MOUNTAIN-PLAINS CONSORTIUM

MPC 21-440 | O. Albatayneh, W. Aleadelat, O. Abu Daoud, and K. Ksaibati

ASSESSING ROAD CONDITIONS FOR WYOMING COUNTY GRAVEL ROADS

MOUNTAIN-PLAINS CONSORTIUM REGION 8

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Technical Report Documentation Page

1. Report No. MPC-541	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Assessing Road Conditions for Wyoming County Gravel Roads		5. Report Date November 2021
		6. Performing Organization Code
7. Author(s) Omar Albatayneh, PhD, PE Waleed Aleadelat, PhD Osama Abu Daoud, MSc Khaled Ksaibati, PhD, PE		8. Performing Organization Report No. MPC 21-440
9. Performing Organization Name and Address Department of Civil and Architectural Engineering University of Wyoming Laramie, WY 82071		10. Work Unit No. (TRAIS)
		11. Contract or Grant No.
12. Sponsoring Agency Name and Address Mountain-Plains Consortium North Dakota State University PO Box 6050, Fargo, ND 58108		13. Type of Report and Period Covered Final Report
		14. Sponsoring Agency Code

15. Supplementary Notes

Supported by a grant from the US DOT, University Transportation Centers Program

16. Abstract

Gravel road safety is a crucial area of road safety since gravel roads represent a substantial proportion of the entire nation’s roadway network. Also, gravel roads pose inherent hazards that are otherwise absent in paved roads. Nonetheless, research related to assessing road conditions for county gravel roads has been rarely undertaken. The focus of this research study is to develop a systematic method for ascertaining gravel road conditions in the state of Wyoming. This research is part of a multi-year study that was conducted by the Wyoming Technology Transfer Center (WYT2) at the University of Wyoming to assist the Wyoming Department of Transportation (WYDOT) and local agencies in managing, maintaining, and optimizing gravel road performance and conditions in the state. The study utilizes field data and exploratory and statistical analysis to assess and evaluate the gravel road network performance. The established methodologies consider different factors related to the gravel road itself, such as the number of fines in the surfacing materials, average daily traffic (ADT), average driving speed, and moisture content. In addition, it considers different factors related to the surrounding environment, such as oil production rates, annual rainfall, average monthly temperatures, agricultural lands, and households. The results of this study will be used in developing cost-effective maintenance strategies that will aid in optimizing the Wyoming asset management program. The developed methodologies are intended to benefit traffic engineers, decision-makers, and any other stakeholders.

17. Key Word asset management, condition surveys, data collection, evaluation and assessment, gravel roads, optimization, performance measurement		18. Distribution Statement Public distribution	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 134	22. Price n/a

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

Assessing Road Conditions for Wyoming County Gravel Roads

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November 2021

Acknowledgments

The WYT^2/LTAP center provided extensive resources to this research, assisted in the compilation of data, and assisted with many tasks involved in delivering a safety improvement program to the Standing Rock Sioux Tribe. Special acknowledgment goes to WYDOT, FHWA, and MPC for providing the resources to make this research possible. The Standing Rock transportation office worked diligently to coordinate meetings, respond to technical feedback, and actively participate in the application of the methodology.

ABSTRACT

Gravel road safety is a crucial area of road safety since gravel roads represent a substantial proportion of the entire nation's roadway network. Also, gravel roads pose inherent hazards that are otherwise absent in paved roads. Nonetheless, research related to assessing road conditions for county gravel roads has been rarely undertaken. The focus of this research study is to develop a systematic method for ascertaining gravel road conditions in the state of Wyoming. This research is part of a multi-year study that was conducted by the Wyoming Technology Transfer Center (WYT2) at the University of Wyoming to assist the Wyoming Department of Transportation (WYDOT) and local agencies in managing, maintaining, and optimizing gravel road performance and conditions in the state. The study utilizes field data and exploratory and statistical analysis to assess and evaluate the gravel road network performance. The established methodologies consider different factors related to the gravel road itself, such as the number of fines in the surfacing materials, average daily traffic (ADT), average driving speed, and moisture content. In addition, it considers different factors related to the surrounding environment, such as oil production rates, annual rainfall, average monthly temperatures, agricultural lands, and households. The results of this study will be used in developing cost-effective maintenance strategies that will aid in optimizing the Wyoming asset management program. The developed methodologies are intended to benefit traffic engineers, decision-makers, and any other stakeholders.

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LIST OF ABBREVIATIONS

The following table describes the abbreviations and acronyms used in this document:

Abbreviation	Description
AASHTO	American Association of state highway and transportation officials
ADT	Average daily traffic
ADTT	Average daily truck traffic
ASTM	American society of testing and material
CMAQ	Congestion mitigation and air quality
EPA	Environmental Protection Agency
FHWA	Federal highway administration
GIS	Geographic Information System
NAAQS	National Ambient Air Quality Standards
PASER	Pavement Surface evaluation rating
PMS	Pavement Management system
PM	Particulate Matter
STP	Surface Transportation Program
USACR	United States Army Corps of Engineers
WYDOT	Wyoming Department of transportation
WYT2/LTAP	Wyoming Technology Transfer Center/Local Technical Assistance program

1. INTRODUCTION

1.1 Introduction

Unpaved roads, whether dirt or gravel, represent roughly 35% of the U.S. roadway network by mileage as per the Federal Highway Administration (2012). In Wyoming, local agencies own and manage over 13,000 miles of gravel roads. These roads formulate 90% of the entire local roads network in the state (Huntington & Ksaibati, 2009). Gravel roads satisfy the criteria for low-volume (≤ 2,000 vpd) roads as per the American Association of State Highway and Transportation Officials (AASHTO, 2019). Such roads pose safety concerns that ought to be alleviated. Gravel roads are maintained regularly to have a smooth surface providing an acceptable ride quality; whereas, dilapidated ones are characterized by road surface erosion, washboarding, rutting, raveling, potholes, and loose surface material (Aleadelat et al., 2018).

Although managing an asset of gravel roads can be a cost-effective preference for many local agencies, the amount of generated dust is considered a major flaw of these roads (Fay et al., 2016). Moreover, gravel roads in Wyoming are prone to frequent heavy truck traffic due to the various mineral and drilling activities. This additional heavy traffic impacts the structural capacity of these roads and increases the amount of generated dust enormously (Aleadelat & Ksaibati, 2017). This has led to higher demands from counties and local jurisdictions to apply for and receive Congestion Mitigation and Air Quality (CMAQ) improvement funds. WYDOT and the Federal Highway Administration are facing a significant increase in CMAQ funding applications and are looking for more cost-effective ways to allocate these funds. As a result, counties are left incapable of maintaining their roads due to budget constraints. Considering these issues, it is important to research and investigate more effective strategies in creating and maintaining gravel roads in Wyoming and developing cost-effective strategies to use CMAQ funds where they are most needed.

Generally, researchers were incurious when it came to the management of gravel roads. Researchers were concerned more about how to set general guidelines or rules for managing these roads by investing minimal efforts (Huntington & Ksaibati, 2011a; Huntington & Ksaibati, 2011b). When it comes to gravel road dust, most of the previous work focused on the evaluation and the performance of dust palliatives. Currently, there are over 300 commercially available products to abate the different impacts arising from gravel road dust. These products vary in terms of performance, efficiency, and economic value. Additionally, the majority of these studies strived to introduce a set of guidelines or methodologies to select the most appropriate dust palliative (Jones & Surdahl, 2014; Sanders, Quayenortey, & Jorgensen, 2015; Omane et al., 2017). In addition, there are no specific comprehensive guidelines or methodologies available to help local agencies in identifying the best set of gravel roads that are ideal for dust chemical treatment projects. Since local agencies are not able to treat all gravel roads under their jurisdictions, a methodology undertaking negative environmental impacts, road surface materials, traffic characteristics, mineral production, and weather conditions, is required to select gravel roads for chemical treatment projects. Such a methodology, in addition to introducing a sort of systemization to the entire process, will help decision makers in allocating the available funds efficiently, enhancing the planning process, and maximizing the reflected social welfare on the local economy.

Ultimately, as part of the WYT2/LTAP efforts to develop a gravel roads management system (GRMS), this research study developed user-friendly tools, using JavaScript, that implement optimization models based on genetic algorithms (GAs). The developed tools will help decision makers and local agencies in allocating limited funds efficiently.

1.2 Research Objectives

The study looks to assess road conditions for Wyoming county gravel roads and develop cost-effective management strategies to implement with the available funds by undertaking the following objectives:

1. Help local agencies define the most appropriate treatment type suitable for each gravel road under their jurisdiction.
2. Estimate the cost of applying road treatments, service level, and the potential road conditions with or without applying a treatment.
3. Develop user-friendly tools that will implement an optimization model based on GAs.
4. Develop tools that will help local agencies in optimizing their budgets by suggesting specific roads for maintenance and rehabilitation projects in a way that preserves the overall network condition.
5. Develop a systematic method for ascertaining the level of service (LOS) of gravel roads. To date, such a method does not exist in the Highway Capacity Manual (HCM).
6. Evaluate whether the HSM's methodology for predicting counts of crashes on rural two-lane highways is applicable to gravel roads in Wyoming.
7. Investigate road condition factors affecting the traffic-generated dust on gravel roads.

1.3 Expected Outcomes

In this study, valuable information and data will be provided to decision-makers and legislators in the state of Wyoming, including WYDOT and the Federal Highway Administration. These data and the information will assist the allocation of the funds. The results of this study can help evaluate the gravel road network in the state, identify current practices and, therefore, recommend improvements.

Accurate detection of dust amounts is very crucial in GRMS. Another expected outcome of this study is that it establishes novel methods for automatic detection and classification of dust amounts on gravel roads by digital image processing techniques. Such methods can assist local agencies in data collection and maintenance planning, as well as help state engineers classify the dust amount on gravel roads more efficiently and cost-effectively. The ultimate goal of this study is to develop a more rigorous understanding of assessing road conditions for Wyoming county gravel roads and to recommend the most efficient mitigation practices.

1.4 Report Organization

This report is organized into seven chapters as follows:

Chapter 1 provides an introduction of the research topic and objectives, the expected outcomes of the study, and comprehensive asset management systems in Wyoming.

Chapter 2 discusses the various literature related to gravel roads, factors affecting their performance, and maintenance and management.

Chapter 3 provides a summary of the developed methodologies in this research study. It discusses the different data collection steps followed to conduct these experimental studies. A flow chart of the overall report organization is included in this chapter.

Chapter 4 discusses the first objective of this study. The chapter explains the data collection conducted and illustrates how the newly developed tools can help local agencies. Also, this chapter describes the analysis conducted and the results obtained from analyzing the collected data.

Chapter 5 includes detailed discussions of the methodologies and results of the second objective. This includes a discussion of the road sections tested, testing procedures, and types of data analyses conducted.

Chapter 6 concludes this study by summarizing and highlighting the results and conclusions reached in the study. Chapter 6 also includes recommendations developed based on the findings and provides insights for future research work to be done to better understand dust behavior on gravel roads.

2. LITERATURE REVIEW

2.1 Introduction

Gravel roads are considered one of the critical constructed transportation infrastructures. There are thousands of miles of gravel roads in the United States, especially in the Midwest and Mountain West states. As an example, Wyoming has different mineral extraction and drilling activities utilizing more than 13,000 miles of local gravel roads. These unpaved roads are used daily by ranchers, loggers, industrial users, and recreational area visitors (Aleadelat & Ksaibati, 2018). Many of these gravel roads have acceptable riding qualities. Conversely, some of them have very low riding and safety scores. Improving and maintaining these gravel roads is legally the responsibility of the various local agencies in the state. In this chapter, a literature review is conducted to determine key topics related to the management and maintenance of gravel roads.

2.2 Background

The WYT2/LTAP is currently in the process of developing a GRMS in Wyoming. One of the major components of this new GRMS is developing comprehensive methodologies for maintenance and rehabilitation (M&R) activities. To support the new methodologies, this study established a comprehensive review of the literature related to the management of gravel roads.

2.2.1 Dust Generation

Gravel roads require extensive maintenance and rehabilitation. That is because of the dynamic behavior of gravel road conditions. This study is aimed at investigating road condition factors affecting the traffic-generated dust on gravel roads. The quality of gravel roads depends greatly on the composition of the surface, namely the mixture of gravel, sand, and clay. In most states in the nation, the mileages of unpaved roads exceed those of paved roads. There are over two million miles of gravel roads crisscrossing the United States. These roads are mostly located throughout industrial and rural areas (Albatayneh et al., 2019). However, if these roads are not well maintained, deterioration will occur, leading to several defects and dust generation. Dust emanating from gravel road surfaces affects human health and the environment. It is also a safety concern that ought to be alleviated.

Inhaling dust particulates irritates the respiratory system and may result in diseases. Airborne dust coats crops and vegetation hindering their growth. Sand, gravel, and particulates drift into waterways and contribute to sedimentation. This pollutes the aquatic life's ecosystem. Settling dust is unsightly and requires intensive care around homes and businesses. Dust clouds reduce visibility creating hazardous driving conditions. Also, airborne dust particles may damage vehicle windshields, paint, headlights, and suspension systems. The menacing effects of dust emanations may be mitigated. By examining the factors affecting gravel road dust generation, roadway engineers are able to put forth better-informed decisions regarding maintenance plans. These will improve driving surface conditions, protect the health of vehicle occupants, improve motor vehicle safety, minimize pollution, and extend the service life of the gravel roads while optimizing budgets.

Gravel road performances vary depending on several factors, such as the roadway surface composition, sub-surface soil conditions, topography, weather conditions, traffic volumes, drainage, stabilization practices, and maintenance practices (Henning et al., 2008; Linard 2010; Linard, 2008). Typically, gravel roads require frequent maintenance, unlike paved roads. In Wyoming, local agencies are diligently maintaining around 12,000 miles of gravel roads. Traffic volumes, the gravel road network's needs, and available funding factor heavily into gravel road maintenance plans. The long-term maintenance costs of gravel roads are costly due to the high rate at which such roads deteriorate. In general, maintaining gravel roads is considered a cost-effective alternative compared with paved roads. However, traffic-generated dust is considered one of the major drawbacks of gravel roads. Therefore, the CMAQ improvement program is used by local agencies and state DOTs to enhance gravel road performance in order to reduce the amount of traffic-generated dust using chemical dust control treatments regularly. Also, many other maintenance activities for gravel roads are performed, such as blading, stabilization, drainage maintenance, and reshaping.

2.2.2 Dust Generation and Machine Learning Techniques

Until recently, using machine learning with TensorFlow has been applied in several computer science and medical applications. However, only a few attempts have been made to use this supervised learning technique in transportation engineering applications. This is the first study to undertake the implementation of TensorFlow in GRMSs. In this section, several applications of using machine learning with TensorFlow are discussed. In the past decade, machine learning has been widely used in various applications and is still one of the most ambiguous AI sub-fields (Angelova et al., 2015; Ba et al., 2014; Frome et al. 2013; Gonzalez-Dominguez et al., 2015; Karpathy et al., 2014; Vinyals et al. 2015; and Szegedy et al., 2015). In general, machine learning techniques can basically be divided into two main groups: supervised learning and unsupervised learning. Supervised learning methods are trained using a labeled input data; whereas, unsupervised learning methods are trained without using labels to the input data (Libbrecht & Noble, 2015). However, some real applications and problems would have labeled and unlabeled input datasets. In this case, the learning technique would be called semi supervised learning (Chapelle et al., 2009).

In this study, TensorFlow, which is a supervised learning technique, was used to develop an image classifier. TensorFlow is a system used for operating large-scale machine learning applications (Abadi et al., 2016). This system is a developed version of the DistBelief framework to train deep neural networks (Dean et al., 2012). One of the main concepts of deep learning is to extract features from data (Bengio et al., 2013; Bengio, 2009). In this study, one of the deep learning neural network models, the Inception-v3 model, was utilized in TensorFlow to extract and classify image features. This model was found to have significant effects on increasing the deep learning neural networks' performance and efficiency (Szegedy et al., 2015). For instance, the Inception-v3 model was utilized in TensorFlow for developing an image classifier to classify flower images based on three features: texture, shape, and color. The results showed that utilizing the Inception-v3 model can significantly increase the precision of flower classification (Xia et al., 2017).

Generally, the TensorFlow framework has been utilized in pavement management systems (PMS) in many applications and mainly for pavement distress detection. In 2017, a pavement crack detection tool was developed using TensorFlow. This tool detects and classifies pavement cracks effectively and offers information to be used for maintenance purposes (Wang & Hu, 2017). A recent study was conducted to predict alligator cracking, or fatigue cracking, using the TensorFlow framework and then comparing the results with the fatigue cracking transfer function. The results showed that the developed model has significantly better performance than the fatigue cracking transfer function (Gong et al., 2019). Also, a study was conducted using TensorFlow for detecting pavement distress across the pavement surface (cracks, loose material, deformations, and others). The results showed the developed model can successfully classify road surface distresses with better performance (Nie & Wang, 2018). More recently, a study emerged with the concept of using TensorFlow to detect and recognize road objects. The study showed that TensorFlow can detect and recognize road objects accurately (Warrier & Sathish, 2018).

2.2.3 Gravel Roads Ride Quality Through an Android-Based Smartphone

Gravel road assessment methods are mostly manual and dependent on visual surveys or actual measurements of road surface conditions (Huntington & Ksaibati, 2015). The U.S. Army Corps of Engineers assessment system (USACE) is considered to be one of the earliest efforts to develop a measurable consistent index for gravel roads (Huntington & Ksaibati, 2015; Walker, 1989). This index is known as the Unsurfaced Road Condition Index (URCI) and depends on the actual measurement of the level and extent of each distress related to gravel roads. Then, using a deduct value for each distress type (e.g., potholes and corrugations), an overall URCI, on a scale from 1 to 100, can be calculated (Eaton & Beaucham, 1992). In another study conducted by Chamorro et al. in Chile, a new Gravel Roads Condition Index (UPCI) was developed (Chamorro et al., 2009). Through linear regression equations, a correlation was established between objective distress measures (e.g., rutting depth) and a given subjective rating (UPCI). The developed equations gave the UPCI ratings the required level of objectivity, which may improve data quality and reduce required survey times (Chamorro et al., 2009). Nonetheless, any trial of developing objective-based indices is still impractical for local agencies. Estimating these types of indices requires substantial resources to objectively measure each type of distress, especially when dealing with large networks. In addition, manually measuring the level and extent of each distress still implies some degree of subjectivity. Therefore, these indices are more practical for research purposes than road management (Huntington & Ksaibati, 2015). This encourages local agencies to deal with more practical assessment methods, such as visual surveys.

Currently, there are many available gravel road visual assessment systems, such as the South African Council for Scientific and Industrial Research (CSIR) system, the Federal Highway Administration (FHWA) Central Federal Lands Highway Division method, and the Wisconsin Pavement Surface Evaluation and Rating (PASER) system. The PASER rating system is considered to be the most popular rating system used for gravel road evaluation in the United States (Huntington and Ksaibati, 2015). The PASER system rates the overall gravel road condition on a scale from 1 (failed) to 5 (excellent) by incorporating distresses related to the following aspects of the road:

- Crown
- Drainage
- Gravel layer
- Surface deformation:
  - Washboard
  - Potholes
  - Ruts
- Surface defects:
  - Dust
  - Loose aggregate

In the PASER system, the gravel road is evaluated from a decision-maker’s viewpoint (Huntington et al., 2017). This explains the inclusion of gravel properties and drainage conditions within the rating system. However, the PASER’s short scale limits the rater’s ability to make consistent judgments. In such short scales, the rater tends to make judgments closer to the endpoints (error of leniency). On other occasions, raters avoid making extreme judgments, or what is known as the central tendency error (Nair & Hudson, 1986). Therefore, the WYT2/LTAP modified the current PASER system to a different rating system (RQRG) that uses an expanded scale from 1 to 10. This expanded rating scale is intended to reduce the possibility of errors within the rating process. Moreover, the modified scale reflects the perceptions of road users regarding their comfort while driving over a specific road segment (Huntington and Ksaibati, 2015). Therefore, RQRG is affected more by surface deformation modes such as potholes, washboards, and rutting. These types of deformations are considered to be the main failure mode for gravel roads (Huntington and Ksaibati, 2016). Thus, the RQRG system has an advantage over the PASER system by its ability to alleviate possible rating errors and represent the actual road conditions at the same time, which leads to a better decision-making process (Huntington and Ksaibati, 2015).

A few studies have tried to introduce a sort of platform for automating the gravel road assessment process (Brown et al., 2003). For example, the Forest Engineering Research Institute of Canada (FERIC) developed the Opti-Grade road management system. This system depends on accelerometers and a global positioning system (GPS) to detect and calculate the roughness of the Canadian forest roads. It was found that this system helped improve the effectiveness of maintenance works and reduced their costs (Brown et al., 2003). In another indirect approach, Zhang and Elaksher used an unmanned aerial vehicle (UAV) based imaging system to identify the different surface distresses present in gravel roads. Using aerial imagery, a perceived three-dimensional (3D) surface of gravel roads was created. Using image processing algorithms, they were then able to identify the extent and severity of surface distresses. The derived measurements from the perceived 3D road surface were in good agreement with the actual measurements (14). In 2015, Alhasan et al. used a terrestrial laser scanner to quantify the roughness of gravel roads (Zhang & Elaksher, 2012). The acquired data points using the laser scanner were used to construct 3D representation maps for the road surface. Then, using the quarter car model, Fast Fourier transform (FFT), and statistical analysis, they were able to estimate the international roughness index (IRI) values, locate corrugations within road segments, and infer some information related to surface material characteristics (e.g., gradation). Regarding the use of smartphones in evaluating road conditions, most of the previous work was related to paved roads, in particular, estimating the IRI and locating anomalies within the pavement surface (Mohan et al., 2008). In conclusion, previous efforts made to automate the data collection for gravel roads are still impractical for application and require an analysis level that may supersede the capabilities of small local agencies. In addition, these methods are not able to control the highly changeable conditions of gravel roads. Therefore, an investigation is required to evaluate the ability of smartphones in predicting gravel road conditions. The proposed approach is anticipated, in addition to reducing the cost, to deal with the dynamic conditions of gravel roads and enhance the quality of the collected data through the automation process.

2.2.4 Performance Prediction Models for Gravel Roads

The Wyoming Technology Transfer Center (WYT2/LTAP) is currently in the process of developing a GRMS. Such a GRMS is intended to provide feasible practices to help local agencies deal with the different challenges associated with maintaining gravel roads in the state. One of the main goals of this project is to develop an optimization tool that can help decision-makers at the local level in managing limited budgets and in selecting gravel roads for M&R projects. The tool, which has been developed, implements an optimization model that works on maximizing the overall gravel road network conditions considering traffic volumes and subject to limited budgets. It is well known that the estimation of a gravel road potential service life is one of the integral parts of any maintenance assignment process (Mannisto et al., 1990, Huntington & Ksaibati, 2007, Chamorro & Tighe, 2011). Therefore, this research study aims to develop performance prediction models for gravel roads in Wyoming. Such prediction equations provide a mathematical representation of how a gravel road in Wyoming may deteriorate over time.

In addition to the general lack of the available GRMSs that are tailored to suit the needs of small local agencies, research efforts are more designated toward solving specific issues related to managing gravel roads within the premise of the developing agency (Mannisto et al., 1990, World Bank. 2018; Giummarra, G. 2000; Burger et al., 2007; van Zyl et al., 2007; Chamorro & Tighe, 2009; Huntington & Ksaibati, 2011a; Chamorro & Tighe, 2015). This explains the importance of establishing specific rules, guidelines, and models that are designated for Wyoming gravel roads rather than following the generic practices available in the literature.

Currently, WYT2/ LTAP utilizes inexpensive, less labor-intensive windshield surveys to evaluate gravel road conditions. Most of these surveys are modifications to the PASER guide developed by the Wisconsin Transportation Information Center (Walker, 1989; Huntington & Ksaibati, 2015). Two of these modifications are the Ride Quality Rating Guide (RQRG) and the Gravel Roads Rating Standards (GRRS). The RQRG reflects the perceptions of road users with regard to the driving quality of the gravel road. The GRRS describes the condition of a gravel road by providing a specific rating for each distress or deterioration mode, such as potholes, rutting, washboards, and loose aggregate (Huntington & Ksaibati, 2015). With gravel roads, different maintenance practices are assigned according to the severity and extent of every distress available within the road surface. For example, poor pothole conditions require heavy blading to maintain the road while poor loose aggregate requires chemical treatment. Hence, it is necessary to have a specific performance model that describes the behavior of any gravel road in the means of every distress. These models will be implemented in the optimization process to select the best maintenance practices and to assign cost-effective budgets. Predicted performance models will be developed using Markov Chains (MC) (Hassan et al., 2015). The implementation of this probabilistic modeling approach has been widely used in the management of paved roads as it is flexible and requires minimal historical data to develop performance models. This probabilistic approach requires at least two successive periods of road conditions data. In cases where historical data are not available, expert opinions can be used to develop the performance models (Costello et al., 2005; De Melo e Silva et al., 2000; Uchwat and MacLeod, 2012; Abaza, 2016; Hassan et al., 2017; Osorio-Lird et al., 2017).

Gravel roads are dynamic as their conditions change dramatically based on different traffic and weather conditions. Also, these kinds of roads normally serve very low traffic volumes, which explains some of the indifference when it comes to gravel road management (Huntington & Ksaibati, 2007; Huntington & Ksaibati, 2011a; Huntington & Ksaibati, 2015). To predict the performance of these roads, the World Bank developed software such as the Roads Economic Decisions Model, the Deterioration of Unpaved Roads (DETOUR) Model, Highway Development and Management Model (HDM-4), and the Roads Economic Decision Model (RED) (Chamorro and Tighe, 2011; World Bank, 2018; van Zyl et al., 2007; Archondo-Callao, 2001). These models are used to run economic evaluations related to road investment projects. However, these models require a lengthy input list that may supersede the capabilities of small local agencies. These inputs are related to surface roughness, terrain type, traffic conditions, crashes, fatalities, injuries, speed, and geometric features (World Bank, 2018; van Zyl et al., 2007). Also, they are more appropriate for project-level analysis rather than network-level analysis. Moreover, the extensive outputs may overthrow the small operating agencies. Nonetheless, a few studies report the implementation of MC to predict the performance of gravel roads (Mannisto, et al., 1990; Chamorro & Tighe, 2011). However, the models or methodologies are still exclusive and cannot be generalized for use by developing agencies. For example, the models by Chamorro and Tighe depend on specific indices like the Unpaved Roads Condition Index (UPCI), which was developed solely to evaluate gravel roads in Chile (Chamorro & Tighe, 2011). In addition, it is apparent that local agencies in Chile use other deep stabilization methods for gravel roads different from the ones followed in the United States, which explains the long service life of these roads (e.g., four years). Deep stabilization processes, such as the Full Depth Reclamation (FDR) method, include deeply mixing chemical stabilizers into the roadbed. In such methods, roadbed materials are deeply crushed, blended, and mixed with chemical stabilizers to achieve a more stable road surface that can serve traffic for multiple years (Bushman et al., 2005).

This research study utilizes gravel road condition data collected from Laramie County, located in the southeastern part of Wyoming, to develop the performance prediction models. The following sections describe the data collection efforts and the application of MC to develop these predictions. The prediction models developed here will be used solely to establish a large-scale optimization model applicable to the gravel road network for every county in Wyoming. The reader is referred to Hassan et al., 2015 for more extensive details of the methodology behind the MC and its implementation in road management (Hassan et al., 2015). This methodology involves characterization of the states, setting the initial state vector and start condition, investigating the number of cycles, and obtaining the transition probability matrix (TPM). This phase describes each of these steps as well as the data collection process and the development of one performance prediction model using the MC approach.

2.2.5 Optimization Techniques for Selecting Gravel Roads Maintenance Strategies

Researchers have been mainly concerned about setting general rules or guidelines for managing gravel roads with minimum effort. This has resulted in a general lack of GRMSs that are suitable for small local agencies (Huntington & Ksaibati, 2011; World Bank, 2018; Mannisto & Tapio, 1990; Giummarra, 2000; Burger et al., 2007; Van Zyl et al., 1989; Chamorro & Tighe, 2009; Huntington & Ksaibati, 2011). Additionally, researchers' efforts were more directed toward solving specific issues related to managing gravel roads within the jurisdiction of a particular agency (Huntington & Ksaibati, 2011). For example, in Finland, an analytical optimization method was developed by Mannisto and Tapio in 1990 (Mannisto & Tapio, 1990). This optimization method is aimed at identifying the most appropriate maintenance strategies for gravel roads. The developed optimization model depends on semi-Markovian performance models to predict the condition of gravel roads. The linear optimization method was used to minimize the societal costs associated with these roads. It was found that the developed model can be used to allocate funds among the different road maintaining districts and suggesting roads for maintenance and rehabilitation works.

Later, the World Bank developed several software programs, such as the Roads Economic Decisions model, Deterioration of Unpaved Roads model (DETOUR), Highway Development and Management Model (HDM-4), and Roads Economic Decision model (RED). These models are used to run economic evaluations related to road investment projects. However, these models require a lengthy list of inputs that may exceed the capabilities of small local agencies, and they are more appropriate for project-level analysis rather than network-level analysis. Moreover, the extensive outputs may exceed the requirements of small operating agencies (World Bank, 2018; Archondo-Callao, 1999). In Canada, the Forest Engineering Research Institute (FERIC) developed the Opti-Grade road management system. Opti-Grade utilizes accelerometers and geographic information systems (GIS) to estimate the roughness of forest roads. The system was used to schedule routine blading works. It was found that this system was helpful in improving the effectiveness of maintenance works and reducing their costs (Brown, 2003). In another study, two algorithms for scheduling routine maintenance of gravel roads were developed in South Africa's Western Cape Province. The first algorithm worked on maximizing the overall network ride quality. The second algorithm worked on minimizing the total transportation costs. The focus of both algorithms was to set the sequence at which the roads should be bladed. It was found that the second algorithm was more efficient in improving the overall network roughness and reducing the total transportation costs (Burger et al., 2007).

In conclusion, previous efforts at developing GRMS are not generic and are tailored more for specific conditions. Every agency tends to set rules and guidelines for managing its own roads and to satisfy its particular needs. This creates the necessity to develop comprehensive guidelines and rules appropriate to manage gravel roads in Wyoming. As a result, WY2/LTAP conducted a pilot study to set the main rules for building a GRMS in Wyoming. In addition to addressing the inadequacy of the currently available GRMS, this pilot study resulted in many recommendations, guidelines, and some practical methodologies for maintaining gravel roads in Wyoming (Huntington & Ksaibati, 2011; Albatayneh et al., 2019; Huntington et al., 2013; Huntington & Ksaibati, 2015). The outcomes of this pilot study and other efforts by WYT2/LTAP are gathered in this research study to formulate the optimization model and develop the tool.

Introducing artificial intelligence (AI) to pavement management systems (PMS) has created a leap in the process. AI can substitute for existing management systems or enormously increase their efficiency. Genetic algorithms (GA), in addition to artificial neural networks (ANN) and fuzzy systems, are considered valuable tools for answering many questions related to the PMS, such as what should be done, when, how, and where (Sundin & BrabanLedoux, 2001). GAs were first introduced to pavement management by Fwa et al. in 1994, where they solved a network-level optimization problem related to maintenance planning. GAs later become a basic solution for various optimization problems related to roads management (Fwa et al., 1994b; Ferreira et al., 2002; Morcous & Lounis, 2005). However, most of the previous work was related to either a project or a network level optimization and mainly was applied to primarily paved roads. Comprehensive online research yielded only one study that implemented GA's to solve optimization problems related to rural roads (Mathew & Isaac, 2014). However, the implementation of the aforementioned study focuses only on paved roads. This present study introduces a large-scale optimization model, based on GA, which can be applied to the entire gravel road network in Wyoming. The developed model will help decision-makers and local agencies in selecting roads for chemical treatment projects. The following subsections describe the process of building the optimization model using GAs.

2.2.6 Gravel Roads' Level of Service

Numerous efforts have been made to develop and update systematic methods to manage gravel roads. For instance, various manuals provide guidance for designing, constructing, and managing gravel roads. They include the Low-Volume Roads Engineering: Best Management Practices Field Guide, US Army Corps of Engineers (USACE's) assessment system, Gravel Roads Maintenance and Design Manual, Rural Road Design, Maintenance, and Rehabilitation Guide, AASHTO Guidelines for Geometric Design of Very Low-Volume Local Roads (ADT≤400 vpd), Pennsylvania's Environmentally Sensitive Maintenance for Dirt and Gravel Roads and the RQRG. The development of the USACE's assessment system was one of the first efforts made to establish measurable indices pertaining to gravel roads (Aljarrah & Masad, 2020; Eaton & Beaucham, 1992; Huntington & Ksaibati, 2015; Walker, 1989). However, none of the aforementioned manuals provide a systematic method for evaluating the gravel roads' LOS.

The RQRG is used for assessing gravel road ride quality. It is developed based on the Wisconsin Transportation Information Center's PASER gravel road manual. This guide is designed to assess the quality of the road's surface as perceived by the road users. However, the RQRG is limited to the assessment of ride quality and surface conditions but not traffic operations. Thus, it is not adequate for a comprehensive LOS evaluation. Furthermore, a few studies were conducted to evaluate gravel roads' performance using one or two criteria. However, in most of these studies, subjective assessment methods were employed. For instance, a visual rating system was developed to visually evaluate gravel roads based on individuals' perspectives. The PASER system is considered the most common visual assessment system used for gravel road evaluation in the United States (Huntington & Ksaibati, 2015; Huntington et al., 2013). Yet, several studies paved the way to objectively assess gravel roads by evaluating traffic-generated dust and its effect on the environment. Also, the evaluation of gravel roads' ride quality using smartphone applications was previously undertaken (Abu Daoud et al., 2021; Aleadelat et al., 2018b). Nevertheless, an extensive methodology for gauging gravel roads' LOS in terms of traffic operations, ride quality, and dust levels are still lacking. This research addresses this issue by proposing the gravel road LOS methodology.

2.2.7 Chapter Summary

This chapter included a literature review of existing knowledge and common practices related to gravel roads. A review of dust generation on gravel roads suggested that traffic is the main generator of dust from gravel roads. In addition, this chapter also discussed different measurement tools used to measure dust emission rates.

Local agencies and state departments of transportation (DOTs) select various approaches to determine the performance of their gravel road networks. The majority of these approaches are based on either practical experience (engineering judgment) or reference manuals. Yet, there is a lack of extensive research on the operating characteristics of gravel roads let alone a robust methodology used to determine the LOS. This research study is aimed at addressing this knowledge gap.

3. METHODOLOGY

3.1 Introduction

This chapter summarizes the techniques and methods used in this research study. Figure 3.1 outlines the organization of this report. This research focused on assessing road conditions for Wyoming county gravel roads and collecting real-time data and then analyzing these data using machine learning, AI, and different techniques. Actual field data were collected from several counties around Wyoming and mainly from Laramie county. Descriptive and exploratory analyses were conducted to examine trends and behaviors of gravel roads. Statistical analysis was also conducted to validate the developed methodologies. The main goal of this research study is to assess road conditions for Wyoming county gravel roads and develop a more comprehensive understanding of gravel road performance. This study was divided into two main objectives, which are organized as follows:

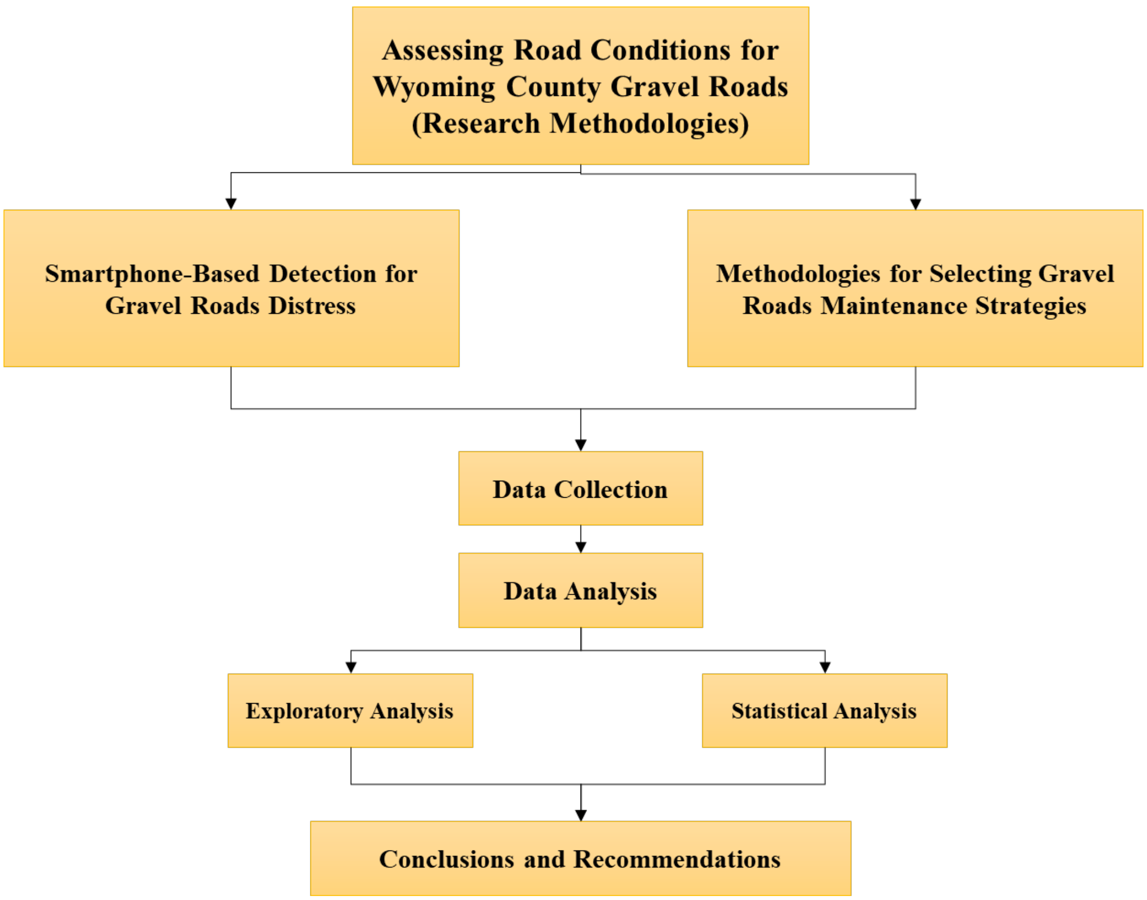

Figure 3.1 Schematic diagram for research methodology

3.2 Objective 1: Smartphone-Based Detection for Gravel Roads Distress

Objective 1 was to continue the efforts of the WYT2/LTAP office to develop and implement smartphone applications and technologies to assess gravel road conditions and performance. This included the continuation of the data collection process, where gravel roads from various counties around Wyoming were tested. Testing, as described in Chapter 4, included measuring dust emitted from gravel roads via Dustometer and smartphone application; it also included the collection of temperature and vehicle speed, as well as locations. A descriptive analysis was conducted to explore dust generation trends from gravel roads.

3.3 Objective 2: Methodologies for Selecting Gravel Roads Maintenance Strategies

As part of the efforts by the Wyoming Technology Transfer Center (WYT2/LTAP) to develop a gravel roads management system (GRMS) in Wyoming, Objective 2 was to develop user-friendly tools, using JavaScript and other programming languages, which implement an optimization model based on genetic algorithms (GA). The developed tool will help decision-makers and local agencies manage gravel roads efficiently. Using these tools, decision-makers will be able to identify the most appropriate treatment type for each road based on service level, estimated project costs, predicted road conditions, and whether or not to fund a project. The optimization models aim to maximize the overall condition of the gravel road network subject to the average daily traffic (ADT) on each road. The developed tools can be applied to large-scale optimization problems (i.e., gravel road network). The tools operate with minimal data requirements that are in line with procedures regularly followed at these agencies. In addition to having an engineered outcome, these tools can help local agencies allocate their limited available funds efficiently, thereby enhancing the planning process, maximizing the social welfare of the local economy, and promoting a sense of general satisfaction within the local community. A case study using data from Laramie County was used to develop these tools. Different types of analyses were conducted to carefully validate the performance of the developed tools. Both exploratory and statistical analyses were conducted. Chapter 5 includes comprehensive explanations of the analyses conducted and the results obtained.

3.4 Chapter Summary

This chapter described the organization followed throughout this report. The first objective of this study was to develop and implement smartphone applications and technologies to assess the gravel road conditions and performance in Wyoming. The second objective was to develop user-friendly tools, using JavaScript and other programming languages, which implement an optimization model based on GAs. The developed tool will help decision-makers and local agencies manage gravel roads efficiently.

4. SMARTPHONE-BASED DETECTION FOR GRAVEL ROADS DISTRESS

4.1 Introduction

Daily traffic on arid gravel roads can easily generate dust. Dust emitted from gravel roads creates several problems, such as aggravated asthma, breathing difficulties, reduced crop yields, and even death. Therefore, local agencies tend to track the dust amounts on gravel roads to maintain them in good condition. Accurate detection of dust amounts is very crucial in the GRMS. Data collection is considered one of the main challenges facing local agencies due to budget constraints. This research study establishes novel methods for automatic recognition of gravel road distress, such as dust amounts on gravel roads and washboarding. Dustometer and field measurements, supported by statistical analysis, demonstrate that the proposed algorithms achieve outstanding classification accuracy. Hence, the proposed algorithms are a promising alternative to assist local agencies in data collection and maintenance planning.

4.2 Data Collection

Gravel roads are relatively inexpensive and easy to build because of the materials used in the construction process. However, gravel roads have greater demand for maintenance and rehabilitation than paved roads. The Wyoming Technology Transfer Center (WYT2/LTAP) is implementing new management systems, such as GRMS. This new system can provide decision-makers and local agencies with cost-effective solutions. One of these managing solutions is to overcome the high cost of data collection. Data collection, which is a systematic process of collecting and gathering information on specifically targeted variables, is considered a time-consuming and expensive step in any management system. The WYT2 /LTAP is developing many cost-effective approaches to collect gravel road condition data. One of these approaches is to use the smartphone application to provide information about the gravel road conditions by classifying gravel road distress using newly developed image processing algorithms.

4.3 Methodology

This section presents an overview of the classification algorithms used in this research study. This methodology is divided into four major steps: (1) Experiment design; (2) Classification algorithms; (3) Dustometer measurement; and (4) Validation. The four steps are briefly described in the following subsections.

4.3.1 Experiment Design

In this research study, an Android smartphone was used with a preinstalled Roadroid Application; a Samsung Galaxy S5 was used to take images from the rear windshield of the testing vehicle. A smartphone windshield mount with a long arm clamp and double clip, strong suction cup was used in order to keep the smartphone steady without obscuring the camera lens. Images were taken every 100 m segments (GPS linked) and then uploaded to a web service. Image analysis was then performed on the survey images via the classification algorithms. Gravel roads (1 mile each) in Wyoming were selected. Each gravel road was chosen based on its condition levels.

For dust measurements, four phases were conducted. First, a portable dust collection system called "Dustometer" was used to classify and validate the results from the developed algorithm. Second, visual classification (evaluation) of the dust on the selected roads was done based on the Ride Quality Rating Guide (RQRG) in order to assess and compare the results. Third, a simple dust classification algorithm was developed to provide information about the dust on gravel roads. This image processing algorithm is a (.NET) class library used to extract information and data from images. Fourth, one of the machine learning frameworks (TensorFlow) was used to build an image classifier. This classifier can classify the dust amounts on gravel roads into four major levels (none, low, medium, and high). This classifier is based on the aspect of optimizing one of the deep neural network models, the Inception-v3 model. This model contains a pretrained package used to extract and recognize dust patterns from dust images automatically. In this phase, a dataset of 4,000 images of gravel roads was collected. For training, 80% of the dataset was used, and 20% was used for testing.

For the corrugation (washboard) measurements, more than 4,000 images, showing different severity levels of corrugation, were collected from gravel roads in order to build and develop this image classifier for gravel roads corrugation. For the purpose of developing a corrugation image classifier, the collected images were divided into two groups; 80% of the images were used to train the model, where the remaining 20% were used to test it. The data preparation phase started with the appropriate visualization of the collected images by seeking trends and patterns among the images. Then, the images were sorted randomly. After that, the images were cropped to have an appropriate and suitable size for the Inception-v3 model and its ImageNet database. Afterward, the Inception-v3 model was chosen to build the gravel roads corrugation classifier.

