate dataset for testing the regression model. This step entails separating the collected historical data into a training dataset and a testing dataset. As with most models, approximately, 80% of the data will be used to train the models, while 20% of the data will be used to test models.

Step 4: Developing a regression model

Completing all the steps explained above, the most important task is to develop a regression model for the TSS. While there are three different methods in use for the model development, one of the common methods is the 'Backward Selection Method.' In this method, all the fifteen predictor variables (identified in section 4.1) will be added first, then insignificant variables ($p>0.05$) will be eliminated. After eliminating the insignificant variables, the regression model will look like:

Condition of TSS = b_0 + b_1(critical factor 1) + b_2 (critical factor 2) + …. + b_n (critical factor n)

Where critical factor 1, critical factor 2, critical factor n and b_0, b_1, b_0, b_n will be determined during the model development.

Step 5: Validate the model

The developed regression model will be trained using the training dataset. Residual analysis is then performed to assess the validity of the model by comparing observed values with predicted values of a part of training dataset. The residual analysis provides information on the distribution of errors (actual outcome of the model versus the predicted outcome of the model) throughout the model. A reliable residual analysis will show that the mean is centered at about zero.

Step 6: Test the model

The goal of model testing, in contrast, is to evaluate the model performance with new data (testing data) that was not utilized for training or validation. This gives an estimate of how the model will perform with the new dataset not previously seen by the model.

Step 7: Making predictions using the final model and evaluation

After the model is validated and tested, it is ready to predict the LOS condition of the TSS. The regression model output will be originally continuous variable (such as 3.86) that can be easily converted into a continuous variable, such as LOS A, LOS B, LOS C. Now, using the model, the base fund required or fund required to keep the TSS at LOS 'B' or 'A' can be computed using the model.

4.7.4 Algorithm for Prediction Model Development for Ditch LOS

Step 1: Identify, collect and understand the predictor variables of ditch maintenance

Collect all predictor variables: The predictor variables are the factors that impact the LOS of ditches. The authors collected these variables through literature and a two-phase survey with WSDOT professionals with extensive experience in their field. The following predictor variables were identified in this study.

- Collect condition data of ditches and predictor variables
- Clean the data so that data is accurate and reliable to be used for data analysis. Once the data has been collected, it must be cleaned to eliminate any duplicates, errors, or inconsistencies. This may entail updating missing data, deleting outliers, and ensuring that the data is formatted consistently. Cleaning the data is necessary to ensure that the prediction model functions correctly. The 'Power Query tool' can be utilized to automate the data cleaning process.

Step 2: Visualizing the data

This step is also called exploratory data analysis. In this step, the collected data is explored for visualizing the condition of ditches. The researchers will be identifying past trends. For this task, we will conduct descriptive and statistical analyses to uncover patterns and trends in data. To understand the patterns of the numerical variables, scatter plots can be utilized; to understand the patterns of the categorical variables, bar charts or boxplots can be used.

Predictor Variables of Ditches:

- Slope (steepness) of ditch
- Width and depth of ditch
- Local weather patterns, rainfall, snowfall
- Unstable slopes / Slide area
- Proximity to falling rocks nearby
- Sediment type
- Type and density of vegetation
- Timely drainage, no pooling
- Drainage outlets nearby
- Connection to local stream system
- Geographical location (coastal vs mountain passes)
- Upstream land use (forestry and agricultural)
- Previous date of cleaning
- Access connections / man made barriers
- Applying sand or other abrasives for snow and ice control
- Type of the road (paved/ unpaved)
- Frequency of sweeping
- Wind erosion from farmers' fields

Step 3: Splitting the data into training and test datasets

Regression models must be trained, validated, and tested before using. Therefore, it is necessary to prepare a separate dataset for training/ validating and a separate dataset for testing the regression model. This step entails separating the collected historical data into a training dataset and a testing dataset. As with most models, approximately 80% of the data will be used to train the models, while 20% of the data will be used to test models.

Step 4: Developing a regression model

Completing all the steps explained above, the most important task is to develop a regression model for the ditch maintenance asset. While there are three different types of methods in use for the model development, one of the common methods is the 'Backward Selection Method.' In this method, all the eighteen predictor variables (identified in section 4.1) will be added first; then insignificant variables ($p>0.05$) will be eliminated. After eliminating the insignificant variables, the regression model will look like:

Condition of Ditch = $b_0 + b_1$(critical factor 1) + b_2 (critical factor 2) + …. + b_n (critical factor n)

Where critical factor 1, critical factor 2, critical factor n and b_0, b_1, b_0, b_n will be determined during the model development.

Step 5: Validate the model

The developed regression model will be trained using the training dataset. Residual analysis is performed to assess the validity of the model by comparing observed values with predicted values of a part of training dataset. The residual analysis provides information on the distribution of errors (actual outcome of the model versus the predicted outcome of the model) throughout the model. A reliable residual analysis will show that the mean is centered at about zero.

Step 6: Test the model

The goal of model testing, in contrast, is to evaluate the model performance with new data (testing data) that was not utilized for training or validation. It gives an estimate of how the model will perform with the new dataset not previously seen by the model.

Step 7: Making predictions using the final model and evaluation

After the model is validated and tested, it is ready to predict the LOS condition of the ditches. The regression model output will be originally continuous variable (such as 3.86) that can be easily converted into a continuous variable, such as LOS A, LOS B, LOS C. Now, using the model, the base fund required or fund required to keep the Ditch at LOS ‘B’ or ‘A’ can be computed using the model.

4.7.5 Algorithm for Prediction Model Development for Shoulder LOS

Step 1: Identify, collect and understand the predictor variables of Shoulder maintenance

Collect all predictor variables: The predictor variables are the factors that impact the LOS of roadway shoulders. The authors collected these variables through literature and a two-phase survey with WSDOT professionals with extensive experience with their field. The following predictor variables were identified in this study.

- Collect condition data of shoulders and predictor variables
- Clean the data so that data is accurate and reliable to be used for data analysis: Once the data has been collected, it must be cleaned to eliminate any duplicates, errors, or inconsistencies. This may entail updating missing data, deleting outliers, and ensuring that the data is formatted consistently. Cleaning the data is necessary to ensure that the prediction model functions correctly. The 'Power Query tool' can be utilized to automate the data cleaning process.

Predictor Variables of Shoulders:

- Edge drop off adjacent to paved shoulder
- Cracks, type and width of cracks present
- Erosion of gravel shoulder
- Current state of shoulder
- Type of shoulder: paved, unpaved, or composite
- Potholes
- Frequency of shoulder maintenance
- Edge build-up adjacent to shoulder
- Raveling
- Grade of road/ shoulder
- Porosity of pavement and water infiltration
- Age of shoulder
- Unpaved shoulder types: gravel, earth, or mixed
- Lateral slope of shoulder
- Total shoulder width
- Width of paved/ unpaved shoulder
- Presence of rumble strips
- Presence of vegetation on unpaved shoulder
- Local hydrology and connection to drainage system
- Soil type below the pavement
- Presence of guardrail
- Curb Presence
- Condition/ type of topography adjacent to shoulder
- Annual rainfall intensity in the area
- Average annual temperature, temperature variation
- Presence of shoulder liner
- Presence of vegetation beyond shoulder
- AADT (general/ truck)

Step 2: Visualizing the data.