4.3.2 Dustometer Measurement

The Dustometer was used to classify and validate the results from the developed algorithm. This device consists of a portable electric generator, a suction pump, a metal box, and #200 size glass fiber filter paper. Figure 4-1 shows the 2001 Suburban Chevy, which was used in this study, as well as the arrangement of the smartphone and the Dustometer.

Figure 4.1 Dustometer and Smartphone Arrangement

In addition to the collected dust measurements using the Dustometer, the WYT2/LTAP provided the necessary historical data to classify the dust measurement into three major classes: high, medium, and low. Figure 4.2 shows the visual depiction of the historical Dustometer measurement data distribution. As seen from the figure, the data range anywhere from 0.05 (g/mile) to approximately 0.9 (g/mile). However, the skew of the distribution indicates most of the data seem to fall in the lower part of this plot. More specifically, most of the gravel roads have relatively low dust amounts. Using the available data, data-driven threshold values were assigned based on the 25th and 75th percentiles of the boxplot to classify the dust amount on gravel roads. It was assigned that the low dust level is less than 0.2, the medium dust level is from 0.2 to 0.5, and the high dust level is greater than 0.5.

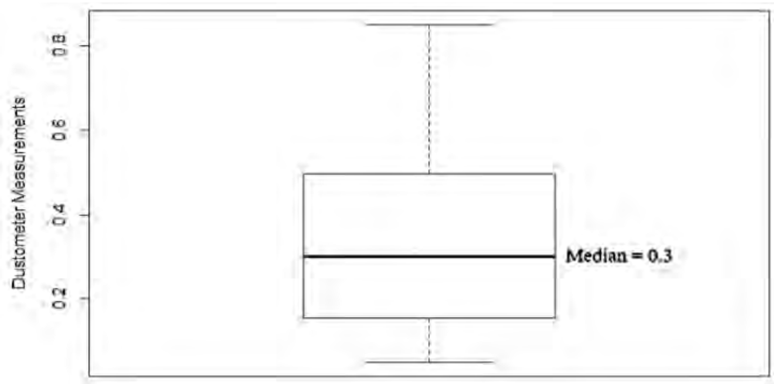

Figure 4.2 Boxplot Distribution of the Dust Measurements

4.3.3 Classification Algorithm

4.3.3.1 Dust

Simple Dust Classification Algorithm

The main objective of this phase was to develop and validate the simple dust classification algorithm for classifying the dust amount on gravel roads. The simple dust classification algorithm was developed to provide information about the dust on gravel roads. The image processing algorithm is a (.NET) class library used to extract information and data from images. AForge.NET is used for image processing operations. Figure 4.3 shows the architecture of the image analysis.

Dust amount classification is a combination of color filtering, binarization, smoothing, and feature extraction to extract areas of the image containing dust, and comparing the number of dust pixels to non-dust-pixels to choose from one of the dust amount classes. All of these steps can be determined by performing the five steps of AForge.NET filters.

Binary images may contain various imperfections. Therefore, a five-step process of AForge.NET filters and operations are performed to remove imperfections and smooth the image before applying the SDCA. Figure 4.4 clearly illustrates the five steps: preprocessing, global thresholding, remove noise and smooth, feature extraction, and classification. For example, in the remove noise and smooth step, a morphological closing, which is a collection of non-linear operations, was performed to remove the noise and the texture. Moreover, in the feature extraction step, the biggest blob extraction was performed to isolate a region of a digital image that has constant properties (blobs), in that it tends to extract regions in the image that differ in properties such as color or brightness. When it comes to classifying the image, the simple dust classification algorithm has pre-defined scores of dust/color. For example, an image with 10,000 pixels (100×100 pixels) has either white pixels (dust particles) or black (something else). If it scores 4,000 pixels as white pixels, it will give a score of 40 ([4,000/10,000] × 100), which will have a dust value of 4 indicating high dust. The dust score value cannot exceed 100 since it is the number of pixels in percent the algorithm defines as having dust in the analyzed part of the image.

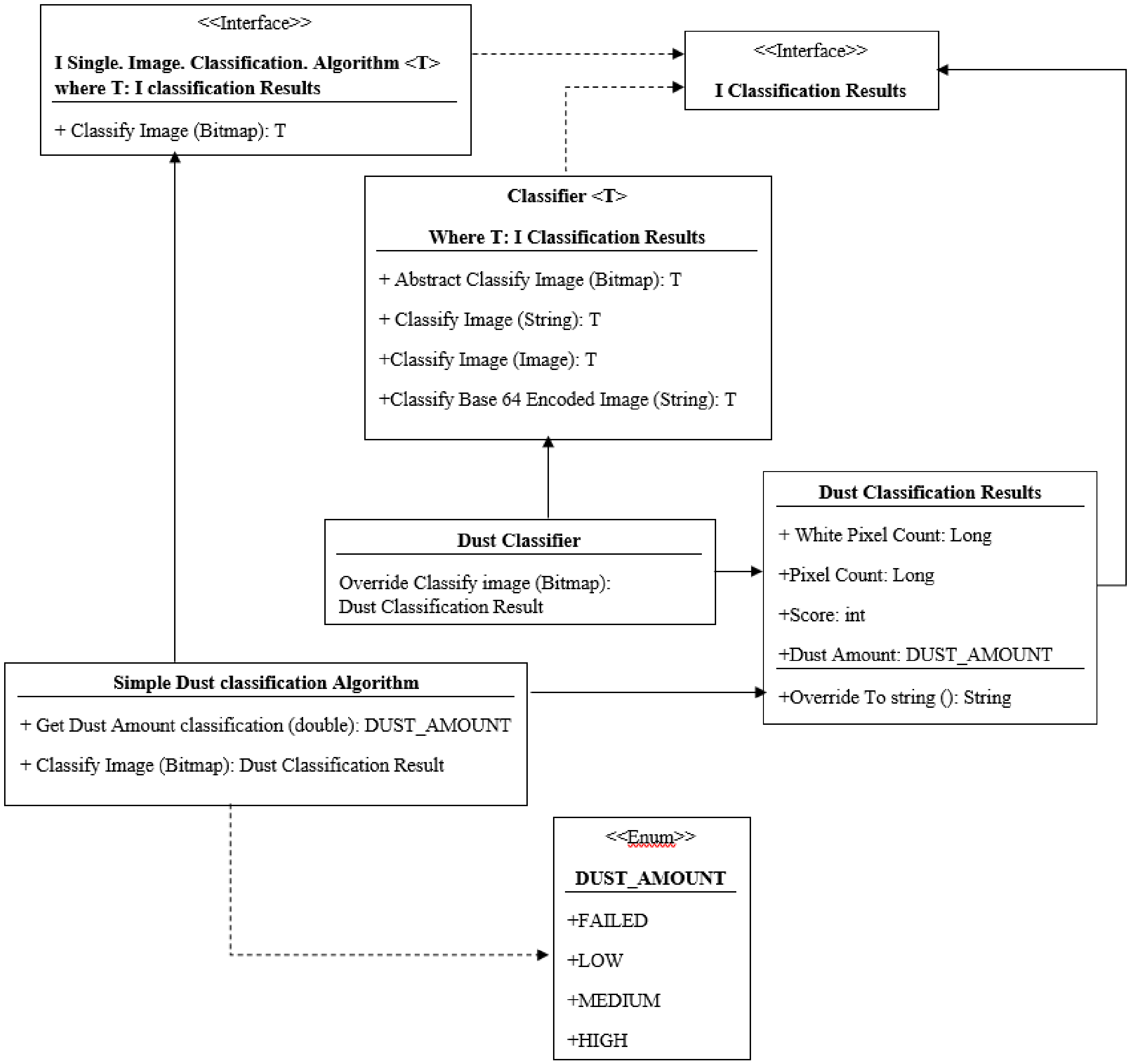

Figure 4.3 Simple Dust Classification Algorithm Architecture

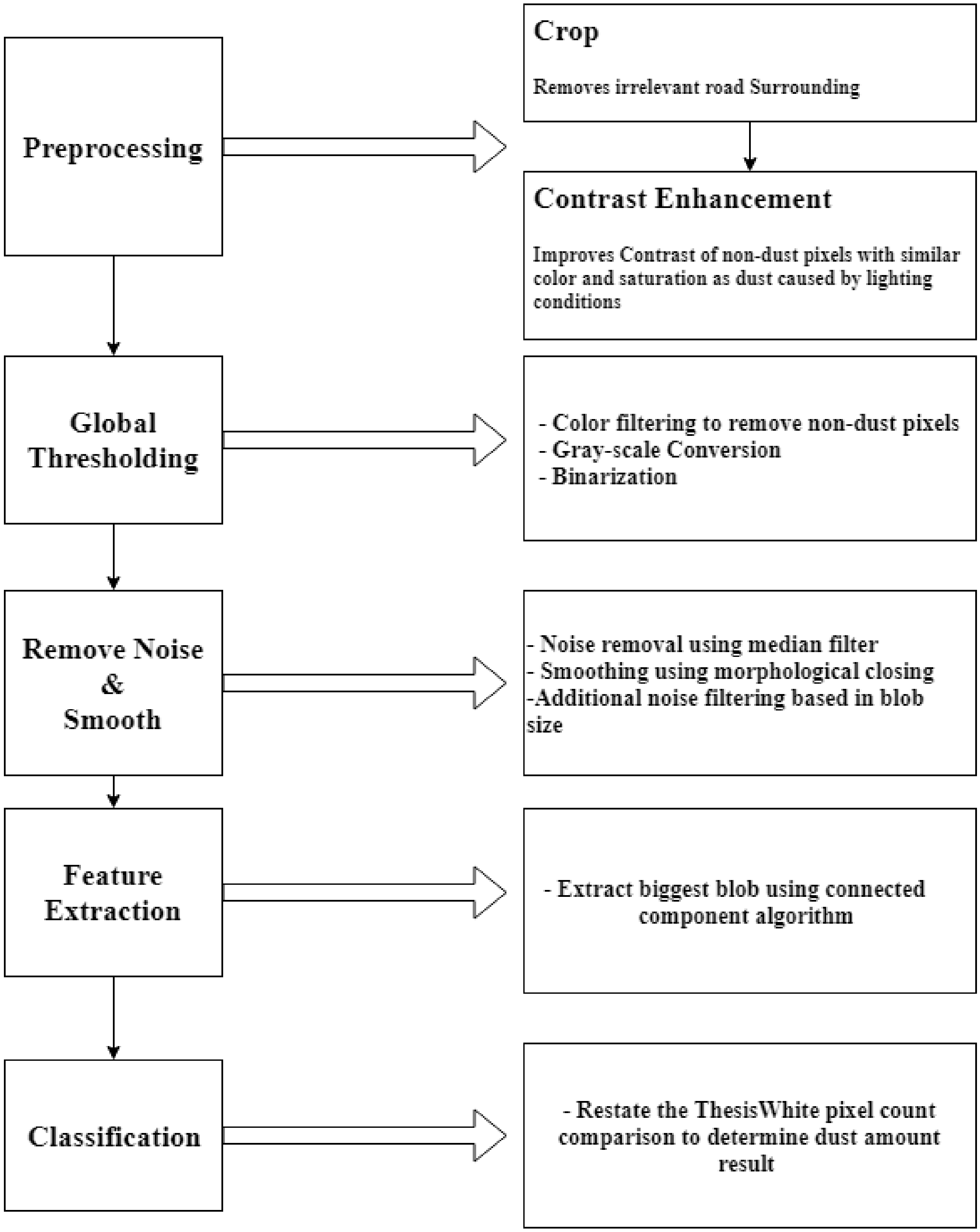

Figure 4.4 Simple Dust Classification Algorithm Basic Five Steps

Machine Learning: Tensorflow

The objective of this study is to build a TensorFlow image classifier with a transfer learning process using a pre-trained Inception-v3 model. This classifier is trained to detect the dust on gravel roads and then classify them into four major levels. This classifier is considered a function that takes some data as inputs (dust images) and assigns a label (dust levels) to it as outputs. This is done by an automatic technique called supervised learning. Generally speaking, this technique begins with the following few standard steps:

- Step 1 starts with examples (images) of the problem that is being solved.
- Step 2 is to use the input images to train the classifier using pre-trained models and learning algorithms.
- Step 3 is finding patterns in the trained images and then predicting the dust levels.

Figure 4.5 shows a canonical data model (CDM) of the three steps in this study. This figure shows the data entities and their relationships in the developed machine learning workflow. Also, Python version 3.6 was used in this study to develop this image classifier by implementing the Inception-v3 model in TensorFlow.

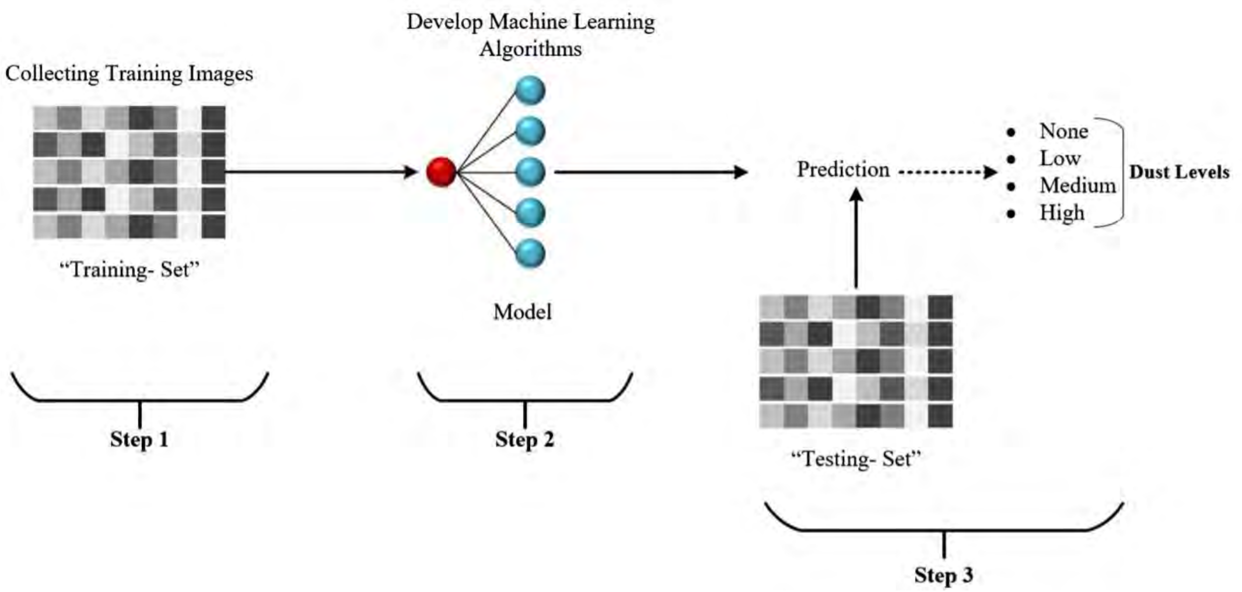

Figure 4.5 Canonical Data Model of The Developed Machine Learning Workflow

The quality and quantity of the collected images (inputs) will directly determine how well the classifier can be. In this phase, more than 4,000 images of gravel road dust from Wyoming and Gävleborg County, Sweden, were collected representing the four dust levels (none, low, medium, and high). A smartphone with a preinstalled Android application called Roadroid was used to collect the dust images. This application uses the built-in GPS unit in smartphones to capture the images at set intervals of 100 m.

In this study, the dataset was divided into two partitions (training and testing) to prepare them for use in the developed classifier. For training, 80% of the data were used, while the remaining 20% were used for testing. Generally, it is good practice to remove highly correlated images from the training set to avoid doubling the count of the image features. Therefore, the process starts with pertinent visualization of the collected images by looking for trends, patterns, correlations, and, most importantly, data imbalances. Then, 800 images were manually classified for each dust level with a total number of images of 3,200 to ensure that the developed classifier is unbiased. Afterward, the data were randomly sorted to remove the effect of ordering on the learning process. Subsequently, the size of the input image was cropped to 299 × 299 pixels, which is the region of interest, to be compatible with the ImageNet database, where the Inception-v3 model was created and trained. The next step in this study was to choose the training model. In the era of developing computer vision techniques, there are many training models that researchers and scientists have created over the years. Some were for numerical data, others were for text-based data or music, and some were well suited for image data. In this study, one of the newly advanced pre-trained models, called the Inception-v3 model, was selected to retrain the dust images and build the classifier.

TensorFlow, which is one of the most popular machine learning libraries, was created by the Google-Brain team for creating deep learning models that use multilayer neural networks. TensorFlow can be used for both production and research applications, but in particular, it targets the training of deep neural networks. TensorFlow has exquisitely crafted features that allow the developers and researchers to create classifiers with the ability to solve many problems that have been reserved for humans in a more efficient and cost-effective technique. In this classifier, a Python 3.6 code was used to train and develop the model. The following steps describe the procedures that were used to install, import, and develop the TensorFlow algorithm in Python 3.6:

Import the input dataset and then split it into training and testing data.

1. Set the hyperparameters, or tuning knobs values. Such hyperparameters include the number of training steps or the number of iterations and the learning rates. In our case, 4,000 training steps and 0.01 learning rates were used.
2. Initialize the model's weights (W) and biases (B).
3. Create name-scope {tf.name_scope} to help organize nodes in the graph visualizer Tensorboard. In this study, three scopes are created:
    a. A scope to implement the logistic regression model and create summary operations to help visualize the distributions of the weights and biases.
    b. A scope to create the cross-entropy function cost_function to help minimize the errors during training.
    c. A scope to create the optimization function called train to automatically improve the model during the training.
4. Start training after initializing all of the created variables.

In machine learning, the learnable parameter weight is used to find evidence of the existence of a particular pattern in an image. The weights are the probabilities that affect how data flows in the model and represent the strength of the connection between the layers. The weights are updated continuously during training so that the results converge to the final solution (optimum solution). In this classifier, the weights are randomly initialized based on one of the common initialization methods for a deep neural network to guarantee that the search space is properly explored during the training (Glorot & Bengio, 2010). Therefore, to initialize weights randomly, a Xavier initialization technique {xavier_initializer()} was used. This command automatically initializes weights from a standard normal distribution (Feng et al., 2019). By this, the gradients, a machine learning function to optimize the weights, will flow from top to bottom without any problems such as warding off the weights from changing their values (vanishing gradient).

In TensorFlow, the developer can adjust, change, and control several parameters to increase the predictive power. These parameters are called hyperparameters. Such parameters are (1) learning rates, which define how fast the weights are updated, and (2) the number of hidden layers in the model. For instance, if the learning rate is too quick, the model might skip the optimal solution, and if the learning rate is too slow, the model might require too many iterations to converge to the optimum results. In this study, a 0.01 learning rate was used.

Using TensorFlow would have many advantages over other AI tools such as data visualization and flexibility. These two are considered the main two advantages that make this tool one of the leading in this field. Visualizing what happens inside the code using graphs and plots would help researchers and developers thoroughly understand the code. Hence, for instance, they can visualize the data to debug and improve the model performance to achieve more accurate predictions. All of that can be carried out using one of the TensorFlow web applications called Tensorboard. This built-in visualizer enables researchers and developers to visualize the training parameters, metrics, hyperparameters, or any statistics of neural networks. Using this tool, many figures can be generated, such as the computational structure of the developed classifier, accuracy plot, and cross-entropy plot. Figure 4.6 shows a visual representation of the developed classifier structure for the various operations and information in the model. This model structure can be used for determining whether the developed model is appropriate or not by zooming, panning, and expanding the model's elements. That is, the depiction of the model can be visualized from different layers of abstraction. Therefore, the dependencies between the different operations in the model can be easily understood to perform debugging and find how the model could be improved. As seen from the model structure, the model confirms that the data have a meaningful tensor flow based on the arrows between the performed operations. The model also confirms that the transformations of the dataset are applied and executed correctly by tracking these metrics through the training process as part of this graph.

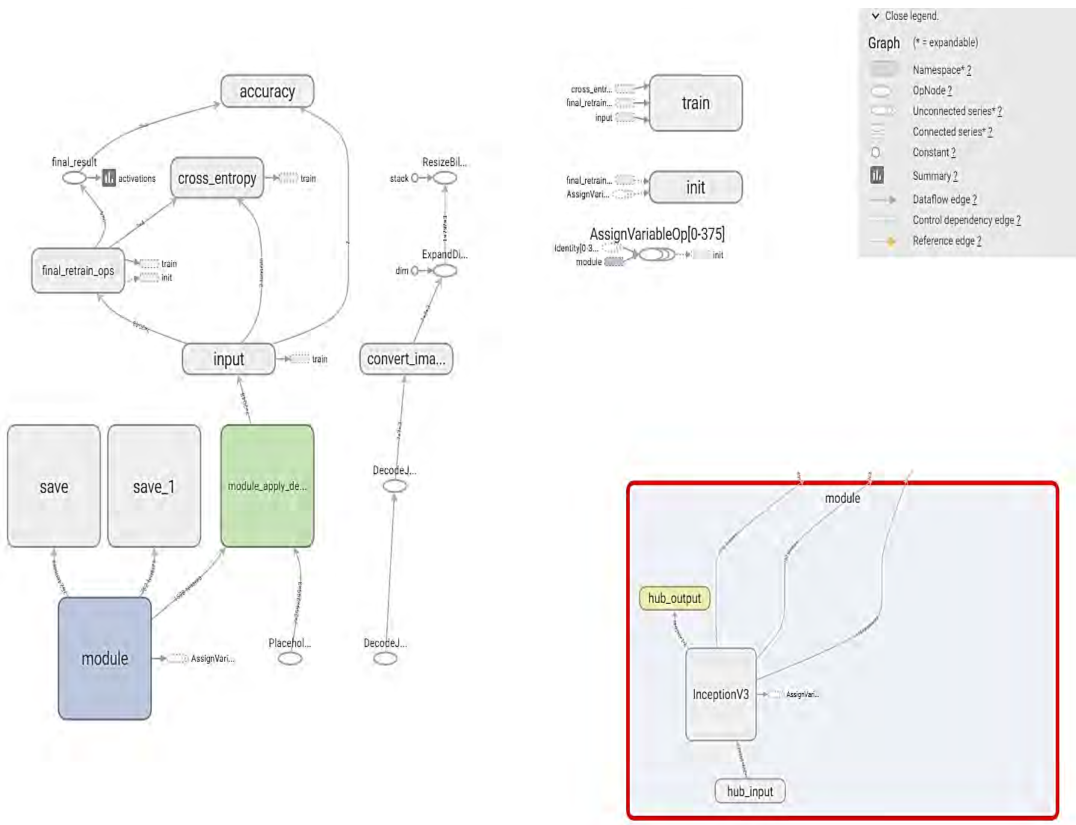

Figure 4.6 The Computational Structure of the Developed Classifier

Machine Learning: Inception-v3 Model

Training a high-performing deep neural network model from scratch requires extensive data collection efforts and computing power. Therefore, retraining a previously constructed deep neural network model is considered an efficient technique for saving time and reducing data collection costs since it requires less training data. This is conducted by a process called transfer learning. This process involves applying the information learned from a previous training session (problem) to a new training session by making small changes to the last layers (bottleneck layers) that are responsible for tuning and the final classification in the deep neural network model. Figure 4.7 shows the general architecture of the deep neural network model with a transfer learning process. The green color indicates the transfer training process in the final layer.

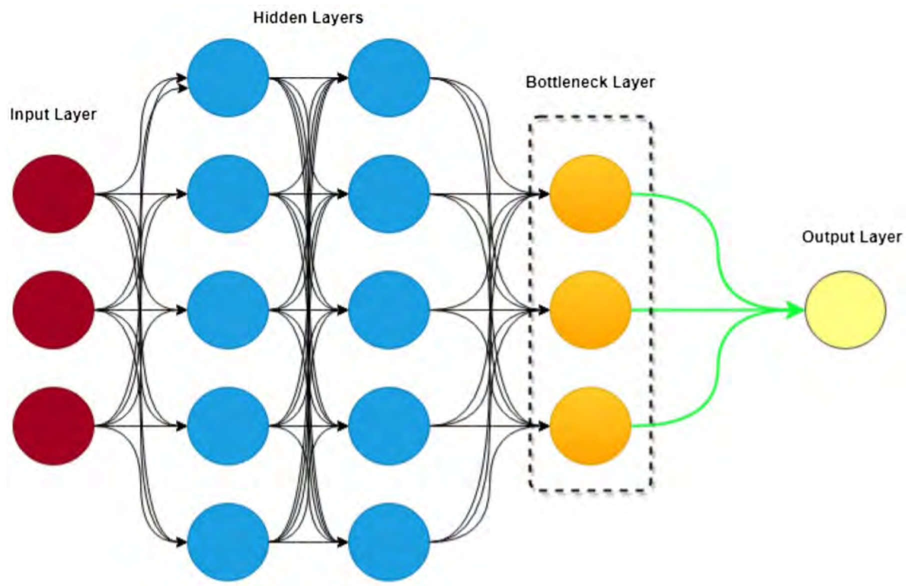

Figure 4.7 Basic Architecture of A Deep Neural Network Model With A Transfer Learning Process

The Inception-v3 model is considered one of the convolutional neural network (CNN) architectures for image classification. It was first introduced by Szegedy et al. in 2016. This model contains more than 25 million fitted parameters and was trained by one of the top hardware experts in the industry. The CNN models are black boxes that construct image features. The Inception-v3 model uses the image feature extraction module that was trained on ImageNet. The ImageNet is an accessible database for high-resolution images designed for developers and researchers in the field of image processing. Generally, the Inception-v3 model consists of two main parts: (1) the convolutional neural network to extract image features; and (2) the image classification with the softmax and the fully connected layers. The softmax layer is used as the final layer of a neural network-based classifier to provide normalized class likelihoods (probabilities) for the outputs (dust levels).

In our case, the developed classifier is built to classify dust images. Nevertheless, the Inception-v3 model was not trained on dust images, and therefore, the transfer learning process is required. Thus, a transfer learning process is applied to the last two layers of the model. In computer vision, especially image classification, customized softmax and fully connected layers are considered essential components for successfully classifying images with high accuracy. For instance, in fully connected layers, each node on the neural network is fully connected to the previous layer. Therefore, customized softmax and fully connected layers were built to be used to classify dust images. In TensorFlow, the number of neurons in the fully connected layer ranges based on the targeted classification accuracy (Krizhevsky et al., 2012; Ciresan et al., 2011). In this study, several network architectures were trained (hyperparameters optimization) using a different number of neurons, and then cross-validation was performed to measure the network performance.

As a result, the number of neurons was chosen to be 1,024. Generally, this customization helps the model to learn more about some image-specific features. Figure 4.8 shows the schematic diagram of the customized Inception-v3 model that was used in this study.

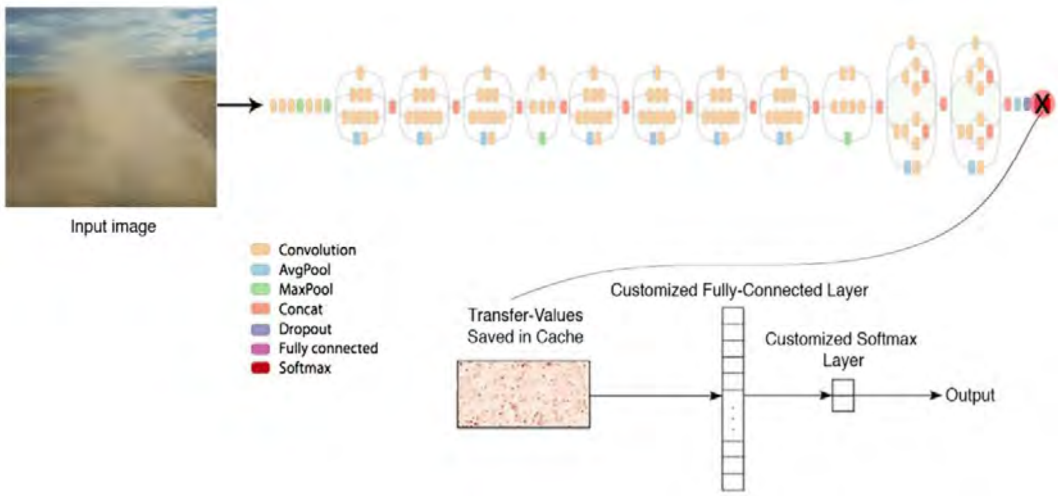

Figure 4.8 Schematic Diagram of The Customized Inception-V3 Model

4.3.3.2 Corrugation

The main purpose of this phase is to validate a recently developed image classifier detecting the corrugation (washboard) on gravel roads and determining its severity levels. This image classifier was built and developed by Roadroid using the TensorFlow framework. A supervised neural network learning technique was used to develop this image classifier. Developing a model using the supervised neural network technique goes through a few general steps: collecting and labeling a sufficient size set of images to form the training set, choosing the learning function structure and algorithm, and then testing and evaluating the designed algorithm in predicting the image feature.

The main advantage of this research work is to provide a smartphone automated detector for gravel roads corrugation. The tested gravel road corrugation detector can be used in data collection to replace both the traditional visual inspection methods and the automated methods that need a lot of equipment. Based on that, this classifier will enhance the data collection process and provide decision-makers and local agencies with a cost-effective data collection tool. Finally, the developed image classifier is a new and necessary step in building a holistic and integrated gravel roads data collection method based on smartphones in collecting all gravel road data.

4.3.4 Validation

To validate the developed algorithms for determining the dust amount on gravel roads, several gravel roads in Wyoming were selected to represent the levels of dust defined earlier. Figure 4.9 shows an example of some of the locations for the included roads in Laramie County, Wyoming. A Dustometer device was used to collect the dust (g/mile) on the tested gravel roads. Since the study was done on unpaved roads (gravel roads), the testing vehicle was operated at a constant speed of 40 mph in dry weather conditions to ensure the maximum amount of dust to be generated.

In this research study, a visual assessment of the quality of the gravel road was conducted based on the RQRG. This guide is based on the Wisconsin Transportation Information Center’s PASER gravel manual to assess the quality of the gravel road’s surface as observed by the road users. Table 4.1 describes the

RQRG scale and how roads are ranked according to that ranking.

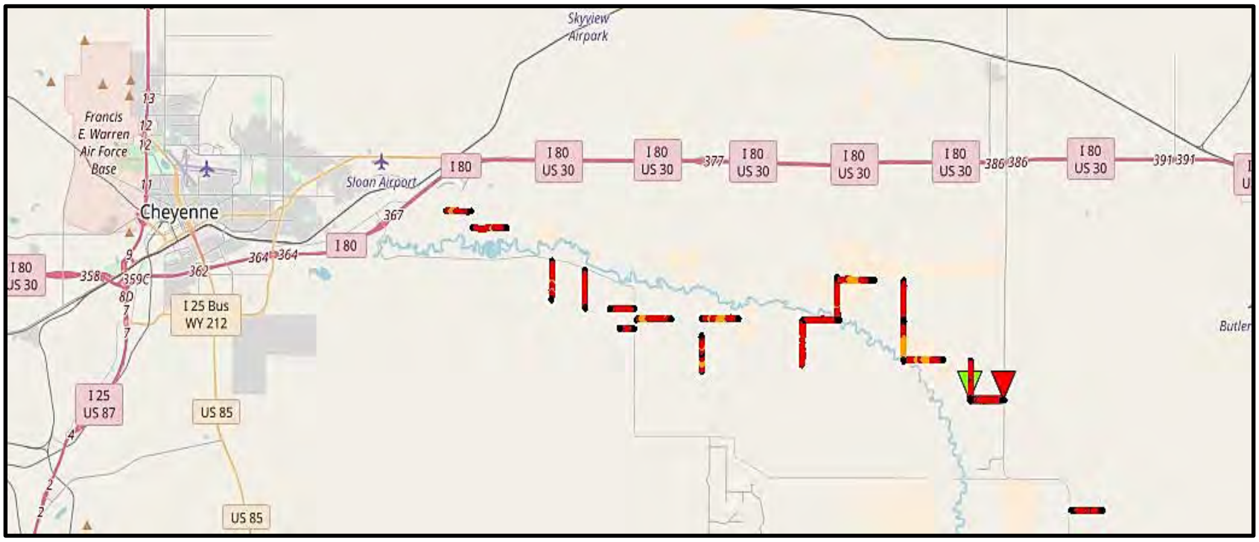

Figure 4.9 Example of The Tested Gravel Roads In Laramie County, Wyoming

Table 4.1 Ride Quality Rating Guide (RQRG)

	Rating	Speed* (mph)	Distresses**
10	Excellent	60+	-
9	Very Good	50-60	-
8	Good	45-50	Dust under dry conditions; Moderate loose aggregate; Slight washboarding.
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7	Good	40-45	
6	Fair	32-40	Moderate washboarding (1" - 2" deep) over 10% - 25% of area; Moderate dust, partial obstruction of vision; None or slight rutting (less than 1" deep); An occasional small pothole (less than 2" deep); Some loose aggregate (2" deep).
----------	-----------------	---------------	
5	Fair	25-32	
4	Poor	20-25	Moderate to severe washboarding (over 3" deep) over 25% of area; Moderate rutting (1" - 3") over 10% - 25% of area; Moderate potholes (2" - 4" deep) over 10% - 25% of area; Severe loose aggregate (over 4").
----------	-----------------	---------------	
3	Poor	15-20	
2	Very Poor	15-Aug	Severe rutting (over 3" deep) over 25% of area; Severe potholes (over 4" deep) over 25% of area; Many areas (over 25%) with little or no aggregate.
----------	-----------------	---------------	
1	Failed	0-8	

* Passenger car speeds based on surface condition allowing for rider comfort and minimal vehicle wear and tear, assuming no safety or geometric constraints force slower travel.
** Adapted from the Gravel - PASER manual.

4.3.4.1 One-way Analysis of Variance (ANOVA)

Generally, an ANOVA test checks if the experiment results are statistically significant. The one-way analysis of variance (ANOVA) is an omnibus test statistic with one independent variable used to determine if there are any statistically significant differences between the means of two or more groups using the F-distribution. Equation 4-1 shows the null hypothesis, which is accepted when the one-way ANOVA returns statistically insignificant results.

$$H0: \mu 1 = \mu 2 = \mu 3 = \ldots\ldots = \mu k$$

Equation 4-1 Null Hypothesis

where: μ: Mean of the group; k: Number of groups.

This step critically examines the significance of the difference between the overall Dustometer rating and the overall algorithm rating. For validation purposes, 30 gravel roads were selected to represent the dust classes. Figure 4.10 shows the percent of each dust amount class on these gravel roads using the current study's Dustometer data. Statistical analysis was performed using ($\alpha = 0.05$) at a 95% confidence interval. Based on the ANOVA analysis, the difference of the dust amount classification between the overall rating of Dustometer (g/mile) and the overall rating from the dust classification algorithm is statistically insignificant ($t_{1,58} = 0.105$; P-value= 0.747). Table 4.2 shows a summary of the basic statistics.

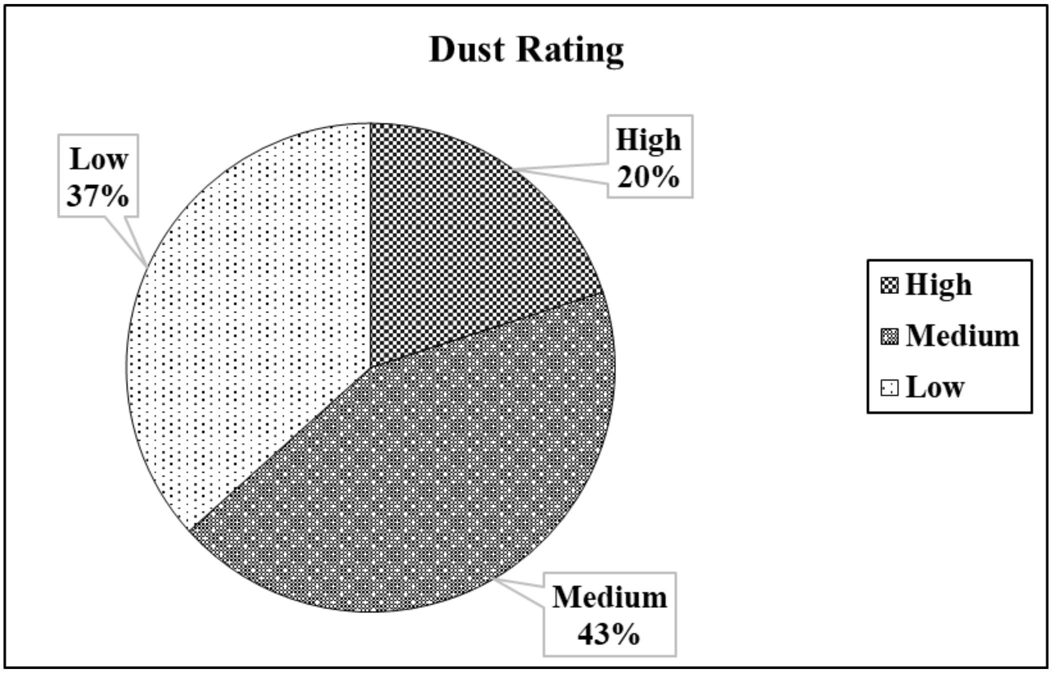


Figure 4.10 Percent of Each Dust Amount Class in the Included Roads

Table 4.2 One-way ANOVA Analysis

	N	Rating means	SD	SE	95% Confidence interval for mean	
					Lower bound	Upper bound
Dustometer	30	2.467	1.196	0.218	2.02	2.913
SDCA*	30	2.567	1.194	0.218	2.121	3.013
Total	60	2.517	1.186	0.153	2.21	2.823

*Simple dust classification algorithm

4.3.4.2 Confusion Matrix

In machine learning and, specifically, classification applications, a confusion matrix is a technique used to summarize the classification performance. This technique provides a summary of prediction results on the developed classification application based on the counts (numbers) of correct and incorrect predictions (Veropoulos et al., 1999). Therefore, prediction accuracy was calculated based on the accuracy-score equation (Eq 2). In this classification application, 83% was found to be the prediction accuracy of this image classifier. Considering the level of accuracy that is sufficient for the gravel road management systems, this prediction accuracy is considered a breakthrough performance. Table 4.3 shows the generated confusion matrix.

$$Accuracy - Score = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions\ made}$$

Equation 4-2 Accuracy-Score Equation

Table 4.3 Confusion Matrix of The Developed Image Classifier

	Dustometer					
	Class	Low	Medium	High	Sum	Accuracy [%]
Classified images	Low	8	2	0	10	80
	Medium	1	11	2	14	78.6
	High	0	0	6	6	100
	Sum	9	13	8	30	
	Accuracy [%]	88.9	84.6	75		

4.3.4.3 Economic Evaluation

Nowadays, smartphone technologies are taking the lead toward providing engineers and users with the most cost-effective methods and solutions to identify road quality. Economic evaluation is the process of measuring the cost-effectiveness of these technologies. Generally, using the developed algorithm will provide engineers and decision-makers with cost-effective road surveys compared with the traditional data collection methods. Table 4.4 shows the major differences between the Dustometer and the developed algorithm. As can be seen, the cost and the time associated with dust collection using the Dustometer are among the major challenges facing local agencies. The Dustometer data collection process needs at least two persons in order to set up the device, drive the testing vehicle, and change the filters; whereas, using the developed image processing method requires only one person with a smartphone to run the test. Furthermore, the number of road kilometers that can be tested is also considered as a limitation of using the Dustometer device. These limitations and challenges associated with using the Dustometer method can be avoided by utilizing the newly developed image processing algorithm introduced in this study.

Table 4.4 Major Differences Between Dustometer and Smartphone App

	Number of people (USD 16/hr)	Setup time	Test segment	Dust filters (USD 10/1.6 km)	Electricity generator- gas (USD 2.72/ gallon)	Maintenance
Dustometer	At least 2	2 hrs	Limited to 1.6 km segment	√	√	√
Roadroid app	1	10 min	Non-stop process	×	×	×

4.3.4.4 Tensorflow & Inception-v3 model

In this section, the performance of the developed classifier is evaluated. Performance evaluation is an essential component of machine learning. To evaluate the performance, we generated a classification accuracy plot based on the accuracy-score equation [Eq. (2)]. The results showed that this classifier has a 72% prediction accuracy. This prediction accuracy is considered a breakthrough for gravel road management systems.

Also in Tensorboard, prediction accuracy and cross-entropy plots were generated. Figure 4.11 shows the maximum accuracy that this classifier achieved. As seen from this figure, at zero steps, the classifier has approximately 52% prediction accuracy, which indicates that the classifier has a good start. The final prediction accuracy that this classifier reached is 72%. Yet, the highest accuracy achieved is 73%. The orange line in Figure 8 denotes the training dataset, and the blue line denotes the test set. The cross-entropy loss plot, which is sometimes named a logistic loss function plot, was generated to measure the performance of the classification model. Generally, the cross-entropy loss decreases as the predictions converge to the actual labels.

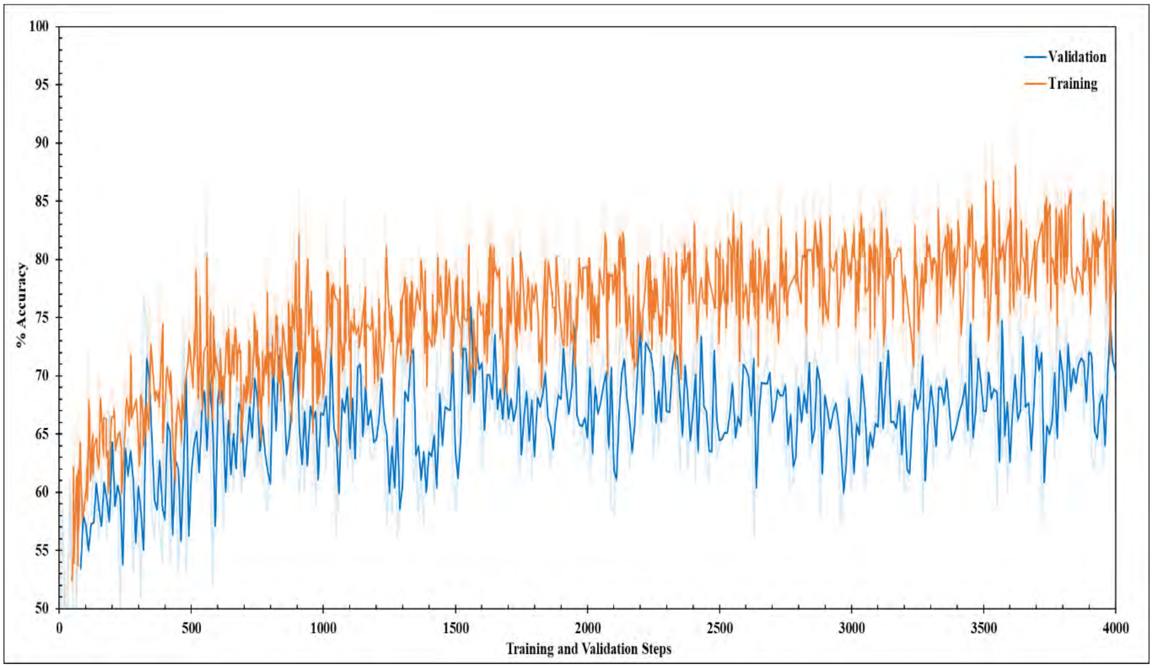


Figure 4.11 The Maximum Prediction Accuracy of the Image Classifier

Therefore, minimizing the model log loss is tantamount to maximizing the prediction accuracy of the classifier. Thus, this plot also quantifies the prediction accuracy and the performance of this classifier. As seen from Figure 4.12, there is a gentle downward slope toward the right, which indicates that the model loss progressively decreases as the prediction accuracy improves.