This step is also called exploratory data analysis. In this step, the collected data is explored for visualizing the condition of roadway shoulders. The researchers will be identifying past trends. For this task, we will conduct descriptive and statistical analyses to uncover patterns and trends in data. To understand the patterns of the numerical variables, scatter plots can be utilized; to understand the patterns of the categorical variables, bar charts or boxplots can be used.

Step 3: Splitting the data into training and test datasets

Regression models must be trained, validated, and tested before using. Therefore, it is necessary to prepare a separate dataset for training/ validating and a separate dataset for testing the regression model. This step entails separating the collected historical data into a training dataset and a testing dataset. As with most models, approximately 80% of the data will be used to train the models, while 20% of the data will be used to test models.

Step 4: Developing a regression model

Completing all the steps explained above, the most important task is to develop a regression model for the roadway shoulders. While there are three different methods in use for the model development, one of the common methods is the 'Backward Selection Method.' In this method, all twenty-nine predictor variables (identified in section 4.1) will be added first; then insignificant variables ($p>0.05$) will be eliminated. After eliminating the insignificant variables, the regression model will look like:

Condition of shoulder = b_0 + b_1(critical factor 1) + b_2(critical factor 2) + …. + b_n(critical factor n)

Where critical factor 1, critical factor 2, critical factor n and b_0, b_1, b_0, b_n will be determined during the model development.

Step 5: Validate the model

The developed regression model will be trained using the training dataset. Residual analysis is performed to assess the validity of the model by comparing observed values with predicted values of a part of training dataset. The residual analysis provides information on the distribution of errors (actual outcome of the model versus the predicted outcome of the model) throughout the model. A reliable residual analysis will show that the mean is centered at about zero.

Step 6: Test the model

The goal of model testing, in contrast, is to evaluate the model performance with new data (testing data) that was not utilized for training or validation. It gives an estimate of how the model will perform with the new dataset not previously seen by the model.

Step 7: Making predictions using the final model and evaluation

After the model is validated and tested, it is ready to predict the LOS condition of the roadway shoulders. The regression model output will be originally continuous variable (such as 3.86) that can be easily converted into a continuous variable, such as LOS A, LOS B, LOS C. Now, using the model, the base fund required or fund required to keep the shoulder at LOS ‘B’ or ‘A’ can be computed using the model.

4.7.6 Algorithm for Prediction Model Development for Roadway Slope LOS

Step 1: Identify, collect and understand the predictor variables of slope repair

- Collect all predictor variables: The predictor variables are the factors that impact the LOS of roadway slopes. The authors collected these variables through literature and a two-phase survey with WSDOT professionals with extensive experience in their field. The following predictor variables were identified in this study.
- Collect condition data of Slope Repairs and predictor variables
- Clean the data so that data is accurate and reliable to be used for data analysis: Once the data has been collected, it must be cleaned to eliminate any duplicates, errors, or inconsistencies. This may entail updating missing data, deleting outliers, and ensuring that the data is formatted consistently. Cleaning the data is necessary to ensure that the prediction model functions correctly. The ‘Power Query tool’ can be utilized to automate the data cleaning process.

Step 2: Visualizing the data.

This step is also called exploratory data analysis. In this step, the collected data is explored for visualizing the condition of roadway slopes. The researchers will be identifying past trends. For this task, we will conduct descriptive and statistical analyses to uncover patterns and trends in data. To understand the patterns of the numerical variables, scatter plots can be utilized; to understand the patterns of the categorical variables, bar charts or boxplots may be used.

Step 3: Splitting the data into training and test datasets

Regression models must be trained, validated, and tested before using. Therefore, it is necessary to prepare a separate dataset for training/ validating and a separate dataset for testing the regression model. This step entails separating the collected historical data into a training dataset and a testing dataset. As with most models, approximately 80% of the data will be used to train the models, while 20% of the data will be used to test models.

Predictor Variables of Slopes:

- Current state of slope
- Existing signs of erosion
- Slope steepness
- Slope material type (earth, gravel, or other)
- Slope height
- Frequency of maintenance
- Condition of paved/gravel shoulder
- Adjacent topography
- Type of vegetation present on slope (grass, other)
- Local weather patterns, rainfall, snowfall, etc.
- Culvert presence
- Vegetation present on slope
- Shoulder build-up along paved shoulder
- On geotechnical unstable slope list
- Local hydrology and connection to drainage system
- History of collapse
- Amount of accumulated debris on the shoulder contributing to water flow
- State of assets- signing, curb, paved shoulder, guardrail
- Adjacent land use
- Wind rates in area
- Curb presence
- Traffic flow or AADT

Step 4: Developing a regression model

Completing all the steps explained above, the most important task is to develop a regression model for the roadway slopes. While there are three different methods in use for the model development, one of the common methods is the ‘Backward Selection Method.’ In this method, all twenty-two predictor variables (identified in section 4.1) will be added first; then insignificant variables ($p>0.05$) will be eliminated. After eliminating the insignificant variables, the regression model will look like:

Condition of slopes = $b_0 + b_1$ (critical factor 1) + b_2 (critical factor 2) + …. + b_n (critical factor n)

Where critical factor 1, critical factor 2, critical factor n and b_0, b_1, b_0, b_n will be determined during the model development.

Step 5: Validate the model

The developed regression model will be trained using the training dataset. Residual analysis is performed to assess the validity of the model by comparing observed values with predicted values of a part of training dataset. The residual analysis provides information on the distribution of errors (actual outcome of the model versus the predicted outcome of the model) throughout the model. A reliable residual analysis will show that the mean is centered at about zero.

Step 6: Test the model

The goal of model testing, in contrast, is to evaluate the model performance with new data (testing data) that was not utilized for training or validation. It gives an estimate of how the model will perform with the new dataset not previously seen by the model.

Step 7: Making predictions using the final model and evaluation

After the model is validated and tested, it is ready to predict the LOS condition of the roadway slopes. The regression model output will be originally continuous variable (such as 3.86) that can be easily converted into a continuous variable, such as LOS A, LOS B, LOS C. Now, using the model, the base fund required or fund required to keep the roadway slopes at LOS ‘B’ or ‘A’ can be computed using the model.

5. CONCLUSIONS AND RECOMMENDATIONS

This research project primarily focuses on the challenges that the Maintenance Division of the Washington State Department of Transportation (WSDOT) is facing in dealing with the deteriorating state of roadway assets. It is impossible to overstate the significance of well-maintained roadways for economic development and mobility. Minimally, transportation assets need to meet expectations. The primary goal of this project is the development of algorithms that will help create prediction models to forecast the performance condition of six important highway assets: traffic signal systems (TSS), barrier maintenance/guardrail, ditches, and slope repairs. The algorithms will give WSDOT the ability to predict levels of service (LOS), performance, conditions, and trends under various funding allocations, using a data-driven approach. Essentially, this predictive capacity will help define performance objectives that align with the available funds, the performance expectations, and the priorities of the maintenance division, potentially avoiding the need for expensive reactive maintenance actions.