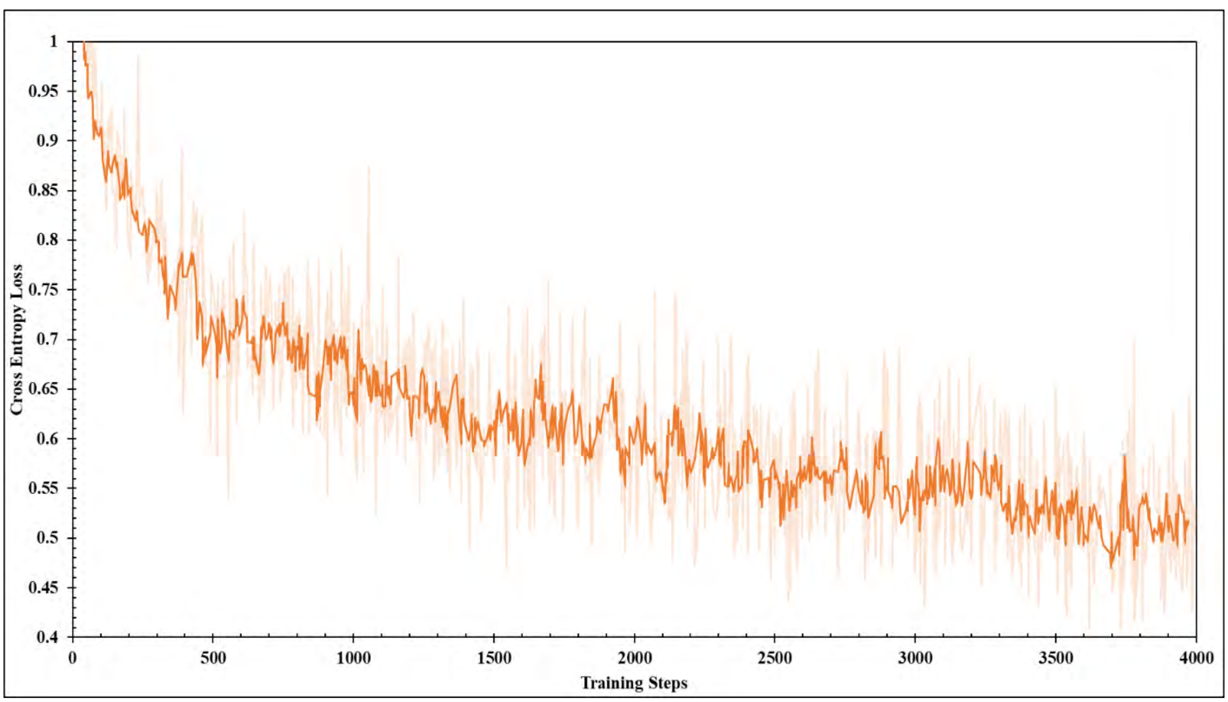


Figure 4.12 The Cross-Entropy Plot of the Image Classifier

In TensorFlow, histogram plots are used to describe the clarity of the model. Figure 4.13 shows a 3D mean histogram plot for the weights in the developed classifier's model at each step. This figure confirms that the model has accurate hyperparameters and weights initialization. It shows that the model has approximately a constant rate of development over time. The histogram slices are fragmented into steps. For instance, the darker histogram slices represent older steps while lighter histogram slices represent the latest steps. In addition, at 4,000 steps, the model has a value of 0.00299, which is near zero indicating that changing the inputs will not significantly improve predictive power. Therefore, it is not efficient to continue tuning and retraining the model. Also, this confirms that using 4,000 steps was sufficient without overfitting the data. Furthermore, Figure 4.14 shows the progress of the image classifier's biases. As can be seen, there is a variation in the standard deviation over time.

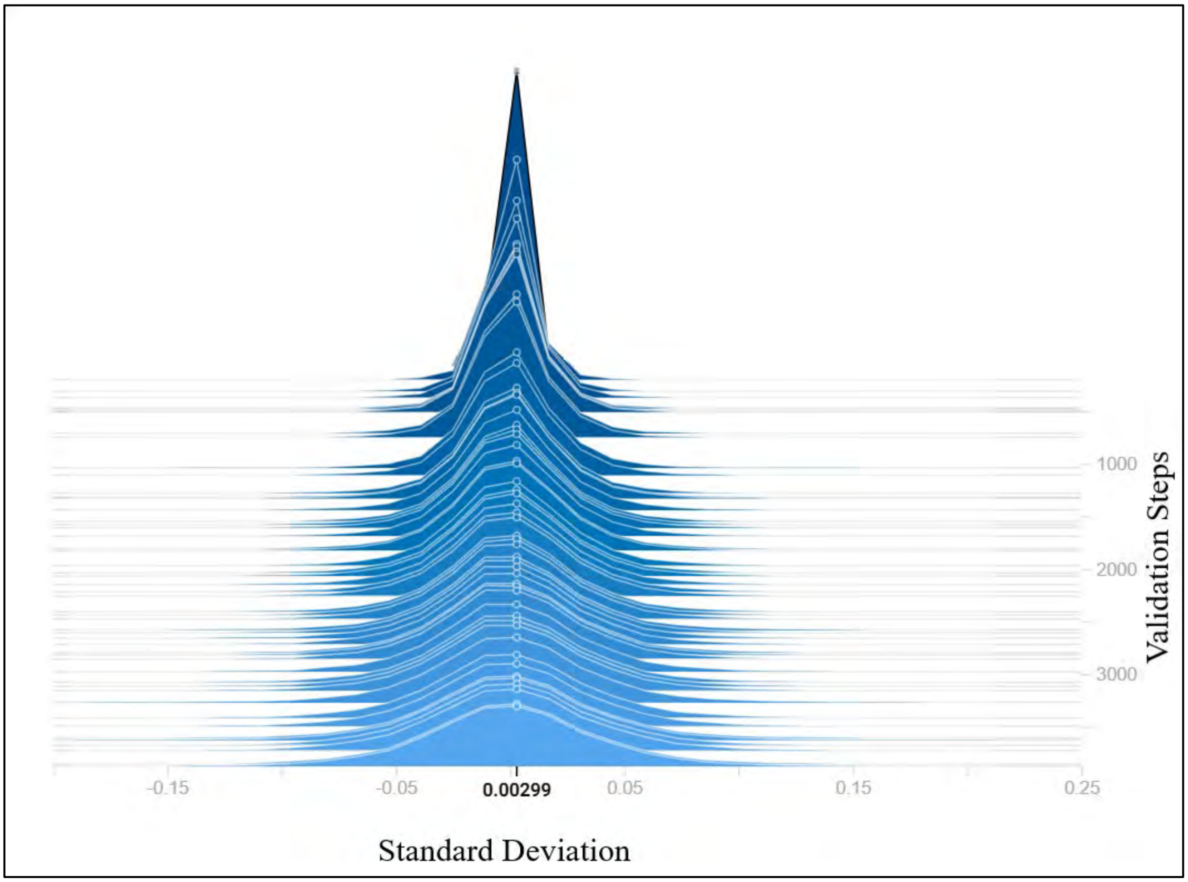


Figure 4.13 The Development of the Image Classifier Weights Over 4,000 Steps

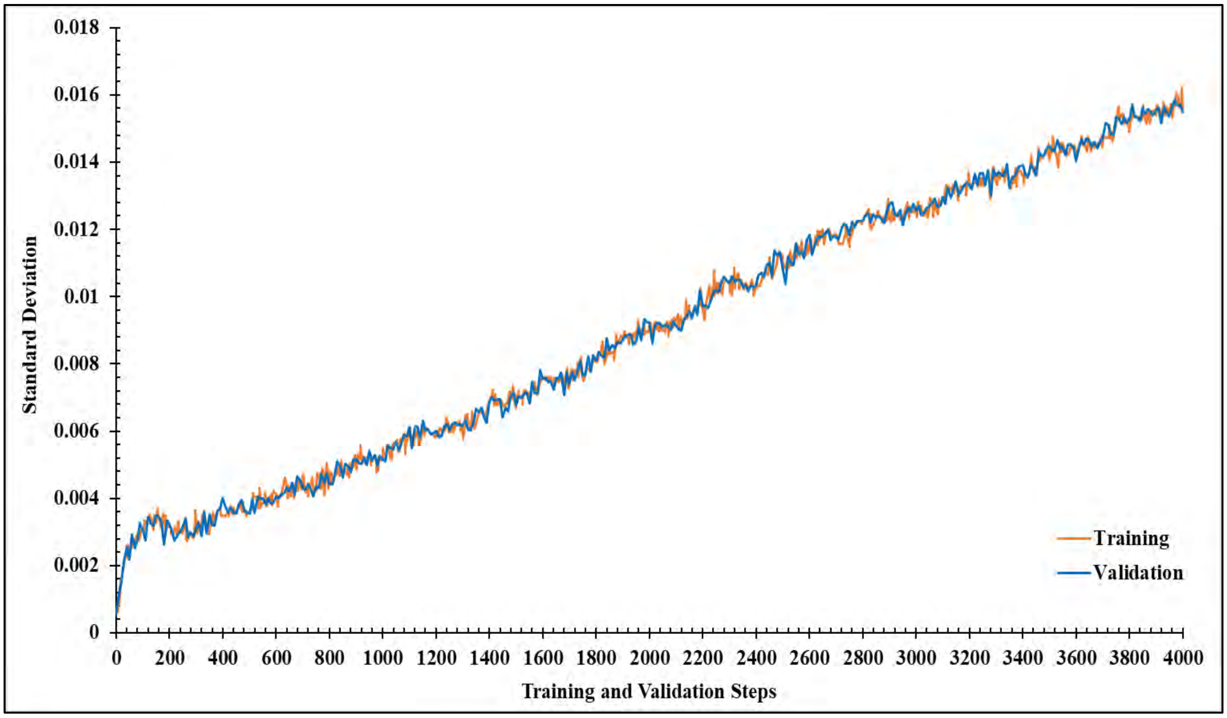


Figure 4.14 The Development of the Image Classifier Biases Over 4,000 Steps

4.4 Chapter Summary

The general research approach of this chapter was to develop image classifiers. These classifiers were mainly developed based on the implementation of the Inception-v3 model in TensorFlow. This study created artificial intelligence classification tools for detecting and classifying corrugation and traffic-generated dust from gravel roads automatically, where the automatic detection of traffic-generated dust is still one of the most challenging tasks for local agencies due to heterogeneity characteristic of the factors related to gravel roads. This study demonstrated, for the first time, that TensorFlow can be used to develop an image classifier for detecting gravel road distress.

5. METHODOLOGIES FOR SELECTING GRAVEL ROADS MAINTENANCE STRATEGIES

5.1 Introduction

In Wyoming, local agencies own and manage over 13,000 miles of gravel roads. These roads formulate 90% of the entire local roads network in the state (Huntington & Ksaibati, 2009). Even though managing an asset of gravel roads can be a cost-effective preference for many local agencies, the amount of generated dust is considered a major flaw of these roads (Fay et al., 2016). Moreover, gravel roads in Wyoming are prone to frequent heavy truck traffic due to the various mineral and drilling activities. This additional heavy traffic impacts the structural capacity of these roads and increases the amount of generated dust enormously (Aleadelat & Ksaibati, 2017). Generally, researchers were incurious when it came to the management of gravel roads. Researchers were concerned more about how to set general guidelines or rules for managing these roads by investing minimal efforts (Mannisto & Tapio, 1990; Giummarra, 2000; Burger et al., 2007). For example, there are no specific comprehensive guidelines or methodologies available to help local agencies identify the best set of gravel roads that are ideal for dust treatment projects. Since local agencies are not able to treat all gravel roads under their jurisdictions, new methodologies, undertaking several factors, are required to select gravel roads for chemical treatment projects. Such a methodology, in addition to introducing a sort of systemization to the entire process, will help decision-makers in allocating the available funds efficiently, enhancing the planning process, and maximizing the reflected social welfare on the local economy.

As part of the WYT2/LTAP efforts to develop a gravel roads management system (GRMS), this research study developed multiple user-friendly tools, using mainly JavaScript, to implement optimization models based on genetic algorithms (GA). The developed tools will help decision-makers and local agencies in allocating the limited funds efficiently by reducing the overall amount of road distress over the entire gravel road network. The implemented optimization models consider different factors related to the road itself, such as the number of fines, average daily traffic (ADT), average driving speed, and moisture content. In addition, it considers other factors related to the surrounding environment, like mineral extraction activities, annual rainfall, average monthly temperatures, agricultural lands, and households. The developed tools can be simply operated by uploading a spreadsheet representing the required input data for the competing roads, which makes it more feasible to be used by small local agencies with limited expertise and resources.

5.2 Methodology

5.2.1 An Optimization Tool to Select Gravel Roads for Dust Chemical Treatment Projects Using Genetic Algorithms

5.2.1.1 Genetic Algorithm Outline

Genetic algorithms are robust search algorithms that simulate natural selection and evolution inspired by Darwinian evolutionary theory (Shiffman, 2012). Basically, GAs search for a set of solutions that meet a prior defined criterion (i.e., objective function) from an initial pool of solutions. Then, the found set of solutions is used to generate an offspring, which has better characteristics related to the objective function, depicting the natural selection process. The generation process will simulate the main three natural selection elements, which are heredity, variation, and selection (Fwa et al., 1994; Shiffman, 2012). The generation process will continue in the same fashion until the search process reaches an optimum solution for the defined objective function. This process is controlled by a predefined stopping criterion. For example, the process can be stopped when there is a smaller magnitude of improvement in the new offspring or if the algorithm has reached a certain predefined number of iterations. The general outlines of the GA adopted in this study are described as follows:

1. This study is based on a key assumption that chemically treating a gravel road will entirely eliminate dust by the next day after the treatment.
2. An objective function is identified to maximize the inclusive amount of reduced dust over the entire gravel road network and to maximize the environmental benefits gained from suppressing dust.
3. A binary coding system of 1's for treatment projects and 0's for non-treatment projects is followed to formulate chromosomes (i.e., potential solutions) with a length that is equal to the total number of roads competing for funds. Figure 5.1 shows a coding sample for a typical chromosome of 18 roads.
4. An initial pool of solutions (i.e., chromosomes) is randomly created to start the search and the natural selection process.
5. Each potential solution is evaluated in the means of its feasibility in accordance with the objective function. This process is called "Fitness Evaluation." For example, roads with a higher potential for generating dust will have higher fitness.
6. An offspring is created simulating the natural selection process.
7. The entire process is repeated until no or small change in fitness is reached within a defined time interval.

1	0	0	0	1	0	1	1	1	0	1	0	1	1	0	0	1	1

Figure 5.1 Coding Sample For A Set of Competing Projects (Chromosome)

5.2.1.2 Fitness evaluation

For every potential solution, the amount of dust that might be generated from each road is predicted using the EPA dust prediction equation (Equation 5-1) (EPA, 2006). The main goal is to select solutions with roads that have the highest potential of generating dust.

$$E = \left[\frac{1.8 \left(\frac{fines}{12}\right)\left(\frac{speed}{30}\right)^{0.5}}{\left(\frac{moisture}{0.5}\right)^{0.2}} - 0.00047 \right] * ADT * L$$

Equation 5-1 EPA Dust Prediction Equation

Where:

- *E* is the amount of generated dust (lbs)
- *fines* is the percentage of material passing sieve No. 200 (%)
- *speed* is the average driving speed over a gravel road (mph)
- *moisture* is the surface material water content (%)
- *ADT* is the average daily traffic reported on the road (Vpd)
- *L* is the total length of a road considered for treatment (miles)

Then, for each chromosome, the fitness is evaluated according to the following formula:

$$Fitness = \sum_{i=1}^{n} E_i * \left(a * \left(\frac{B}{C} \right)_i + b * Oil_i \right) * x_i$$
$$x_i \quad \in \{0, 1\},$$

Equation 5-2 Fitness Evaluation

where

- *n* is the total number of roads that are competing for chemical treatment projects;
- Oil is the oil production ratio of the county from the state production (i.e., to account for the mineral extraction activities at a specific region), and
- B/C is the benefit-to-cost ratio of treating a certain gravel road.

The B/C is used to account for the type of surrounding lands (i.e., agricultural lands or households) and calculated according to Equation 5-3. This equation is developed after incorporating the environmental damage costs related to gravel road dust. According to a previous study conducted by the WYT2/LTAP, the damage costs are $912/mile/year for the impacts on human health and $1,490/mile/year for the changes in crops yield. The impacts on livestock are minor and are neglected in this study (Aleadelat & Ksaibati, 2017). Accordingly, roads with more agricultural lands or households will have a higher weight. Then, 'a' and 'b' are introduced to the equation as weighting factors. These weighting factors will provide decision-makers with the ability, according to their discretion, to set higher weights to favor one of the two factors. It is well established that counties that have more oil production tend to receive more funds.

$$B/C_i = \quad (1490 * AgLength_i + 0.435 * 912 * HH_i)/(CT * L_i)$$

Equation 5-3 B/C Equation

where:

- AgLength is the total length of agricultural land on both sides of the road (miles).
- HH is the number of households that fall within a 984-ft. buffer on both sides of the road. According to (Aleadelat & Ksaibati, 2017), the effect of dust will reach up to 300 m (984 ft.) downwind of a road.
- CT is the approximate cost of applying chemical dust treatment ($/mile).

Since the roulette wheel selection method is adapted in the used GA, the actual fitness values are normalized using Equation 5-4. Where j is the total number of chromosomes in each generation and NF is the normalized fitness for each chromosome in the generation. This gives chromosomes with higher fitness a higher probability of being selected in the evolution process. Moreover, a uniform crossover approach is adopted to create offspring or new generations from previous chromosomes with high normalized fitness.

$$NF_i = \quad \frac{Fitness_i}{\sum_{i=1}^{j} Fitness_i}$$

Equation 5-4 The Actual Fitness Values

5.2.1.3 Objective functions and constraints handling

The optimization problem examined in this study deals with a single objective function that maximizes the inclusive amount of reduced dust over the entire gravel road network and the environmental benefits gained from suppressing dust. There are two constraints in this optimization problem. The first constraint is the total assigned budget. The second constraint is that any county submitting an application for CMAQ funds must receive some money. The optimization problem is summarized in the following equation:

$$\text{Maximise} \sum_{i=1}^{n} E_i*(a*\left(\frac{B}{C}\right)_i+b*Oil_i)*x_i;$$

$$\text{Subject to (5)}$$

$$\sum_{i=1}^{n} CT*L_i*x_i \quad \leq budget \quad ;$$

$$\textit{For each county:} \quad \sum_{i=1}^{m} CT*L_i*x_i > 0 \; ; x_i \quad \in \{0,\, 1\}$$

Equation 5-5 Optimization Problem

Where m is the total number of submitted gravel roads in a specific county. To handle infeasible solutions that have total costs which exceed the assigned budget or solutions that deny any county from funding, an adaptive penalty function is used according to Equation 5-6. This function uses the ratio between the actual cost of treating the selected projects and the total cost of treating the entire network to penalize the infeasible solutions. This way, fitness is linearly modified according to how far a solution is from a feasible one, which preserves the good features during the natural selection process. The same penalty function is used to penalize solutions that deny funding to any county.

$$Fitness = \begin{cases} \sum_{i=1}^{n} E_i*\left(a*\left(\frac{B}{C}\right)_i + b*Oil_i\right)*x_i; & Cost \leq budget \\ \sum_{i=1}^{n} E_i*\left(a*\left(\frac{B}{C}\right)_i + b*Oil_i\right)*P_i\;; & Cost \geq budget \end{cases}$$

$$P_i = 1 - \frac{\sum_{i=1}^{n} CT*L_i*x_i}{\sum_{i=1}^{n} CT*L_i}; \qquad x_i \in \{0,\, 1\}$$

Equation 5-6 Adaptive Penalty Function

5.2.1.4 Incorporating Weather Conditions

Weather conditions, especially rainfall and average temperatures, are one of the most important rational factors related to dust emissions. Additionally, using the actual water content at the road surface (see Equation 5-1) might be misrepresentative or misleading during the optimization process. The actual surface water content determined through lab testing is prone to variations, even for the same road, due to daily changes in weather or traffic conditions. Thus, approximations for the actual water content during the dry season (i.e., summer) are used. These approximations are estimated using the linear reservoir concept applied to every county separately. The variation of the amount of water in the soil (ds/dt) can be calculated using Equation 5-7 (Yoo et al., 1998).

$$\frac{ds}{dt} = input - output$$

Equation 5-7 The Variation of the Amount of Water In the Soil

The input represents the amount of rainfall and the output represents the loss due to evapotranspiration and surface runoff. The amount of evapotranspiration can be approximated using the Blaney–Criddle formula (Equation 5-8) (Brouwer & Heibloem, 1986). The rational method can be used to estimate the surface runoff (Equation 5-4) (UDFCD, 2017). The loss due to deep percolation is discarded for simplification purposes.

$$ET_o = p(0.46T_{mean} + 8)$$

Equation 5-8 Blaney–Criddle formula

$$Q = CIA$$

Equation 5-9 Peak Rate of Runoff (m3/day)

Where:

- ET_o is the average evapotranspiration rate for a period of a month (mm/day);
- T_{mean} is the mean daily temperature (Celsius);
- p is the mean daily percentage of annual daytime hours;
- Q is the peak rate of runoff (m3/day);
- C is the runoff coefficient—a non-dimensional coefficient;
- I is the average intensity of rainfall (m/day);
- A is the catchment area (m2).

The average regular meteorological data are obtained from the U.S. Climate Data website. Then, using a standard value for a gravel road dry density, which is 110 lb/ft3 (1762 kg/m3), an approximation for surface water content is calculated for each specific county. This way, moisture content will be a significant factor when comparing roads from different counties only. Figure 5.2 shows a map that represents the different water content estimations for all counties in Wyoming.

To confirm the reasonability of these water content estimations, Figure 5.3 shows a plot for the estimated and the actual water content measured at the site for some of the counties in Wyoming. It can be noticed that there is a reasonable agreement between both the estimated and the measured water contents.

Finally, all parts of this research methodology are put together using JavaScript and Hypertext Markup Language (HTML) to build an optimization tool that can be easily used by decision-makers and local agencies. The tool will be a webpage that can be hosted on the WYT2/LTAP website and be accessible to the public. This will keep the annotated programming code available for everyone for future modifications, enhancement, and even criticism. Figure 5.4 shows a screenshot of the initial version of the developed optimization tool.

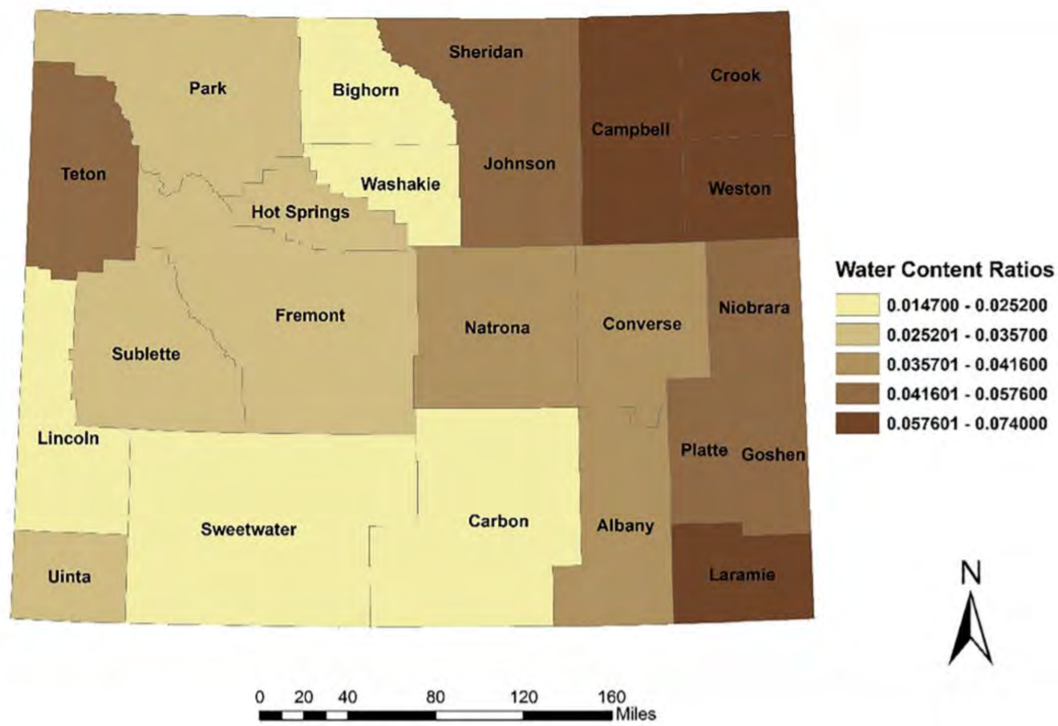


Figure 5.2 Water Content Estimation Map

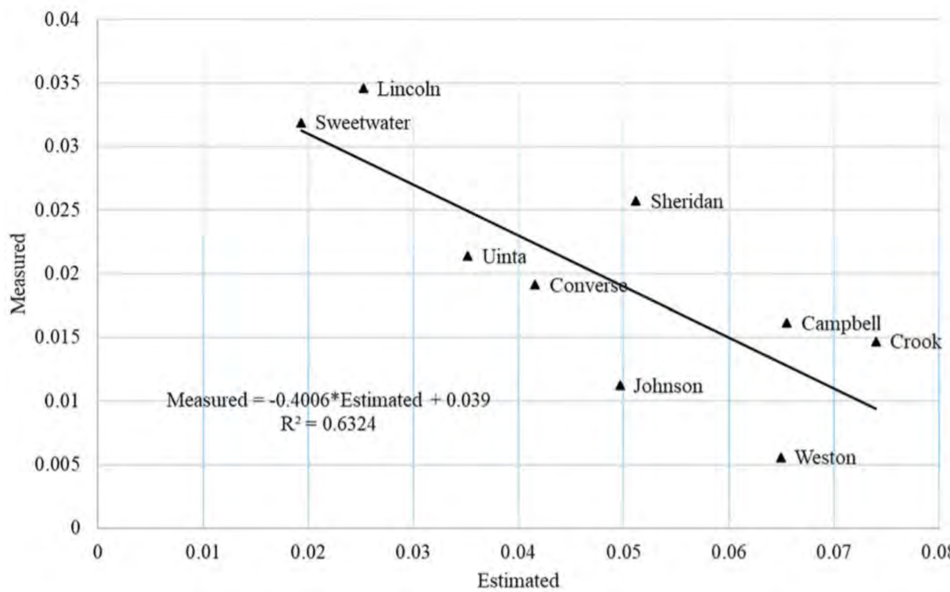
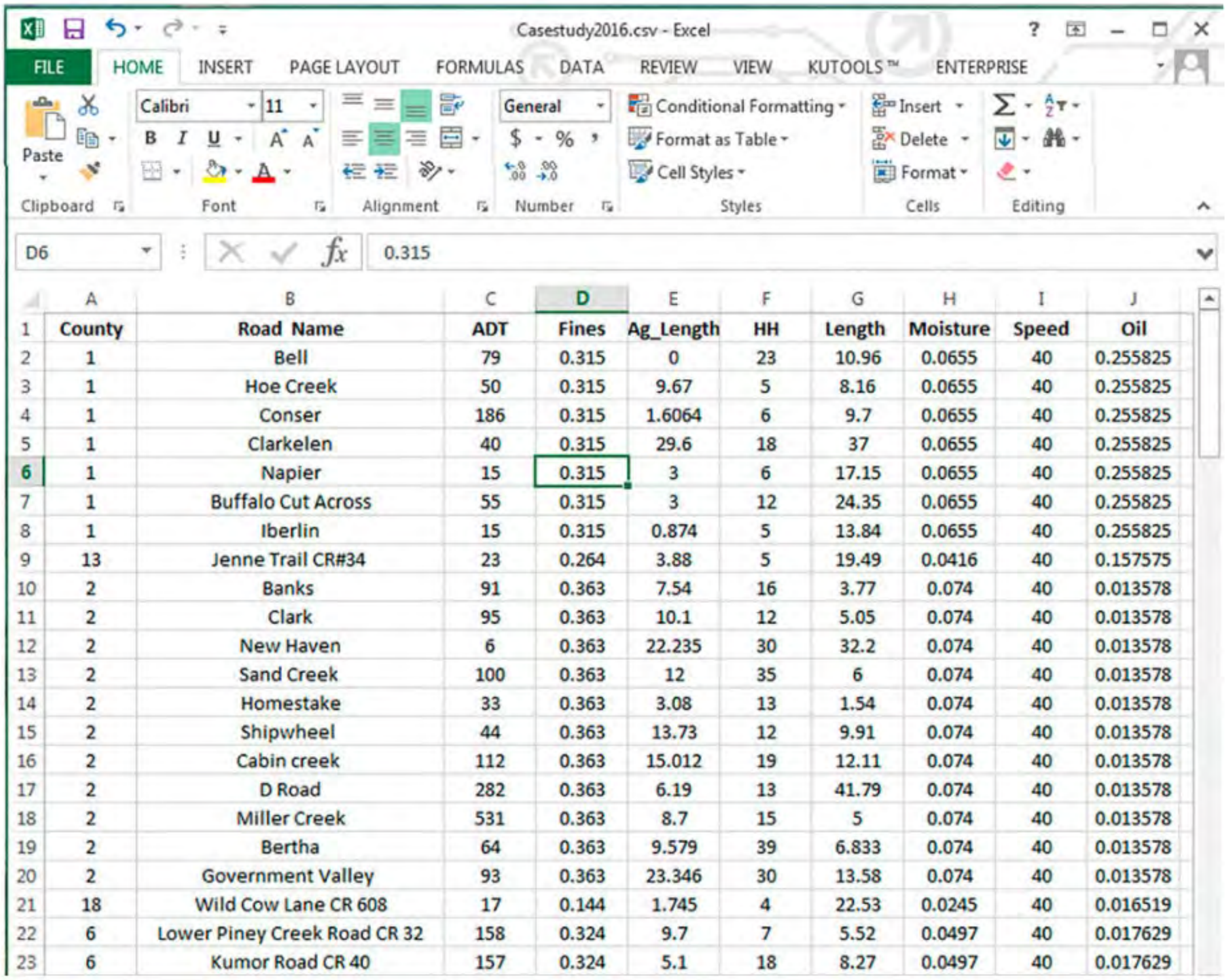


Figure 5.3 Estimated vs. Measured On-Site Water Content for Some Counties In Wyoming

Figure 5.4 A Screenshot for the Developed Optimization Tool

To run this tool, local agencies need to prepare a comma-separated values (CSV) sheet with the required parameters and upload it using this tool. In addition, some of the parameters related to the GA should be inputted. By trial and error, it is found that a mutation rate of 0.05 and a population size that is equal to the number of competing projects can yield the best results. However, any user should operate the tool with different parameters to cope with the stochastic nature of the GA. It is well known that higher mutation rates work well with smaller population sizes and vice versa (Haupt, 2000). Figure 5.5 shows a sample CSV sheet that can be used to run the tool. However, the sequence of the variables must be preserved as shown in Figure 5.5 (i.e., road name, ADT, fines %, etc.) for the tool to run correctly. For simplicity, a coding system is adapted to refer to the different counties. After running the tool, the optimization results can be displayed in a tabular format or in a histogram that displays the distribution of CMAQ funds among the different counties. Also, the results can be saved and downloaded directly in the same CSV format for further analysis.



	County	Road Name	ADT	Fines	Ag_Length	HH	Length	Moisture	Speed	Oil
2	1	Bell	79	0.315	0	23	10.96	0.0655	40	0.255825
3	1	Hoe Creek	50	0.315	9.67	5	8.16	0.0655	40	0.255825
4	1	Conser	186	0.315	1.6064	6	9.7	0.0655	40	0.255825
5	1	Clarkelen	40	0.315	29.6	18	37	0.0655	40	0.255825
6	1	Napier	15	0.315	3	6	17.15	0.0655	40	0.255825
7	1	Buffalo Cut Across	55	0.315	3	12	24.35	0.0655	40	0.255825
8	1	Iberlin	15	0.315	0.874	5	13.84	0.0655	40	0.255825
9	13	Jenne Trail CR#34	23	0.264	3.88	5	19.49	0.0416	40	0.157575
10	2	Banks	91	0.363	7.54	16	3.77	0.074	40	0.013578
11	2	Clark	95	0.363	10.1	12	5.05	0.074	40	0.013578
12	2	New Haven	6	0.363	22.235	30	32.2	0.074	40	0.013578
13	2	Sand Creek	100	0.363	12	35	6	0.074	40	0.013578
14	2	Homestake	33	0.363	3.08	13	1.54	0.074	40	0.013578
15	2	Shipwheel	44	0.363	13.73	12	9.91	0.074	40	0.013578
16	2	Cabin creek	112	0.363	15.012	19	12.11	0.074	40	0.013578
17	2	D Road	282	0.363	6.19	13	41.79	0.074	40	0.013578
18	2	Miller Creek	531	0.363	8.7	15	5	0.074	40	0.013578
19	2	Bertha	64	0.363	9.579	39	6.833	0.074	40	0.013578
20	2	Government Valley	93	0.363	23.346	30	13.58	0.074	40	0.013578
21	18	Wild Cow Lane CR 608	17	0.144	1.745	4	22.53	0.0245	40	0.016519
22	6	Lower Piney Creek Road CR 32	158	0.324	9.7	7	5.52	0.0497	40	0.017629
23	6	Kumor Road CR 40	157	0.324	5.1	18	8.27	0.0497	40	0.017629

Figure 5.5 Sample CSV Sheet for Running the Tool

5.2.1.5 Case Study

To validate the established optimization model associated with the developed tool, WYDOT CMAQ program officials provided the WYT2/LTAP with CMAQ funding applications and recommendations for the 2016 and 2017 fiscal years. Table 5.1 shows a summary of the proposed CMAQ projects. These data are inferred from the actually submitted applications and after matching the data with the actual geographical information system (GIS) maps available for gravel roads. This may result in reduced accuracy or errors for some of the obtained data compared with the actual data submitted by counties.

From Table 5.1, it can be noticed that CMAQ funds can cover only around 65% of the total requests by counties each year. This shows the severe competition for CMAQ funds each year by the different counties.

Table 5.1 A Summary for the Submitted CMAQ Funding Applications

Year	County	Number of roads	Length (miles)	Oil production (%)	Recommended funds by WYDOT ($)	Requested funds ($)
2016	Campbell	7	128.6	0.256	373,678.00	585,600.00
	Carbon	1	22.5	0.017	171,993.00	240,000.00
	Converse	1	19.9	0.158	469,050.00	836,000.00
	Crook	11	137.8	0.014	151,000.00	198,669.00
	Johnson	11	184.8	0.018	266,053.00	300,000.00
	Lincoln	56	254.9	0.004	281,988.00	400,000.00
	Sheridan	15	126.8	0.002	285,278.00	403,200.00
	Subtotal	102	875.4	0.470	1,999,040.00	2,963,469.00
2017	Campbell	12	123.2	0.230	380,000.00	564,000.00
	Crook	11	129.3	0.013	160,000.00	221,000.00
	Johnson	7	104.5	0.014	200,000.00	300,000.00
	Laramie	7	60.9	0.097	116,000.00	280,949.00
	Lincoln	11	62.2	0.004	280,000.00	688,000.00
	Sheridan	20	125.1	0.001	250,000.00	400,000.00
	Sweetwater	9	148.14	0.078	240,000.00	400,000.00
	Uinta	16	125.5	0.009	184,000.00	243,985.00
	Weston County	2	44.3	0.011	190,000.00	229,300.00
	Subtotal	95	923.1	0.460	2,000,000.00	3,327,234.00
Grand Total		197	1798.5	0.93	3,999,040.00	6,290,703.00

To run the tool and to perform the optimization, oil production rates for each county are obtained from the Wyoming Oil and Gas Conservation Commission (WOGCC). Google Earth maps and Wyoming agricultural land GIS maps are used to obtain the length of agricultural lands and the number of households adjacent to each road. Since the submitted CMAQ applications lack any ADT, fines, or speed data, several approximation approaches are adapted. For example, regression and logistic models developed at the WYT2/LTAP are used to predict the ADT data on the proposed gravel roads (Apronti et al., 2016). The output of these ADT prediction models is presented in GIS maps, available at the WYT2/LTAP website, for all gravel roads in Wyoming. Additionally, soil data obtained from the web soil survey (WSS) application are used to estimate the amount of fines (i.e., passing sieve No. 200) for a specific region according to the parent rock data (USSDA) (NRCS, 2009). This might be a very generic approach. However, the lack of any available data or resources makes it a feasible option, at least at this stage, to validate the established optimization model. The obtained data reflect the in situ fines content, which may give a reasonable representation of the nature of soil in every county. Table 5.2 shows some of the estimated fines content based on the available parent rock data for some Wyoming counties.

Table 5.2 Approximate Fines Content (%) Based on Parent Rock Data for CMAQ Counties

County	% Fines (Passing sieve No. 200)
Campbell	31.5
Carbon	14.4
Converse	32.4
Crook	36.3
Johnson	32.4
Lincoln	23.6
Sheridan	33.9
Laramie	33.9
Sweetwater	09.3
Uinta	31.9
Weston	34.0

Regarding average driving speed, there are no available data for gravel roads that can be related to driving speed. Furthermore, the street viewer of Google Maps is not available for such rural areas to inspect the posted speed limits. CMAQ roads mostly serve mineral/oil activities and they are expected to be in good driving condition most of the time. Hence, an assumption of 40 mph for the average driving speed is made for these roads. Nonetheless, actual data related to such roads are recommended to reflect the actual conditions and to provide more realistic prioritization within the proposed network. Additional research is recommended to validate these assumptions after local agencies begin the implementation of the proposed model and tools.

For both 2016 and 2017 fiscal years, the optimization results were obtained after running the tool using a budget of $2 million, a cost of treatment that equals $5,000 per mile, 100 as the initial population size, 0.05 as the mutation rate, and 2 minutes without improvement as the stopping criterion. Different optimization scenarios are proposed to show decision-makers how the different factors can influence the funding distribution and counties receiving funding. These scenarios are applied for both fiscal years 2016 and 2017. Table 5.3 shows the different optimization scenarios included in this case study.

Table 5.3 Different Optimization Scenarios

Scenario	Objective function	Budget
1	Maximise $\sum_{i=1}^{n} E_i * Oil_i$	\$ 2,000,000
2	Maximise $\sum_{i=1}^{n} E_i * (B/C)_i$	\$ 2,000,000
3	Maximise $\sum_{i=1}^{n} E_i * Oil_i * (B/C)_i$	\$ 2,000,000
4	Maximise $\sum_{i=1}^{n} E_i * ((B/C)_i + Oil_i)$	\$ 2,000,000
5	Maximise $\sum_{i=1}^{n} E_i * ((B/C)_i + 2.5 * Oil_i)$	\$ 2,000,000
6	Maximise $\sum_{i=1}^{n} E_i * ((B/C)_i + 5 * Oil_i)$	\$ 2,000,000

Figure 5.6 shows the optimization results for the 2016 fiscal year compared with the actual assigned funds by WYDOT. It can be noticed that different optimization scenarios allocate more funds for specific counties. For example, scenarios 1 and 3 allocate more funds to the high oil-producing counties like Campbell and Crook. However, Converse County (a high oil-producing county) received fewer funds as it submitted only one road for chemical treatment and it was fully funded. The same applies to Carbon County. Scenarios 2 and 4 allocate more funds to counties like Johnson, Lincoln, and Sheridan. These counties submitted roads that are located nearby residential areas or agricultural lands. Hence, they have more environmental damage due to gravel road dust, which explains their high funding opportunities according to these scenarios. Scenarios 5 and 6 appear to give the most balanced funding distributions among the different counties. These scenarios allocate funds to both high oil-producing counties and counties with high environmental impacts. Some counties like Johnson and Crook are not significantly affected by the different scenarios as their submitted roads have more environmental impacts, and these counties have reasonable oil production rates as well.

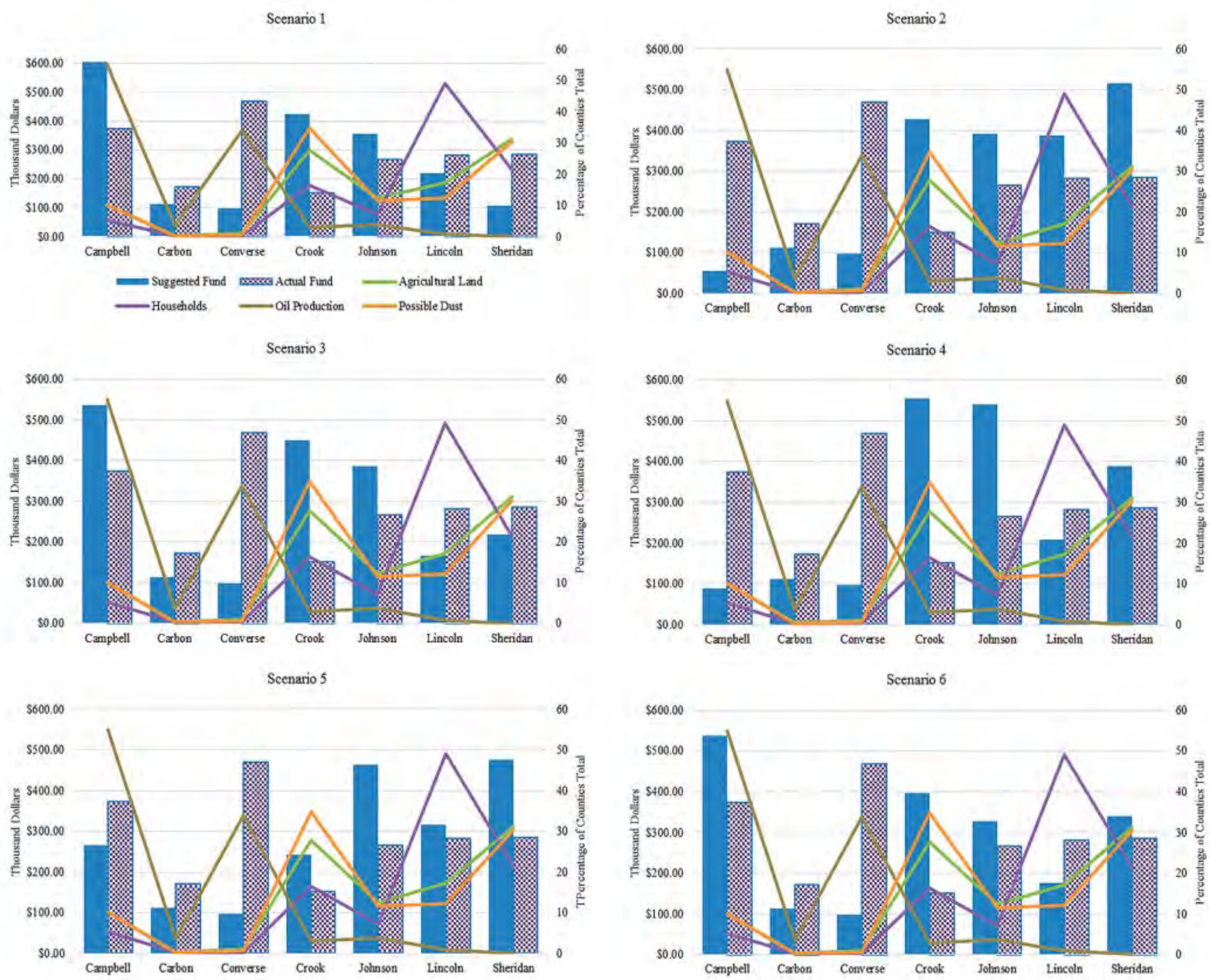


Figure 5.6 Optimization Results for the 2016 Fiscal Year

Figure 5.7 shows the optimization results for the 2017 fiscal year. The same trend noticed earlier in Figure 5.6 applies here. However, more counties submitted gravel roads for CMAQ funding. For example, Laramie County submitted roads that fall within household or agricultural land proximities and have a reasonably high oil production. Hence, it does not get affected significantly by the different scenarios.

In 2017, Campbell County submitted roads with high agricultural lands and households. Thus, Campbell County still gets a good share of funds even with scenarios that favor the environmental impacts, which contradicts what was noticed in 2016. Crook and Johnson Counties are still holding their positions in the comparison by submitting roads associated with high environmental impacts in addition to their reasonable oil production rates. Furthermore, an association between the amount of possible dust, households, and agricultural lands is noticeable among the different counties. More people and agricultural lands mean more traffic, which leads to more dust and more environmental impacts. On one hand, it can be concluded that counties with high oil production rates tend to submit roads that might be closer to oil production wells, which explain the low environmental damage costs (i.e., B/C ratios) associated with these roads. On the other hand, counties with lower oil production rates tend to submit roads that are within household and agricultural land proximities. Therefore, decision-makers should select the most appropriate scenario by weighting the different factors at hand. In other words, decision-makers may favor reducing the impacts resulting from the different mineral extraction activities, increasing the benefits gained by abating the environmental damages, or even both at the same time. This may require counties to reassess their road selection strategies for CMAQ projects. Hence, the importance of having a clear systematic process within an engineering basis can be appreciated. Actually, having a prior clear understanding of the funding procedures by counties can enhance the funding allocation process, increase the reflected welfare on the local economy, and imply general satisfaction among the different competing counties.

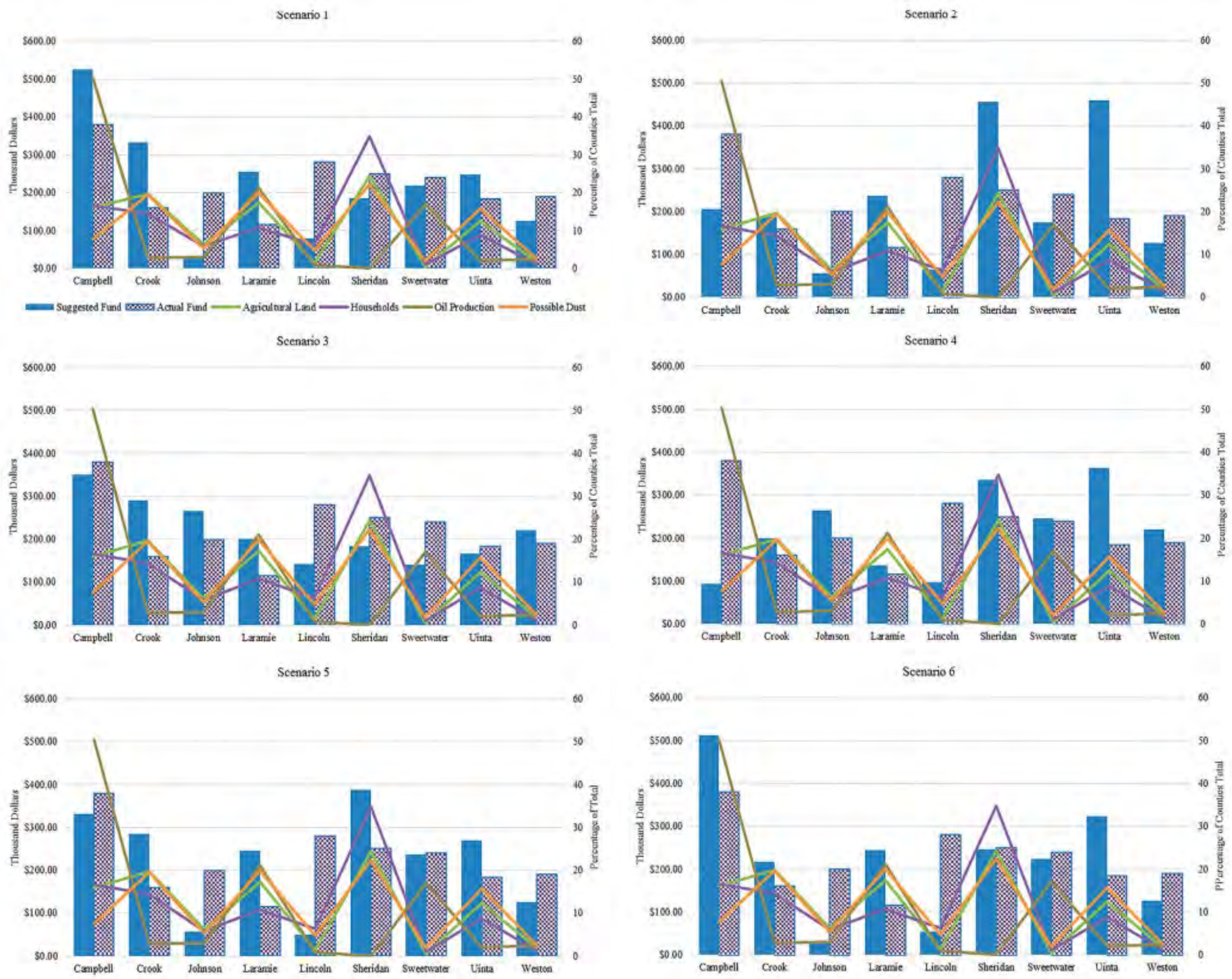


Figure 5.7 Optimization Results for the 2017 Fiscal Year

5.2.2 Developing an Optimization Tool for Selecting Gravel Roads Maintenance Strategies Using a Genetic Algorithm

This research study combines the outcomes of previous work on gravel roads conducted at the WYT2/LTAP into a useful optimization tool that can be easily used by local agencies in Wyoming. The main goal of this tool is to help local agencies define the most appropriate treatment type suitable for each gravel road under their jurisdiction. Additionally, the cost of applying such treatments, service level, and the potential road condition with or without applying a treatment will be estimated. This tool will help local agencies optimize their budgets by suggesting specific roads for maintenance and rehabilitation projects in a way that preserves the overall network condition. The following subsections describe this process.

5.2.2.1 Previous Work by WYT2/LTAP

Previous efforts by WYT2/LTAP resulted in the development of a stepwise algorithm for selecting the most appropriate treatment for any gravel road. This stepwise algorithm is shown in Figure 5.8.

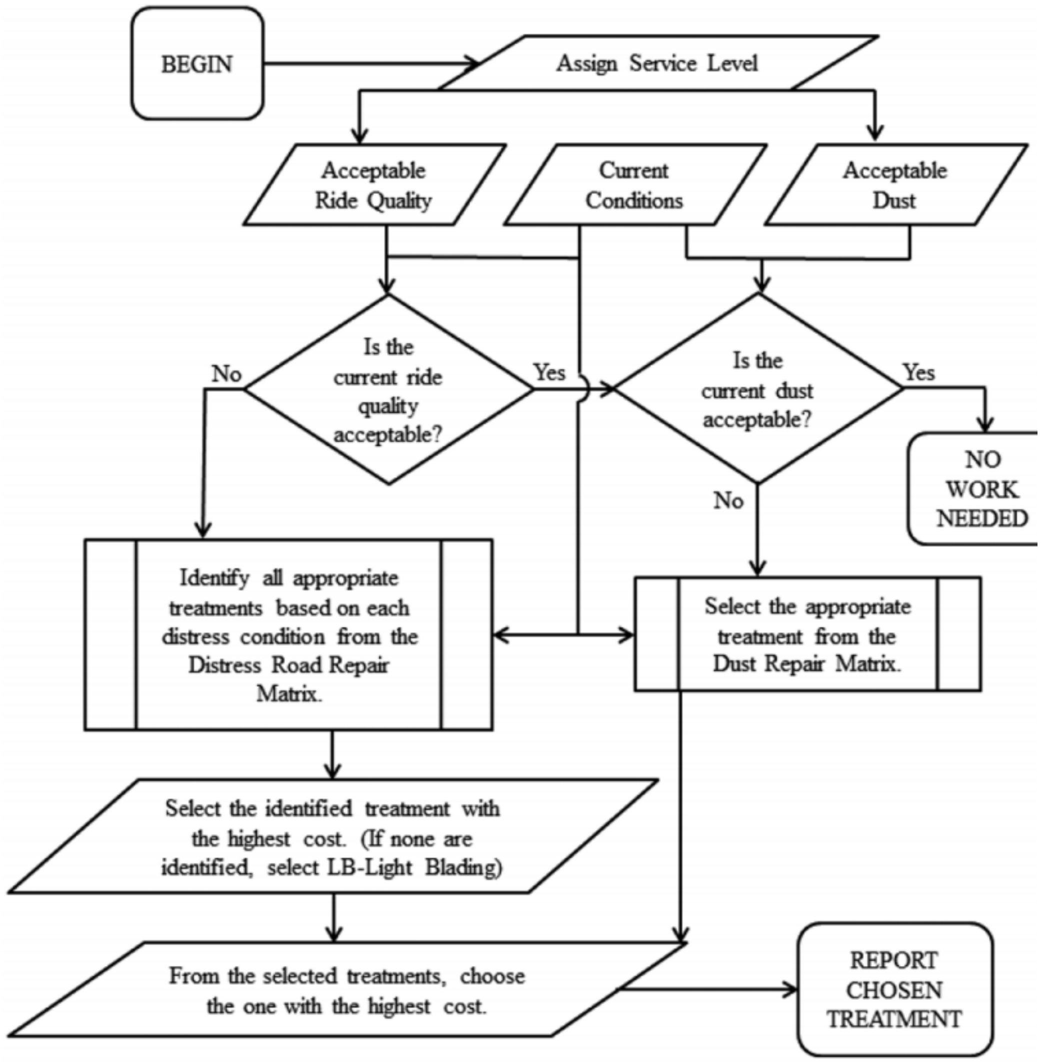


Figure 5.8 WYT2/LTAP Algorithm for Selecting the Best Maintenance Practice (Huntington & Ksaibati, 2011)

According to this algorithm, an agency must first assign a specific service level for each gravel road. The assigned service levels are based on traffic volume and average road width as follows:

- Very high: ADT greater than 400 vehicles per day (vpd) with a top width greater than 28 ft.
- High: ADT of 151–400 vpd with a top width of 23–27.5 ft.
- Medium: ADT of 51–150 vpd with a top width of 18–22.5 ft.
- Low: ADT of 16–50 vpd with a top width of 13– 17.5 ft.
- Very low: ADT of 5–15 vpd with a top width of 9– 12.5 ft.
- None: ADT less than 5 vpd with a top width less than 8.5 ft.

The different distresses of the road surface should then be evaluated according to the Gravel Roads Rating Standards (GRRS) manual. This also includes evaluating dust, cross-section, and drainage conditions. Each road should be rated for the overall ride quality in accordance with the Ride Quality Rating Guide (RQRG) manual. Both manuals represent inexpensive windshield surveys used regularly by local agencies in Wyoming to evaluate the conditions of their gravel roads.

The RQRG and the GRRS are modifications of the Pavement Surface Evaluation and Rating (PASER) system. The RQRG system rates gravel roads based on ride quality on a scale from 1 (failed) to 10 (excellent). The distresses included in the GRRS and their scale of rating are shown in Figure 5.9. For all conditions, a higher rating means a better condition. Both surveys were used to evaluate gravel roads in this study.

Figure 5.9 GRRS Distresses and their Scale of Rating

The defined service level and the different distress ratings are combined and used together to select a suitable treatment for each distress type, as shown in Table 5.4. For each road, a treatment type is selected according to its service level and distress condition. The most expensive treatment among all the required treatments will be the most appropriate treatment for that road. This way, the structural integrity of the road will be preserved. The different costs of each treatment type are shown in Table 5.5. These costs were estimated after consulting with representatives from many Wyoming counties. The potential improvement in the condition of a gravel road after applying a certain type of treatment is estimated using the improvement matrix shown in Table 5.6. If there is no treatment, or the applied treatment does not improve specific distress, the condition should be estimated according to gravel roads performance models.

The developed performance models included all seven possible deterioration modes of gravel roads according to WYT2/LTAP as shown in Table 5.7. These models were developed based on the Markovian process. According to these models, the performance score of any road segment will drop significantly if it is left without maintenance interference for 12 months.

Table 5.4 Decision Matrix for Gravel Roads Maintenance by Types of Distress (Huntington et al., 2013).

Condition	Service level: Very high	High	Medium	Low	Very low	None
			Cross-section/crown			
Poor	HB	HB	HB	HB	LB	N
Fair	LB	LB	LB	LB	N	N
Good	N	N	N	N	N	N
			Roadside drainage			
Poor	RC	RC	DR	DR	HB	N
Fair	DR	DR	HB	HB	N	N
Good	N	N	N	N	N	N
			Rutting			
Failed	RC	RC	RC	RG	HB	N
Very poor	RC	RC	RC	RG	HB	N
Poor	RC	RG	HB	HB	LB	N
Poor	RG	HB	LB	LB	N	N
Fair	HB	LB	N	N	N	N
Fair	LB	N	N	N	N	N
Good	N	N	N	N	N	N
Good	N	N	N	N	N	N
Very good	N	N	N	N	N	N
			Potholes			
Failed	RC	RC	RC	RG	HB	N
Very poor	RC	RC	RC	RG	HB	N
Poor	RG	RG	RG	HB	LB	N
Poor	RG	HB	HB	LB	N	N
Fair	HB	HB	LB	N	N	N
Fair	LB	LB	N	N	N	N
Good	N	N	N	N	N	N
Good	N	N	N	N	N	N
Very good	N	N	N	N	N	N
			Loose aggregate			
Failed	RG	RG	RG	RG	RG	N
Very poor	RG	RG	RG	RG	RG	N
Poor	RG	TG	TG	TG	HB	N
Poor	TG	TG	TG	HB	N	N
Fair	TG	HB	HB	N	N	N
Fair	HB	N	N	N	N	N
Good	N	N	N	N	N	N
Good	N	N	N	N	N	N
Very good	N	N	N	N	N	N
			Corrugations/washboard			
Failed	RG	RG	RG	RG	RG	N
Very poor	RG	RG	RG	RG	RG	N
Poor	RG	RG	TG	RG	N	N
Poor	RG	TG	TG	N	N	N
Fair	TG	TG	TG	N	N	N
Fair	TG	TG	N	N	N	N
Good	N	N	N	N	N	N
Good	N	N	N	N	N	N
Very good	N	N	N	N	N	N
			Dust			
High	RG	RG	RG	N	N	N
Medium	TG	TG	N	N	N	N
Low	N	N	N	N	N	N
None	N	N	N	N	N	N

Note: N = do nothing; LB = light blading; HB = high blading; TG = treating gravel/dust control; DR = major drainage repair; RG = re-graveling or building up the road; RC = reconstruction/rehabilitation.

Table 5.5 Gravel Roads Maintenance Treatments and Costs (Saha & Ksaibati, 2017)

Treatment type	Cost/yard^2	Cost/mile
Do nothing (N)	$ 0	$ 0
Light blading/routine maintenance (LB)	$ 0.014	$250
Heavy blading/reshaping ditch/pulling shoulders (HB)	$ 0.071	$1,250
Treating gravel/dust control (TG)	$ 0.36	$5,000
Major drainage repair (DR)	$1.07	$15,000
Regravel/building up road (RG)	$2.84	$50,000
Reconstruction/rehabilitation (RC)	$14.21	$200,000

Table 5.6 Improvement Matrix for Gravel Roads

Distress/treatment type	N	LB	HB	TG	DR	RG	RC
Potholes	P*	6	7	8	8	9	9
Rutting	P	6	7	8	8	9	9
Loose aggregate	P	6	7	8	8	9	9
Corrugations/washboard	P	6	7	8	8	9	9
Dust	P	P	P	4	P	4	4
Crown	P	3	3	3	3	3	3
Drainage	P	P	3	3	3	3	3

Note: P*: Condition will be according to the performance models. N = do nothing; LB = light blading; HB = high blading; TG = treating gravel/dust control; DR = major drainage repair; RG = re-graveling or building up the road; RC = reconstruction/rehabilitation.

Table 5.7 Performance Models for Gravel Roads (Aleadelat et al., 2019)

Distress index	Model
Potholes	$Y = -0.0008X^3 + 0.0504X^2 - 1.0632X + 9$
Rutting	$Y = 0.000005X^4 - 0.0006X^3 + 0.027X^2 - 0.645X + 9$
Corrugations/washboard	$Y = -0.0009X^3 + 0.0524X^2 - 1.0641X + 9$
Loose aggregate	$Y = 0.0000005X^4 - 0.0001X^3 + 0.0083X^2 - 0.33X + 9$
Dust	$Y = 0.00002X^3 - 0.0012X^2 - 0.0398X + 4$
Crown	$Y = 0.00003X^3 - 0.0017X^2 - 0.0392X + 3$
Drainage	$Y = 0.00003X^3 - 0.0017X^2 - 0.0392X + 3$

Note: Y = condition index (points); X = time in months.

5.2.2.2 Objective Function and Constraints Handling

For every potential solution, the fitness was evaluated according to the following equation:

$$\text{Fitness} = \sum_{i=1}^{n} \frac{\text{OC}_i{}^* l_i{}^* \text{ADT}_i}{\sum_{i=1}^{n} l_i} * x_i; x_i \in \{0, 1\}$$

Equation 5-10 Fitness Evaluation

Where

- n is the total number of gravel roads in the network;
- OC_i is the sum of all GRRS ratings for gravel road (i);
- ADT_i is the ADT (vpd) for gravel road (i); and
- l_i is the length of gravel road (i).

The objective of this work is to maximize the overall network conditions considering the assigned service levels for every road. The objective function of the optimization problem under study is shown in Equation 5-11.

$$\text{Maximize} \sum_{i=1}^{n} \frac{\text{OC}_i{}^* l_i{}^* \text{ADT}_i}{\sum_{i=1}^{n} l_i} * x_i; x_i \in \{0, 1\}$$

Subject to:

$$\sum_{i=1}^{n} \text{CT}_i{}^* L_i{}^* x_i \leq \text{budget}; x_i \in \{0, 1\}$$

Equation 5-11 The Objective Function of The Optimization Problem

where CTi represents the average cost of the selected treatment according to Table 5.7. There is only one constraint in this optimization problem, which is budget. To handle infeasible solutions with costs that exceed the assigned budget, an adaptive penalty function is used according to Equation 5-12. This function uses the ratio between the actual cost to maintain the selected projects in a solution and the total cost of maintaining the entire network to penalize the infeasible solutions. This guarantees the transformation of the good features to the new offspring during the evolution process.

$$\text{Fitness} = \begin{cases} \sum_{i=1}^{n} \frac{\text{OC}_i{}^* l_i{}^* \text{ADT}_i}{\sum_{i=1}^{n} l_i} * x_i; \text{Cost} \leq \text{budget} \\ \sum_{i=1}^{n} \frac{\text{OC}_i{}^* l_i{}^* \text{ADT}_i}{\sum_{i=1}^{n} l_i} * P_i; \text{Cost} \geq \text{budget} \end{cases};$$

$$P_i = \frac{\sum_{i=1}^{n} \text{CT}_i{}^* L_i{}^* x_i}{\sum_{i=1}^{n} \text{CT}_i{}^* L_i}; x_i \in \{0, 1\}$$

Equation 5-12 Adaptive Penalty Function

Finally, all the parts of this research methodology were combined and implemented under the GA framework using JavaScript and HTML programming languages to build the optimization tool. This tool can be easily used by decision-makers or local agency engineers by uploading a comma-separated values (CSV) sheet that has all the required parameters. The tool will be a webpage that can be hosted on the WYT2/LTAP website and be freely available on the internet. This will keep the annotated programming code available for future modifications, enhancement, and even criticism, by any user.

Figure 5.10 shows a screenshot of an initial version of the developed tool. The optimization results can be displayed in a tabular format or in a histogram that displays the distribution of funds among the different treatment practices. The results can be saved and downloaded directly in the same CSV format for further analysis. The tabular results will include detailed information specific to each road, such as service level, required treatment type, estimated project cost, potential road condition, and whether to assign funds or not. Nonetheless, the user should be aware of the stochastic nature of the implemented algorithm. Any user should operate the tool with different parameters multiple times to cope with this stochastic nature. It is well known that higher mutation rates work well with smaller population sizes, and vice versa (Haupt, 2000).

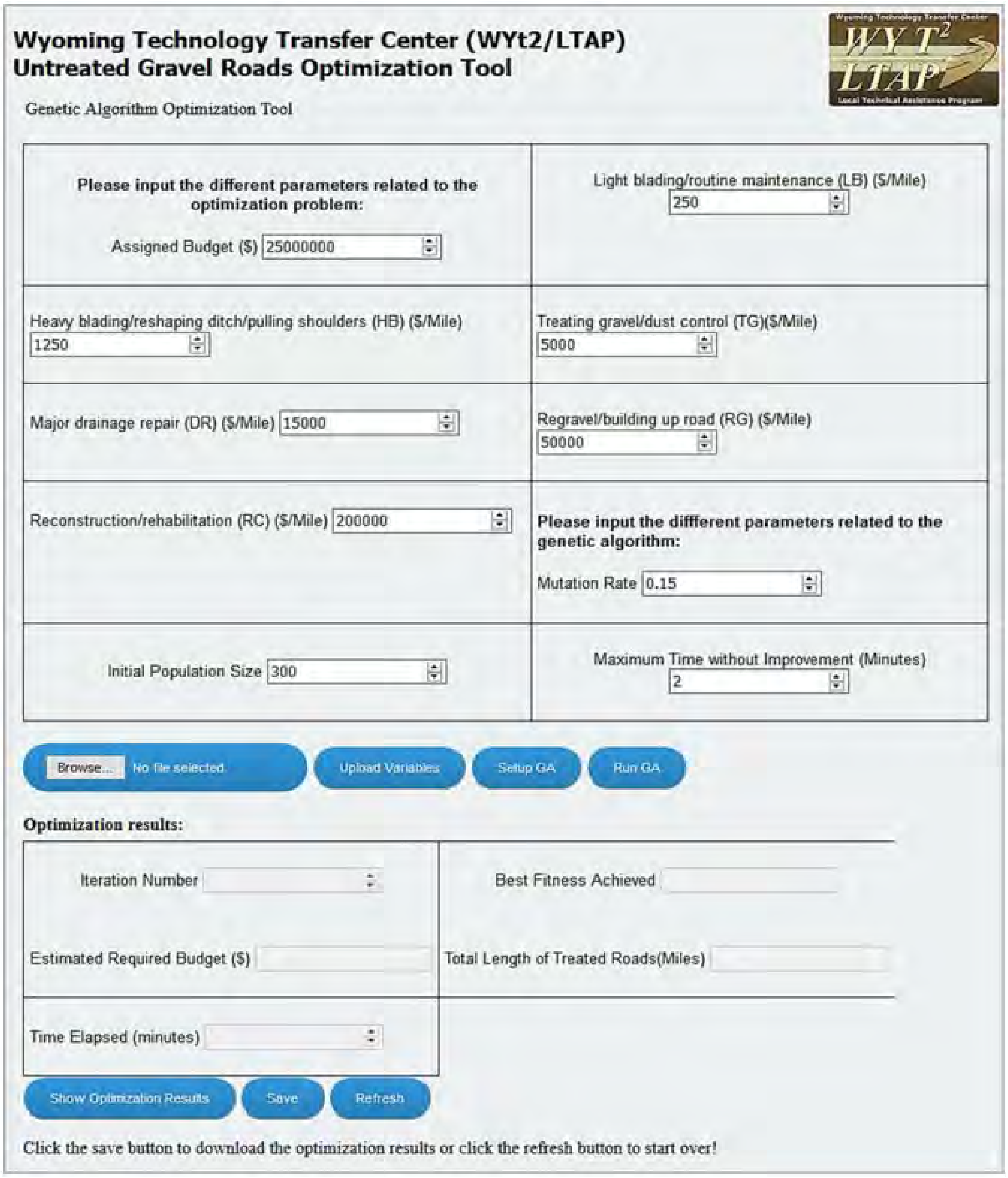


Figure 5.10 Screenshot of the Optimization Tool

5.2.2.3 Laramie County

To validate the optimization model and the developed tool, Laramie County was selected to perform a pilot study prior to statewide implementation. Laramie County has approximately 700 gravel road segments with a total length of 1,200 miles. To run the tool and to perform the optimization on Laramie County, all these gravel roads were evaluated according to the GRRS and RQRG manuals. Evaluating gravel road conditions all over these segments included two major tasks: road segmentation and surface evaluations. These two tasks are described in more detail in the following subsections:

Road Segmentation

To obtain uniform, consistent, homogeneous, and more representative ratings, gravel roads were divided into smaller subsegments. This segmentation process was accomplished on-site during the rating process. Larger gravel roads were divided into smaller segments based on many considerations, such as usage levels, changes in the surface type, intersections, surface conditions, and sometimes the type of surroundings (i.e., crops or houses). The GPS coordinates of the beginning and endpoints of all gravel road segments were provided by the Wyoming Department of Transportation (WYDOT). These coordinates were uploaded into Microsoft Streets and Trips software for the actual identification of these roads on-site. Later, the same software was used during the segmentation process to record the GPS coordinates of the new subsegments for future reference.

Surface Evaluation

In the summer of 2017 one team of two trained raters spent two months driving over all the gravel roads in Laramie County and performed the rating process according to the RQRG and GRRS systems. Because of the varied nature of the gravel roads, the driving speed was variable from road to road and even within some road segments. However, the raters did not exceed the posted speed limits and tried to maintain normal driving conditions. Two vehicles, a 2010 Ford (F-150) pickup truck and a 2010 Chevrolet Suburban SUV, were used to perform the surface evaluation process. These vehicles were selected as the majority of Wyoming residents tend to drive similar vehicles because of the severe weather and road conditions in the state. Regarding ADT estimates, regression and logistic models developed by WYT2/LTAP were used to predict the ADT data on the proposed gravel roads. The output of these ADT prediction models is presented in GIS maps, available at the WYT2/LTAP website, for all gravel roads in Wyoming. Additionally, approximations of the current top surface widths were obtained from Google Earth maps. The evaluation results are described briefly in the following subsection.

Current Conditions of Gravel Roads in Laramie County

Figure 5.11 shows the results of the surface evaluation of gravel roads in Laramie County as of summer 2017. Overall, it can be noticed that the majority of these roads are in fair to good condition; approximately, just 2% of these roads are in failure condition. Almost the same percentage of roads (2%) are in the very good category. Loose aggregate conditions are the best, compared with the other distresses, with almost 96% of the gravel roads evaluated within the fair or good categories. When it comes to dust, approximately 57% of the gravel roads generated very high dust compared with just 7% with no or very low dust. About 81% of the gravel roads had good cross-section or crown conditions, and similarly, for roadside drainage conditions, about 82% of the gravel roads were in the good category.

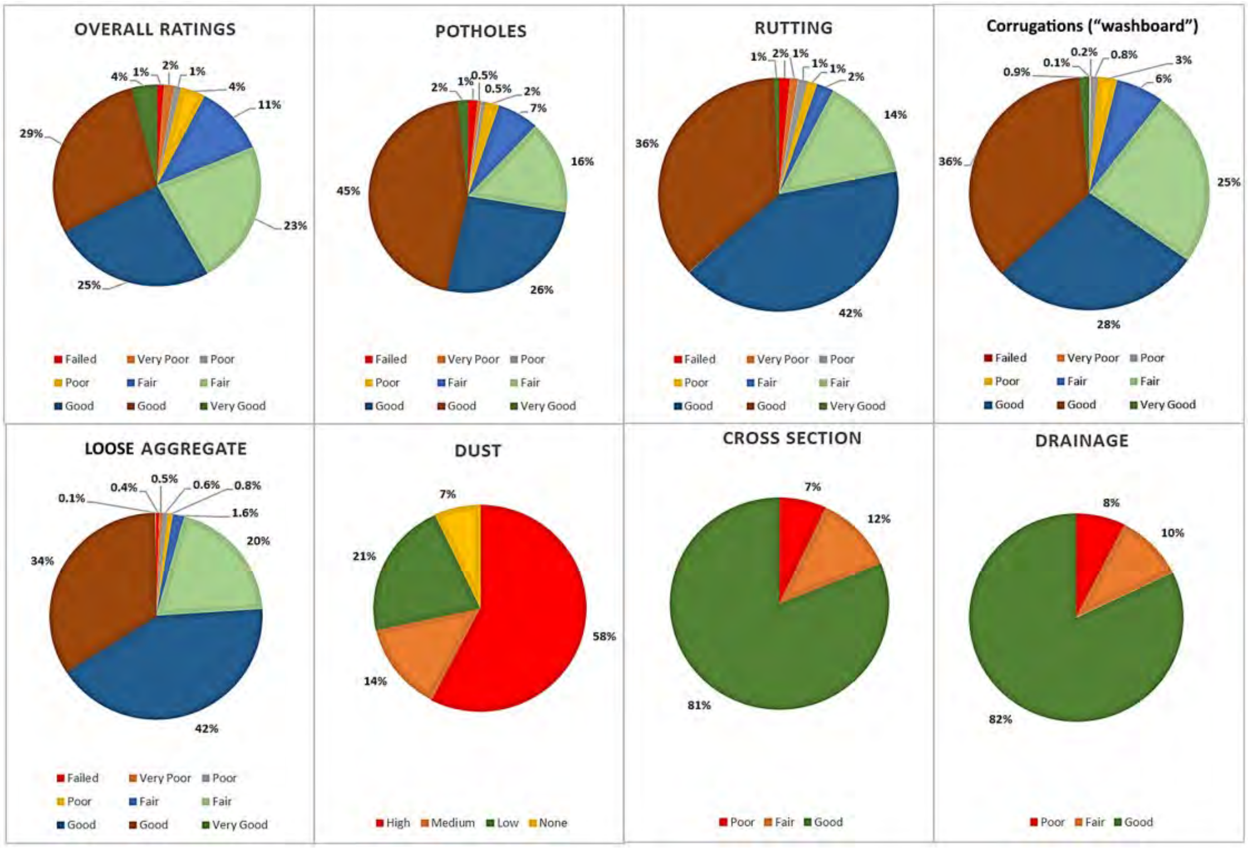


Figure 5.11 Condition Of Laramie County Gravel Roads As Of Summer 2017

Optimization Results

The optimization process started by combining all the required inputs for all gravel roads in Laramie County in a single CSV sheet. This CSV sheet was uploaded to run the optimization model using the developed tool. Different budgets were used to perform a sort of sensitivity analysis to determine a critical budget for Laramie County. Figure 5.12 shows the sensitivity analysis results. It can be noticed that, at $5.15 million, there is an obvious decrease in the slope and the improvement in fitness decreases considerably. Thus, the $5.15 million value can be considered a critical budget. After spending more than $5.15 million, the network conditions will not improve significantly. The anticipated overall improvement in the network condition compared with the actual conditions is about 15% after spending the critical budget. For the purposes of this analysis, the GA was run using a population size of 300, a mutation rate of 0.15, and a duration of 3 minutes without improvement as stopping criteria. It took approximately 15 minutes for the algorithm to converge and generate each solution.

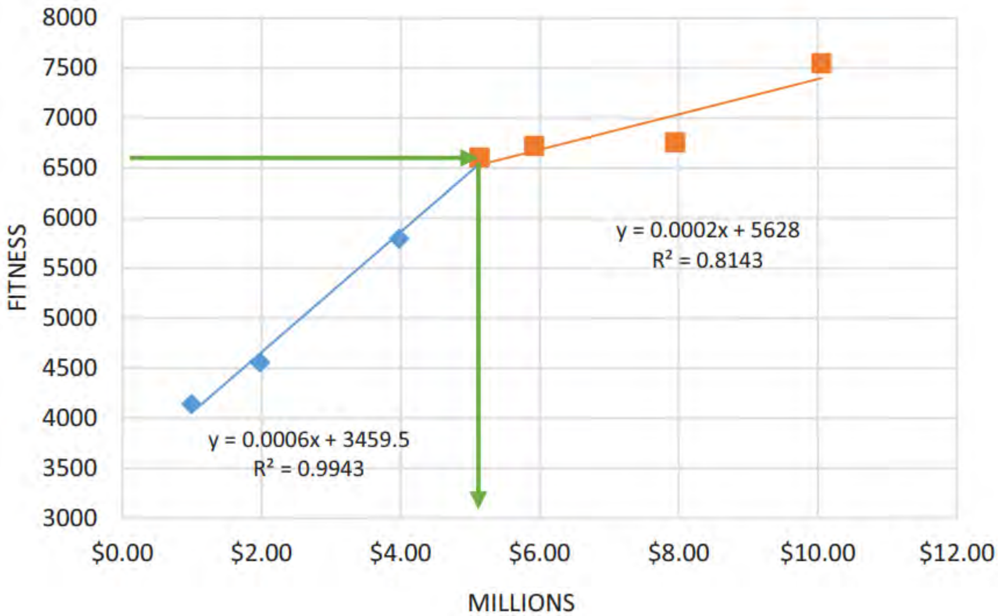


Figure 5.12 Budget Sensitivity Analysis According to the New Decision Matrix

Figure 5.13 shows the assignment of the different service levels in Laramie County based on the optimization results after running the tool. It can be noticed that the majority of gravel roads in Laramie County have high and medium service levels (69%). Just 20% of these roads serve no or low traffic volumes. This means that the majority of these gravel roads will have high ride quality requirements to fulfill such high traffic demands. To maximize the overall network conditions and to improve the provided ride quality, Laramie County should focus its investments on gravel roads that serve medium and high traffic volumes. As a result, the majority of the funded projects were for roads within medium and high service levels.

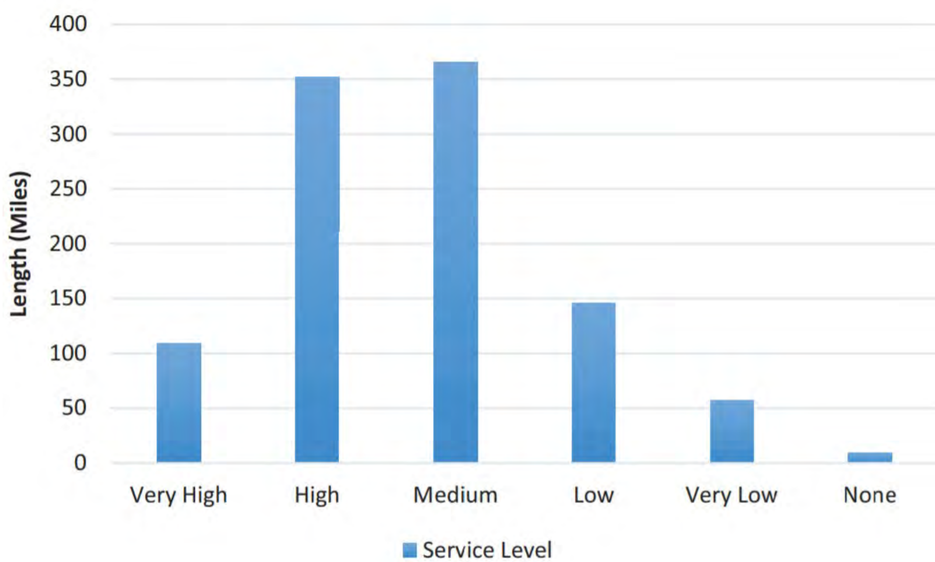


Figure 5.13 Service Levels of Gravel Roads in Laramie County

Furthermore, the implementation of a cost-effective treatment like TG can significantly increase the effectiveness of the adopted GRMS. In Wyoming, it was proven that using chemical suppressants is very efficient in abating dust, is economical, and can improve the ride quality enormously (Aleadelat & Ksaibati, 2017). The implementation of dust chemical treatments can increase the likelihood of creating a larger number of roads and abating the impacts of dust simultaneously, as shown in Figure 5.14. This figure shows the distribution of the various treatments over the road network. TG is the major applied type of treatment among the other six treatments, covering almost 480 miles of gravel roads. The majority of RG projects will be because of corrugated (''washboard'') conditions or loose aggregate. Regardless of the fact that RC is the most expensive treatment, it was not a preference for maintaining many roads. This can be attributed to the overall good conditions of Laramie gravel roads that serve medium to very high traffic. These conclusions are in line with a previous study conducted by WYT2/LTAP to mitigate the impacts of oil and gas vehicle traffic on gravel roads (Huntington et al., 2013).

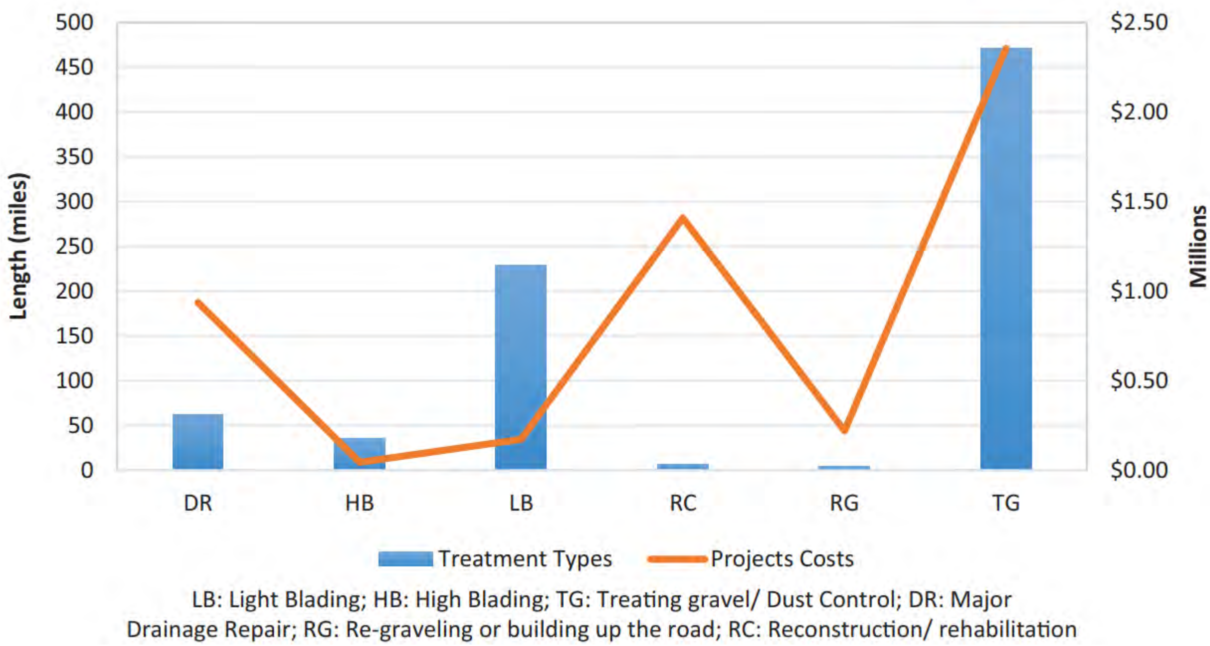


Figure 5.14 Treatment Type versus Budget

Table 5.8 shows a summary of the analysis performed on Laramie County gravel roads. From this table, it is obvious that defining the way to mitigate dust on gravel roads is the main influencing factor in managing gravel roads in Wyoming. It is apparent that using dust suppressants is efficient, cost-effective, and suitable for local agencies. It can also be noted that the implementation of other dust mitigation strategies (i.e., re-graveling) can achieve more improvement to the overall network condition. However, chemically treating gravel roads can be preferable in providing the ability to manage more roads, which means more funded projects. This in turn can help to promote a sense of general satisfaction among the local populace who reside next to these roads, by treating many roads and providing reasonable improvements to the network on a minimal realistic budget at the same time.

Table 5.8 Modified versus Original Treatment Decision Matrix

Criterion	Value
Budget to maintain all roads ($)	10,056,258
Critical budget ($)	5,150,000
Length of selected roads (miles)	810
Improvement in network (%)	15
Number of projects	507
Major treatment	Treating gravel/ dust control (TG)
Reconstruction projects (miles)	7
Treatment projects (miles)	471.3
Re-graveling projects (miles)	4.4

5.2.3 Development of Performance Prediction Models for Gravel Roads Using Markov Chains

5.2.3.1 Introduction

One of the main goals of this phase is to develop an optimization tool that can help decision-makers at the local level in managing limited budgets and in selecting gravel roads for maintenance and rehabilitation (M&R) projects. The tool, which has been developed, implements an optimization model that works on maximizing the overall gravel road network conditions considering traffic volumes and subject to limited budgets. It is well known that the estimation of a gravel road potential service life is one of the integral parts of any maintenance assignment process. Therefore, this phase developed performance prediction models for gravel roads in Wyoming. Such prediction equations provide a mathematical representation of how a gravel road in Wyoming may deteriorate over time.

In addition to the general lack of the available GRMS that are tailored to suit the needs of small local agencies, research efforts are more designated toward solving specific issues related to managing gravel roads within the premise of the developing agency. This explains the importance of establishing specific rules, guidelines, and models that are designated for Wyoming gravel roads rather than following the generic practices available in the literature.

5.2.3.2 Case Study: Laramie County

Laramie County is located in the southeastern part of the state of Wyoming. In this county, there are about 700 gravel roads with a total approximate length of 1,931 km (1,200 miles). This county was selected to perform a pilot study prior to the statewide implementation of the new GRMS. One team spent two months performing fieldwork in Laramie County and evaluated the entire gravel road network during the summer of 2017. This intensive data collection effort resulted in a comprehensive dataset that is used to build the performance prediction models and ultimately the GRMS. The following subsections describe the data collection process and the current network conditions.

Surface Evaluation

The WYT2/LTAP utilizes inexpensive, less labor-intensive windshield surveys, such as GRRS and RQRG, to evaluate gravel road conditions. The RQRG reflects the perceptions of roads users with regard to the driving quality of gravel roads. Figure 5.9 shows a brief description of the RQRG system. This system rates gravel roads on a scale from 1 (failed) to 10 (excellent) and it is more affected by surface deformation modes like potholes, washboards, and rutting.

Laramie Gravel Road Conditions

Figure 5.15 illustrates the evaluation results of gravel roads in Laramie County. From the figure, it can be noted that 75% of the roads are found to be in fair to good overall condition, and only 1% of the roads are in failure condition. It is apparent from this figure that the loose aggregate conditions represent the best condition compared with the other distresses, with 96% of the roads falling in the fair to the good categories. On one hand, the evaluation results show that the majority of Laramie County gravel roads (57%) generate very high dust. On the other hand, only 27% of these roads have no or very low dust emissions. Generally, gravel roads in Laramie County have good cross-section or crown conditions, as 81% of these roads fall in the good category. Similarly, 82% of these roads have good drainage conditions.

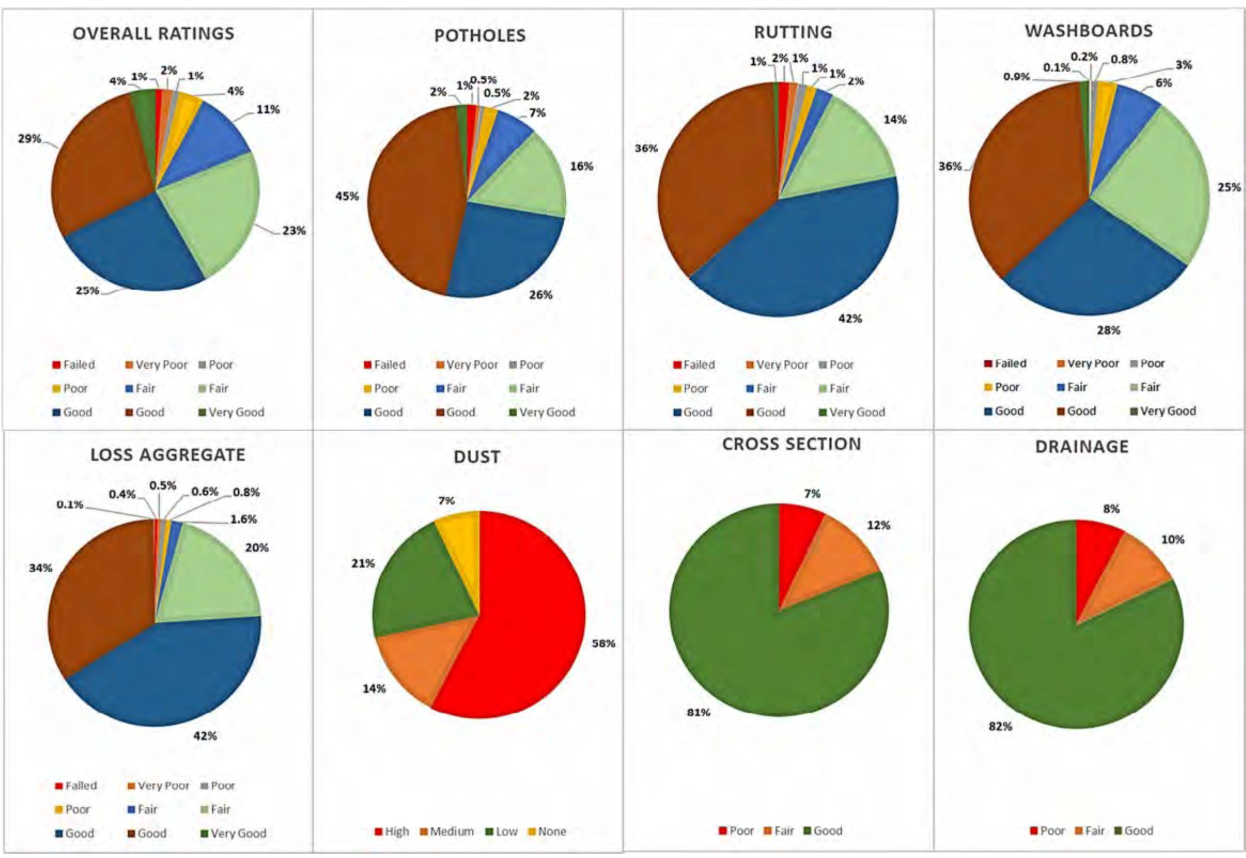


Figure 5.15 Laramie County Gravel Road Conditions as of Summer 2017

5.2.3.3 Performance Modeling

Markov chain theory is used to develop the performance prediction models for each distress or deterioration mode related to gravel roads. The implementation of this probabilistic approach within any stochastic process requires that such a process be discrete in time and has determinate states. Additionally, the future condition of this process should be solely dependent on the present condition of the process (Hassan et al., 2015). These prerequisites apply to gravel road networks. For example, it is prevalent to analyze road networks within definite time points and to establish stationary states that describe road conditions at various time periods. Furthermore, the future condition of any gravel road is solely dependent on its current state, not its previous conditions.