The results of this study will enable WSDOT to prioritize funding allocations based on asset condition or LOS, resulting in more effective and efficient highway infrastructure maintenance programs. The project findings, therefore, show great potential for enhancing the general state of roadway infrastructure, providing greater mobility and future economic growth for millions of Americans.

Two major data collection methods were used to accomplish the goal of this project: (1) direct data collection from WSDOT regarding asset condition and expense and (2) a two-phase survey to collect factors impacting the LOS of the six assets. Asset managers reviewed the first phase survey and provided input that went into the second phase survey. Six asset-specific surveys were distributed to each asset professionals, and they ranked the provided factors on a Likert scale. A descriptive analysis of the key elements influencing the LOS of each asset was conducted before beginning the statistical data analysis. Following that, the factors for each asset were ranked using the Relative Importance Index (RII) technique. Statistics were examined using the Statistical Package for Social Sciences (SPSS). If the dataset was not normally distributed, the Shapiro-Wilk test was performed to determine this, and the Mann-Whitney U test was used in its place.

This study aimed to rank and determine the crucial elements influencing the LOS conditions of six roadway assets. A thorough list of variables was provided for each asset in the Phase 2 surveys done with WSDOT professionals, and they were asked to rank them in order of significance. The top five culvert maintenance variables, according to the RII approach, are a) hydrological/weather condition in the area – precipitation, b) previous date of cleaning, c) current LOS, d) scoured around culvert/pipe and headwalls, and e) material type: concrete vs. galvanized steel vs. PVC vs. HDPE.

Similarly, the top five factors for Barrier Maintenance, TSS, Ditches, Shoulder, and Slope Repair assets are a) type of highways - divided, two-lane, multi-lane, b) location - ramp; corner, illuminated intersection/corridor, c) average annual daily traffic, d) types of barrier – beam, jersey, cable, and e) previous date of repair or replacement; a) age of wiring system including connections, b) age of the control system, c) inability to complete preventive maintenance due to lack of FTEs, d) age of the bulbs, and e) previous date of repair (wiring and connections); a) slope (steepness) of ditch, b) width and depth of ditch, c) local weather patterns, rainfall, snowfall, d) unstable slopes / slide area, and e) proximity to falling rocks nearby; a) edge drop off adjacent to paved shoulder, b) cracks, type, and width of cracks present, c) erosion of gravel shoulder, d) current state of shoulder, and e) type of shoulder: paved, unpaved, or composite (combined); a) current state of slope, b) existing signs of erosion, c) slope steepness, d) slope material type (earth, gravel, other), and e) slope height, respectively.

Since the datasets were not normally distributed, Mann-Whitney U tests were employed in SPSS to identify critical factors testing significant group differences. The existing studies showed that the insignificant variables can be eliminated during the prediction model development if some variables are insignificant based on p-value (>0.05). The findings of this study give WSDOT a strong foundation on which to build predictive models that will aid in better resource allocation and asset management decision-making, ultimately leading to better maintenance plans, improved road conditions, and greater overall efficiency in managing the assets of the highway system. The results of the study have the potential to improve highway asset management methods not just within the WSDOT but also in other states, resulting in safer and more sustainable highways for the benefit of the public.

Several critical processes were included in developing the algorithm for predicting the LOS condition of culvert maintenance. First, through a literature analysis and a two-phase survey with experienced WSDOT professionals, the predictive variables that affect the LOS of culvert maintenance are determined. The predictive variables identified were hydrological/weather conditions, past maintenance dates, material kinds, culvert age, and other pertinent data. The data is gathered and cleaned to guarantee accuracy and reliability for data analysis, including culvert condition data and predictor factors. The data is then examined and investigated using descriptive and statistical analysis to uncover patterns and trends. The dataset is divided into training and testing datasets to train and test the regression model. The regression model is developed using the 'Backward Selection Method,' which keeps crucial factors, while eliminating insignificant factors. The model is trained, validated, and tested with separate dataset to determine its dependability and performance.

Finally, the validated model is utilized to make predictions and evaluate the LOS condition of culverts. With this prediction model, individuals can also calculate the required funding to maintain the culverts at desirable LOS conditions. The resulting prediction model is a valuable tool for the WSDOT in optimizing maintenance plans and effectively allocating resources to guarantee successful management and preservation of culvert assets for the benefit of transportation infrastructure and the public. The same algorithm processes are used to construct algorithms for the other five assets.

Developing prediction models utilizing Machine Learning (ML) techniques as a future study is a viable option for further research. This study suggests using regression models to predict asset conditions. This model can process high-dimensional datasets and non-linear correlations between variables, leading to more robust and accurate predictions. Furthermore, including historical and real-time data in the model may improve its prediction capabilities, allowing for real-time monitoring and adaptive maintenance techniques. The future deployment of ML approaches opens up significant potential for further refinement and progress in asset LOS prediction. WSDOT and other states may improve their asset management processes, optimize resource allocation, and maintain the durability and resilience of their vital infrastructure by embracing these innovative, cutting-edge techniques.

ACKNOWLEDGEMENTS

I would like to acknowledge the Washington State Department of Transportation (WSDOT) for providing funding for this research project. In particular, I would like to acknowledge Kelly Shields, Performance Measurement Manager, HQ Maintenance Office, Doug Brodin, Research Manager, Greg Selstead, Assistance Maintenance Engineer (retired), Andrea Fortune, Assistant State Maintenance Engineer, Bruce Castillo, Performance Measure Manager for their support to this project. I also appreciate all the state DOT professionals who provided their insights in this study.

REFERENCES

1. Adams, T. M., Wittwer, E., O'Doherty, J., Venner, M., and Schroeckenthaler, K. (2014). Guide to Level of Service (LOS) Target Setting for Highway Assets. National Cooperative Highway Research Program (NCHRP), Transportation Research Board of the National Academies.
2. Albuquerque, F. D., Sicking, D. L., Faller, R. K., and Lechtenberg, K. A. (2011). Evaluating the cost-effectiveness of roadside culvert treatments. Journal of Transportation Engineering, 137(12), 918–925. DOI: 10.1061/(asce)te.1943-5436.0000266
3. American Society of Civil Engineers (ASCE). (2021). Report Card for America's Infrastructure, Roads. Road Infrastructure | ASCE's 2021 Infrastructure Report Card
4. Akhmudiyanto, A., Rahardjo, P.P., and Karlinasari, R. (2021). Repair Performance Landslide and Slope Using Bore Pile and Ground Anchor on Cipali Toll Road KM 103. UKaRsT, 5(2), 236. https://doi.org/10.30737/ukarst.v5i2.1583
5. Baladi, G.Y., Dawson, T., Musunuru, G. Prohaska, M., and Thomas, K. (2017). Pavement Performance Measures and Forecasting and the Effects of Maintenance and Rehabilitation Strategy on Treatment Effectiveness. Federal Highway Administration, FHWA-HRT-17-095.
6. Baral, A. and Shahandashti, S. M. (2022). Identifying critical combination of roadside slopes susceptible to rainfall-induced failures. Natural Hazards, 113(2), 1177–1198. https://doi.org/10.1007/s11069-022-05343-6
7. Barman, S., and Bandyopadhyaya, R. (2020). Crash severity analysis for low-speed roads using structural equation modeling considering shoulder- and pavement-distress conditions. Journal of Transportation Engineering, Part A: Systems, 146(7). https://doi.org/10.1061/jtepbs.0000373