The modeling process using the Markov chain theory involves three main steps, which are, in order, the development of state vectors, transition probability matrices (TPM), and the development of the prediction models. These steps will be described in more detail in the following subsections. However, before starting the Markov process, the number of states for each distress and the length of stages or duty cycles must be defined. Due to the dynamic nature of gravel roads and their short service life, monthly duty cycles are selected. Table 5.9 shows the number of states (categories) assigned for each distress. Any gravel road, during its service life, will transition through these different states without any maintenance intervention. According to the GRRS standards, it is advised to give integer ratings to place a gravel road within any condition category for simplicity purposes. In the field, it is not rational to discriminate between any two gravel roads by tenths of a point.

Table 5.9 Number of States Assigned for Each Distress

Distress	Category	Given Rating (R)	Possible Field Ratings
Potholes; Rutting; Washboards; Loose Aggregate	Very Good (VG)	$8 < R$	9
	Good (G)	$6 < R \leq 8$	7,8
	Fair (FA)	$4 < R \leq 6$	5,6
	P (Poor)	$3 \leq R \leq 4$	3,4
	Very poor (VP)	$2 \leq R < 3$	2
	Failed (F)	$R < 2$	1
Dust	None (N)	$3 < R$	4
	Low (L)	$2 < R \leq 3$	3
	Medium (M)	$1 < R \leq 2$	2
	High (H)	$R \leq 1$	1
Cross Section (Crown); Drainage	Good (G)	$2 < R \leq 3$	3
	Fair (FA)	$1 < R \leq 2$	2
	Poor (P)	$R \leq 1$	1

State Vectors

There are two types of state vectors according to the MC modeling approach. These types are the initial vector and the start vector, which both define the probability of a gravel road to be in one of the condition states at age (0) of the duty cycle. The difference between these types is that the initial vector assumes that all gravel roads have conditions similar to the conditions right after construction (i.e., perfect shape).

The start vector is based on the current gravel road conditions and the proportion of the network length that falls in each state category. The initial vector concept is followed in this study. Based on the collected data in the summer of 2017, some of the estimated start vectors and an initial vector for Laramie County gravel roads are shown in Table 5.10. It should be noted that the sum of proportions in every vector should be 1.

Table 5.10 Start Vectors for Laramie County Gravel Roads

Distress & Category	*F	VP	P	FA	G	VG
Initial Vector	0	0	0	0	0	1
Potholes	0.0154	0.0061	0.0298	0.2257	0.7064	0.0167
Rutting	0.0152	0.0110	0.0258	0.1669	0.7746	0.0065
Washboards	0.0010	0.0017	0.0352	0.3093	0.6397	0.0131
Loose Aggregate	0.0045	0.0045	0.0160	0.2146	0.7586	0.0017
Distress & Category	H	M	L	N		
Initial Vector	0	0	0	1		
Dust	0.5759	0.1405	0.2143	0.0694		
Distress & Category	P	FA	G			
Initial Vector	0	0	1			
Cross Section	0.0696	0.1189	0.8115			
Drainage	0.0750	0.1040	0.8210			

*F: Failed; VP: Very Poor; P: Poor; FA: Fair; G: Good; VG: Very Good; H: High; M: Medium; L: Low.

Transition Probability Matrices (TPM)

In this phase, a stationary TPM is developed for each distress type. The developed TPMs will be used to predict the development of each distress with time. In Laramie County and for the purposes of this pilot study, gravel road conditions are available for only one duty cycle. Therefore, average deterioration rates, in points per day, are used to estimate gravel road conditions for the next duty cycle and in the development of the TPM. The average deterioration rates were used along with the collected data to establish a historical database. In this process, the average deterioration rates were deducted daily from the collected data for a period long enough to reach failure for every gravel road. This process provided this study with the necessary historical data to build the Markov chains. After examining the established historical database, different duty cycles were defined to simplify the Markov chains building process. Later, the established historical database and the defined duty cycles were used to build the TPM.

Hence, both the states and the transition probabilities will have the same cycle length for every deterioration mode. The utilized deterioration rates and the different selected duty cycles are shown in Table 5.11. It can be noticed that potholes and washboards have the highest deterioration rates compared with the other distresses. The average deterioration rates were estimated, using the same rating scale used in this study, after monitoring 20 well-constructed gravel roads segments at sites in north-central Wyoming for 10 months (Huntington & Ksaibati, 2007). During this 10-month period, gravel roads were rated weekly. Some distresses required more than a week or even a month to deteriorate from one stage to another. Therefore, the number of days required for each distress condition (i.e., potholes) to deteriorate from one stage to the next was used to calculate the average deterioration rates by points per day. Then, the overall average among all the stages was used to estimate the final deterioration rates used in this study. Considering the dynamic and arbitrary nature of gravel roads, following this approach saved time, effort, and resources required to collect multiple duty cycle historical data.

According to the National Oceanic and Atmospheric Administration (NOAA), the Wyoming north-central areas are part of the Wyoming climatic division 5, or what is known as “the Powder, Little Mo, and Tongue Drainages,” while the data collected in this study were from Laramie County, which follows the Wyoming climatic division 8, or what is known as “Lower Platte.” Both climatic regions share similar short, warm, and dry summers with average precipitation rates from 1.8 to 2.2 inches. During the warm season, region 5 has an average daily high temperature of around 78°F while region 8 is around 70°F. During the cold season, region 5 has an average daily high temperature of around 45°F while region 8 is around 41°F. Additionally, both regions serve similar rural traffic conditions. Hence, these estimates can be used in this study to develop TPM. Different duty cycles were selected to allow reasonable transitions from one stage to another, which can simplify the modeling process.

Table 5.11 Average Deterioration Rates for Gravel Roads in Wyoming

Distress	Deterioration Rate (points per day)	Duty Cycle (months)
Potholes	0.0397	1
Rutting	0.0216	2
Washboards	0.0429	1
Loose Aggregate	0.01	4
Dust	0.002	17
Cross Section (Crown)	0.002	17
Drainage	0.002	17

Table 5.12 shows a TPM for potholes where rows denote the current state and the columns represent the future state after the transition period. According to this TPM, the probability of a gravel road in a very good (VG) or a very poor state (VP) to remain in that state is zero. There is a rather high probability (greater than 0.7) for a road in a fair (F) or poor state (P) to remain in that state. These results can be attributed to the dynamic nature of these kinds of roads. Frequent light M&R interventions, such as light blading, are required to keep a gravel road in the very good (VG) state for more than one duty cycle. The same behavior can be noticed for rutting and washboards. When it comes to loose aggregates, dust, drainage, and crown conditions, the deterioration patterns are slower. Thus, a gravel road may stay in the same state for more than one duty cycle as seen in Table 5.13. For dust, drainage, and cross-section the deterioration rates are very small. Thus, a cycle of 17 months is assumed to develop the TPM.

Table 5.12 TPM for Potholes

	VG	G	FA	P	VP	F
VG	0.000	1.000	0.000	0.000	0.000	0.000
G	0.000	0.634	0.366	0.000	0.000	0.000
FA	0.000	0.000	0.701	0.299	0.000	0.000
P	0.000	0.000	0.000	0.767	0.233	0.000
VP	0.000	0.000	0.000	0.000	0.000	1.000
F	0.000	0.000	0.000	0.000	0.000	1.000

Table 5.13 TPM for Loose Aggregate

	VG	G	FA	P	VP	F
VG	0.000	1.000	0.000	0.000	0.000	0.000
G	0.000	0.448	0.552	0.000	0.000	0.000
FA	0.000	0.000	0.918	0.082	0.000	0.000
P	0.000	0.000	0.000	0.491	0.509	0.000
VP	0.000	0.000	0.000	0.000	0.000	1.000
F	0.000	0.000	0.000	0.000	0.000	1.000

Models Development

Finally, the TPM and the initial vector are used together to build Markov chains for the different deterioration modes. For example, Table 5.14 shows a Markov chain for loose aggregate and the associated weighted average condition for each stage. The weighted averages were calculated based on the actual possible ratings that a rater might give to a road in the field and the possible transition probabilities. For example, the average weighted loose aggregate condition of a gravel road can be estimated as follows:

1. After 4 months = 0*9 + 1*7.5 + 0*5.5 + 0*3.5 + 0*2 + 0*1= 7.500.
2. After 12 months = 0*9 + 0.201*7.5 + 0.754*5.5 + 0.045*3.5 + 0*2 + 0*1= 5.811.

These weighted averages, accompanied with the time duration, are used to predict the performance model for loose aggregate as shown in Figure 5.16. The value *y* in Figure 5.16 denotes the predicted rating at a given age (months).

Table 5.14 Markov Chain for Loose Aggregate

Stage	Month	VG	G	FA	P	VP	F	Average Condition
0	0	1.000	0.000	0.000	0.000	0.000	0.000	9.000
1	4	0.000	1.000	0.000	0.000	0.000	0.000	7.500
2	8	0.000	0.448	0.552	0.000	0.000	0.000	6.396
3	12	0.000	0.201	0.754	0.045	0.000	0.000	5.811
4	16	0.000	0.090	0.803	0.084	0.023	0.000	5.431
5	20	0.000	0.040	0.787	0.107	0.043	0.023	5.113
6	24	0.000	0.018	0.744	0.117	0.055	0.066	4.815
7	28	0.000	0.008	0.693	0.119	0.060	0.120	4.529
8	32	0.000	0.004	0.641	0.115	0.060	0.180	4.256
9	36	0.000	0.002	0.590	0.109	0.059	0.240	3.999
10	40	0.000	0.001	0.543	0.102	0.056	0.299	3.758
11	44	0.000	0.000	0.499	0.095	0.052	0.354	3.535
12	48	0.000	0.000	0.458	0.087	0.048	0.406	3.329
13	52	0.000	0.000	0.421	0.080	0.044	0.454	3.139
14	56	0.000	0.000	0.386	0.074	0.041	0.499	2.964
15	60	0.000	0.000	0.355	0.068	0.038	0.540	2.803
16	64	0.000	0.000	0.325	0.062	0.035	0.577	2.655
17	68	0.000	0.000	0.299	0.057	0.032	0.612	2.520
18	72	0.000	0.000	0.274	0.053	0.029	0.644	2.395
19	76	0.000	0.000	0.252	0.048	0.027	0.673	2.281
20	80	0.000	0.000	0.231	0.044	0.025	0.700	2.176
21	84	0.000	0.000	0.212	0.041	0.023	0.724	2.079
22	88	0.000	0.000	0.195	0.037	0.021	0.747	1.991
23	92	0.000	0.000	0.179	0.034	0.019	0.768	1.910
24	96	0.000	0.000	0.164	0.032	0.017	0.787	1.835

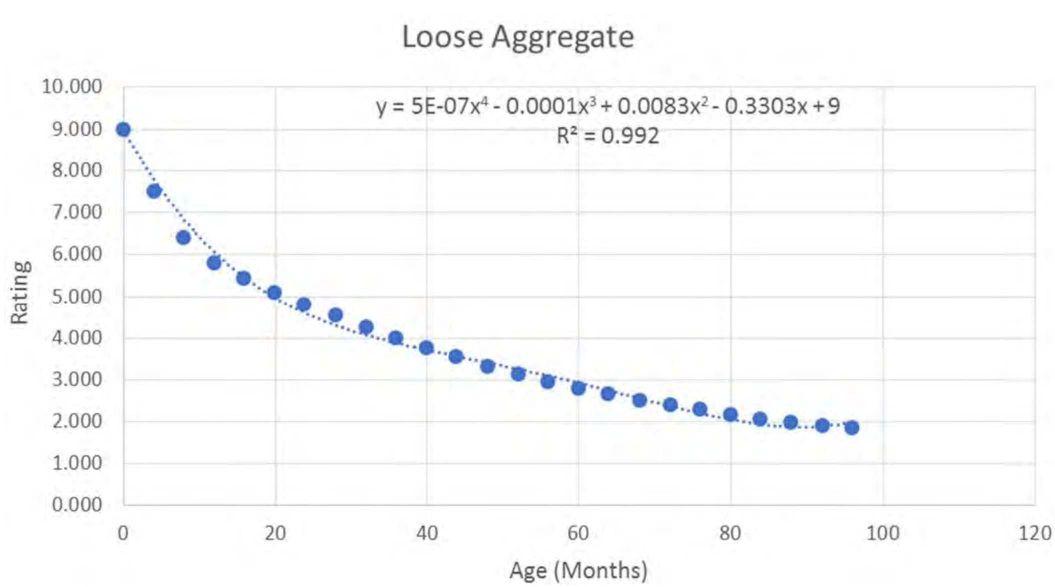


Figure 5.16 Loose Aggregate Performance Model

Figure 5.17 shows another representation of the developed Markov chain using a bar chart based on the start vector of loose aggregate. This chart shows the probability of any gravel road segment to be in a specific condition state at any given period of time. For example, a gravel road has a 55% chance to be in fair loose aggregate condition after eight months of construction. The same segment has a 45% chance to be in good loose aggregate condition at the same age. Based on the current conditions of the network (i.e., start vector), the probability of having a gravel road at the first month of its service life in the very good category is less than 1%.

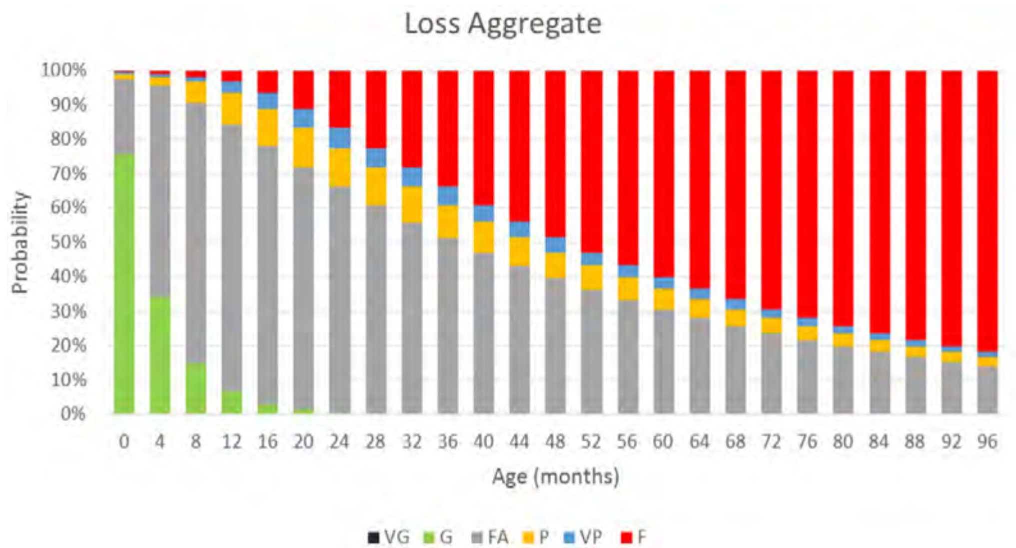


Figure 5.17 Markov Chain for Loose Aggregate

Table 5.15 shows a summary of the developed performance prediction models using the MC approach for all the distresses according to the GRRS. According to this table, and based on the actual conditions and deterioration rates, crown and drainage have similar predicted performance equations. This can be attributed to the strong link between drainage and crown conditions. Roads with poor drainage tend to allow more water to filtrate the subgrade, which increases the likelihood of a cross-section failure. The developed prediction equations are based on the GRRS system, which is a modification to the PASER system. Thus far, and at least in the United States, these prediction equations are unique and thoroughly describe the deterioration modes of gravel roads based on a popular visual evaluation method.

Table 5.15 Performance Models for Gravel Roads

Distress Index	Model
Potholes	$Y = -0.0008X^3 + 0.0504X^2 - 1.0632X+9$
Rutting	$Y = 0.000005X^4-0.0006X^3 + 0.027X^2 - 0.645X + 9$
Washboards	$Y = -0.0009X^3 +0.0524X^2 -1.0641X + 9$
Loose Aggregate	$Y = 0.0000005X^4 - 0.0001X^3 + 0.0083X^2 - 0.33X + 9$
Dust	$Y = 0.00002X^3-0.0012X^2 - 0.0398X+ 4$
Crown	$Y = 0.00003X^3-0.0017X^2 - 0.0392X+ 3$
Drainage	$Y = 0.00003X^3-0.0017X^2 - 0.0392X+ 3$

Y: Condition index (points); X: Time in months.

Figure 5.18 graphically shows all the developed predicted performance models. As seen from this figure, the fastest distresses to reach failure conditions are washboards and potholes. These two distresses can reach failure (R < 2) within only 13 months, and both distresses have similar performance throughout the road service life. For rutting, it takes about 28 months to reach failure conditions. The deterioration that is based on loose aggregate conditions is the longest. A gravel road requires about 88 months to reach failure ($R < 2$) compared with cross-section, dust, and drainage-based deteriorations (34 months). Nonetheless, gravel road conditions are sometimes harder to predict.

Gravel road deterioration modes are interrelated to each other and every distress may encourage the development of other distresses, which is apparent from the Pearson correlation matrix shown in Table 5.16. According to this matrix, there are strong positive correlations among potholes, washboards, and rutting. The same association can be noticed among roadside drainage, crown, and rutting. Also, there is an association among dust, loose aggregate, and washboards, but the association is not as strong. Lastly, it can be noticed that potholes, washboards, and rutting are most highly correlated with the overall ride quality. Thus, these deterioration modes are the main contributing factors to the comfort of road users and the reason behind the failure of gravel roads.

Table 5.16 Pearson Correlation Matrix

	Overall	Potholes	Rutting	Washboards	Loose Aggregate	Dust	Crown	Drainage
Overall	1.000	0.775	0.655	0.566	0.210	-0.065	0.371	0.331
Potholes	0.775	1.000	0.592	0.529	0.144	-0.029	0.271	0.260
Rutting	0.655	0.592	1.000	0.345	0.265	0.080	0.459	0.419
Washboards	0.566	0.529	0.345	1.000	0.164	0.247	0.074	0.081
Loose Aggregate	0.210	0.144	0.265	0.164	1.000	0.208	0.097	0.042
Dust	-0.065	-0.029	0.080	0.247	0.208	1.000	-0.094	-0.120
Crown	0.371	0.271	0.459	0.074	0.097	-0.094	1.000	0.790
Drainage	0.331	0.260	0.419	0.081	0.042	-0.120	0.790	1.000

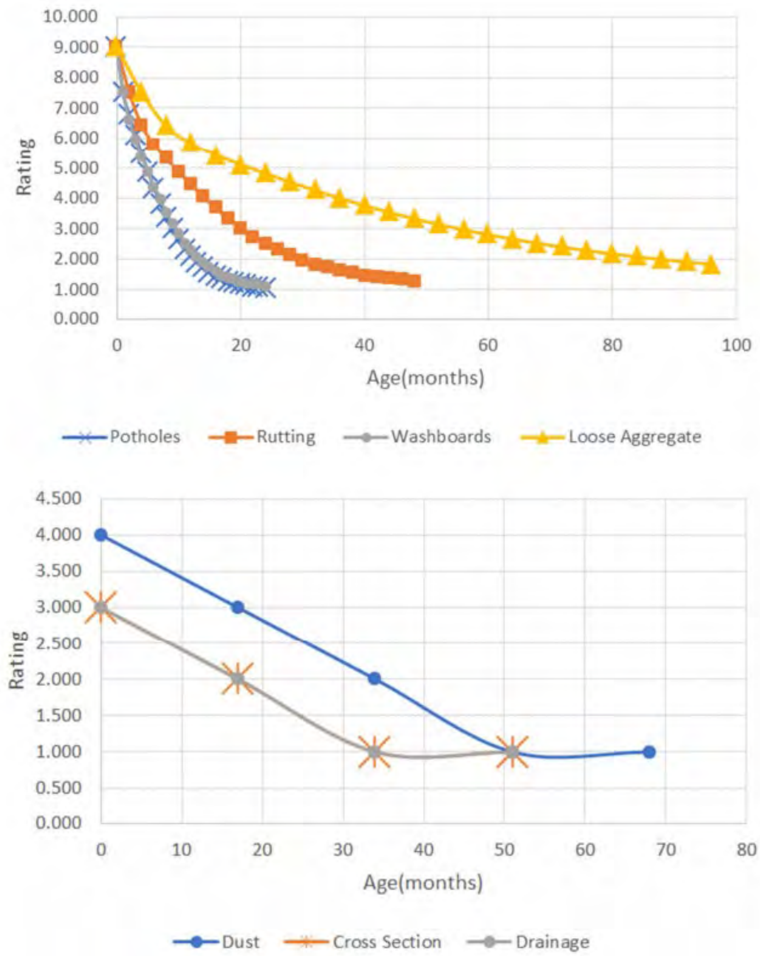


Figure 5.18 Markov Performance Models of Average Condition Values for All Distresses

5.2.4 A Developed Methodology for Determining Gravel Roads' Level of Service: A Case Study of Wyoming

5.2.4.1 Introduction

The focus of this phase is to develop a systematic method for ascertaining the level of service (LOS) of gravel roads in the US. To date, such a method does not exist in the Highway Capacity Manual (HCM). In this phase, a methodology comprising eight criteria that affect gravel road traffic operations is developed. For each criterion, a rating is assigned. It is either "Good," "Fair," or "Poor." The results of each individual criterion rating are combined to develop an overall LOS rating. Furthermore, a non-parametric machine learning technique, namely the classification and regression tree (CART) modeling structure, is employed to quantify the contribution of each criterion to the overall gravel roads' LOS. As a case study, the developed methodology is implemented to assess traffic operations of gravel roads in Laramie County, Wyoming. The studied gravel road network is compiled and managed in a geographic information system (GIS) shapefile prepared for the purpose of this research. It provides decision-makers in local agencies a computerized tool to efficiently track the performance of their gravel road network. The developed methodology is intended to benefit traffic engineers, decision-makers, and any other stakeholders. The gravel road LOS methodology was developed and applied to Wyoming's conditions. Minor adjustments might be needed for implementation in other jurisdictions.

5.2.4.2 Methodology

In this phase, the gravel roads' LOS is based on combined measures adapted from the HCM's two-lane highway methodology, Wyoming County Road Manual, Rural Road Design, Maintenance, and Rehabilitation Guide, and the AASHTO Guidelines for Geometric Design of Very Low-Volume Local Roads (ADT ≤ 400 vpd). This phase is focused on expressing the gravel road quality of service as a function of multiple variables. They are the road's surface width, ride quality, dust level, access point density, terrain conditions, average operating speed, traffic volume, heavy vehicle traffic volume, and the number of dwelling units per mile.

When it comes to traffic volume, the HCM is based on an hourly analysis period accounting for variations in travel demand. Yet, since peak hour volumes of gravel roads are low (typically less than 50 vph assuming a maximum volume of 400 vpd), performing a peak hour analysis is not meaningful for unpaved roads. Hence, the peak hour factor is not used. Furthermore, the traffic directional split is a key measure for LOS calculations of the HCM. However, this metric is precluded since the traffic volumes evaluated are 400 vpd or less and it is assumed that passing opportunities are not possible since centerline pavement markings are not applicable and the gravel roads are narrow and dusty. Also, all gravel road segments analyzed in this research are on rolling terrain and not on specific grades. For analysis purposes, the difference in the effect of the grade on each travel direction's traffic operations is the same for level and rolling terrain conditions. In this research, a methodology comprising eight criteria that affect gravel road traffic operations is developed. For each criterion, a rating is assigned. It is either "Good," "Fair," or "Poor." Table 5.17 presents the criteria variables selected for evaluating the LOS of gravel roads.

Table 5.17 Input Measures for the LOS Criteria

Criteria	Description
Surface width	Combined width of both opposing travel lanes
Ride quality rating guide (RQRG)	Quantified gravel road's surface quality as perceived by the general public
Dust level	The quantity of dust generated by the traffic
Access point density	Number of entries/exits per mile on a given road
Terrain	Vertical grade
Speed	Average operating speed
AADT	Average annual daily traffic volume (vpd)
AADTT	Average annual daily heavy vehicle traffic volume (vpd)
Number of dwelling units	Total number of dwelling units along a given unpaved road per mile

5.2.4.3 Data Collection

The gravel road data of Laramie County, Wyoming, are provided by the Wyoming Department of Transportation (WYDOT) and the Wyoming Technology Transfer Center (WYT2) of the University of Wyoming. The data include records of the variables presented in Table 5.17.

5.2.4.4 Unpaved Road Level of Service Criteria Approach

The HCM methodology is followed to compute the LOS measures, and additional measures are obtained using the Wyoming County Road Manual. This blend is selected since the operating characteristics of gravel roads are dependent on the ride quality and the dust levels, which are factors not accounted for in the HCM's two-lane highway LOS methodology. The variables considered in the proposed methodology, used for assessing gravel roads, are detailed in the following sections. Each variable is assigned a rating, and the overall gravel road's LOS is computed as an aggregate rating of each variable's rating.

Surface Width

Regarding gravel roads, the AASHTO Guidelines for Geometric Design of Very Low-Volume Local Roads (ADT ≤ 400 vpd) states there is no evident difference between the "roadway" and the "shoulder" (AASHTO, 2001). Therefore, the gravel road width is used as a variable. In this research, this variable is established based on the total surface width standards of the Wyoming County Road Manual (Hesterberg, 2011). Table 5.18 illustrates the surface width ratings. As shown in Table 5.18, the ratings are provided by the number of dwelling units (DU). Typically, the gravel road width is proportional to the number of dwelling units.

Table 5.18 Surface Width Ratings

Number of dwelling units (DU)	Width standard (ft)	Poor (ft)	Fair	Good (ft)
$DU \leq 4$	18	< 18	≥ 18 ft, < 22 ft	≥ 22
$5 \leq DU < 9$	20	< 20	≥ 20 ft, < 24 ft	≥ 24
$DU \geq 9$	22	< 22	≥ 22 ft, < 28 ft	≥ 28

Surface Conditions

The Gravel Road Management Systems (GRMS) manual states that surface conditions may affect the average operating speed. In this study, the surface condition data of gravel roads are those of the quality indices. Table 5.19 illustrates the distress conditions and their ratings as labeled in the PASER manual (Walker et al., 1987). This manual rates and evaluates gravel road segments based on some of the criteria, such as ride comfort, safety, travel speeds, and vehicle wear and tear. Based on the RQRG measurements, surface condition ratings of gravel roads are developed and shown in Table 5.20, where, for example, gravel roads with RQRG value (RQRG ≥ 7) will be rated as a "Good" LOS rate.

Table 5.19 Ride Quality Rating Guide's Ratings (WYT2/LTAP, 2014)

Rating		Distresses*
10	Excellent	–
9	Very good	–
8	Good	Dust under dry conditions; moderate loose aggregate; slight washboarding
7	Good	
6	Fair	Moderate washboarding (1 in—2 in deep) over 10%-25% of area; moderate dust, partial obstruction of vision; none or slight rutting (less than 1 in deep); an occasional small pothole (less than 2 in deep); some loose aggregate (2 in deep)
5	Fair	
4	Poor	Moderate-to-severe washboarding (over 3 in deep) over 25% of area; Moderate rutting (1 in—3 in) over 10–25% of area; moderate potholes (2 in—4 in deep) over 10–25% of area; severe loose aggregate (over 4 in)
3	Poor	
2	Very poor	Severe rutting (over 3 in deep) over 25% of area; severe potholes (over 4 in deep) over 25% of area; many areas (over 25%) with little or no aggregate
1	Failed	

*Adapted from the Gravel—PASER manual

Table 5.20 Surface Condition Ratings

Good	Fair	Poor
$RQRG \geq 7$	$5 \leq RQRG < 7$	$RQRG < 5$

Dust Level

Unlike paved road conditions, daily traffic on gravel roads generates dust. Traffic-generated dust creates major safety, health, and environmental problems (Albatayneh et al., 2019-b; Albatayneh et al., 2020-c). For instance, it is estimated that fatal and injury crashes on unpaved roads in developing countries, attributed to dust generation, cost $800 million annually (Greening, 2011). Local agencies regularly track gravel road performance, especially the generated dust quantities in order to maintain such roads. Therefore, it is crucial to consider traffic-generated dust as one of the variables for determining the overall gravel roads' LOS. Table 5.21 presents the dust ratings by level based on the Gravel Roads Rating Standards (Ksaibati, 2014). As seen, the "Good" rating is assigned to gravel roads with low dust, the "Fair" rating is assigned to gravel roads with medium dust, and the "Poor" rating is assigned to gravel roads with high dust.

Table 5.21 Dust Level Ratings

Good	Fair	Poor
Low dust	Medium dust	High dust

Access Point Density

In access management, the density of access points is considered a measure of the number of entries/exits along a given road. It is inversely proportional to the average operating speed. The access points include intersections, streets, and driveways on either travel direction. Thus, access points are an essential criterion for establishing the overall LOS criteria. The access point data are available in the form of GIS shapefiles. However, the GIS data did not cover all the roads in the case study. Hence, the missing data are collected from Google Earth. The access point density is calculated as the average number of access points per mile. Ratings are assigned to the access point density values obtained based on the Rural Road Design, Maintenance, and Rehabilitation Guide. The ratings are presented in Table 5.22.

Table 5.22 Access Point Density Ratings

Good	Fair	Poor
Access points ≤ 3	$3 <$ Access points ≤ 6	Access points > 6

Terrain

Based on the Rural Road Design, Maintenance, and Rehabilitation Guide, the level terrain is defined as flat or rugged terrain that does not constrain heavy vehicle drivers, particularly truck drivers, to reduce their travel speeds noticeably below passenger car speeds. In the rolling terrain, the pavement gradient is more than the level terrain and is characterized by heavy vehicle speeds that are lower than those of heavy vehicles traveling on level terrain. On the other hand, mountainous terrain is known for its steep grades, which significantly affect travel speeds. Note that when implementing the HCM's LOS methodology of two-lane highways, the user specifies the grade and its length when analyzing the conditions of steep two-lane roads.

With the use of the GIS shapefile data and Google Earth, interpolation is made to obtain the elevation at each end of each gravel road segment. The change in elevation (Δ Elevation) is calculated and divided by the length of the gravel road segment in order to compute the segment's gradient. In Wyoming, most of the county roads are often not paved. Based on the Wyoming County Road Manual, ratings are developed to gauge the effect of the grade on traffic operations. The ratings are presented in Table 5.23.

Table 5.23 Grade Ratings

Terrain	Good (%)	Fair	Poor (%)
Level	≤ 6	$> 6\%, < 8\%$	≥ 8
Rolling	≤ 7	$> 7\%, < 11\%$	≥ 11
Mountainous	≤ 12	$> 12\%, < 16\%$	≥ 16

Speed

The average travel speed on gravel roads is one of the decisive factors that determine the gravel roads' LOS. Regarding Wyoming, the design criteria for speeds on a newly constructed gravel road are available in the Wyoming County Road Manual. The design speed values range from 20 to 55 mph based on the gravel roads' terrain. Additionally, the number of dwelling units is a critical factor to be considered when evaluating average operating speeds on gravel roads. The ratings used for evaluating gravel road average operating speeds are illustrated in Table 5.24.

Table 5.24 Speed Criteria for the Gravel Roads' LOS

Number of dwelling units (DU)	Speed standards (mph)	Poor (mph)	Fair	Good (mph)
$DU \leq 7$	15–45	< 15	≤ 15 mph, < 45 mph	≥ 45
$DU > 7$	20–55	< 20	≤ 20 mph, < 55 mph	≥ 55

Average Annual Daily Traffic (AADT)

The AASHTO Guidelines for Geometric Design of Very Low-Volume Local Roads (ADT $\leq$ 400 vpd) states there are no specific standards for maximum traffic volumes for which gravel roads are appropriate (AASHTO, 2001). However, in the NCHRP Report 362, it is mentioned that for gravel roads, crash rates become pronounced for traffic volumes of 250 vpd or more. For instance, 250 vpd is considered the breakpoint between the "Poor" and "Fair" AADT ratings according to the AASHTO Guidelines for Geometric Design of Very Low-Volume Local Roads (ADT $\leq$ 400 vpd), from which the AADT ratings are presented in Table 5.25. In the case of a gravel road with an AADT greater than 400 vpd, a chemical surface treatment is recommended, and therefore the road is considered paved.

Table 5.25 Traffic Volume Ratings

Good	Fair	Poor
$AADT < 100$	$100 \leq AADT < 250$	$250 \leq AADT \leq 400$

Average Annual Daily Truck Traffic

In the United States, heavy trucks play a critical role in the economy. Heavy vehicles are considered the main transportation mode for moving goods. Heavy vehicles have different operating characteristics as compared with other vehicles and therefore affect traffic flow operations. When truck traffic is significant, there is a chance that the gravel road will be frequented by vehicles tailgating trucks. This tailgating substantially increases the percent-time-spent-following (PTSF), which is the average proportion of time spent following a slower-moving vehicle ahead due to limited passing opportunities. Also, when a gravel road becomes increasingly dominated by truck traffic, special roadway design treatments are required. Therefore, the daily truck traffic should be considered in the gravel roads' LOS methodology.

In the gravel road design and repair section of the Rural Road Design, Maintenance, and Rehabilitation Guide, ratings are provided regarding daily truck traffic on gravel roads (Beckemeyer & McPeak, 1995). Table 5.26 illustrates these ratings.

Table 5.26 Truck Traffic Volume Ratings

Good	Fair	Poor
AADTT ≤ 25 vpd	25 vpd < AADTT ≤ 50 vpd	AADTT > 50 vpd

Miscellaneous Variables

In addition to the previously discussed variables, an assumption is made in this study about unpaved arterials and collectors. Generally, gravel arterials are rated as "Poor" since, ideally, all arterial roads should be paved. Likewise, collectors should be paved even though unpaved collectors do exist. For this research, collectors with grades greater than 9%, which is the maximum design grade for collectors as per the Wyoming County Road Manual, are rated as "Poor." Furthermore, the Wyoming County Road Manual requires that collectors have a minimum design speed of 30 mph. Hence, collectors with a design speed less than 30 mph are rated as "Poor."

Overall Level of Service

Given the ratings of the previously discussed variables, the overall LOS criteria are developed. For each variable namely, the surface width, surface conditions, dust level, access point density, terrain, speed, AADT, and AADTT, the corresponding ratings are input in the overall LOS computations. The overall LOS computations involve assigning a score of 0, 1, or 2 for the variable ratings "Good," "Fair," and "Poor," respectively. The sum of each variable's score is calculated to obtain the overall LOS score. Once the score is computed, the overall LOS was assigned as a percent (%) as seen in Table 5.27, where a score of less than 33% is Good, a score between 33% and 66% is Fair, and a score of more than 66% is Poor. Therefore, this table is used as a basis for stratifying the scores into gravel roads' LOS.

Table 5.27 Gravel Roads' LOS criteria

Gravel roads' LOS			
Score	≤33%	>33%, <66%	≥66%
Overall LOS	Good	Fair	Poor

Classification and Regression Tree (CART)

The CART machine learning modeling technique is a non-parametric method. That is, it does not require an assumption to be made regarding the relationship between the response and the predictors. The CART method is used on data of 63 gravel road segments in Laramie County, Wyoming. The LOS score is modeled as a function of the previously discussed variables. It should be noted that 70% of the data are used for model training and the remaining 30% are used for testing. In CART modeling, generating the variable importance can assist researchers to exclude certain variables (predictors) that have no contribution to the response variable. According to the analysis results, all variables are found to influence the overall LOS. Figure 5.19 illustrates the relative importance of each variable. For instance, as shown in the figure, the AADTT is the variable that has the most powerful impact on the LOS. That is possibly due to surges in dust levels generated by heavy trucks and in PTSFs resulting from light vehicles tailgating trucks. Furthermore, the CART model is evaluated using a confusion matrix whose results are shown in Table 5.28. As shown in the table, the overall prediction accuracy of the classification model is estimated at 84.2% when applied to the test dataset. Simply put, classification accuracy can generally provide an indication of how accurate your predictions are. In the confusion matrix, this prediction accuracy is measured as the summation of true negatives and positives divided by the total population used. This degree of accuracy is considered high, especially for gravel road management systems.

Table 5.28 Classification and Regression Tree's Confusion Matrix Results

	Predicted					
	Class	Good	Fair	Poor	Sum	Accuracy (%)
Actual	Good	**4**	**1**	**0**	5	80.00
	Fair	**1**	**10**	**0**	11	90.90
	Poor	**0**	**1**	**2**	3	66.67
	Sum	5	12	2	**19**	
	Accuracy (%)	80.00	83.34	100.00	Overall% correct	**84.2 %**

Variable	Score (%)	Variable Importance
Average Annual Daily Truck Traffic	100.0	
Dust Level	99.4	
Ride Quality Rating Guide's Ratings	94.6	
Access Point Density	82.7	
Road Width	49.7	
Average Annual Daily Traffic	40.7	
Terrain	18.9	
Speed	14.4	

Figure 5.19 Gravel Roads' LOS— Variable Importance

5.2.4.5 CASE STUDY: WYOMING'S GRAVEL ROADS

The sample of the previously mentioned 63 gravel road segments in Laramie County is evaluated using the proposed methodology for determining the overall LOS. The computations are conducted in a spreadsheet. Table 5.29 presents the individual LOS for each variable.

Table 5.29 Gravel Roads' LOS for Each Criterion

Number of segments								
	Surface width	Surface conditions	Dust level	Access points	Terrain	Speed	AADT	AADTT
Good	25	21	33	23	16	24	12	14
Fair	18	21	12	23	27	33	32	23
Poor	20	21	18	17	20	6	19	26

As the data are analyzed, they are compiled and managed in a GIS shapefile prepared for the purpose of this research. This will provide decision-makers in local agencies a computerized tool to efficiently track the performance of their gravel road network. Figure 5.20 shows the GIS map of the gravel road network under study and its LOS results obtained using the developed methodology. As a result, this map can be considered as one of the resources that engineers and stakeholders can use to maintain and manage their gravel road network. Furthermore, stakeholders and managers can also gain insights on the individual rating for each gravel road segment in order to precisely identify and investigate the road segments that need immediate attention. Figure 5.21 shows the individual rating for each gravel road segment included in this study. As shown in Figure 5.22, roughly 63.5% of the gravel road segments are operating at an LOS of “Fair,” while 19% are operating at an LOS of “Poor,” and, unexpectedly, 17.5% are operating at an LOS of “Good.”

A separate analysis is conducted on the sample of segments of Laramie County’s gravel road network using the HCM’s methodology pertaining to two-lane highways to calculate the PTSF and proportion of free-flow speed (PFFS). Both measures are required to determine the LOS. The PFFS is the ratio of the average travel speed to the free-flow speed, which is the maximum speed achievable during minimal volume conditions. The PFFS is a surrogate measure of the proportion of travel time in which traffic operates at the free-flow speed. Note that the gravel road segments assessed in this research closely resemble Class II and Class III two-lane highways depending on the number of DUs. Class II two-lane highways are characterized by hilly terrain and moderate travel speeds. They are typically shorter than intercity routes. The LOS of Class II two-lane highways is solely dependent on the PTSF. On the other hand, Class III two-lane highways are those that pass through towns, and thus travel speeds are lower than those of Class II two-lane highways. The LOS of Class III two-lane highways is based on the PFFS only. Regardless, both the PTSF and PFFS are computed for the segments under study. According to the results of both measures, all except one segment are operating at an LOS of “A.” The remaining segment is operating at a LOS of “B.” The discrepancy of the LOS results of the proposed methodology and that of the HCM belonging to two-lane highways is plausible because of multiple factors. They are the ride quality and dust level. Also, since the results of the variable importance plot presented in Figure 5.19 indicate that the truck volume is the chief variable influencing the LOS of gravel roads, it may be suspected that the operating characteristics of heavy vehicles vary by road surface type. Heavy vehicles may possibly generate more dust relative to light vehicles. Moreover, it is inferred from the findings of this research that the HCM’s LOS methodology of two-lane highways is not applicable to gravel roads.