8. Barrett, M. E., Kearfott, P., and Malina, J. F. (2006). Stormwater Quality Benefits of a Porous Friction Course and Its Effect on Pollutant Removal by Roadside Shoulders. Water Environment Research, 78(11), 2177–2185. DOI: 10.2175/106143005x82217
9. Bisht, L.S. and Tiwari, G. (2022). Safety Effects of Paved Shoulder Width on a Four-Lane Divided Rural Highway in India: A Matched Case-Control Study. Safety Science, ScienceDirect, Elsevier, 147, 105606. https://doi.org/10.1016/j.ssci.2021.105606
10. Buchanan, B., Easton, Z. M., Schneider, R. L., and Walter, M. T. (2013). Modeling the hydrologic effects of Roadside Ditch Networks on receiving waters. Journal of Hydrology, 486, 293–305. DOI: 10.1016/j.jhydrol.2013.01.040
11. Carlson, B. and Sands, G.R. (2018). What to consider when planning an agricultural drainage system. Extension at the University of Minnesota. Retrieved March 31, 2023, from https://extension.umn.edu/agricultural-drainage/what-consider-when-planning-agricultural-drainage-system
12. Cheng, G., Cheng, R., Pei, Y., and Han, J. (2021). Research on Highway Roadside Safety. Journal of Advanced Transportation, 2021, 1–19. https://doi.org/10.1155/2021/6622360
13. Chen, W., Henley, L., and Price, J. (2009). Assessment of Traffic Signal Maintenance and operations needs at Virginia Department of Transportation. Transportation Research Record: Journal of the Transportation Research Board, 2128(1), 11–19. https://doi.org/10.3141/2128-02
14. Dafalla, M., Shaker, A., and Al-Shamrani, M. (2022). Sustainable Road Shoulders and Pavement Protection for Expansive Soil Zones. Transportation Research Record: Journal of the Transportation Research Board, 2676(10), 341–350. DOI: 10.1177/03611981221089295
15. Dahal, R.K. (2015). Earthquake-induced Slope Failure Susceptibility in Eastern Nepal. Journal of Nepal Geological Society, 49(1), 49–56. https://doi.org/10.3126/jngs.v49i1.23141

16. Dahal, R. and Hasegawa, S., Masuda, T., and Yamanaka, M. (2006). Roadside Slope Failures in Nepal during Torrential Rainfall and their Mitigation. Disaster Mitigation of Debris Flow, Slope Failures and Landslides, University Academy Press, Inc., Tokyo, Japan, 503-514.
17. Das, T. (2021). Steps for Linear Regression Algorithm (Simplified). Published in DataDrivenInvestor. https://medium.datadriveninvestor.com/steps-for-linear-regression-algorithm-simplified-daf685dcceee
18. Davis, J. W. and Shakoor, A. (2005). Evaluation of the Effectiveness of Catchment Ditches Along Ohio Roadways. Transportation Research Record: Journal of the Transportation Research Board, 1913(1), 197–204. DOI: 10.1177/0361198105191300119
19. Fitzpatrick, K., Dixon, K., and Avelar, R. (2016). Evaluating Operational Implications of Reduced Lane and Shoulder Widths on Freeways. Journal of Transportation Engineering, 142(11). https://doi.org/10.1061/(asce)te.1943-5436.0000884
20. Food and Agriculture Organization of the United Nations (FAO). (1998). Chapter 4 Drainage Design. https://www.fao.org/3/t0099e/T0099e04.htm
21. FRED. (2022). Vehicle Miles Travelled. Economic Data. St. Louis FED. https://fred.stlouisfed.org/series/TRFVOLUSM227NFWA
22. Gassman, S., Sasanakul, I., Pierce, C., Gheibi, E., Ovalle Villamil, W., Rahman, M., and Starcher, R. (2016). Geosystem Failures from a 1000-yr Flood Event: Pipe Culverts. The Geological Society of America, Southeastern Section – 65th Annual Meeting, Paper No. 34-5. https://doi.org/10.1130/abs/2016se-273421
23. Gharaibeh, N. G., and Lindholm, B. (2013). Development of Performance-Based Specifications for Roadside Maintenance. Green Streets, Highways, and Development. https://doi.org/10.1061/9780784413197.007
24. Gross, F., and Jovanis, P. P. (2007). Estimation of the Safety Effectiveness of Lane and Shoulder Width: Case-control approach. Journal of Transportation Engineering, 133(6), 362–369. https://doi.org/10.1061/(asce)0733-947x(2007)133:6(362)

25. Hallmark, S. L., Qiu, Y., Pawlovitch, M., McDonald, T. J. (2013). Assessing the Safety Impacts of Paved Shoulders. Journal of Transportation Safety and Security, 5(2), 131–147. https://doi.org/10.1080/19439962.2012.711438

26. Hearn, G. J., and Massey, C. I. (2009). Engineering Geology in the Management of Roadside Slope Failures: Contributions to Best Practice from Bhutan and Ethiopia. Quarterly Journal of Engineering Geology and Hydrogeology, 42(4), 511–528. https://doi.org/10.1144/1470-9236/08-004

27. Huber, S., Henzinger, C., and Heyer, D. (2020). Influence of Water and Frost on the Performance of Natural and Recycled Materials Used in Unpaved Roads and Road Shoulders. Transportation Geotechnics, 22, 100305. https://doi.org/10.1016/j.trgeo.2019.100305

28. Intharasombat, N., Puppala, A. J., and Williammee, R. (2007). Compost Amended Soil Treatment for Mitigating Highway Shoulder Desiccation Cracks. Journal of Infrastructure Systems, 13(4), 287–298. https://doi.org/10.1061/(asce)1076-0342(2007)13:4(287)

29. Irwin, P., Zisis, I., Berlanga, B., Hajra, B., and Chowdhury, A. (2016). Wind Testing of Span-Wire Traffic Signal Systems. Proceeding of Canadian Society of Civil Engineers (CSCE). https://ir.lib.uwo.ca/cgi/viewcontent.cgi?article=1068&context=csce2016

30. Jankauskas, B., Jankauskiene, G., Fullen, M., and Booth, C.A. (2008). Utilizing Palm-Leaf Geotextiles to Control Soil Erosion on Roadside Slopes in Lithuania. Zemes Ukio Mokslai, 22-28. Retrieved March 31, 2023, from https://www.researchgate.net/publication/32117270_Utilizing_palm-leaf_geotextiles_to_control_soil_erosion_on_roadside_slopes_in_Lithuania

31. Jensen, P.G., Curtis, P.D., Lehnert, M.E., and Hamelin, D.L. (2001). Habitat and Structural Factors Influencing Beaver Interference with Highway Culverts. Wildlife Society Bulletin, 29(2), 654-664. DOI: 10.2307/3784192.

32. Hawzheen, K. (2008). Improved Road Design for Future Maintenance - Analysis of Road Barrier Repair Costs. Licentiate Thesis in Highway Engineering, Royal Institute of Technology, Stockholm, Sweden.

33. Karim, H., Alam, M., and Magnusson, R. (2011). Road Barrier Repair Costs and Influencing Factors. Journal of Transportation Engineering, 137(5). DOI: 10.1061/(ASCE)TE.1943-5436.0000227.

34. Kim, S.-H., Kim, H.-G., Oak, Y.-S., Lee, J.-H., and Koo, H.-B. (2013). Analysis of Priority Investments for Preventing Roadside Slope Failures. The Journal of Engineering Geology, 23(3), 257–269. https://doi.org/10.9720/kseg.2013.3.257

35. Karimzadeh, A. and Shoghli, O. (2020). Predictive Analytics for Roadway Maintenance: A Review of Current Models, Challenges, and Opportunities. Civil Engineering Journal, 6(3), 602-625. DOI: 10.28991/cej-2020-03091495

36. Li, Z., Kepaptsoglou, K., Lee, Y., Patel, H., Liu, Y., and Kim, H. G. (2013). Safety Effects of Shoulder Paving for Rural and Urban Interstate, Multilane, And Two-Lane Highways. Journal of Transportation Engineering, 139(10), 1010–1019. https://doi.org/10.1061/(asce)te.1943-5436.0000580

37. Liu, Y.-J., Wang, T.-W., Cai, C.-F., Li, Z.-X., and Cheng, D.-B. (2014). Effects of Vegetation on Runoff Generation, Sediment Yield and Soil Shear Strength on Road-Side Slopes Under A Simulation Rainfall Test in The Three Gorges Reservoir Area, China. Science of The Total Environment, 485-486(1), 93–102. https://doi.org/10.1016/j.scitotenv.2014.03.053

38. Liu, C. (2013). Exact Sight Distance Determination on Compound Vertical and Horizontal Curves in The Presence of Road Barriers. International Journal of Transportation Science and Technology, 2(2), 159–166. https://doi.org/10.1260/2046-0430.2.2.159

39. National Cooperative Highway Research Program (NCHRP). (2017). Consequences of Delayed Maintenance of Highway Assets. NCHRP Research Report 859.

40. Neranjan, A.M., Edirisinghe, J.A.G.H., and Dissanayake, P.B.G. (2018). Vulnerability Assessment for the Roadside Slope Failures: Case study for Selected Roads in Badulla and Ratnapura Districts. Engineer Journal of the Institutions for Engineers Sri Lanka, Annual Sessions of IESL, 273-281.
41. Nuri, S., Mahmood, S.M., Abdulrazzaq, O.A., and Abdullah, A.A. (2022). Design and Fabrication of Smart Traffic Signal Using Arduino Card. Iraqi Journal of Industrial Research, 9(3), 23-32. DOI: 10.53523/ijoirVol9I3ID251.
42. Okafor, C.C., Rojas, O.L., Liu, B., Turner, K., Anderson, J.B., and Davidson, J.S. (2023). Load Rating Corrugated Metal Culverts with Shallow Soil Cover. Journal of Performance of Constructed Facilities, 37(2). https://doi.org/10.1061/jpcfev.cfeng-4136
43. Pajouh, M.A., Bielenberg, R.W, Schmidt-Rasmussen, J.D., and Faller, R.K. (2020). Crash Testing and Evaluation of Culvert-Mounted Midwest Guardrail System. Transportation Research Record: Journal of the Transportation Research Board, 2674 (7), DOI: 10.1177/0361198120921168.
44. Park, J. and Abdel-Aty, M. (2016). Safety Effects of Widening Shoulders on Rural Multilane Roads: Developing Crash Modification Functions with Multivariate Adaptive Regression Splines. Transportation Research Record: Journal of the Transportation Research Board, 2583(1), 34–41. https://doi.org/10.3141/2583-05
45. Parsakhoo, A., Mirniazi, S. J., and Motlaq, A.R. (2019). Effectiveness of Wheat Straw Mulch and Polyacrylamide on Shallow Stability of Roadside Slopes. Journal of Forest Science, 65(11), 445–449. https://doi.org/10.17221/93/2019-jfs
46. Puget Sound Regional Council (PSRC). (2018). Vehicle Miles Travelled.
47. RAI Amsterdam. (2022). Smart Asset Management: Managing Expectations. InterTraffic. https://www.intertraffic.com/news/smart-asset-management-managing-expectations

48. Saleh, M.H., Ayesh, A.N., and Sathyaprakash, P. (2023). Development Prediction Algorithm of Vehicle Travel Time Based Traffic Data. Journal of Periodicals of Engineering and Natural Sciences, Vol. 11(1), 197-207.
49. Schneider, R. and Orr, D. (2019). Roadside Ditches: Best Management Practices to Reduce Floods, Droughts, and Water Pollution. Center for Watershed Protection.
50. Schneider, R., Orr, D., and Johnson, A. (2019). Understanding Ditch Maintenance Decisions of Local Highway Agencies for Improved Water Resources Across New York State. Transportation Research Record: Journal of the Transportation Research Board, 2673(12), 767–773. https://doi.org/10.1177/0361198119854092
51. Schrock, S.D., Parsons, R.L., and Zeng, H. (2011). Estimation of Safety Effectiveness of Widening Shoulders and Adding Passing Lanes on Rural Two-Lane Roads. Transportation Research Record: Journal of the Transportation Research Board, 2203(1), 57–63. https://doi.org/10.3141/2203-07
52. Shahandashti, M., Hossain, S., Baral, A., Adhikari, I., Pourmand, P., Abediniangerabi, B. (2022). Slope Repair and Maintenance Management System. The University of Texas at Arlington, Arlington, Texas.
53. Sheikh, N.M., Bligh, R.P., Albin, R.B., and Olson, D. (2010). Application of Precast Concrete Barrier Adjacent to Steep Roadside Slope. Transportation Research Record: Journal of the Transportation Research Board, 2195(1), 121–129. https://doi.org/10.3141/2195-13
54. Shields, K. and Fortune, A. (2021). Maintenance Accountability Process. Washington State Department of Transportation. Presentation.
55. Shuangcheng, T., Xinzhu, X., Lingyun, L., Chengyong, C., Hua, L., and Yaping, K. (2018). Emission Characteristic Analysis on Highway Rainwater Runoff Pollution of Asphalt Pavement. IOP Conference Series: Earth and Environmental Science, 186, 012001. DOI: 10.1088/1755-1315/186/3/012001

56. Slaughter, D.C., Giles, D.K., and Tauzer, C. (1999). Precision Offset Spray System for Roadway Shoulder Weed Control. Journal of Transportation Engineering, 125(4), 364–371. https://doi.org/10.1061/(asce)0733-947x(1999)125:4(364)

57. STAC. (2014). Re-plumbing the Chesapeake Watershed: Improving roadside ditch management to meet TMDL Goals. STAC Workshop Report, STAC Publication 16-001, Easton, MD.

58. Tsai, Y. and Wang Z. (2015). Development of an Asphalt Pavement Raveling Detection Algorithm Using Emerging 3D Laser Technology and Macrotexture Analysis. Final Report for NCHRP IDEA Project 163.