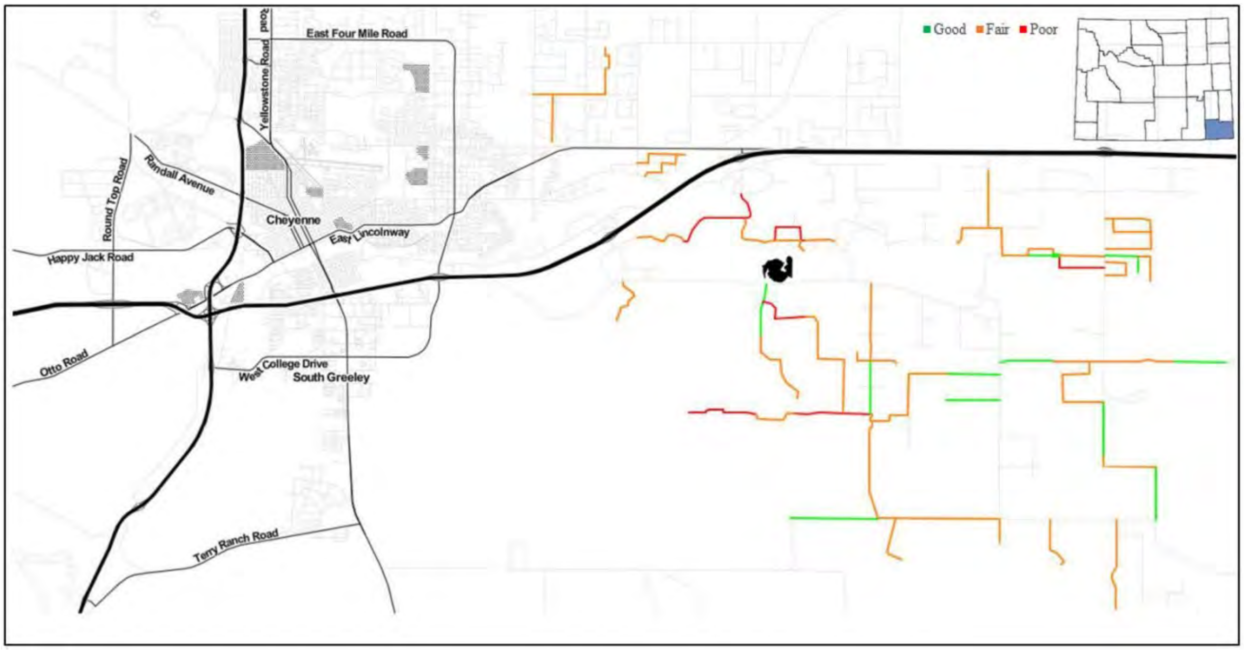


Figure 5.20 A GIS Map of the Overall Gravel Roads' LOS in Wyoming

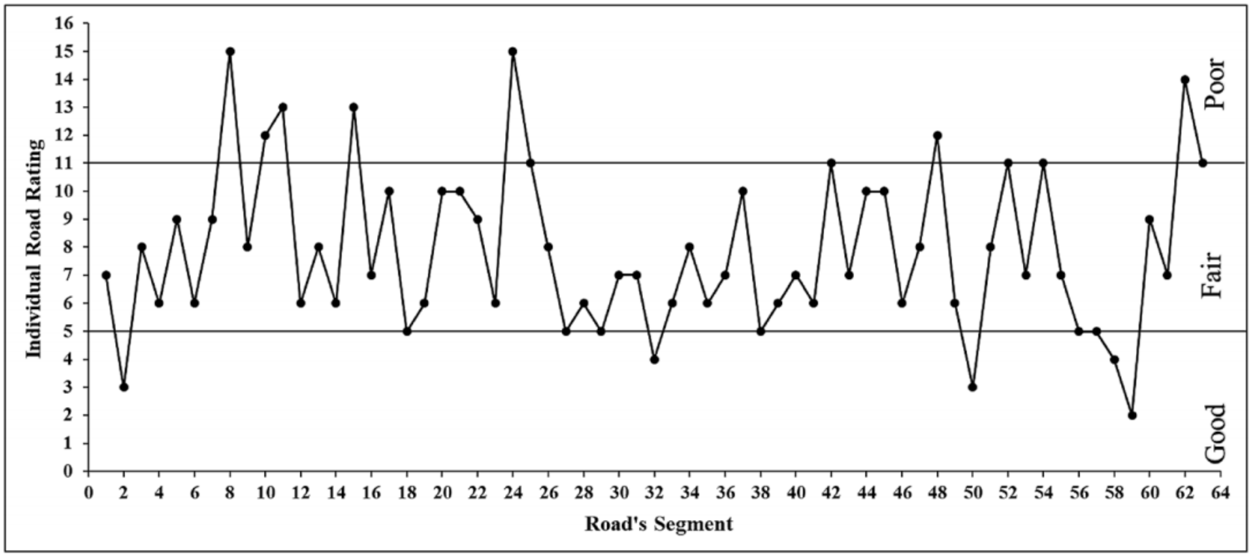


Figure 5.21 Overall Gravel Roads' LOS in Laramie, County, Wyoming

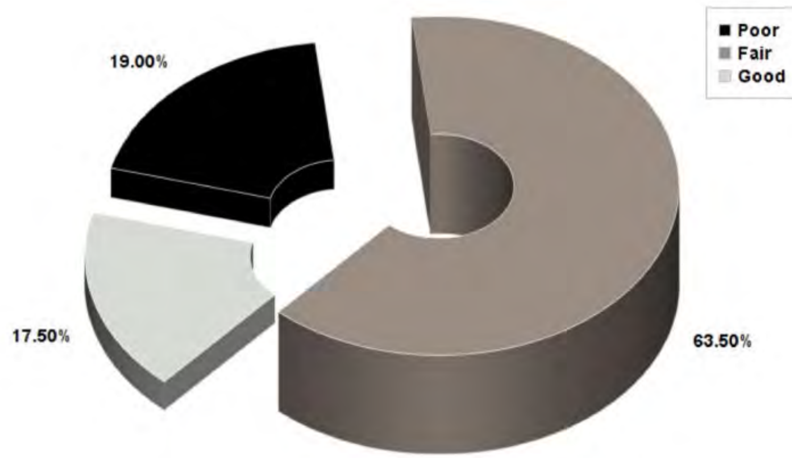


Figure 5.22 Overall Gravel Roads' LOS in Laramie

5.3 Chapter Summary

This chapter discussed the methodologies, data analysis, and results of this research study's second objective. The chapter explained the methodologies and the data collection procedures conducted to develop an optimization tool to select gravel road treatment projects using genetic algorithms. This objective established optimization models to help decision-makers within local agencies allocate their limited funds among the various gravel road projects.

Ultimately, the results found in this chapter contribute to a growing body of literature about the behavior and performance of selecting treatment for gravel roads. Such knowledge can aid agencies and decision-makers in implementing more cost-effective strategies to manage and maintain their gravel road asset network.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This research study was part of a multiple-year study conducted by the Wyoming Technology Transfer Center to assess road conditions for Wyoming county gravel roads. The research study was divided into two objectives and included the use of smartphones, machine learning, optimization techniques, collected data, and statistical analysis.

This chapter summarizes the valuable information and knowledge in terms of managing and maintaining gravel roads in Wyoming. Moreover, the recommendations presented in this chapter will guide transportation agencies to better understand the performance of gravel roads and therefore develop cost-effective strategies to manage and maintain the state's gravel road networks.

Objective 1 was to continue the efforts of the WYT2/LTAP office to develop and implement smartphone applications and technologies to assess gravel road conditions and performance. This included the continuation of the data collection process, where gravel roads from various counties around Wyoming were tested. Testing, as described in Chapter 4, included measuring dust emitted from gravel roads via a Dustometer and smartphone application; it also included the collection of temperatures and vehicle speeds, as well as locations. A descriptive analysis was conducted to explore dust generation trends from gravel roads.

For this research study and as part of the WYT2/LTAP's efforts to develop a gravel roads management system (GRMS) in Wyoming, objective 2 was to develop user-friendly tools, using JavaScript and other programming languages, which implement an optimization model based on genetic algorithms (GA). The developed tool will help decision-makers and local agencies in managing gravel roads efficiently. Using these tools, decision-makers will be able to identify the most appropriate treatment type for each road based on service level, estimated project costs, predicted road conditions, and whether to fund a project or not. The optimization models aim to maximize the overall condition of the gravel road network subject to the average daily traffic (ADT) on each road. The developed tools can be applied to large-scale optimization problems (i.e., gravel road network). The tools operate with minimal data requirements that are in line with procedures regularly followed at these agencies. In addition to having an engineered outcome, these tools can help local agencies allocate their limited available funds efficiently, enhance the planning process, maximize the social welfare of the local economy, and promote a sense of general satisfaction within the local community. A case study using data from Laramie County was used to develop these tools. Different types of analyses were conducted to carefully validate the performance of the developed tools. Both exploratory and statistical analyses were conducted. Moreover, objective 2 of this research study developed an optimization tool that can help decision-makers at the local level in managing limited budgets and in selecting gravel roads for maintenance and rehabilitation (M&R) projects. The tool, which has been developed, implements an optimization model that works on maximizing the overall gravel road network conditions considering traffic volumes and subject to limited budgets.

6.2 Recommendations

This research study has developed several methodologies to assess gravel road conditions in Wyoming. For Wyoming agencies responsible for managing gravel roads, the following are recommendations based on the findings of the study:

- This research study presented a simple image processing algorithm to extract data about the dust amount on gravel roads. Based on the promising findings presented in this phase, utilizing an artificial neural network (ANN) using high-level programming languages such as JavaScript and C-Sharp would be helpful to train and tune the current algorithm.
- Based on the promising findings of this research study, it is recommended that the proposed data collection/analysis tool be implemented by local agencies nationwide. Also, this image classifier can be extrapolated to other problem domains where the same principles apply.
- For local agencies managing gravel roads, it is recommended to employ and implement the developed image classifiers to collect dust and corrugation data.
- The established performance prediction equations should be used in developing a comprehensive optimization model for gravel roads in Wyoming. Other local agencies in the United States can follow the same methodology developed in this study to develop their own prediction equations for the evaluation of road conditions. Additionally, the developed prediction equations are based on modifications to the PASER system, which means that the new equations might be transferable for direct use by other local agencies in the United States.
- It is recommended that local agencies in Wyoming incorporate the developed tools within their gravel road management strategies and follow the modified decision matrix implemented in this research study. At this stage, the developed tools can provide good guidance to decision-makers at local agencies. The tools' outputs can deliver valuable insights into how to select roads for maintenance projects in a way that maximizes the overall network conditions subject to the traffic volumes served. Other local government agencies in the United States can follow the same methodology developed in this study to select gravel roads for maintenance projects. The process is systematic and can be duplicated to ensure limited available funding is allocated in the most cost-effective manner.
- The CMAQ program officials at WYDOT and the counties are advised to use the developed optimization tools for allocating CMAQ funds among the different counties. This entails that Wyoming counties need to follow the new requirements and support their CMAQ applications with the necessary data, such as ADT, surfacing material fines, speeds, agricultural lands, and households.

6.3 Future Studies

For gravel roads, additional efforts are required at this stage to implement smartphones in the data collection process. Furthermore, experimental work is still required to improve the reliability of using smartphones in gravel road data collection. Also, using different types of smartphones, testing vehicles, and smartphone locations in the vehicle should be examined in more detail to provide and simulate better real-time circumstances.

For more comprehensive management systems, it is suggested that the recommended practices and available resources be collected by a survey questionnaire for each county to balance between the current practices and proposed solutions in this research. After that, specific performance curves are recommended to be developed for road condition indices to project future road performance along a multi-year planning horizon.

In the course of this research study, numerous learned lessons suggest more research is needed to better quantify and assess the long-term use of the developed tools on gravel roads. Future research should therefore concentrate on investigating the following:

- Monitor the gravel road conditions after the implementation of the developed tools.
- Maintain a regular data collection process in order to include more gravel roads in the analysis.
- Document long-term gravel road deterioration, performance, and user cost to develop predicting performance models.
- Increase the efficiency and the functionality of the developed tools, incorporating GIS maps directly, comparing different optimization techniques, and looking for more influential variables to the optimization process.

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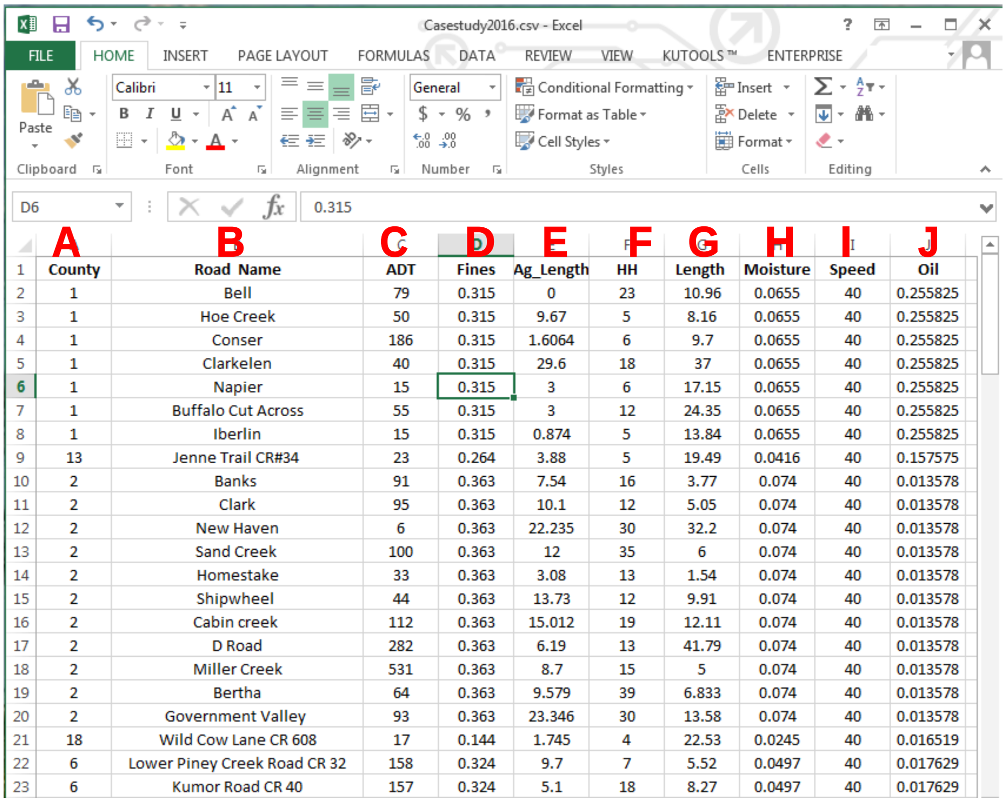
APPENDIX A

Appendix A-1: Instructions on How to Use the Dust Optimization Tool

The following instructions provide the necessary steps to run the dust optimization tool:

1. Prepare a CSV file with the required inputs as shown exactly in Figure A.1. Table A.1 shows a description for each column.



	A	B	C	D	E	F	G	H	I	J
1	County	Road Name	ADT	Fines	Ag_Length	HH	Length	Moisture	Speed	Oil
2	1	Bell	79	0.315	0	23	10.96	0.0655	40	0.255825
3	1	Hoe Creek	50	0.315	9.67	5	8.16	0.0655	40	0.255825
4	1	Conser	186	0.315	1.6064	6	9.7	0.0655	40	0.255825
5	1	Clarkelen	40	0.315	29.6	18	37	0.0655	40	0.255825
6	1	Napier	15	0.315	3	6	17.15	0.0655	40	0.255825
7	1	Buffalo Cut Across	55	0.315	3	12	24.35	0.0655	40	0.255825
8	1	Iberlin	15	0.315	0.874	5	13.84	0.0655	40	0.255825
9	13	Jenne Trail CR#34	23	0.264	3.88	5	19.49	0.0416	40	0.157575
10	2	Banks	91	0.363	7.54	16	3.77	0.074	40	0.013578
11	2	Clark	95	0.363	10.1	12	5.05	0.074	40	0.013578
12	2	New Haven	6	0.363	22.235	30	32.2	0.074	40	0.013578
13	2	Sand Creek	100	0.363	12	35	6	0.074	40	0.013578
14	2	Homestake	33	0.363	3.08	13	1.54	0.074	40	0.013578
15	2	Shipwheel	44	0.363	13.73	12	9.91	0.074	40	0.013578
16	2	Cabin creek	112	0.363	15.012	19	12.11	0.074	40	0.013578
17	2	D Road	282	0.363	6.19	13	41.79	0.074	40	0.013578
18	2	Miller Creek	531	0.363	8.7	15	5	0.074	40	0.013578
19	2	Bertha	64	0.363	9.579	39	6.833	0.074	40	0.013578
20	2	Government Valley	93	0.363	23.346	30	13.58	0.074	40	0.013578
21	18	Wild Cow Lane CR 608	17	0.144	1.745	4	22.53	0.0245	40	0.016519
22	6	Lower Piney Creek Road CR 32	158	0.324	9.7	7	5.52	0.0497	40	0.017629
23	6	Kumor Road CR 40	157	0.324	5.1	18	8.27	0.0497	40	0.017629

Figure A.1 Sample CSV File to Run the Dust Optimization Tool

Table A.1 Description for the Dust Optimization Tool Inputs

Column	Description	Source
A	County code	
B	Road name	Google Earth, GIS maps
C	Average Daily Traffic (ADT)	WYT2/LTAP ADT Maps
D	% Passing sieve No. 200 (Ratio)	WSS or Soil Samples
E	Agricultural length on both sides of the road (miles)	Google Earth, GIS maps
F	Number of households on both sides of the road (Within 984ft buffer)	Google Earth, GIS maps
G	Road length submitted for treatment (miles)	Google Earth, GIS maps
H	Soil moisture content (Ratio)	Figure *A-2*
I	Average driving speed (mph)	County Engineers
J	County to state oil production ratio	WOGCC

Table A.2 County Codes

Code	COUNTY	Code	County
0	Park	12	Natrona
1	Campbell	13	Converse
2	Crook	14	Sublette
3	Bighorn	15	Lincoln
4	Sheridan	16	Goshen
5	Teton	17	Platte
6	Johnson	18	Carbon
7	Weston	19	Albany
8	Washakie	20	Sweetwater
9	Hot Springs	21	Laramie
10	Fremont	22	Uinta
11	Niobrara		

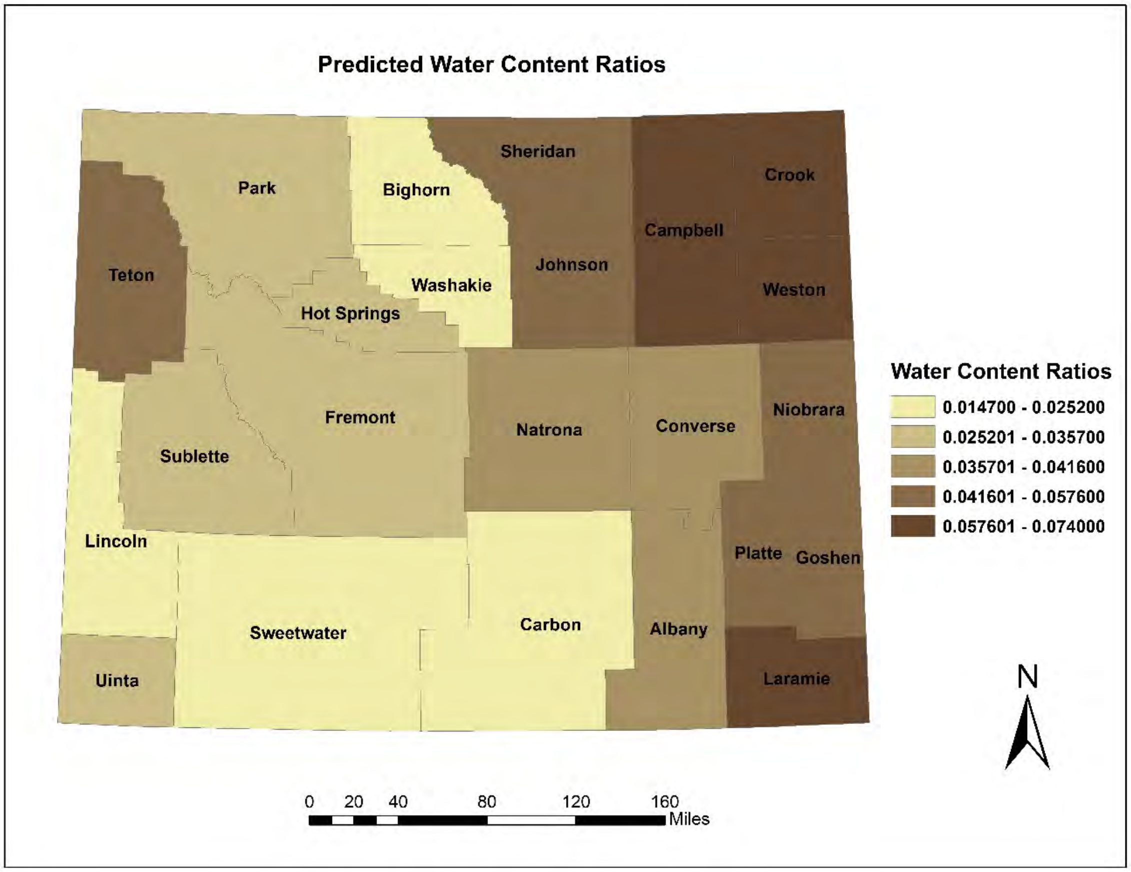


Figure A.2 Soil Moisture Content for Every County in Wyoming

2. Please fill the required fields and select the counties that are submitting for CMAQ funds as shown in Figure A.3. For mutation rate, the recommended values are between 0 and 0.1. The recommended initial population size is equal to the total number of gravel road segments. As a rule of thumb, a small population rate goes with higher mutation rates and vice versa.

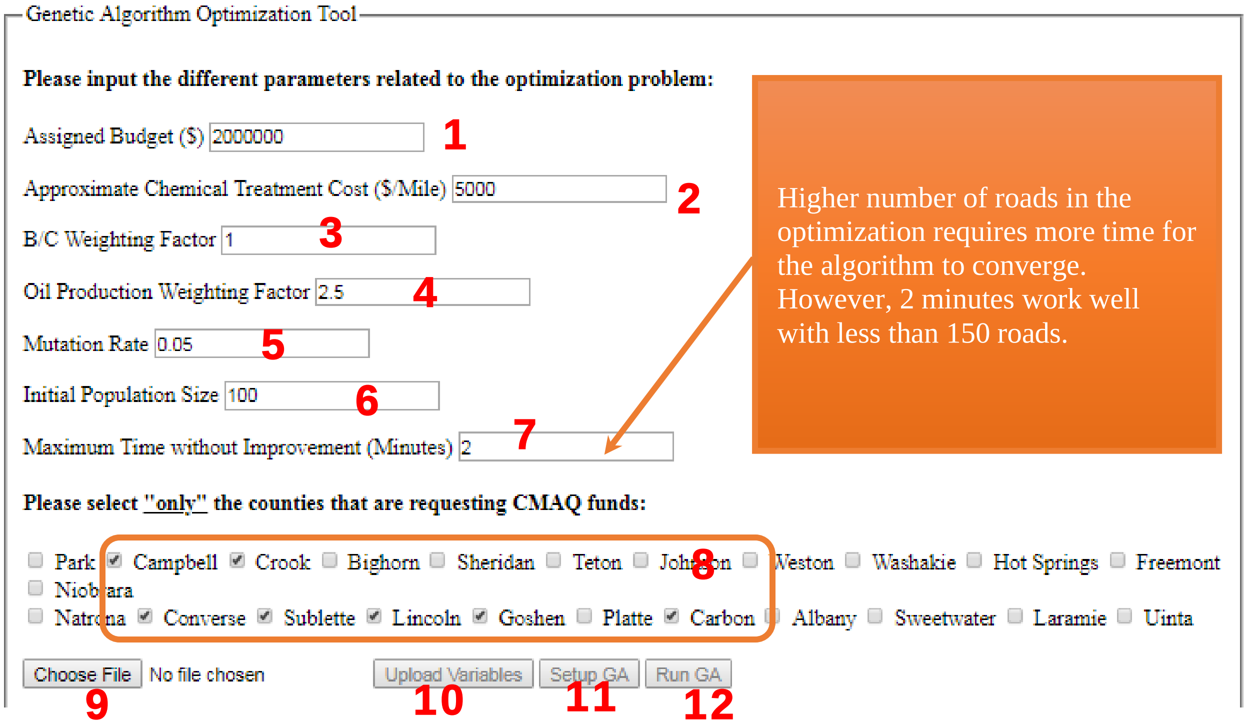


Figure A.3 Sample Inputs to Run the Optimization Tool

3. Click on the “Choose File” button and select the CSV file from step 1.
4. Click on the “Upload Variables” button to upload the GA variables.
5. Click on the “Setup GA” button to initialize the algorithm.
6. Click on the “Run GA” button to run the algorithm. Please follow the numbers shown in Figure A.3.
7. After the convergence of the algorithm, please click on the “Show Optimization Results” button to show the optimization results.
8. Click the “Save” button to download the optimization results. The results will be a CSV file that can be uploaded to Excel for further analysis.

The tool generates two figures directly with the results. The first figure shows a fitness curve that displays the optimization progress with time. The second figure shows a histogram for the distribution of funding among the different counties. A sample of these two figures are shown in Figure A.4. In addition to these figures, the optimization results will be shown in a tabular format.

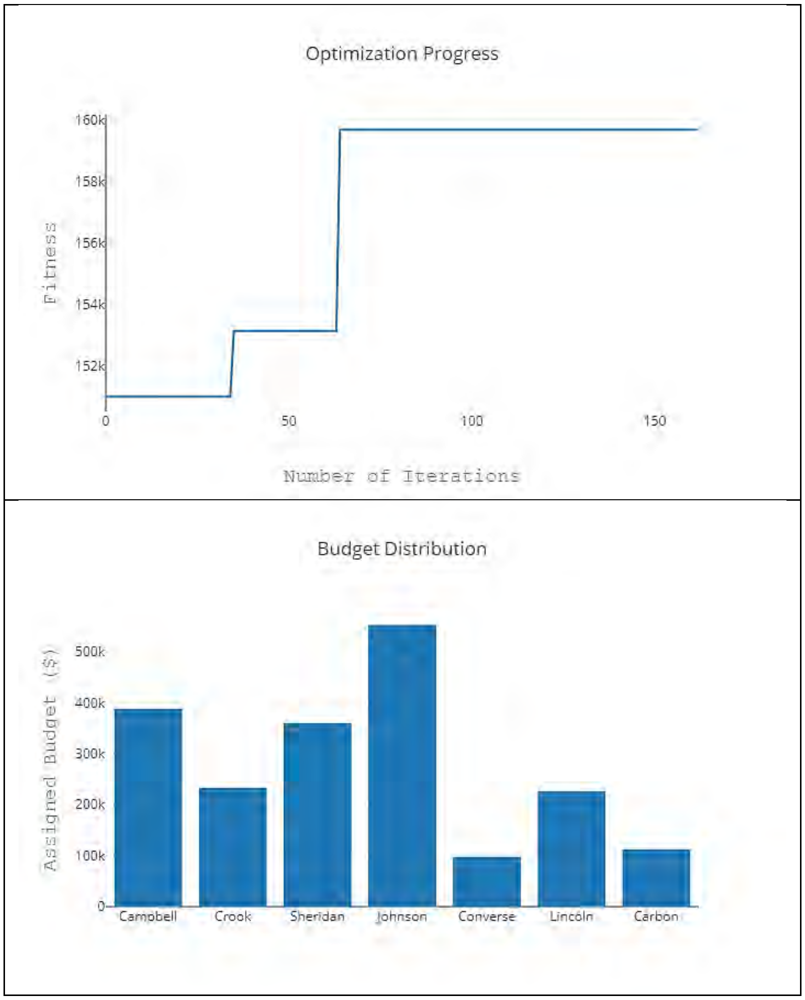


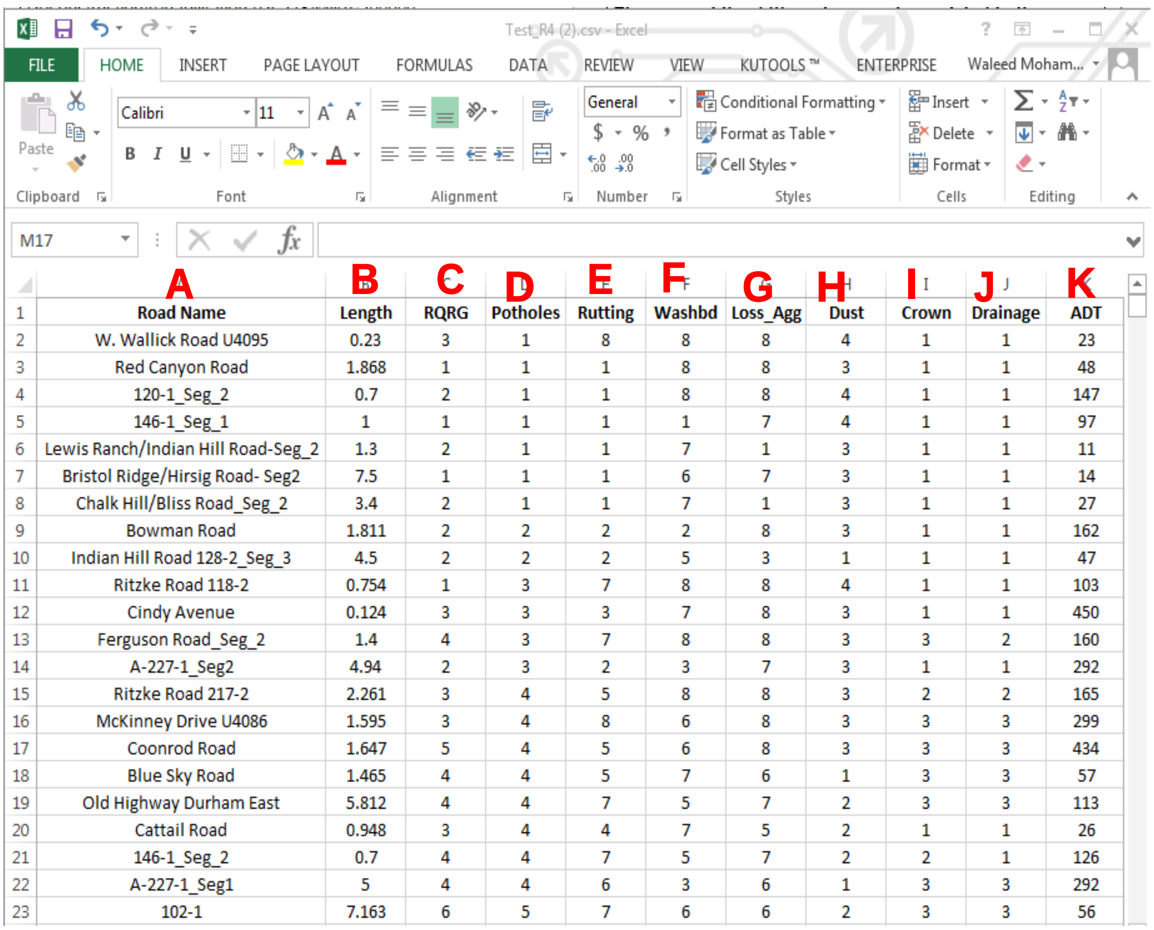
Figure A.4 Optimization Tool Sample Output

To get the best results and to cope with the stochastic nature of the used algorithm, it is highly recommended to run the tool multiple times with different GA inputs. After that, a user should compare between the final results and select the most suitable result according to his/her discretion.

Appendix A-2: Instructions on How to Use the Untreated Gravel Roads Optimization Tools

The following instructions provide the necessary steps to run the untreated gravel roads optimization tool:

1. Prepare a CSV file with the required inputs as shown exactly in Figure A.5. Table A.3 shows a description for each column.



	A	B	C	D	E	F	G	H	I	J	K
1	Road Name	Length	RQRG	Potholes	Rutting	Washbd	Loss_Agg	Dust	Crown	Drainage	ADT
2	W. Wallick Road U4095	0.23	3	1	8	8	8	4	1	1	23
3	Red Canyon Road	1.868	1	1	1	8	8	3	1	1	48
4	120-1_Seg_2	0.7	2	1	1	8	8	4	1	1	147
5	146-1_Seg_1	1	1	1	1	1	7	4	1	1	97
6	Lewis Ranch/Indian Hill Road-Seg_2	1.3	2	1	1	7	1	3	1	1	11
7	Bristol Ridge/Hirsig Road- Seg2	7.5	1	1	1	6	7	3	1	1	14
8	Chalk Hill/Bliss Road_Seg_2	3.4	2	1	1	7	1	3	1	1	27
9	Bowman Road	1.811	2	2	2	2	8	3	1	1	162
10	Indian Hill Road 128-2_Seg_3	4.5	2	2	2	5	3	1	1	1	47
11	Ritzke Road 118-2	0.754	1	3	7	8	8	4	1	1	103
12	Cindy Avenue	0.124	3	3	3	7	8	3	1	1	450
13	Ferguson Road_Seg_2	1.4	4	3	7	8	8	3	3	2	160
14	A-227-1_Seg2	4.94	2	3	2	3	7	3	1	1	292
15	Ritzke Road 217-2	2.261	3	4	5	8	8	3	2	2	165
16	McKinney Drive U4086	1.595	3	4	8	6	8	3	3	3	299
17	Coonrod Road	1.647	5	4	5	6	8	3	3	3	434
18	Blue Sky Road	1.465	4	4	5	7	6	1	3	3	57
19	Old Highway Durham East	5.812	4	4	7	5	7	2	3	3	113
20	Cattail Road	0.948	3	4	4	7	5	2	1	1	26
21	146-1_Seg_2	0.7	4	4	7	5	7	2	2	1	126
22	A-227-1_Seg1	5	4	4	6	3	6	1	3	3	292
23	102-1	7.163	6	5	7	6	6	2	3	3	56

Figure A.5 Sample CSV File to Run the Untreated Gravel Roads Optimization Tool

Table A.3 Description for the Untreated Gravel Roads Optimization Tool Inputs

Column	Description	Source
A	Road name	Google Earth, GIS maps
B	Road length (miles)	Google Earth, GIS maps
C	Ride Quality Rating Guide Rating	Windshield Survey
D	Potholes Rating	Windshield Survey
E	Rutting Rating	Windshield Survey
F	Washboards Rating	Windshield Survey
G	Loose Aggregate Rating	Windshield Survey
H	Dust Rating	Windshield Survey
I	Crown Rating	Windshield Survey
J	Drainage	Windshield Survey
K	ADT	WYT2/LTAP ADT maps

2. Please fill the required fields as shown in Figure ***A-6***. Mutation rate and initial population size inputs are highly dependent on the network size. As a rule of thumb, use high mutation rates with small initial population sizes for a higher efficiency while dealing with large networks (i.e. greater than 300 roads).

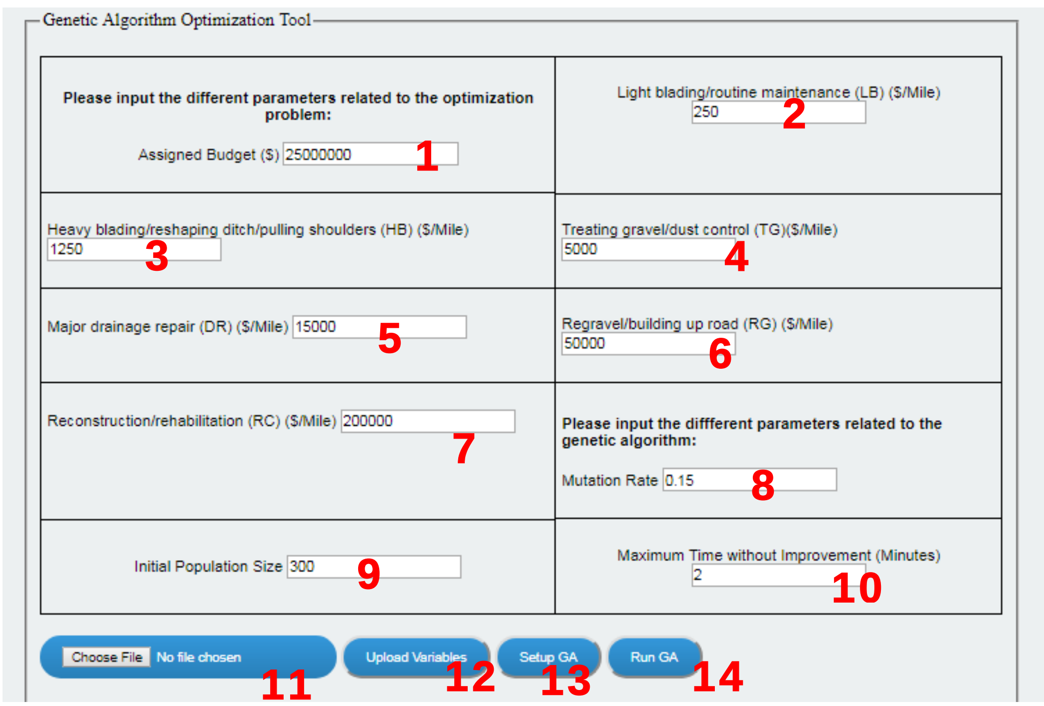


Figure A.6 Sample Inputs to Run the Untreated Gravel Roads Optimization Tool

3. Click on the "Choose File" button and select the CSV file from step 1.
4. Click on the "Upload Variables" button to upload the GA variables.
5. Click on the "Setup GA" button to initialize the algorithm.
6. Click on the "Run GA" button to run the algorithm. Please follow the numbers shown in Figure A.6.
7. After the convergence of the algorithm, please click on the "Show Optimization Results" button to show the optimization results.

8. Click the “Save” button to download the optimization results. The results will be a CSV file that can be uploaded to Excel for further analysis.

The tool generates one figure directly with the optimization results. The figure shows a fitness curve that displays the optimization progress with time. The optimization results are shown in tabular format. The outputs will include service level, required maintenance strategy, predicted gravel road condition, whether to fund a project or not and potential project cost. To get the best results and to cope with the stochastic nature of the used algorithm, it is highly recommended to run the tool multiple times with different GA inputs. After that, a user should compare between the final results and select the most suitable result according to his/her discretion.

APPENDIX B: IMAGE CLASSIFIER FOR DUST LEVELS ON GRAVEL ROADS

The developed image classifier in this research is considered as AForge.NET class library that provides functionality to extract information related to road conditions from images dataset. Currently, the only implemented operation is the classification of gravel roads' dust, but the class library structure is built to be able to support a large set of image analysis tasks. The following instructions provide the necessary steps to use and run the dust classifier:

1. Install the Roadroid application on the smartphone that will be used to collect data (Android OS > 5.0).
2. Register the phone IMEI number.
3. The smartphone setup in the vehicle:
   a. The phone should be horizontally/landscape mode as seen in Figure B.1.

Figure B.1 Smartphone Setup in the Testing Vehicle

   b. It should be easy to reach the display.
   c. Make sure camera lens capture road as seen in Figure B.2.

Figure B.2 Example of the Smartphone Position and Location at the Vehicle's Rear Windshield

Note: It is recommended to use a good mount car rack quality in order to avoid any data corruption.

4. Tap the Roadroid application icon to start the program and then press the yellow "fitting" button.
5. Try to park the testing vehicle on flat ground in order to ensure the accuracy of the fitting process.
6. Adjust the smartphone to X, Y and Z axis close to the zero value as possible. Then, the √ button will turn green when you are within the tolerances as seen in Figure B.3. This procedure is important in order to ensure that vertical (Y) accelerations is accurately picked exclude influence by braking (X) or turning (Z).

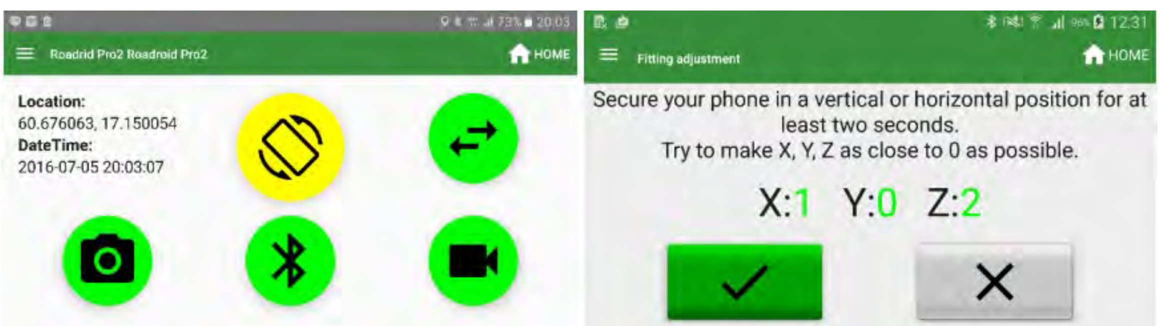


Figure B.3 Smartphone Adjustment

7. Capture Dust images of the tested gravel road segments:
   a. As seen from Figure B.4, the top bar displays if GPS is connected, time, memory space, speed, and distance surveyed. Also, it shows the current smartphone's battery temperature. In some cases, where the survey is conducted in warm/sunny conditions, overheating is observed. Therefore, it is recommended to keep turn on the testing vehicle's AC in order to cool the smartphone down.

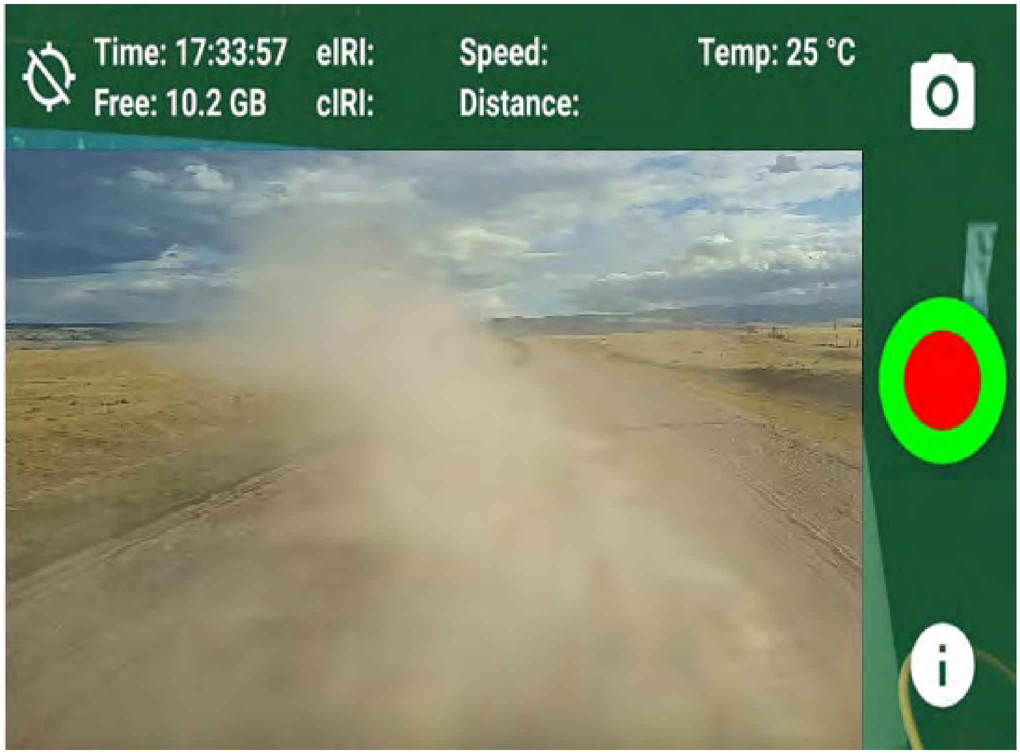


Figure B.4 Smartphone Display

a. It is important to keep the vehicle speed above 15 mph. That is because under 15 mph the application will show “low speed” and dust image data is not captured. Also, driving the testing vehicle 60 mph will show “high speed” and dust data is not captured either.
b. Info button gives current survey info.

8. Upload the collected dust images to the web server in order to be analyzed:
   a. Dust images are automatically saved on the smartphone memory while surveying. Also, there is no need to have internet (3G/4G) connection to make the surveys. However, a strong and stable internet connection (e.g. Wi-Fi) is recommended to upload image data after a survey.
   b. When you are connected, go to Menu-> Manage uploads. Then, upload dust image data to the cloud. Generally, photos can vary in size between 500 kb - 2 Mb.
   c. Figure B.5 shows an example of the smartphone application interface for uploading data.