59. U.S. Department of Transportation (USDOT). (2022). Office of Highway Policy Information, Traffic Volume Trends. https://www.fhwa.dot.gov/policyinformation/travel_monitoring/tvt.cfm

60. Washington State Department of Transportation (WSDOT). (2017). WSDOT Fish Passage Performance Report. WSDOT, Environmental Services.

61. Washington State Department of Transportation (WSDOT). (2018). Maintenance Accountability Process (MAP), Manual.

62. Washington State Department of Transportation (WSDOT). (2021). MAP Field Surveys, WSDOT Maintenance Division Presentation by Kelly Shields, Andrea Fortune, and Team.

63. Weston, J. (2021). Asset Management and Performance, WSDOT Maintenance/WSU Research Partnership. Washington State Department of Transportation.

64. Wemple, B.C. and Jones, J.A. (2003). Runoff Production on Forest Roads in a Steep, Mountain Catchment. https://doi.org/10.1029/2002WR001744

65. Westbrook, M. and Rasdorf, W. (2023). LED Traffic Signal Repair and Replacement Practices. Sustainability, 15(1):808. https://doi.org/10.3390/su15010808

66. Liu, Y., Wang, T., Cai, C., Li, Z. (2014). Impacts of Vegetation and Pavement Runoff Concentration on Rural Roadside Slope Erosions in Three Gorge Reservoir Area. Journal of Advances in Water Science, 25(1), 98-105.
67. Yin, W., Zhu, D., and Lei, J. S. (2014). Investigation and Analysis on Vegetation Characteristics of Roadside Slopes in Zigui County of Three Gorges Reservoir Area. In Advanced Materials Research, 1073-1076, 1128–1133. https://doi.org/10.4028/www.scientific.net/amr.1073-1076.1128
68. Zeng, H., and Schrock, S.D. (2012). Estimation of Safety Effectiveness of Composite Shoulders on Rural Two-Lane Highways. Transportation Research Record: Journal of the Transportation Research Board, 2279(1), 99–107. https://doi.org/10.3141/2279-12

APPENDIX

Phase 1 Survey Questionnaires

A1.1 Culvert Maintenance

A Survey on Factors Affecting the LOS of Culverts

1. From the literature review and the research team's experience, the factors affect the LOS of a Culvert next year include the following 11 items. Please add other factors that you think may affect the LOS of a Culvert.
    a. Previous date of maintenance
    b. Material Type: Concrete vs. Galvanized Steel vs. PVC vs. HDPE
    c. Length of Culvert or serving for Inter State, US, or SR roadways
    d. Height or Diameter of the Culvert
    e. Orientation of the Culvert (Cross or Approach)
    f. Inlet / Outlet and End Type
    g. Current LOS
    h. Funding allocated for the current year
    i. Hydrological/ weather condition in the area – Precipitation
    j. Location: Urban, Suburban, Rural area, Alluvial fan, Upstream land use
    k. Age of Culvert
    l. Culvert pass fish life (Yes/No)
    m. Water/soil related – PH, saltwater exposure, bed loading
    n. Record of repair – Repaired and functional (Yes/No)
    o. Depth of fill or depth of buried
    p. Scoured around culvert/pipe and headwalls

A1.2 Barrier Maintenance

A Survey on Factors Affecting the LOS of Barrier Maintenance

1. From the literature review and the research team's experience, the factors that may affect the Level of Service (LOS) of Barriers include the following items below. The outcome of the system is measured as "the percent of barrier that is damaged or missing." More information is presented in the Table below. <u>Please add other factors that you think may affect the LOS of the Barriers</u>.

   a. Average Daily Traffic
   b. Types of Barrier – Beam; Jersey; Cable
   c. Location – Ramp; Corner, illuminated intersection/corridor
   d. Type of Highways – divided, two lane, multi-lane
   e. Pavement Type – Portland Cement Concrete Pavement, Hot Mix Asphalt, Bituminous Surface Treatment
   f. Shoulder Build-up
   g. Weather
   h. Last year's Outcome Threshold
   i. Previous date of repair or replace (after repaving or third-party damage)
   j. Funding allocated current year for potential repairs
   k. Record of repair – Repaired and functional (Yes/No)
   l. Age of the Barrier elements (guardrail posts,)

Maintenance Accountability Process
Perfomance Measures

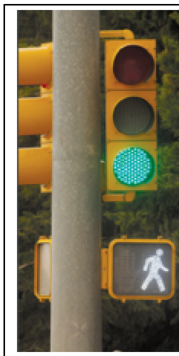
Group -

Activity Number:	**6A7**		**Priority Rank**		**13**
Activity Name:	Barrier Maintenance				
Survey Period:	Summer		**Detail Level:**		Statewide
Indicator:	Damaged or defective barrier.				
Outcome Measure:	Percent of barrier that is damaged or missing.				
Outcome Unit:	% Def.				
Outcome Thresholds	**Service Level**				
	A	**B**	**C**	**D**	**F**
	0 - 1%	1.1% - 3%	3.1% - 5%	5.1% - 10%	> 10%
Comments:	Surveys indicate type of barrier, i.e. beam or jersey barrier.All barrier types including cable barrier will be collected under field surveys separately.				
Data Source	Field Surveys				

A1.3 Traffic Signal Systems

A Survey on Factors Affecting the LOS of Traffic Signal System

1. From the literature review and the research team's experience, the factors that may affect the Level of Service (LOS) of Traffic Signal System include the following items below. The outcome of the system is measured as "Total number of repairs for a percentage of malfunctions against the total inventory of signal systems." More information is presented in the Table below. Please add other factors that you think may affect the LOS of the Traffic Signal System.
    a. Types of signal system (Regular traffic signal vs Dynamic Message single vs Reversible lane signal vs emergency vehicle signal vs data accumulator stations vs ramp meter signal, etc.)
    b. Location: Corrosion vs non-corrosion areas
    c. High accident area
    d. High storm/ hurricane location
    e. Last year's Outcome Threshold
    f. Previous date of repair (wiring and connections)
    g. Funding allocated current year for potential repairs
    h. Record of repair – Repaired and functional (Yes/No)
    i. Age of the bulbs
    j. Age of wiring system including connections
    k. Age of the pole
    l. Age of the control system
    m. Method of operating the system (in-house workforce vs outsourcing through performance-based contracting)



Activity Number:	6B1	Priority Rank			5
Activity Name:	Traffic Signal Systems				
Survey Period:	Fiscal Year			Detail Level:	Statewide
Indicator:	Traffic signals at an intersection flashing, with burned out bulbs, or with a control system malfunction.				
Outcome Measure:	Total number of repairs for a percentage of malfunctions against the total inventory of signal systems. Preventive maintenance is NOT included.				
Outcome Unit:	Rep./Sig./Yr.				
Outcome Threshold:	Service Level				
	A	B	C	D	F
	1 per 2 years	1 per year	2 per year	3 per year	4 per year
Comments:	Reporting period is July 1 ___ through June 30 ___. Do not include 3rd party damages or lightning strikes as these are not an indicator of the asset condition.				
Data Source:	SIMMS database, with regional concurrence.				

A1.4 Ditches

A Survey on Factors Affecting the LOS of Ditch Maintenance

1. From the literature review and the research team's experience, the factors that may affect the Level of Service (LOS) of Ditches include the following items below. The outcome of the system is measured as "the percent of fill with sediment/ debris." More information is presented in the Table below. Please add additional factors (or remove) that you think may affect the LOS of the Ditches.

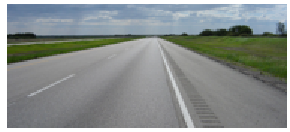
   a) Slope (steepness) of ditch
   b) Width and depth of ditch
   c) Upstream land use (forestry and agricultural)
   d) Proximity to falling rocks nearby
   e) Type of the road (paved or unpaved)
   f) Sediment type
   g) Previous date of cleaning
   h) Type and density of vegetation
   i) Connection to local stream system
   j) Drainage outlets nearby
   k) Timely drainage, no pooling
   l) Local weather patterns, rainfall, snowfall
   m) Geographical location (Coastal vs Mountain passes)
   n) Unstable slopes / Slide area
   o) Access connections / man made barriers
   p) Applying sand or other abrasives for snow and ice control
   q) Frequency of sweeping
   r) Wind erosion from farmers' fields

Activity Number:	**2A1**		**Priority Rank**		**20**
Activity Name:	Ditch Maintenance				
Survey Period:	Summer		**Detail Level:**		Statewide
Indicator:	Ditches with sediment build-up, unable to carry design flow.				
Outcome Measure:	Percent of ditches greater than 50% filled with sediment/debris.				
Outcome Unit:	% Full				
Outcome Thresholds	**Service Level**				
	A	**B**	**C**	**D**	**F**
	0 - 1%	1.1% - 5%	5.1% - 10%	10.1% - 15%	>15%
Comments:					
Data Source	Field Surveys				

A1.5 Shoulders

A Survey on Factors Affecting the LOS of Shoulder Maintenance

1. From the literature review and the research team's experience, the factors that may affect the Level of Service (LOS) of Shoulder include the following items below. The outcome of the system is measured as "percent of paved shoulder area with deficiencies." More information is presented in the Table below. <u>Please add additional factors (or remove) that you think may affect the LOS of Shoulders</u>.



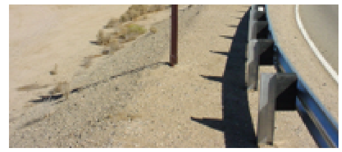
1) Total shoulder width
2) Type of shoulder: paved, unpaved, or composite
3) Unpaved shoulder types: Gravel, earth, or mixed
4) Width of paved and/or unpaved shoulder
5) Porosity of pavement and water infiltration
6) Cracks, type and width of cracks present
7) Potholes
8) Raveling
9) Presence of rumble strips
10) Presence of guardrail
11) Age of shoulder
12) AADT (general)
13) AADT (Truck)
14) Condition/type of topography adjacent to shoulder
15) Soil type below the pavement
16) Presence of vegetation on unpaved shoulder
17) Presence of vegetation beyond shoulder
18) Grade of road/ shoulder
19) Lateral slope of shoulder
20) Annual rainfall intensity in the area
21) Local hydrology and connection to drainage system
22) Presence of shoulder liner (for water drainage and flow control)
23) Average annual temperature, temperature variation
24) Frequency of shoulder maintenance
25) Current state of shoulder

Activity Number:	**1A3**		**Priority Rank**		**26**
Activity Name:	Shoulder Maintenance				
Survey Period:	Summer		**Detail Level:**		Statewide
Indicator:	Paved shoulder with deficiencies.				
Outcome Measure:	Percent of paved shoulder area with deficiencies.				
Outcome Unit:	% SF				
Outcome Thresholds	**Service Level**				
	A	**B**	**C**	**D**	**F**
	0 - 2%	2.1% - 4%	4.1% - 8%	8.1% - 15%	> 15%
Comments:	All deficincies are rolled up to include; shoulder potholes, alligator cracking, longitudinal and transverse shoulder cracking, humps and sags, edge ravelling, and edge drop-off.				
Data Source	Field Surveys				

A1.6 Slopes

A Survey on Factors Affecting the LOS of Slope Repair

1. From the literature review and the research team's experience, the factors affecting the LOS of a slope repair next year include the following 16 items. The outcome of the system is measured as "percent of paved shoulder area with deficiencies." Please add other factors that you think may affect the LOS of roadside slope repair.



   a. Slope steepness
   b. Slope height
   c. Local weather patterns, rainfall, snowfall, etc.
   d. Local hydrology & connection to drainage system
   e. Wind rates in area
   f. Slope material type (earth, gravel, other)
   g. Vegetation present on slope
   h. Type of vegetation present on slope (grass, other)
   i. Adjacent topography
   j. Adjacent land use
   k. Frequency of maintenance
   l. Current state of slope
   m. History of collapse
   n. Amount of accumulated debris on the shoulder contributing to water flow
   o. Existing signs of erosion
   p. Traffic flow

Activity Number:	**2A5**		**Priority Rank**		**10**
Activity Name:	Slope Repair				
Survey Period:	Summer		**Detail Level:**		Statewide
Indicator:	Unrepaired erosion or slides encroaching on, or undermining the shoulder or traveled lane.				
Outcome Measure:	Percent of centerline miles with slides or erosion encroaching on, or undermining the shoulder or traveled way.				
Outcome Unit:	% CLM				
Outcome Thresholds	**Service Level**				
	A	**B**	**C**	**D**	**F**
	0 - 2%	2.1% - 4%	4.1% - 7%	7.1% - 10%	>10%
Comments:	Presence of one or more slope failures (Spring 01), reported as a yes or no.				
Data Source	Field surveys				

Phase 2 Survey Questionnaires

A2.1 Culvert Maintenance

1. From the earlier Round 1 survey, we identified the following 16 factors that affect the Level of Service (LOS) of Culverts in the following years. Rank these factors on a scale of 1 - 16, where 1 is the ‘most important factor’ and 16 is the ‘least important factor’.

   Note: Please start ranking from number 1. This ranking is based on your personal opinion rather than a group opinion.

Table 1. Rank the Factors That Affect the LOS of Culverts in the Following Years

Factors	**Rank Numbers**	**Clarification if any (optional)**
Previous date of maintenance		
Material Type: Concrete vs. Galvanized Steel vs. PVC vs. HDPE		
Length of Culvert or serving for Inter State, US, or SR roadways		
Height or Diameter of the Culvert		
Orientation of the Culvert (Cross or Approach)		
Inlet / Outlet End Type		
Current LOS		
Funding allocated for the current year		
Hydrological/ weather condition in the area – Precipitation		
Location: Urban, Suburban, Rural area, Alluvial fan, Upstream land use		
Age of Culvert		
Culverts that pass fish life (Yes/No)		
Water/soil related – PH, saltwater exposure, bed loading		
Record of repair – Repaired and functional (Yes/No)		
Depth of fill or depth of buried		
Scoured around culvert/pipe and headwalls		

A2.2 Barrier Maintenance

Round 2 Survey on Factors Affecting the LOS of Barrier Maintenance

1. From the earlier Round 1 survey, we identified the following 12 factors that affect the Level of Service (LOS) of Barrier Maintenance in the following years. Please rank these factors on a scale of 1 - 12, where 1 is the 'most important factor' and 12 is the 'least important factor'.