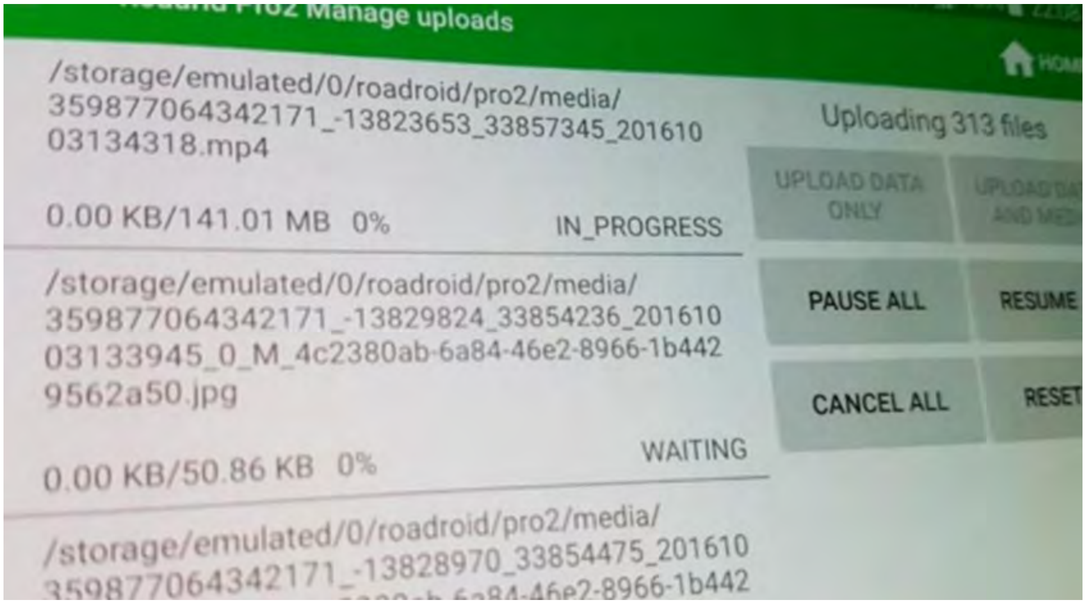


Figure B.5 Upload Collecting Data

9. Go to www.roadroid.com to import the uploaded surveys as seen in Figure B.6.

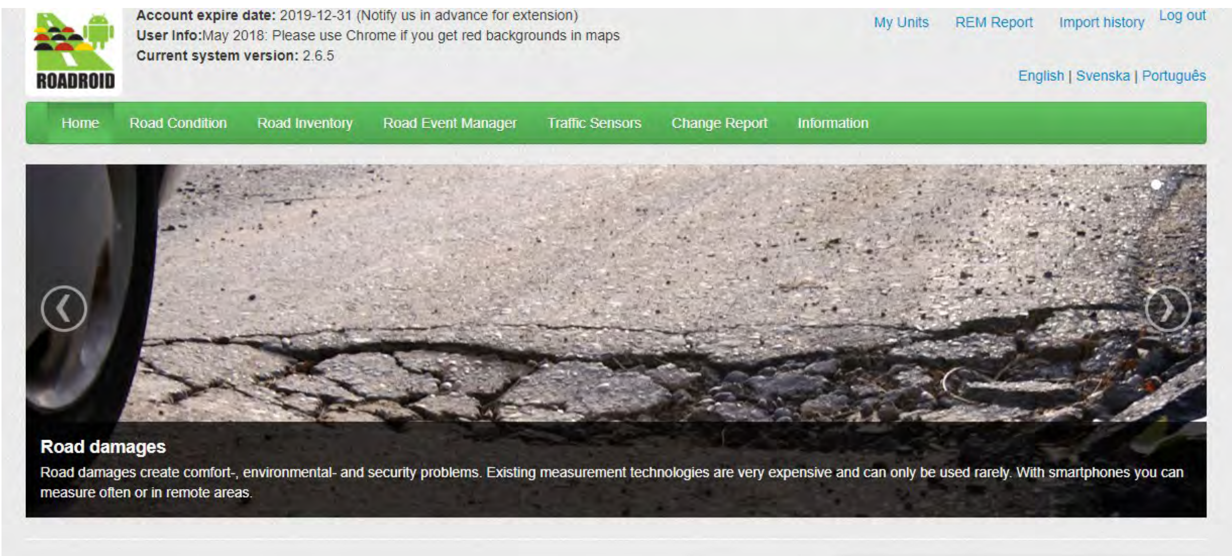


Figure B.6 Roadroid Website Interface

10. Click on "Details" as shown in Figure B.7 to open the required survey.

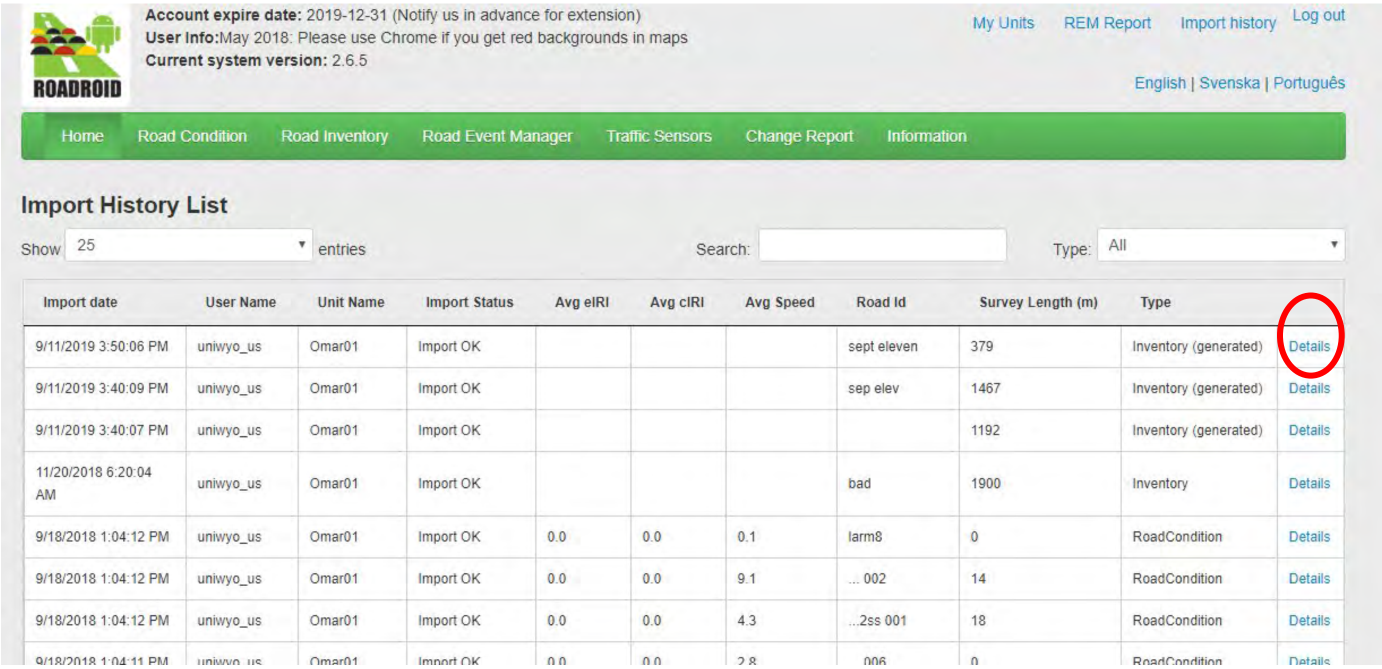


Figure B.7 Collected Surveys

11. Click on “Show survey data on a map” as shown in Figure B.8 to view the result of the classification process with a GPS-linked images.

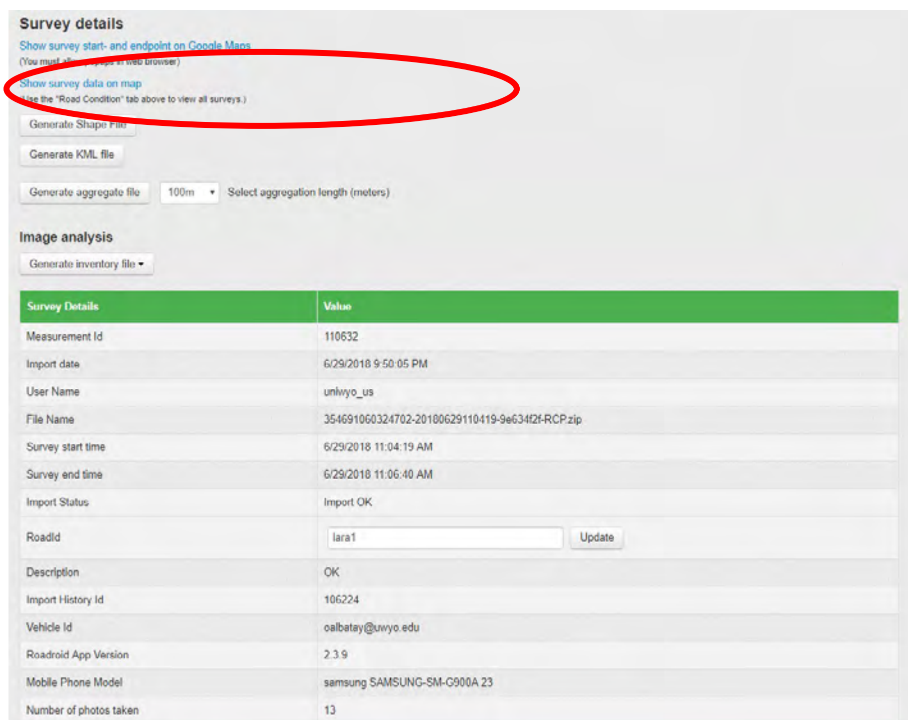
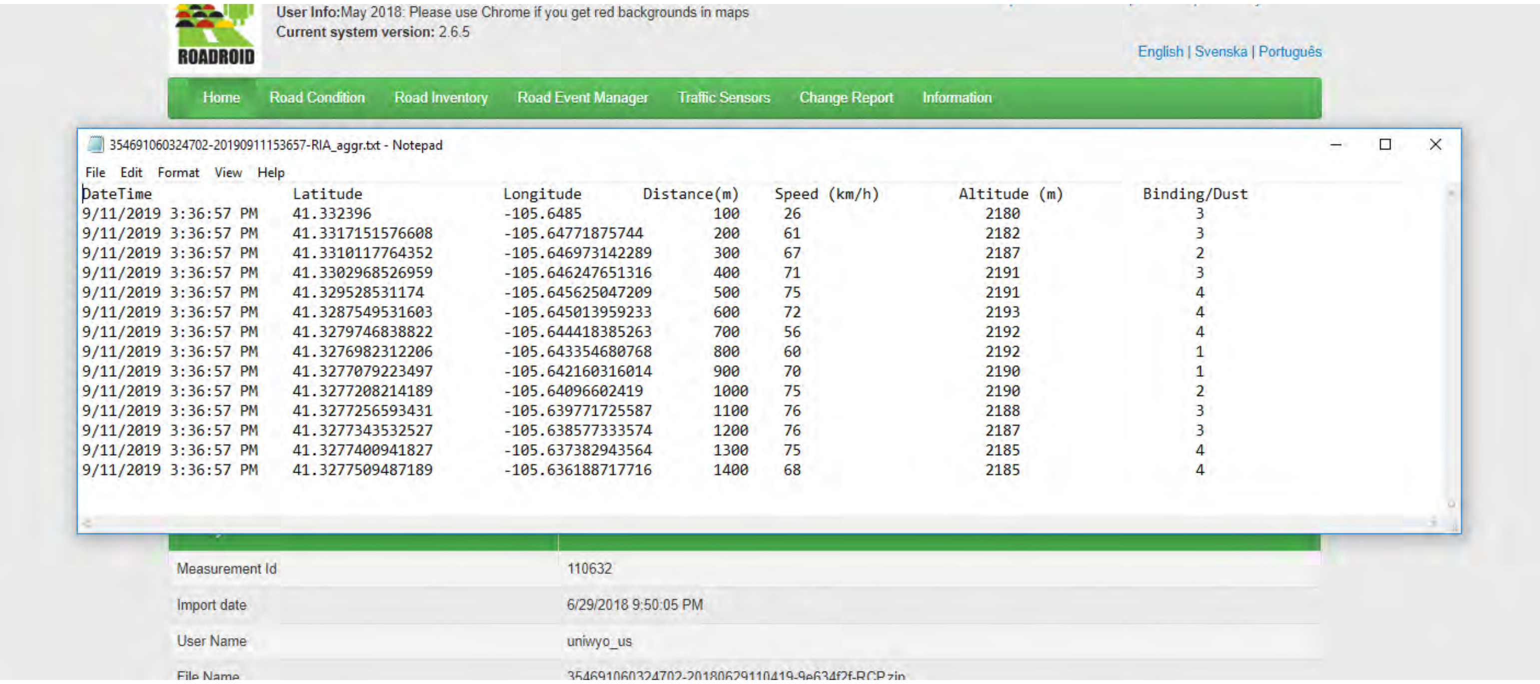


Figure B.8 Process to Open the Required Survey

12. A downloadable text file can be generated as shown in Figure B.9. This file contains information, such as date, time, location, distance, speed, altitude, and dust rating.



DateTime	Latitude	Longitude	Distance(m)	Speed (km/h)	Altitude (m)	Binding/Dust
9/11/2019 3:36:57 PM	41.332396	-105.6485	100	26	2180	3
9/11/2019 3:36:57 PM	41.3317151576608	-105.64771875744	200	61	2182	3
9/11/2019 3:36:57 PM	41.3310117764352	-105.646973142289	300	67	2187	2
9/11/2019 3:36:57 PM	41.3302968526959	-105.646247651316	400	71	2191	3
9/11/2019 3:36:57 PM	41.329528531174	-105.645625047209	500	75	2191	4
9/11/2019 3:36:57 PM	41.3287549531603	-105.645013959233	600	72	2193	4
9/11/2019 3:36:57 PM	41.3279746838822	-105.644418385263	700	56	2192	4
9/11/2019 3:36:57 PM	41.3276982312206	-105.643354680768	800	60	2192	1
9/11/2019 3:36:57 PM	41.3277079223497	-105.642160316014	900	70	2190	1
9/11/2019 3:36:57 PM	41.3277208214189	-105.64096602419	1000	75	2190	2
9/11/2019 3:36:57 PM	41.3277256593431	-105.639771725587	1100	76	2188	3
9/11/2019 3:36:57 PM	41.3277343532527	-105.638577333574	1200	76	2187	3
9/11/2019 3:36:57 PM	41.3277400941827	-105.637382943564	1300	75	2185	4
9/11/2019 3:36:57 PM	41.3277509487189	-105.636188717716	1400	68	2185	4

Figure B.9 Downloadable Text File

13. Finally, Figure B.10 illustrates a sample of the images taken from smartphone using the android application at a (100 m) interval.

Figure B.10 Sample of the GPS-linked Gravel Road Images

APPENDIX C: Dust Measurements for Laramie County

Descriptive Analysis of The Included Gravel Roads.

Name	County	Length (Km)	Width (m)	RQRG	Visual Dust Classification	Weather
Century Hills Rd	Laramie	1.6	7.47	7	High	Sunny/Dry
Reeder Rd	Laramie	1.6	7.92	8	High	Sunny/Dry
207 & Missle Rd	Laramie	1.6	8.50	6	High	Sunny/Dry
143 Rd	Laramie	1.6	7.68	5	High	Sunny/Dry
208 Rd	Laramie	1.6	9.39	7	High	Sunny/Dry
206 Rd	Laramie	1.6	8.59	7	High	Sunny/Dry
Hales Ranch Rd	Laramie	1.6	7.07	7	Medium	Sunny/Dry
Spring Beauty	Laramie	1.6	7.13	7	Medium	Sunny/Dry
Patrick Rd	Laramie	1.6	6.98	7	Medium	Sunny/Dry
Rd 207	Laramie	1.6	7.95	8	Medium	Sunny/Dry
207 & 143 Rd	Laramie	1.6	7.07	8	Medium	Sunny/Dry
144 Rd	Laramie	1.6	8.44	7	Medium	Sunny/Dry
146 & 207 Rd	Laramie	1.6	7.44	6	Medium	Sunny/Dry
205 Rd	Laramie	1.6	7.38	7	Medium	Sunny/Dry
Wlesh Ln seg1	Albany	1.6	7.65	7	Medium	Sunny/Dry
Wlesh Ln seg2	Albany	1.6	7.99	7	Medium	Sunny/Dry
Wlesh Ln seg3	Albany	1.6	8.75	8	Medium	Sunny/Dry
Happy Lack	Albany	1.6	6.52	5	Medium	Sunny/Dry
Wlesh Ln seg4	Albany	1.6	8.29	7	Medium	Sunny/Dry
HR Ranch Rd	Laramie	1.6	8.29	7	Low	Sunny/Dry
Morning Glory Rd	Laramie	1.6	6.46	9	Low	Sunny/Dry
146 Rd	Laramie	1.6	6.52	4	Low	Sunny/Dry
148 Rd	Laramie	1.6	9.39	6	Low	Sunny/Dry
202 Rd	Laramie	1.6	8.90	6	Low	Sunny/Dry
Stockyards Rd	Albany	1.6	8.59	7	Low	Sunny/Dry
Curtis St	Albany	1.6	7.38	7	Low	Sunny/Dry
Old Stocky Rd	Albany	1.6	7.74	7	Low	Sunny/Dry
W Curt St	Albany	1.6	8.17	6	Low	Sunny/Dry
Grandview Rd	Albany	1.6	9.20	7	Low	Sunny/Dry
Wlesh Ln seg5	Albany	1.6	8.90	7	Low	Sunny/Dry

RQRG Table

	Rating	Speed* (mph)	Distresses**
10	Excellent	60+	-
9	Very Good	50-60	-
8 **--------------------** **7**	Good -------------------- Good	45-50 -------------------- 40-45	Dust under dry conditions; Moderate loose aggregate; Slight washboarding.
6 **--------------------** **5**	Fair -------------------- Fair	32-40 -------------------- 25-32	Moderate washboarding (1" - 2" deep) over 10% - 25% of area; Moderate dust, partial obstruction of vision; None or slight rutting (less than 1" deep); An occasional small pothole (less than 2" deep); Some loose aggregate (2" deep).
4 **--------------------** **3**	Poor -------------------- Poor	20-25 -------------------- 15-20	Moderate to severe washboarding (over 3" deep) over 25% of area; Moderate rutting (1" - 3") over 10% - 25% of area; Moderate potholes (2" - 4" deep) over 10% - 25% of area; Severe loose aggregate (over 4").
2 **--------------------** **1**	Very Poor -------------------- Failed	8-15 -------------------- 0-8	Severe rutting (over 3" deep) over 25% of area; Severe potholes (over 4" deep) over 25% of area; Many areas (over 25%) with little or no aggregate.

* Passenger car speeds based on surface condition allowing for rider comfort and minimal vehicle wear and tear, assuming no safety or geometric constraints force slower travel.
** Adapted from the Gravel - PASER manual

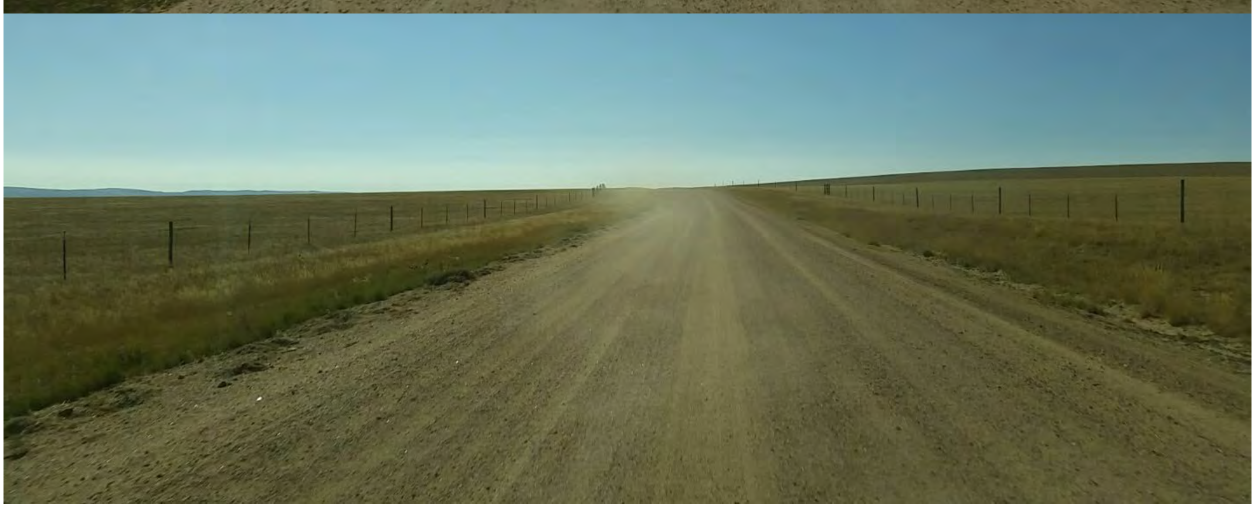
Sample of the Classified Images Using

High Dust

Medium Dust

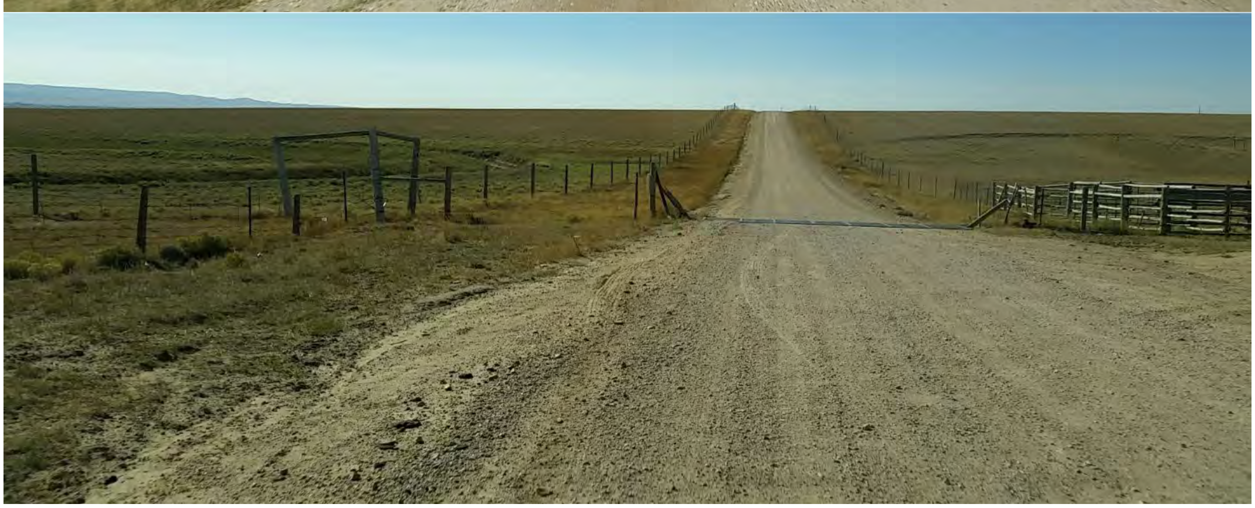
Low Dust





None- Dust





Appendix D: Laramie County Gravel Roads Surface Evaluation Results as of Summer 2017

*GR: Gravel Road; NE: Natural Earth; TG: Treated Gravel; RQRG: Ride Quality Rating Guide rating																
FID	SN	Zone	FROM_MP	TO_MP	Road Name	Length (Miles)	Speed (mph)	*RQRG	Potholes	Rutting	Washboards	Loose Aggregate	Dust	Crown	Drainage	*Aggregate Type
60	1	1	0	0.23	W. Wallick Road U4095	0.230	10	3	1	8	8	8	4	1	1	NE
146	2	5	0	1.88	Red Canyon Road	1.868	8	1	1	1	8	8	3	1	1	NE
11	3	1	5	5.7	120-1_Seg_2	0.700	15	2	1	1	8	8	4	1	1	NE
103	4	3	0	1	146-1_Seg_1	1.000	20	1	1	1	1	7	4	1	1	NE
663	5	16	2.2	4.5	Lewis Ranch/Indian Hill Road-Seg_2	1.300	8	2	1	1	7	1	3	1	1	NE
664	6	16	7.78	15.28	Bristol Ridge/Hirsig Road- Seg2	7.500	10	1	1	1	6	7	3	1	1	NE
700	7	21	1	4.4	Chalk Hill/Bliss Road_Seg_2	3.400	8	2	1	1	7	1	3	1	1	NE
141	8	4	0	1.89	Bowman Road	1.811	15	2	2	2	2	8	3	1	1	GR
619	9	12	9.8	14.3	Indian Hill Road 128-2_Seg_3	4.500	20	2	2	2	5	3	1	1	1	NE
214	10	6	0	0.58	Ritzke Road 118-2	0.754	25	1	3	7	8	8	4	1	1	NE
325	11	7	0	0.12	Cindy Avenue	0.124	20	3	3	3	7	8	3	1	1	NE
144	12	5	0.7	2.1	Ferguson Road_Seg_2	1.400	30	4	3	7	8	8	3	3	2	TG
671	13	18	5	9.94	A-227-1_Seg2	4.940	20	2	3	2	3	7	3	1	1	NE
165	14	6	0	2.28	Ritzke Road 217-2	2.261	40	3	4	5	8	8	3	2	2	GR
174	15	6	0	1.59	McKinney Drive U4086	1.595	30	3	4	8	6	8	3	3	3	TG
185	16	6	0	1.37	Coonrod Road	1.647	35	5	4	5	6	8	3	3	3	TG
392	17	7	0	1.49	Blue Sky Road	1.465	40	4	4	5	7	6	1	3	3	GR
412	18	7	0	5.99	Old Highway Durham East	5.812	40	4	4	7	5	7	2	3	3	GR
666	19	17	0	1	Cattail Road	0.948	25	3	4	4	7	5	2	1	1	NE
103	20	3	1	0.7	146-1_Seg_2	0.700	40	4	4	7	5	7	2	2	1	GR
151	21	5	0	4.3	Gilchrist Road_Seg1	4.300	40	4	4	7	6	7	3	3	3	TR
671	22	18	0	5	A-227-1_Seg1	5.000	50	4	4	6	3	6	1	3	3	GR
4	23	0	0	7.32	102-1	7.163	40	6	5	7	6	6	2	3	3	TG/GR
47	24	1	0	0.1	Mitchell Court	0.092	20	5	5	8	9	8	3	3	3	GR
95	25	3	0	2	A-143-3	1.994	40	5	5	7	6	7	1	3	3	GR

101	26	3	0	0.47	Monroe Avenue -Carpenter	0.471	40	5	5	6	7	8	1	2	1	GR
182	27	6	0	0.7	826-1	0.701	25	4	5	8	6	8	4	1	1	GR
187	28	6	0	1.6	Thunder Ridge Road	1.598	30	6	5	8	6	7	1	3	3	GR
225	29	6	0	0.19	Ponderosa Trail	0.186	30	5	5	8	8	8	4	3	3	GR
245	30	6	0	1.22	624	1.210	30	4	5	8	6	8	4	2	3	TG
261	31	6	0	0.41	El Camino Real	0.405	30	4	5	8	6	8	4	3	3	GR
331	32	7	0	0.19	629	0.244	30	4	5	6	8	8	3	1	3	GR
333	33	7	0	0.64	McCann Avenue	0.126	25	4	5	6	7	8	1	3	3	GR
509	34	7	0	0.56	Carla Drive U4047	0.369	30	5	5	7	5	7	3	1	1	GR
516	35	8	0	0.89	A-209-4	1.013	40	4	5	7	4	8	3	3	1	GR
522	36	8	0	16.8	Hillsdale Road West	16.619	40	5	5	7	5	6	3	3	3	GR
587	37	11	0	4.06	Ridley Road	4.009	35	5	5	8	6	8	3	3	3	GR
595	38	11	1	0.998	712	0.466	30	6	5	8	7	8	3	3	3	GR
610	39	11	0	1.08	Lodgepole Drive	1.062	35	7	5	8	8	8	3	3	3	TG
616	40	12	6	8.23	136-1	2.010	55	6	5	7	7	7	1	3	3	GR
620	41	12	0	2.66	Berry Road	2.621	50	6	5	7	7	7	1	3	3	GR
639	42	13	0	5.4	King Road	5.349	40	5	5	6	5	7	2	2	2	GR
11	43	1	16.1	19.2	120-1_Seg_6	3.100	40	6	5	6	6	7	2	3	3	GR
98	44	3	0	1.3	Oline Road_Seg_1	1.300	30	4	5	6	6	7	1	1	1	NE
586	45	11	0	2.8	Farris Road_Seg_1	2.800	35	5	5	7	7	8	3	3	3	TG
612	46	12	0	8.1	Divide Road_Seg_1	8.100	45	5	5	7	6	7	2	3	3	GR
630	47	13	3	6.08	Lyons Road_Seg2	3.080	50	6	5	7	5	7	3	3	3	GR
631	48	13	4	8	A-220-4_Seg2	4.000	60	5	5	6	5	7	1	3	3	GR
13	49	1	0	0.43	Beverly Blvd.	0.433	30	7	6	8	8	8	1	3	3	GR
53	50	1	0	0.15	Hartford Avenue	0.150	20	6	6	8	8	8	3	3	3	GR
56	51	1	0	0.33	Citrus Street	0.335	30	6	6	8	7	8	2	3	3	GR
70	52	1	0	0.05	Long Shadow Lane	0.030	8	3	6	3	9	8	4	1	1	NE
106	53	3	0	2.05	Dump Road	1.543	30	4	6	7	4	7	1	3	3	GR
108	54	3	3	4.86	151-1	1.994	40	6	6	6	6	8	1	3	3	GR
118	55	3	0	36.8	Chalk Bluff/""""78"""" Road	36.406	55	6	6	6	6	7	4	3	3	GR

135	56	4	0	5.87	A-156-2	5.786	50	6	6	6	5	8	1	3	3	GR
152	57	5	0	0.93	110-A	0.927	30	7	6	7	7	8	3	3	3	TG
153	58	5	0	10.8	Crystal Lake Road	10.661	40	5	6	7	4	6	3	3	3	TG/GR
154	59	5	0	3.56	Romsa Road	3.362	35	7	6	7	8	5	3	3	3	GR
156	60	5	0	2.07	North Table Mountain	2.058	35	8	6	7	7	7	3	3	2	TG
167	61	6	0	0.43	A-118-B	0.660	30	5	6	7	8	8	3	3	3	GR
186	62	6	0	1.94	835	1.937	35	6	6	7	6	7	3	3	3	GR
221	63	6	0	0.26	Kersey Drive	0.250	30	7	6	8	8	8	4	3	3	GR
243	64	6	0	0.4	McAllister Lane	0.429	30	5	6	6	7	7	3	1	1	GR
256	65	6	0	0.51	East Laughlin Road	0.512	30	6	6	8	7	7	3	3	3	GR
272	66	6	0	3	Milliron Road W,E,N,S	2.994	30	6	6	7	7	6	3	3	3	GR
280	67	6	0	1.14	Legend Trail	1.134	35	6	6	8	7	7	1	3	3	GR
295	68	6	0	0.35	Kentucky Street	0.356	30	7	6	8	9	8	4	3	3	GR
313	69	7	0	0.95	Tate Road	0.988	30	5	6	7	6	8	2	3	3	GR
323	70	7	3	6.22	136-1	2.777	30	4	6	7	5	7	1	3	3	GR
363	71	7	0	0.75	Ford Road	0.766	30	5	6	7	6	8	1	3	3	GR
460	72	7	0	0.44	Pine Bluff Street	0.444	35	5	6	8	6	7	1	3	3	GR
543	73	8	0	1.02	Landfill Road	1.002	50	6	6	7	6	8	1	3	2	GR
557	74	8	0	0.51	A-147-2	0.491	50	7	6	8	5	8	1	3	3	GR
563	75	9	0	0.51	A-211-3	0.488	30	4	6	7	4	7	2	3	3	GR
564	76	9	0	8.92	Old Highway Pine Bluffs West	9.068	45	5	6	7	4	7	1	3	3	GR
565	77	9	0	2.01	Macy Road	1.995	30	4	6	7	4	6	1	3	3	GR
573	78	9	0	1.08	A-162-1	1.069	40	5	6	7	4	7	1	3	3	GR
590	79	11	0	2.48	Pry Road	2.480	40	5	6	7	8	8	3	3	3	GR
592	80	11	0	0.85	Morgan Drive	0.876	40	7	6	8	8	8	3	3	3	GR
598	81	11	0	0.92	Channell Drive	0.911	35	7	6	8	8	8	3	3	3	GR
600	82	11	0	0.29	742	0.290	30	7	6	8	8	8	3	3	3	TG
603	83	11	0	0.37	Chugwater Drive	0.367	25	6	6	8	8	7	3	3	3	GR
609	84	11	0	0.91	Petersen Drive	0.911	30	5	6	7	8	8	4	3	3	GR
617	85	12	0	0.41	Continental Road	0.474	30	6	6	7	6	8	2	3	3	GR

683	86	19	0	0.53	A-158-7	0.538	45	6	6	7	6	7	1	3	3	GR
704	87	23	0	6.18	Coad Road	6.061	45	6	6	6	6	7	1	3	3	GR
11	88	1	11.1	16.1	120-1_Seg_5	5.000	40	7	6	6	7	8	3	3	3	TG
111	89	3	0	4	Arcola Road_Seg_1	4.000	55	5	6	6	5	7	1	3	3	GR
572	90	9	4	8.25	A-161-3_Seg2	4.250	50	6	6	7	6	6	1	3	3	GR
586	91	11	2.8	6.1	Farris Road_Seg_2	3.300	35	5	6	4	8	8	3	3	3	GR
619	92	12	0	6.4	Indian Hill Road 128-2_Seg_1	6.400	45	7	6	6	7	8	2	3	3	GR
631	93	13	0	4	A-220-4_Seg1	4.000	60	6	6	7	6	7	1	3	3	GR
640	94	13	6	11	Ogle Road_Seg2	5.000	60	6	6	7	6	7	1	3	3	GR
648	95	14	0	5	Berggren Road_Seg1	5.000	50	6	6	7	6	7	1	3	3	GR
648	96	14	5	9.5	Berggren Road_Seg2	4.500	50	6	6	5	6	7	1	3	3	GR
654	97	14	0	5	Lindbergh Road North_Seg1	5.000	50	6	6	7	6	7	1	3	3	GR
654	98	14	5	10.7	Lindbergh Road North_Seg2	5.700	50	6	6	7	6	7	1	3	3	GR
657	99	14	0	2.4	158-4_Seg1	2.400	30	5	6	4	6	6	1	1	1	NE
668	100	17	0	1	Indian Hill Road 131-3_Seg_1	1.000	30	4	6	5	7	6	1	1	2	NE
694	101	19	0	1	Larson Road_Seg1	1.000	30	4	6	6	6	7	1	1	1	NE
709	102	23	0	4	Hunter Ranch Road_Seg1	4.000	35	5	6	3	6	3	1	2	2	NE
14	103	1	0	0.28	800	0.308	30	7	7	8	8	8	1	3	3	GR
35	104	1	0	0.33	Division Road	0.216	30	7	7	7	7	8	2	3	3	GR
48	105	1	0	0.2	Apple Street	0.200	30	7	7	8	8	8	3	3	2	GR
50	106	1	0	0.44	Third Avenue	0.442	30	6	7	8	8	6	3	3	3	GR
57	107	1	0	0.22	Milatzo Avenue	0.216	30	7	7	8	7	8	3	3	3	GR
79	108	2	0	0.04	Lake Place	0.046	10	7	7	8	8	8	2	2	2	GR
80	109	2	0	0.21	Drew Court	0.209	15	7	7	7	7	8	1	3	2	GR
91	110	2	0	1.53	Rosetta Lane	1.530	40	7	7	8	6	7	1	3	3	GR
93	111	3	0	1.07	A-141-2	0.992	45	7	7	6	6	7	3	3	2	GR
102	112	3	0	0.14	408	0.197	30	7	7	7	8	8	1	1	1	GR
105	113	3	0	3.85	A-147-1	3.827	45	6	7	7	6	8	1	3	3	GR
107	114	3	0	1.77	Ragland Road	1.756	55	8	7	7	8	8	1	2	2	NE
110	115	3	0	3.03	Miller Road West 144-1	2.996	60	7	7	8	7	6	1	3	3	GR

112	116	3	0	0.3	Fifth St. -Carpenter	0.306	30	7	7	7	7	8	2	2	1	GR
113	117	3	0	0.27	First St. -Carpenter	0.301	30	7	7	7	7	8	2	2	1	GR
116	118	3	0	0.37	Second St. -Carpenter	0.369	30	7	7	7	7	8	2	2	1	GR
122	119	3	0	1.01	Glassburn Road	0.997	40	5	7	7	5	8	2	1	1	GR
133	120	4	0	2.02	Edwards Road	1.999	60	8	7	6	6	7	1	3	3	GR
134	121	4	0	2.74	Bauman Road	2.836	60	6	7	6	7	8	2	2	2	GR
137	122	4	3	5.85	158-1	2.991	60	6	7	6	7	8	1	3	3	GR
138	123	4	0	2.776	158-1	2.777	50	7	7	7	7	8	1	3	3	GR
142	124	4	0	6.07	Suchomel Road	5.991	50	6	7	4	6	8	1	2	2	GR
145	125	5	0	4.18	N. Crow Rd	3.824	30	5	7	8	5	8	3	1	1	NE
159	126	5	0	1.63	E & S Mule Trl.	1.613	35	6	7	8	7	6	4	3	3	GR
162	127	5	0	0.15	Stable Drive	0.155	5	3	7	2	9	9	4	1	1	NE
168	128	6	0	1.01	Blazer Road	1.000	35	7	7	8	8	7	2	3	3	GR
173	129	6	0	0.6	Rolling HIlls Road	0.598	30	6	7	8	7	8	3	3	3	GR
183	130	6	0	0.62	Orion Drive	0.609	30	7	7	8	8	8	4	3	3	GR
188	131	6	0	1.84	Morning Star Road	1.841	30	6	7	7	6	7	2	3	3	GR
190	132	6	0	1.63	888	1.629	30	7	7	7	8	7	3	3	3	GR
195	133	6	0	0.14	Iron Mountain Lane	0.135	30	7	7	8	8	8	3	3	3	GR
200	134	6	0	0.08	DeCastro Drive	0.125	30	6	7	8	8	8	3	3	3	GR
212	135	6	0	0.18	Road 116	0.179	30	7	7	8	8	8	4	1	1	GR
215	136	6	0	0.98	Military Road	1.041	30	6	7	8	7	8	4	3	3	TG
216	137	6	0	0.49	Riding Club Road	0.483	30	7	7	8	8	8	3	3	3	GR
219	138	6	0	0.38	Utah Street	0.364	25	7	7	8	8	8	3	3	3	GR
230	139	6	0	0.51	Lupe Road	0.512	30	6	7	7	8	8	4	3	2	GR
232	140	6	0	0.68	Hackamore Road	0.683	25	7	7	8	7	8	4	3	3	GR
238	141	6	0	0.26	Monte Carlo Drive	0.253	30	6	7	8	7	8	3	3	3	GR
240	142	6	0	0.25	Skyline Drive 574	0.246	30	6	7	8	8	8	4	2	1	GR
246	143	6	0	1	Barrington Road	0.992	30	7	7	8	7	6	2	3	3	GR
257	144	6	0	0.69	Silver Spur Road	0.684	30	7	7	8	8	8	3	3	3	GR
276	145	6	0	0.7	Star Valley Drive	0.697	30	7	7	8	8	8	3	3	3	GR

278	146	6	0	0.59	836	0.589	30	7	7	8	8	8	3	3	3	GR
279	147	6	0	0.43	Foxhill Road	0.432	30	7	7	8	8	7	2	3	3	GR
288	148	6	0	0.23	W. Idaho Street	0.235	20	7	7	8	7	8	3	3	3	GR
296	149	6	0	0.37	Michigan Street	0.372	30	7	7	8	8	8	3	3	3	GR
336	150	7	1	0.63	Laramie St	0.121	30	6	7	7	8	8	2	3	3	GR
339	151	7	0	0.52	645	0.512	35	7	7	8	7	8	3	3	1	GR
351	152	7	0	0.36	Albin Lane	0.365	30	7	7	8	7	7	3	3	3	GR
352	153	7	0	0.46	Kaycee Place	0.453	30	6	7	8	6	7	3	3	3	GR
354	154	7	0	1.18	Obsidian Road	1.168	40	5	7	8	5	8	1	3	3	GR
364	155	7	0	0.24	Anthoney Road	0.259	10	2	7	3	8	7	3	1	1	GR
368	156	7	0	0.12	Jillian Drive	0.127	30	8	7	8	8	8	2	3	3	GR
372	157	7	0	0.62	821	0.622	35	6	7	8	6	7	1	3	3	GR
373	158	7	0	0.62	822	0.622	35	6	7	8	6	7	1	3	3	GR
377	159	7	0	3.08	Hales Ranch Road	3.097	40	7	7	7	7	6	1	3	3	GR
380	160	7	0	3.07	HR Ranch Road	3.077	40	6	7	7	7	6	1	3	3	GR
381	161	7	0	0.25	Morgan Ranch Road	0.252	30	7	7	8	7	8	1	3	3	GR
403	162	7	1	1.49	Thomas Road	0.993	40	7	7	8	7	8	3	3	3	GR
407	163	7	0	0.77	137-1, Skyway Ave.	0.749	30	6	7	8	6	8	1	3	3	GR
415	164	7	0	0.48	John Drive	0.480	25	7	7	7	7	7	1	3	3	GR
425	165	7	0	0.88	GLencoe Drive	0.871	35	6	7	7	7	7	3	3	2	GR
431	166	7	0	1.03	597	0.845	30	5	7	7	4	6	1	3	3	GR
433	167	7	0	1.02	Chief Twomoon Road	1.009	30	6	7	7	6	6	1	3	3	GR
441	168	7	0	0.13	Craigy-J Drive	0.114	30	6	7	8	6	8	1	3	3	GR
452	169	7	0	0.3	Farthing Road	0.294	30	6	7	7	7	8	1	3	3	GR
455	170	7	0	0.31	Woodhouse Road	0.213	30	7	7	8	8	8	2	3	3	GR
458	171	7	0	1.04	Cody Lane	1.194	30	6	7	8	7	7	3	3	3	GR
461	172	7	0	1.01	Agate Road	0.994	45	7	7	8	7	8	1	3	3	GR
463	173	7	0	0.6	Turqoise Road	0.591	40	7	7	8	7	8	1	3	3	GR
474	174	7	0	1.06	Powderhouse Road	1.047	30	5	7	7	5	7	1	3	3	GR
483	175	7	0	1.06	Red Fox Road	1.045	30	6	7	7	6	7	1	3	3	GR

518	176	8	0	1.68	Louth Road	1.748	40	6	7	6	6	8	1	1	1	NE
519	177	8	12	18.47	215-3	6.029	60	6	7	7	6	7	1	3	3	GR
521	178	8	0	1.36	McWilliams Road	1.366	40	5	7	4	5	8	1	1	2	NE
525	179	8	0	0.15	Higday Road	0.154	25	6	7	8	5	8	1	3	3	GR
533	180	8	1	3.86	A-148-4	3.165	60	6	7	7	6	6	1	2	3	GR
536	181	8	0	0.5	A-150-2	0.561	50	8	7	8	7	8	1	2	2	GR
539	182	8	0	28.38	Hillsdale North Road/Midway	28.104	50	6	7	7	6	8	1	3	3	GR
544	183	8	0	0.87	Paradise Drive	0.857	50	8	7	8	7	7	3	3	3	GR
545	184	8	0	0.13	Coates Avenue-Hillsdale	0.138	25	7	7	6	7	8	2	1	1	NE
547	185	8	0	0.2	Third Street-Hillsdale	0.203	25	8	7	7	8	8	2	2	1	NE
554	186	8	0	0.89	Summerset Drive	0.867	50	7	7	7	6	6	3	3	3	GR
561	187	9	0	1.2	A-208-2	1.198	50	7	7	8	7	8	2	3	3	GR
562	188	9	0	6.05	A-210-4	5.986	45	6	7	7	7	8	1	3	3	GR
571	189	9	0	2.48	A-161-2	2.449	50	7	7	7	7	8	1	3	3	GR
574	190	9	0	2.02	Potato Plant Road West	2.000	50	6	7	7	5	8	1	3	3	GR
575	191	9	0	2.15	Wisroth Road	2.137	50	6	7	7	6	7	2	3	3	GR
579	192	9	0	2.23	A-158-2	2.230	60	6	7	8	6	8	1	3	3	GR
602	193	11	0	1.02	Federer Road	0.993	35	6	7	8	7	8	3	3	3	GR
611	194	11	0	1.01	Bridger Drive	0.998	30	7	7	8	8	7	3	3	3	GR
613	195	12	0	5	Keslar Road	4.954	50	6	7	7	6	7	1	3	3	GR
615	196	12	0	2.37	Epler Road	2.354	50	6	7	7	6	7	1	3	3	GR
622	197	12	0	1	A-139-3	0.992	30	7	7	8	7	8	1	3	3	GR
624	198	12	0	0.66	Chrysler Road	0.683	30	8	7	7	8	8	1	3	3	GR
626	199	12	0	0.64	Studebaker Road	0.613	30	8	7	7	8	7	2	3	3	GR
633	200	13	0	1	A-147-3	0.987	60	7	7	7	6	7	1	3	3	GR
637	201	13	0	2.04	Martin Road	2.047	60	7	7	7	6	8	1	3	3	GR
641	202	13	0	7.04	Golden Prairie Road	6.969	60	7	7	7	7	6	1	3	3	GR
642	203	14	0	4.07	Scheel Road	4.052	50	7	7	6	6	6	1	3	3	GR
644	204	14	0	1.13	A-224-3	1.464	50	6	7	7	7	5	1	3	3	GR
649	205	14	0	2.01	A-164-2	1.993	50	6	7	6	7	5	1	3	3	GR