   Note: Please start ranking from number 1. This ranking is based on your personal opinion rather than a group opinion.

   Table 1. Rank the Factors That Affect the LOS of Barrier Maintenance

Factors	**Rank Numbers**	**Clarification if any (optional)**
Average Daily Traffic		
Types of Barrier – Beam; Jersey; Cable		
Location – Ramp; Corner, illuminated intersection/corridor		
Type of Highways – divided, two lane, multi-lane		
Pavement Type – Portland Cement Concrete Pavement, Hot Mix Asphalt, Bituminous Surface Treatment		
Shoulder Build-up		
Weather		
Last year's Outcome Threshold		
Previous date of repair or replace (after repaving or third-party damage)		
Funding allocated current year for potential repairs		
Record of repair – Repaired and functional (Yes/No)		
Age of the Barrier elements		

A2.3 Traffic Signal Systems

Round 2 Survey on Factors Affecting the LOS of Traffic Signal System

1. From the earlier Round 1 survey, we identified the following 15 factors that affect the Level of Service (LOS) of Traffic Signal System in the following years. Rank these factors on a scale of 1 - 15, where 1 is the 'most important factor' and 15 is the 'least important factor'.

   Note: Please start ranking from number 1. This ranking is based on your personal opinion rather than a group opinion.

Table 1. Rank the Factors That Affect the LOS of Culverts in the Following Years

Factors	**Rank Numbers**	**Clarification if any (optional)**
Types of signal system (Regular traffic signal vs Dynamic Message single vs Reversible lane signal vs emergency vehicle signal vs data accumulator stations vs ramp meter signal, etc.)		
Location: Corrosion vs non-corrosion areas		
High accident area		
High storm/ hurricane location		
Last year's LOS		
Previous date of repair (wiring and connections)		
Funding allocated current year for potential repairs		
Record of repair - Repaired and functional (Yes/No)		
Age of the bulbs		
Age of wiring system including connections		
Age of the pole		
Age of the control system		
Method of operating the system (in-house workforce vs outsourcing through performance-based contracting)		
Inability to complete preventive maintenance due to lack of FTEs		
Theft/Vandalism location		

A2.4 Ditches

Round 2 Survey on Factors Affecting the LOS of Ditch Maintenance

1. From the earlier Round 1 survey, we identified the following 18 factors that affect the Level of Service (LOS) of Ditch/ Channel Maintenance in the following years. Please rank these factors on a scale of 1 - 18, where 1 is the 'most important factor' and 18 is the 'least important factor'.

   Note: Please start ranking from number 1. This ranking is based on your personal opinion rather than a group opinion.

   Table 1. Rank the Factors That Affect the LOS of Barrier Maintenance

Factors	**Rank Numbers**	**Clarification if any (optional)**
Slope (steepness) of ditch		
Width and depth of ditch		
Upstream land use (forestry and agricultural)		
Proximity to falling rocks nearby		
Type of the road (paved or unpaved)		
Sediment type		
Previous date of cleaning		
Type and density of vegetation		
Connection to local stream system		
Drainage outlets nearby		
Timely drainage, no pooling		
Local weather patterns, rainfall, snowfall		
Geographical location (Coastal vs Mountain passes)		
Unstable slopes / Slide area		
Access connections / man made barriers		
Applying sand or other abrasives for snow and ice control		
Frequency of sweeping		
Wind erosion from farmers' fields		

A2.5 Shoulders

Round 2 Survey on Factors Affecting the LOS of Shoulder Maintenance

1. From the earlier Round 1 survey, we identified the following 29 factors that affect the Level of Service (LOS) of Shoulder Maintenance in the following years. Please rank these factors on a scale of 1 - 29, where 1 is the 'most important factor' and 29 is the 'least important factor'.

   Note: Please start ranking from number 1. This ranking is based on your personal opinion.

Table 1. Rank the Factors That Affect the LOS of Shoulder Maintenance

Factors	**Rank Numbers**	**Clarification if any (optional)**
Total shoulder width		
Type of shoulder: paved, unpaved, or composite (combined)		
Unpaved shoulder types: Gravel, earth, or mixed		
Width of paved and/or unpaved shoulder		
Porosity of pavement and water infiltration		
Cracks, type and width of cracks present		
Potholes		
Raveling		
Presence of rumble strips		
Presence of guardrail		
Age of shoulder		
AADT (general)		
AADT (Truck)		
Condition/type of topography adjacent to shoulder		
Soil type below the pavement		
Presence of vegetation on unpaved shoulder		
Presence of vegetation beyond shoulder		
Grade of road/ shoulder		
Lateral slope of shoulder		
Annual rainfall intensity in the area		
Local hydrology and connection to drainage system		
Presence of shoulder liner (for water drainage and flow control)		
Average annual temperature, temperature variation		
Frequency of shoulder maintenance		
Current state of shoulder		
Edge drop off adjacent to paved shoulder		
Edge buildup adjacent to paved shoulder		
Erosion of gravel shoulder		
Curb Presence		

A2.6 Slopes

Round 2 Survey on Factors Affecting the LOS of Slope Repair

1. From the earlier Round 1 survey, we identified the following 22 factors that affect the Level of Service (LOS) of Slope Repair in the following years. Please rank these factors on a scale of 1 - 22, where 1 is the 'most important factor' and 22 is the 'least important factor'.

   Note: Please start ranking from number 1. This ranking is based on your personal opinion rather than a group opinion.

Table 1. Rank the Factors That Affect the LOS of Slope Repair

Factors	**Rank Numbers**	**Clarification if any (optional)**
Slope steepness		
Slope height		
Local weather patterns, rainfall, snowfall, etc.		
Local hydrology & connection to drainage system		
Wind rates in area		
Slope material type (earth, gravel, other)		
Vegetation present on slope		
Type of vegetation present on slope (grass, other)		
Adjacent topography		
Adjacent land use		
Frequency of maintenance		
Current state of slope		
History of collapse		
Amount of accumulated debris on the shoulder contributing to water flow		
Existing signs of erosion		
Traffic flow		
State of assets- signing, curb, paved shoulder, guardrail		
Culvert presence		
Curb Presence		
Shoulder build up along paved shoulder		
Condition of paved/gravel shoulder		
On Geotechnical unstable slope list		

Title VI Notice to Public

It is the Washington State Department of Transportation's (WSDOT's) policy to assure that no person shall, on the grounds of race, color, or national origin, as provided by Title VI of the Civil Rights Act of 1964, be excluded from participation in, be denied the benefits of, or be otherwise discriminated against under any of its programs and activities. Any person who believes his/her Title VI protection has been violated, may file a complaint with WSDOT's Office of Equity and Civil Rights (OECR). For additional information regarding Title VI complaint procedures and/or information regarding our non-discrimination obligations, please contact OECR's Title VI Coordinator at (360) 705-7090.

Americans with Disabilities Act (ADA) Information

This material can be made available in an alternate format by emailing the Office of Equity and Civil Rights at wsdotada@wsdot.wa.gov or by calling toll free, 855-362-4ADA(4232). Persons who are deaf or hard of hearing may make a request by calling the Washington State Relay at 711.