655	206	14	0	4.37	Zimmerman Road	4.321	50	7	7	7	7	7	1	3	3	GR
660	207	15	0	2.16	Quarry Road	2.235	45	8	7	8	8	7	2	3	3	NE/GR
670	208	17	0	2.95	Boughsty Road	2.915	50	7	7	7	8	7	1	2	2	NE
680	209	19	0	1.01	A-231-1	0.994	45	7	7	8	7	7	1	3	3	GR
684	210	19	0	5.06	A-159-4	5.000	45	6	7	7	6	7	1	3	3	GR
705	211	23	1	4.69	150-6	3.695	60	8	7	7	7	7	1	3	3	GR
708	212	23	0	2.14	Petsch Road	2.115	40	7	7	7	7	5	1	2	2	GR
710	213	23	0	4.71	Schliske Road	4.661	40	5	7	6	7	2	1	2	3	NE
711	214	23	0	1.58	A-152-5	1.565	40	6	7	6	7	6	1	2	1	NE
11	215	1	0	5	120-1_Seg_1	5.000	55	7	7	5	6	7	1	3	2	GR
11	216	1	5.7	6.9	120-1_Seg_3	1.200	30	4	7	5	7	8	3	3	3	GR
99	217	3	0.5	1.5	A-205-1_Seg_2	1.000	45	7	7	8	7	7	2	3	3	GR
100	218	3	0	6	Pulver Road_Seg_1	6.000	60	8	7	8	7	6	1	3	3	GR
111	219	3	4	11	Arcola Road_Seg_2	7.000	60	7	7	7	7	6	1	3	3	GR
117	220	3	0	1	A-201-Seg2	1.000	30	6	7	6	7	7	1	1	1	NE
132	221	4	8	12	154-1_Seg2	4.000	60	7	7	8	7	7	1	3	3	GR
132	222	4	15	23	154-1_Seg4	8.000	60	7	7	7	7	8	1	3	3	GR
532	223	8	0	5	Tremble Road_Seg_1	5.000	50	7	7	8	7	6	2	3	3	GR
589	224	11	3.6	6	Holmes Road_Seg_2	2.400	35	5	7	5	7	8	1	3	3	GR
612	225	12	8.1	12	Divide Road_Seg_2	3.900	45	7	7	7	6	7	2	3	3	GR
614	226	12	0	3.05	Jay Road_Seg_2	3.006	40	8	7	7	8	8	1	3	3	GR
619	227	12	6.4	9.8	Indian Hill Road 128-2_Seg_2	3.400	45	8	7	7	8	8	3	2	2	GR
640	228	13	0	6	Ogle Road_Seg1	6.000	60	8	7	7	7	7	1	3	3	GR
653	229	14	0	5	Lindbergh Road_Seg1	5.000	50	7	7	7	6	7	1	3	3	GR
653	230	14	5	10	Lindbergh Road_Seg2	5.000	50	8	7	7	7	7	2	3	3	GR
657	231	14	2.4	4.3	158-4_Seg2	1.900	40	6	7	6	5	6	1	3	3	GR
663	232	16	0	2.2	Lewis Ranch/Indian Hill Road-Seg_1	2.200	45	5	7	6	8	7	3	1	1	NE
667	233	17	5	7.86	Kirkbride Road_Seg_2	2.860	50	7	7	6	7	6	1	3	3	GR
694	234	19	1	2	Larson Road_Seg2	1.000	45	7	7	7	7	7	1	3	3	GR
709	235	23	4	6.84	Hunter Ranch Road_Seg2	2.840	50	7	7	7	7	7	1	3	3	GR

0	236	0	0	3.72	Remount Road	3.651	40	7	8	8	7	8	3	3	2	TG
2	237	0	0	0.15	Cougar Lane	0.153	30	8	8	8	8	7	3	3	3	TG
6	238	0	0	0.4	Jaymers Lane	0.399	30	6	8	7	8	7	3	2	2	GR
7	239	0	0	0.4	Louise Lane	0.411	30	6	8	8	8	6	3	3	3	GR
15	240	1	0	0.06	Elmwood Court	0.049	30	8	8	8	8	8	3	3	3	GR
16	241	1	0	0.38	Rawhide Ridge	0.373	30	7	8	7	7	7	1	3	3	GR
17	242	1	0	0.13	Blue Roan Road	0.107	30	8	8	8	8	8	3	2	3	GR
18	243	1	0	0.44	854	0.412	30	8	8	8	8	8	2	3	3	GR
19	244	1	0	0.4	Troyer drive	0.399	30	8	8	8	8	7	1	3	3	GR
20	245	1	0	0.2	880	0.216	30	8	8	8	8	7	1	3	3	GR
21	246	1	0	0.08	881	0.084	20	7	8	8	8	6	3	2	1	GR
22	247	1	0	0.09	Scofield Court	0.093	20	8	8	8	8	8	1	3	2	GR
25	248	1	0	0.12	Woodenshoe Drive	0.121	20	7	8	8	9	8	4	1	2	NE
26	249	1	0	0.25	Avenue B-6	0.249	30	8	8	8	8	8	3	3	1	GR
28	250	1	0	0.06	Blossom Court	0.059	10	8	8	8	9	8	3	3	1	GR
29	251	1	0	0.5	Fifth Avenue	0.494	30	7	8	8	8	8	3	3	2	GR
30	252	1	0	0.45	Fourth Avenue	0.441	30	7	8	8	8	8	3	3	2	GR
31	253	1	0	0.06	Greene Acres Court	0.060	10	8	8	8	9	8	3	3	1	GR
32	254	1	0	0.31	Second Avenue	0.310	30	8	8	8	8	8	3	3	3	GR
33	255	1	0	0.2	Lampman Court	0.192	30	8	8	8	8	7	2	3	3	GR
34	256	1	0	0.49	York Avenue	0.495	30	8	8	8	8	7	3	3	3	GR
36	257	1	0	0.66	469	0.938	30	6	8	8	6	7	1	3	3	GR
37	258	1	0	0.06	Colt Court	0.049	15	9	8	8	8	9	4	2	2	GR
38	259	1	0	0.6	Remington Way	0.585	30	8	8	8	8	7	1	3	3	GR
39	260	1	0	0.21	Avenue B	0.203	30	8	8	8	8	8	1	2	2	GR
40	261	1	0	0.3	Avenue B-4	0.297	30	8	8	8	8	8	1	3	3	GR
41	262	1	0	0.24	Hyndman Road	0.245	30	8	8	8	8	8	3	2	2	GR
49	263	1	0	0.41	Cherry Street	0.410	30	8	8	8	9	8	3	3	3	GR
51	264	1	0	0.25	Draper Road	0.189	30	7	8	7	8	7	3	2	1	GR
52	265	1	0	0.09	Mitchell Place	0.091	20	8	8	8	9	8	1	3	3	GR

54	266	1	0	0.2	Hellwig Road	0.193	30	8	8	8	8	7	3	3	3	GR
55	267	1	0	0.88	S. Avenue B-6	0.877	30	8	8	8	7	7	3	3	3	GR
58	268	1	0	0.14	Terry Road North	0.142	30	8	8	8	8	8	2	3	3	GR
59	269	1	0	0.25	Terry Road South	0.248	30	8	8	8	8	8	2	2	3	GR
61	270	1	0	0.42	Nation Road 462	0.411	30	8	8	8	8	8	2	3	3	GR
62	271	1	0	0.09	Remington Court	0.084	30	8	8	8	8	8	3	2	3	GR
63	272	1	0	0.24	Savage Drive	0.239	30	9	8	8	8	8	1	3	3	GR
64	273	1	0	0.53	Scott Drive	0.524	30	7	8	7	6	7	1	3	3	GR
65	274	1	0	0.96	Weatherby Drive	0.950	30	8	8	8	8	8	3	2	3	GR
66	275	1	0	0.35	Winchester Blvd.	0.358	30	7	8	8	7	8	1	3	3	GR
67	276	1	0	0.75	Pearl Court	0.798	30	8	8	7	8	7	1	2	3	GR/NE
68	277	1	0	0.25	Willson Court	0.246	30	8	8	8	8	7	1	3	3	GR
69	278	1	0	0.27	Caballo Trail	0.216	30	7	8	7	8	7	1	3	3	GR
71	279	1	0	0.18	Remington Drive	0.190	30	7	8	8	8	7	3	2	3	GR
72	280	1	0	0.46	Redhawk Drive	0.464	30	8	8	8	8	8	1	3	3	GR
73	281	2	0	0.51	Blue Bell Trail	0.502	35	7	8	7	8	7	1	3	3	NE
74	282	2	0	0.5	Primrose Trail	0.503	35	7	8	7	7	7	1	3	2	NE
75	283	2	0	0.5	Wild Rose Trail	0.491	40	8	8	7	8	6	1	3	3	NE
76	284	2	0	0.12	Avenue C-3	0.124	20	8	8	5	8	8	2	2	1	NE
77	285	2	0	0.13	Turk Court	0.122	20	8	8	7	8	8	2	2	1	NE
81	286	2	0	0.1	Kopsa Court	0.091	20	8	8	7	8	8	2	3	2	GR
83	287	2	0	0.5	Brome Road	0.509	30	6	8	8	7	7	2	3	3	GR
85	288	2	0	0.63	Persons Road	0.622	30	8	8	8	7	8	3	2	2	GR
86	289	2	0	0.5	Shooting Star Trail	0.504	35	6	8	7	7	7	1	3	3	NE
87	290	2	0	0.25	Sunbright Trail	0.252	35	8	8	7	8	7	1	3	3	NE
88	291	2	0	0.06	Golden Rod Trail	0.245	35	7	8	7	8	7	2	1	2	NE
89	292	2	0	0.26	Blue Gramma Road	0.251	30	7	8	8	8	7	2	3	3	GR
90	293	2	0	0.5	Fox Tail Road	0.508	30	7	8	8	7	7	1	3	3	GR
92	294	3	0	1.58	140-1	1.489	45	8	8	8	7	8	2	3	3	GR
94	295	3	0	1.91	Breeden Road	1.899	50	8	8	7	7	8	1	1	1	NE

96	296	3	0	5.73	Noyer Road	5.622	55	8	8	8	8	8	1	3	3	GR
97	297	3	0	3	Hermann Road	2.972	60	8	8	8	8	7	1	3	3	GR
104	298	3	0	7.985	146-1	7.985	55	8	8	8	8	4	1	3	3	GR
114	299	3	0	0.06	Fourth St. -Carpenter	0.067	30	8	8	7	8	8	2	2	1	GR
115	300	3	0	0.11	Madison Ave. -Carpenter	0.171	30	6	8	7	8	8	3	1	1	GR
120	301	3	0	0.35	Adams Ave. - Carpenter	0.342	30	8	8	8	8	8	2	1	1	GR
121	302	3	0	0.36	Patches Road	0.438	25	8	8	8	8	6	1	3	3	NE
125	303	3	0	1.01	Kranz Road	1.000	40	6	8	5	8	7	1	1	1	NE
127	304	4	0	1.8	A-204-2	1.995	60	7	8	7	8	8	1	3	3	GR
128	305	4	0	1	A-204-3	0.995	50	7	8	7	8	7	1	1	1	NE
129	306	4	3	7.86	153-1	4.990	60	7	8	6	8	7	1	2	2	GR
130	307	4	0	2.806	153-1	2.806	60	8	8	7	8	8	3	3	3	GR
131	308	4	0	2.797	154-1	2.797	60	7	8	6	8	6	1	3	3	GR
136	309	4	0	1	A-157-1	0.999	60	8	8	7	8	8	1	3	3	GR
139	310	4	0	1.01	A-205-3	1.002	40	6	8	6	5	7	1	2	2	GR
140	311	4	0	2.8	Jennings Road	2.807	45	7	8	7	8	8	2	2	3	GR
148	312	5	0	2.13	South Table Mountain	2.139	45	7	8	8	7	6	3	2	3	NE
149	313	5	0	0.75	Blue Mountain Road	0.739	35	6	8	8	7	8	4	3	3	NE
150	314	5	0	0.6	W Plains Road	0.605	35	8	8	7	8	8	4	3	3	GR
155	315	5	0	1.36	Crow Creek Road	1.368	45	8	8	8	7	8	3	3	3	TG
158	316	5	0	4.01	Valley View Drive	3.822	30	7	8	8	6	8	3	2	2	TG
160	317	5	0	0.82	Prairie View Road	0.813	35	8	8	8	8	7	4	3	3	GR
161	318	5	0	1.08	Spring Creek Road	1.094	35	7	8	7	8	7	4	3	3	GR
164	319	6	0	0.87	Adolphson Road	0.995	30	7	8	8	8	7	2	1	1	NE
166	320	6	0	1.03	A-118-A	1.036	30	6	8	6	8	8	3	2	3	NE
171	321	6	0	1	Cox Drive	0.986	30	7	8	8	6	8	3	3	3	GR
172	322	6	0	0.82	Healy Road	0.781	30	5	8	8	6	7	3	3	3	GR
175	323	6	0	0.45	Elling Road	0.418	30	8	8	8	8	8	4	3	3	GR
176	324	6	0	0.28	Phillips Place	0.279	30	8	8	8	8	8	4	3	3	GR
177	325	6	0	0.87	Treadway Trail	0.863	30	7	8	8	9	7	4	3	3	TG

178	326	6	0	0.43	Carls Road	0.407	30	7	8	8	8	6	3	3	3	GR
179	327	6	0	0.31	Draw Drive	0.305	30	7	8	8	8	8	3	3	3	GR
180	328	6	0	0.51	Ninemile Blvd.	0.507	30	7	8	8	8	7	3	3	3	GR
181	329	6	0	0.77	Bell Lane	0.764	25	7	8	8	7	8	3	2	2	GR
191	330	6	0	0.38	889	0.373	30	8	8	8	8	6	3	3	3	GR
192	331	6	0	0.15	890	0.159	30	8	8	8	8	8	3	3	3	GR
193	332	6	0	0.17	891	0.182	30	8	8	8	8	8	3	3	3	GR
194	333	6	0	0.21	892	0.213	30	8	8	8	8	8	3	3	3	GR
196	334	6	0	0.77	Quarter Circle Drive	0.757	30	6	8	8	8	8	3	3	3	GR
197	335	6	0	0.32	Arabian Lane	0.320	30	8	8	8	8	8	2	3	3	GR
198	336	6	0	0.51	Buck Brush Road	0.493	30	7	8	8	8	8	4	3	3	GR
199	337	6	0	0.08	Chief Drive	0.086	30	8	8	8	8	8	3	3	3	GR
201	338	6	0	0.38	Donald Drive	0.374	30	8	8	8	8	8	3	3	3	GR
202	339	6	0	0.2	McGarry Drive	0.210	30	8	8	8	8	8	4	3	3	GR
203	340	6	0	0.31	Arizona Street	0.362	25	8	8	8	9	8	3	3	3	GR
204	341	6	0	0.25	E. Dona Street	0.249	30	4	8	6	8	8	4	3	3	GR
209	342	6	0	0.36	E & W Polo Plate	0.354	30	8	8	8	8	8	2	3	3	GR
213	343	6	0	0.85	Koster Road	0.837	30	6	8	8	8	8	4	1	3	NE
218	344	6	0	3.5	Klipstein Road	3.446	40	7	8	8	8	6	1	3	3	GR
220	345	6	0	0.74	Wind Dancer Road	0.754	30	8	8	8	8	8	3	3	3	GR
222	346	6	0	0.2	Morhia Lane	0.206	30	8	8	8	8	8	4	3	3	GR
223	347	6	0	0.51	Wayne Road	0.503	30	8	8	8	8	7	4	3	3	GR
226	348	6	0	0.52	East Powell Road	0.511	30	7	8	8	9	8	4	3	3	GR
229	349	6	0	1.01	Deer Brooke Trail	1.012	30	7	8	8	8	7	3	3	3	GR
233	350	6	0	0.09	Blue Sky Drive	0.083	30	8	8	8	8	8	4	3	3	GR
234	351	6	0	0.38	Bronco Trail	0.379	30	8	8	8	8	8	4	3	3	GR
235	352	6	0	0.7	Concha Loop	0.715	25	8	8	8	8	8	4	3	3	GR
236	353	6	0	0.16	Jim Court	0.155	30	8	8	8	8	7	3	3	3	GR
237	354	6	0	0.91	Ranch Loop	0.914	30	8	8	7	7	7	3	3	3	GR
244	355	6	0	0.49	Burke Drive	0.485	30	6	8	7	7	7	3	3	3	GR

247	356	6	0	0.39	DeGraw Drive	0.390	30	8	8	8	8	8	4	3	3	GR
248	357	6	0	0.52	Rucker Road	0.499	30	7	8	8	7	8	4	3	3	GR
249	358	6	0	0.41	Twin Mountain Road	0.407	25	8	8	8	8	8	4	3	3	GR
250	359	6	0	0.48	Pole Mountain Road	0.469	30	7	8	7	8	8	3	3	3	GR
255	360	6	0	0.13	Lariat Loop	0.124	25	8	8	8	8	8	4	3	3	GR
258	361	6	0	0.18	Clear View Circle	0.175	25	8	8	8	8	8	3	2	2	GR
259	362	6	0	0.15	Hidden Valley Road	0.143	30	8	8	8	8	8	4	3	3	GR
260	363	6	0	0.14	Kelper Drive	0.139	30	8	8	8	8	8	4	3	3	GR
262	364	6	0	0.18	San Mateo Place	0.173	30	8	8	8	8	8	4	3	3	GR
264	365	6	0	0.09	Trinidad Ct	0.092	30	8	8	8	8	8	4	3	3	GR
265	366	6	0	0.25	Ventura Drive	0.247	30	8	8	8	8	8	4	3	3	GR
266	367	6	0	0.5	Astronaut Drive	0.505	30	8	8	8	8	8	3	3	3	GR
267	368	6	0	0.82	Eagle Drive	0.811	30	7	8	7	8	7	3	3	3	GR
268	369	6	0	0.75	Space Drive	0.743	30	8	8	7	7	8	4	3	3	GR
270	370	6	0	0.77	Cattleman's Drive	0.758	30	6	8	8	8	6	2	3	3	GR
271	371	6	0	0.13	Horse Creek Road	0.107	30	7	8	8	8	5	2	2	3	GR
273	372	6	0	1.26	North Star Loop	1.252	30	8	8	8	8	7	3	3	3	GR
274	373	6	0	0.12	Pegasus Point	0.116	30	8	8	8	8	8	4	3	3	GR
275	374	6	0	0.13	Polaris Point	0.124	30	9	8	8	8	8	3	3	3	GR
277	375	6	0	0.07	Granada Trail	0.071	20	7	8	8	8	6	3	1	1	GR
282	376	6	0	0.14	Evening Star Court	0.138	30	8	8	7	8	8	4	3	3	GR
283	377	6	0	0.15	Star Hill Court	0.147	30	7	8	8	8	8	4	3	3	GR
284	378	6	0	0.13	Stardust Trail	0.139	30	8	8	8	8	8	3	3	3	GR
285	379	6	0	0.13	Twilight Court	0.134	30	8	8	8	8	8	3	3	3	GR
286	380	6	0	0.26	893	0.268	30	7	8	8	8	7	3	3	3	GR
289	381	6	0	0.35	Portugee Phillips Road	0.343	30	8	8	8	8	8	3	3	3	GR
290	382	6	0	0.25	Beulah Avenue	0.243	30	6	8	6	8	7	3	3	3	GR
291	383	6	0	0.43	Crestview Drive	0.433	20	8	8	9	9	8	4	3	3	GR
292	384	6	0	0.27	David Street	0.260	30	6	8	8	8	8	3	3	3	GR
294	385	6	0	0.19	Kansas City	0.187	30	8	8	8	8	8	3	3	3	GR

297	386	6	0	0.83	Branding Iron Drive	0.815	25	8	8	8	8	8	4	3	3	GR
298	387	6	0	0.58	Carbine Trail	0.578	25	8	8	8	8	8	3	3	3	GR
299	388	6	0	0.23	Chaparral Road	0.221	30	8	8	8	8	8	4	3	3	GR
300	389	6	0	0.08	Summer Hill Court	0.072	8	8	8	9	8	8	3	3	3	GR
304	390	6	0	0.48	West Powell Road 523	0.472	30	8	8	8	8	7	3	3	3	GR
305	391	6	0	0.25	West Powell Road 524	0.241	30	7	8	8	7	8	4	2	1	GR
314	392	7	0	2	212-3	2.000	30	8	8	8	7	8	1	3	3	GR
321	393	7	0	2.52	132-1	2.536	15	8	8	8	8	7	3	3	3	GR
322	394	7	0	2.02	Meridan Blvd	2.003	40	9	8	8	8	8	4	3	3	TR/GR
326	395	7	103	103.868	613	1.123	20	8	8	8	8	6	3	2	1	GR
328	396	7	0	0.12	616	0.124	30	8	8	8	8	8	3	1	1	NE
330	397	7	0	0.52	628	0.340	30	8	8	8	8	8	1	1	2	GR
332	398	7	0	0.13	631	0.126	30	8	8	8	8	8	3	3	3	GR
334	399	7	0	0.56	634	0.123	30	8	8	8	8	8	3	3	3	GR
337	400	7	0	1	Empire Drive	0.993	30	8	8	8	8	7	1	3	3	GR
338	401	7	0	0.75	Geronimo Road	0.744	30	8	8	8	8	7	1	3	3	GR
341	402	7	0	0.45	647	0.449	30	6	8	6	8	6	3	3	1	NE
344	403	7	0	0.68	Archie's Road	0.660	30	8	8	8	8	7	1	2	3	GR
345	404	7	0	0.09	Haunted Road	0.099	30	8	8	8	8	8	3	3	3	GR
346	405	7	0	0.27	Hinesley Road	0.265	30	8	8	8	8	8	2	3	3	GR
347	406	7	0	0.5	Blue Mesa Road	0.495	35	8	8	8	8	8	2	3	3	GR
348	407	7	0	0.13	Red Mesa Road	0.133	35	8	8	8	8	8	3	3	3	GR
349	408	7	0	0.4	Whitney Road	0.394	30	8	8	7	7	8	1	3	3	GR
350	409	7	0	0.98	Piper Lane	0.971	40	8	8	8	8	7	1	3	3	GR
353	410	7	0	0.48	Feldspar Road	0.485	40	7	8	8	7	8	1	3	3	GR
355	411	7	0	1.01	Denise Road	0.994	40	8	8	8	8	8	1	3	3	GR
356	412	7	0	0.17	Pamela Lane	0.188	40	8	8	8	8	8	1	3	3	GR
357	413	7	0	0.26	Patricia Ln	0.251	40	8	8	8	8	8	1	3	3	GR
358	414	7	0	0.25	Arthur Avenue	0.250	30	8	8	8	7	7	2	3	3	GR
359	415	7	0	0.83	Horizon Loop	0.822	30	6	8	8	6	7	1	3	3	GR

360	416	7	0	0.72	Orchard Drive	0.710	35	8	8	8	8	8	1	3	3	GR
361	417	7	0	0.75	Cherry Wood Lane	0.742	35	8	8	8	8	8	1	3	3	GR
362	418	7	0	0.36	Cherry Wine Road	0.353	30	8	8	8	8	8	1	3	3	GR
365	419	7	0	0.3	Joe's Road	0.292	30	5	8	8	8	5	3	2	1	GR
366	420	7	0	0.51	Bison Run Loop	0.514	30	8	8	8	8	6	3	3	3	GR
367	421	7	0	0.2	Lupine Trail	0.190	30	9	8	8	8	8	1	3	3	GR
369	422	7	0	0.48	Long Drive	0.482	30	7	8	7	8	8	1	3	3	GR
370	423	7	0	0.37	Conestoga Road	0.380	30	8	8	8	8	7	1	3	3	GR
371	424	7	0	0.63	Harvest Loop	0.632	35	7	8	8	8	6	3	3	3	GR
374	425	7	0	0.62	823	0.626	35	7	8	8	8	7	1	3	3	GR
375	426	7	0	0.82	Whirlaway Road	0.818	30	6	8	8	7	6	3	3	3	GR
376	427	7	0	0.96	Affirmed Road	0.940	35	7	8	8	7	7	3	3	3	GR
378	428	7	0	0.39	Firethorn Lane	0.400	30	8	8	8	8	8	1	3	3	GR
379	429	7	0	0.33	Snowberry Drive	0.323	30	8	8	8	7	7	1	3	3	GR
382	430	7	0	0.35	Swan Trail	0.350	30	8	8	7	7	7	1	3	3	GR
383	431	7	0	0.62	878	0.612	35	7	8	8	7	7	1	3	3	GR
384	432	7	0	0.13	879	0.136	30	9	8	8	8	8	2	3	3	GR
385	433	7	0	0.4	894	0.406	40	7	8	7	7	8	1	3	3	GR
386	434	7	0	0.4	895	0.407	30	8	8	8	8	8	1	3	3	GR
387	435	7	0	0.32	896	0.322	30	8	8	8	8	8	1	3	3	GR
388	436	7	0	0.32	898	0.322	30	9	8	8	8	8	1	3	3	GR
389	437	7	0	0.44	899	0.445	30	8	8	8	8	6	3	3	3	GR
390	438	7	0	0.1	901	0.099	30	9	8	8	8	8	3	3	3	GR
391	439	7	0	0.33	902	0.326	30	8	8	8	8	8	3	3	3	GR
393	440	7	0	1.01	Chochise Road	1.001	30	8	8	7	7	8	1	3	3	GR
394	441	7	0	0.5	Crazy Horse Road	0.450	30	8	8	7	8	7	2	3	3	GR
395	442	7	0	0.06	Crazy Horse Road	0.119	20	8	8	8	8	7	3	3	3	GR
396	443	7	0	1.51	Crazy Horse Road	1.000	30	8	8	8	8	6	2	3	3	GR
397	444	7	0	1.01	Tonto Road	0.993	30	7	8	7	7	6	1	3	3	GR
398	445	7	0	1.01	White Eagle Road	0.990	30	8	8	8	8	6	2	3	3	GR

399	446	7	0	0.5	Gordon Road	0.496	30	7	8	8	7	8	2	2	2	GR
400	447	7	0	1.01	Glencoe Road	0.991	40	8	8	8	8	8	1	3	3	GR
401	448	7	0	0.75	Grace Rd	0.739	40	9	8	8	8	8	1	3	3	GR
402	449	7	0	0.11	Parkhill Road	0.113	30	8	8	7	8	8	1	3	3	GR
404	450	7	0	0.37	611	0.370	20	8	8	8	8	6	3	2	2	GR
405	451	7	0	0.3	130-1	0.306	30	8	8	7	8	8	1	3	3	GR
406	452	7	0	2.99	130-1	2.987	45	7	8	7	7	6	2	3	3	GR
408	453	7	0	1.85	Stewart Road	1.833	40	8	8	8	8	8	1	3	3	GR
409	454	7	0	3.24	East Four Mile Road	3.207	50	8	8	8	8	7	1	3	3	GR
411	455	7	0	0.16	East Four Mile Rd U2135	0.223	30	8	8	8	8	7	3	3	3	GR
413	456	7	0	0.27	Beartooth Drive	0.296	30	7	8	8	6	8	2	2	2	GR
414	457	7	0	0.43	Champion Drive	0.420	30	8	8	8	7	7	1	3	3	GR
416	458	7	0	0.12	Lynx Road	0.128	30	9	8	8	8	8	2	3	3	GR
417	459	7	0	0.37	Bonnie Brae Loop	0.375	30	7	8	7	7	7	1	3	3	GR
418	460	7	0	0.17	Cowboy Road	0.176	30	9	8	8	8	8	2	2	3	GR
419	461	7	0	1.34	559	0.899	30	8	8	7	8	6	1	3	3	GR
420	462	7	0	0.42	559	0.426	30	7	8	8	7	8	3	3	3	GR
421	463	7	0	0.3	Lapaz Drive	0.293	30	7	8	7	8	7	3	3	3	GR
422	464	7	0	0.82	Yarina Way	0.807	30	7	8	7	7	7	3	3	3	GR
423	465	7	0	0.51	Ranch Road	0.502	25	8	8	8	8	7	3	3	3	GR
424	466	7	0	0.51	Surrey Road	0.493	25	8	8	8	8	7	3	3	3	GR
426	467	7	0	0.12	Mynear St	0.122	30	9	8	8	8	8	3	3	3	GR
427	468	7	0	0.27	Oasis St	0.246	20	9	8	8	8	8	1	3	3	GR
428	469	7	0	0.99	590	1.003	30	8	8	8	7	7	1	3	3	GR
429	470	7	0	0.07	Coulter Circle	0.063	20	8	8	8	8	7	1	3	3	GR
430	471	7	0	0.04	Scenic Ct	0.038	20	8	8	8	8	8	3	2	2	GR
432	472	7	0	0.75	Woods Rd	0.747	35	8	8	8	8	8	1	3	3	GR
434	473	7	0	0.76	Little Horse	0.756	30	8	8	8	8	7	1	3	3	GR
435	474	7	0	0.51	Little Shield Road 416	0.503	30	8	8	8	8	7	1	3	3	GR
436	475	7	0	1.02	Yellow Bear Road	1.007	30	7	8	8	7	7	1	3	3	GR

437	476	7	0	0.38	Avenue C-4	0.379	20	8	8	8	7	7	2	2	2	GR
438	477	7	0	0.38	Avenue D	0.379	20	7	8	6	7	8	2	3	3	GR
439	478	7	0	0.14	Green Ct	0.144	15	8	8	8	8	6	3	2	1	GR
440	479	7	0	0.14	Miles Ct	0.144	15	9	8	8	8	6	3	2	1	GR
442	480	7	0	0.33	Vera Lane	0.359	40	8	8	7	8	8	1	3	3	GR
443	481	7	0	0.23	Green River St	0.251	30	8	8	8	8	8	3	3	3	GR
444	482	7	0	0.17	Pierce Avenue	0.169	25	7	8	8	8	8	2	1	1	GR
445	483	7	0	0.12	Uintah Road	0.115	30	6	8	8	8	8	3	1	1	GR
446	484	7	0	1.01	Belmont Avenue	0.990	30	6	8	7	7	6	2	3	3	GR
447	485	7	0	0.16	Cochise Road	0.250	30	6	8	8	8	6	2	2	3	GR
448	486	7	0	0.16	Little Shield Road 643	0.172	30	8	8	7	8	7	2	2	3	GR
449	487	7	0	1.02	Sitting Bull Road	1.000	40	7	8	7	7	7	1	3	3	GR
450	488	7	0	0.12	Parsons Place	0.121	30	8	8	8	8	8	3	3	2	GR
453	489	7	0	0.12	Foster Avenue	0.122	30	8	8	7	8	8	2	3	3	GR
454	490	7	0	0.22	Huisman Road	0.213	25	5	8	5	8	8	3	3	1	GR
456	491	7	0	0.75	Burns Avenue	0.738	30	7	8	8	7	6	3	3	3	GR
457	492	7	0	0.4	Carpenter Place	0.398	30	8	8	8	8	8	3	3	2	GR
459	493	7	0	0.29	Lander Lane	0.279	30	9	8	8	8	8	3	3	3	GR
462	494	7	0	0.38	Jade Road	0.384	40	7	8	8	7	8	1	3	3	GR
464	495	7	0	0.44	Maria E. Lane	0.408	40	8	8	8	8	8	1	3	3	GR
465	496	7	0	1.01	Sherry Road	0.996	40	8	8	8	8	8	1	3	3	GR
466	497	7	0	2.49	Spring Beauty Trail	2.446	35	7	8	7	7	6	1	2	3	GR
467	498	7	0	0.98	Morning Glory Trail	0.963	40	9	8	8	8	8	1	3	3	GR
468	499	7	0	0.32	Balmoral Court	0.305	30	8	8	8	8	7	3	3	2	GR
469	500	7	0	0.15	Schrader Lane	0.143	30	8	8	8	8	7	1	3	3	GR
470	501	7	0	0.18	North Orchard Drive	0.176	35	8	8	8	8	8	1	3	3	GR
471	502	7	0	0.65	Choke Cherry Road	0.647	35	8	8	8	8	8	1	3	3	GR
472	503	7	0	0.47	Cherry Blossom Road	0.473	35	7	8	8	7	8	1	3	3	GR
473	504	7	0	0.65	Dodge Road	0.643	30	7	8	7	8	5	1	3	3	GR
475	505	7	0	0.49	Buttercup Drive	0.478	30	7	8	8	6	8	1	3	3	GR

476	506	7	0	0.4	Chicakadee Drive	0.393	30	7	8	8	7	7	1	3	3	GR
477	507	7	0	0.92	Blazing Star Road	0.907	40	7	8	8	7	7	1	3	3	GR
478	508	7	0	0.54	Chuck Wagon Road	0.508	30	8	8	8	8	7	1	3	2	GR
479	509	7	0	0.38	Wagon Box Road	0.380	30	8	8	8	8	8	3	3	3	GR
480	510	7	0	0.32	Prairie Schooner Road	0.310	30	8	8	8	8	7	3	3	3	GR
481	511	7	0	0.37	Bobcat Road	0.368	30	8	8	8	8	8	3	3	3	GR
482	512	7	0	1.01	Jack Rabbit Road	1.002	30	8	8	8	8	7	2	3	3	GR
484	513	7	0	0.18	Trohpy Drive	0.172	30	9	8	8	8	8	2	3	3	GR
485	514	7	0	0.17	Brahma Road	0.166	30	9	8	8	8	8	2	2	3	GR
486	515	7	0	0.42	Wrangler Road	0.406	30	8	8	8	7	7	1	3	3	GR
487	516	7	0	0.18	Bonita Place	0.184	30	8	8	7	8	8	3	3	3	GR
488	517	7	0	0.3	Shapra Road	0.293	30	8	8	7	8	8	3	3	3	GR
489	518	7	0	0.51	Buckboard Road	0.495	25	8	8	8	8	8	3	3	3	GR
490	519	7	0	0.51	Stagecoach Road	0.498	25	8	8	8	7	7	3	3	3	GR
491	520	7	0	0.52	New Bedford Dr	0.507	30	8	8	8	8	6	1	3	3	GR
492	521	7	0	0.09	Aspen Circle	0.087	20	8	8	8	8	7	2	3	3	GR
493	522	7	0	0.21	Mynear Street	0.206	30	8	8	8	8	7	2	3	3	GR
494	523	7	0	0.28	Skyline Drive 596	0.269	30	8	8	8	8	7	3	3	3	GR
495	524	7	0	0.51	Archer Road	0.500	40	8	8	8	8	8	1	3	3	GR
496	525	7	0	0.47	Citation Road	0.481	30	8	8	8	8	7	3	3	3	GR
497	526	7	0	0.4	Secretariat Road West	0.388	30	7	8	8	6	8	2	3	3	GR
498	527	7	0	0.38	Secretariat Road East	0.382	30	8	8	8	8	7	1	3	3	GR
499	528	7	0	0.61	War Admiral Road	0.612	30	7	8	8	7	7	3	3	3	GR
500	529	7	0	0.39	Arrow Wood Lane	0.400	40	8	8	8	7	7	1	3	3	GR
501	530	7	0	0.33	Smokebrush Lane	0.323	40	8	8	8	8	7	1	3	3	GR
502	531	7	0	0.1	Smokebrush Court	0.097	20	8	8	8	8	8	1	3	3	GR
503	532	7	0	0.87	Lazear Ranch Road	0.875	35	7	8	8	7	7	1	3	3	GR
504	533	7	0	0.32	Nielson Ranch Road	0.321	30	5	8	8	6	8	3	2	2	GR
505	534	7	0	0.13	877	0.137	30	9	8	8	8	7	2	3	3	GR
506	535	7	0	0.1	897	0.097	30	8	8	8	8	8	1	3	3	GR

507	536	7	0	0.4	900	0.405	35	7	8	8	7	7	3	3	3	GR
508	537	7	0	0.1	Arroyo Road	0.099	30	9	8	8	8	8	4	3	3	GR
510	538	7	0	0.11	Hillside Drive	0.110	30	9	8	8	8	8	4	3	3	GR
523	539	8	0	0.14	Nash Avenue-Hillsdale	0.138	25	8	8	7	8	8	2	2	1	GR
524	540	8	0	0.31	Dubois Road	0.323	30	8	8	8	8	8	1	2	3	GR
526	541	8	0	0.95	Lawrence Road	0.947	30	8	8	8	8	8	1	3	3	GR
527	542	8	0	0.86	Big Chief Road	0.855	50	8	8	8	8	8	1	3	3	GR
528	543	8	0	0.25	Seasons Drive	0.248	50	8	8	8	7	7	2	3	3	GR
529	544	8	0	0.89	Winterset Drive	0.883	50	8	8	8	7	7	2	3	3	GR
530	545	8	0	0.23	Sun Down Road	0.225	40	8	8	8	8	8	2	3	3	GR
531	546	8	0	2.06	A-145-2	2.049	50	7	8	6	8	7	2	1	1	NE
537	547	8	0	0.95	Stuckey Road 140-2	1.046	50	8	8	8	7	8	1	3	3	NE
538	548	8	0	2.48	Kauffman Road	2.480	50	8	8	8	7	7	1	3	3	GR
541	549	8	0	2.01	Stuckey Road 212-6	1.994	55	8	8	7	8	7	1	2	2	GR
542	550	8	0	4.11	Old Highay Burns East	4.066	60	9	8	8	8	6	1	3	3	GR
546	551	8	0	0.14	Markley Avenue-Hillsdale	0.137	25	8	8	7	8	8	2	2	1	NE
548	552	8	0	0.37	Conrad Road	0.365	25	7	8	8	6	8	1	3	3	GR
549	553	8	0	0.3	Harding Road	0.326	30	8	8	8	8	8	1	3	2	GR
550	554	8	0	0.86	Old Squaw Lane	0.853	50	9	8	8	8	6	1	3	3	GR
551	555	8	0	0.86	Teal Lane	0.852	50	8	8	8	8	6	1	3	3	GR
552	556	8	0	0.75	Autumset Drive	0.744	50	8	8	8	7	8	1	3	3	GR
553	557	8	0	0.56	Springtime Drive	0.559	50	8	8	8	7	7	3	3	3	GR
555	558	8	0	0.12	Jonathan Drive	0.136	35	8	8	7	8	7	1	3	3	GR
556	559	8	0	1.06	E. and S. Cabot Road	1.048	35	8	8	8	7	8	1	3	3	GR
558	560	8	0	0.5	Nation Road 148-3	0.506	35	7	8	7	8	6	1	2	2	NE
559	561	8	0	1	A-150-3	0.983	60	8	8	7	8	7	1	3	3	GR
560	562	8	0	3.04	Woolington Road	2.993	40	5	8	3	8	8	1	1	1	GR
566	563	9	0	0.23	Central Avenue-Egbert	0.169	30	8	8	8	8	8	3	2	1	GR
567	564	9	0	0.29	Butler Road	0.298	40	8	8	8	8	7	3	1	1	GR
568	565	9	0	0.93	A-153-4	0.925	40	6	8	7	7	7	2	1	1	GR

569	566	9	0	1	Gillard Road	1.000	40	7	8	6	8	7	1	3	2	GR
570	567	9	0	0.49	Dean Road	0.504	40	7	8	7	7	7	1	3	3	GR
576	568	9	0	0.18	Burg Street-Egbert	0.185	30	7	8	7	7	8	3	1	1	GR
577	569	9	0	1.5	Dunsbuergen Rd	1.474	40	8	8	8	8	8	1	3	3	GR
578	570	9	0	1.09	A-156-3	0.996	40	7	8	7	7	7	1	3	3	GR
580	571	10	0	0.69	A-218-1	0.715	35	7	8	8	7	7	4	3	3	TG
581	572	10	0	1.03	A-110-2	1.027	35	7	8	8	7	8	4	3	3	GR
583	573	10	0	0.69	Mesa Tr. North	0.705	30	8	8	8	8	8	4	3	3	GR
584	574	10	0	0.73	Mesa Tr South	0.724	30	7	8	8	8	5	4	3	2	GR
588	575	11	0	4.07	Atlas Road	3.936	50	8	8	8	8	8	3	3	3	GR
591	576	11	0	0.57	Federal Blvd.	0.565	30	8	8	8	8	8	3	3	3	GR
593	577	11	0	0.27	Palomino Lane	0.237	40	8	8	8	8	8	4	3	3	GR
596	578	11	0	0.45	Geyser Road	0.445	30	7	8	8	7	8	3	3	3	GR
597	579	11	0	0.58	Jackson Lake Road	0.573	30	7	8	8	7	8	3	3	3	GR
599	580	11	0	0.92	Hummingbird Trl.	0.907	30	7	8	8	8	8	3	3	3	GR
604	581	11	0	0.37	Guernsey Road	0.367	30	8	8	8	8	8	3	3	3	GR
605	582	11	0	0.37	Wheatland Drive	0.367	30	8	8	8	8	8	2	3	3	GR
606	583	11	0	1.04	Canyon Drive	1.028	30	7	8	8	7	8	3	3	3	GR
607	584	11	0	0.55	Fishing Bridge Road	0.543	30	8	8	8	8	8	3	3	3	GR
618	585	12	0	0.73	Packard Road	0.655	30	7	8	8	7	7	2	3	3	GR
621	586	12	0	2.68	Hutton Road	2.656	60	8	8	8	8	8	1	3	3	GR
623	587	12	0	0.8	Cadillac Road	0.791	30	8	8	7	8	7	1	3	3	GR
625	588	12	0	0.33	Duesenberg Road	0.318	30	7	8	7	8	7	1	3	3	GR
627	589	12	0	1.36	Buick Road	1.338	30	7	8	7	8	8	3	3	3	GR
628	590	12	0	0.77	Chevy Road	0.757	30	4	8	8	6	8	2	3	3	GR
629	591	13	0	4.44	DeSelms Road	4.468	45	7	8	6	8	5	2	2	2	GR
632	592	13	0	0.37	Towns Road	0.336	40	7	8	7	8	8	3	1	2	NE
634	593	13	0	1.58	Corbet Road	1.543	50	8	8	7	8	6	1	2	3	GR
635	594	13	0	3.02	King Road South	2.980	45	8	8	7	8	8	1	3	3	NE
636	595	13	0	1.38	A-140-4	1.384	50	8	8	8	8	7	1	3	3	GR

638	596	13	0	1	A-218-3	0.980	60	8	8	7	8	6	1	3	3	GR
643	597	14	0	1.08	A-224-2	1.001	50	8	8	7	8	7	1	3	3	GR
645	598	14	0	2.02	A-153-2	2.011	50	8	8	7	8	7	1	2	3	GR
646	599	14	0	1.01	A-156-4	0.996	50	8	8	7	8	8	1	3	3	GR
647	600	14	0	2.05	A-159-3	2.035	50	7	8	7	8	6	1	3	3	NE
650	601	14	0	1.73	Mattson Road	1.714	50	7	8	7	7	6	1	3	3	NE
651	602	14	0	1.01	Sundin Road	0.989	50	8	8	7	8	6	1	3	3	NE
652	603	14	0	3.02	A-221-1	2.984	50	7	8	7	8	7	1	3	3	NE
656	604	14	0	2.02	A-157-2	1.981	50	7	8	7	7	7	1	3	3	GR
658	605	15	0	2.75	Dereemer Road	2.750	45	8	8	7	8	8	2	2	2	GR/NE
659	606	15	0	6.73	Fisher Canyon Road	6.011	30	4	8	6	6	7	2	2	1	NE
661	607	16	0	1.45	Whitaker Road	1.441	40	8	8	8	7	7	2	3	3	GR
662	608	16	0	2.5	Nimmo Road	2.515	55	7	8	8	7	7	2	3	3	GR
665	609	17	0	4.04	Sandberg Road	4.000	40	8	8	8	8	8	1	3	3	GR
669	610	17	0	1.95	Bruegman Road	1.928	40	9	8	8	8	8	1	3	3	GR
672	611	18	0	7.1	Eklund Road	7.034	60	8	8	7	7	7	1	3	3	GR
673	612	18	0	1.63	Rutledge Road	1.620	45	7	8	8	7	7	1	3	2	GR
674	613	18	0	2.04	A-147-4	2.018	45	7	8	7	7	8	1	3	2	NE
675	614	18	0	1.02	A-228-4	1.009	45	7	8	7	7	8	1	3	2	NE
676	615	18	0	0.64	Anderson Road	0.633	45	7	8	7	6	7	3	1	1	NE
677	616	18	0	2.02	Debruyn Road	2.005	60	8	8	8	8	8	1	3	3	NE
678	617	18	0	0.2	Helen Avenue	0.198	30	8	8	6	8	4	1	3	3	NE
679	618	19	0	6.44	227-2	6.370	50	7	8	7	7	7	1	3	3	GR
681	619	19	0	2.33	Holgerson Road	2.324	50	8	8	8	8	7	1	3	3	GR
682	620	19	0	1.01	158-5	0.999	50	6	8	7	8	6	1	3	3	GR
685	621	19	0	1.02	160-4	1.009	60	8	8	8	8	7	1	3	3	GR
686	622	19	0	0.43	A-162-3	0.416	40	7	8	7	7	6	1	2	2	NE
687	623	19	0	1.11	163-2	0.997	45	7	8	7	7	7	1	2	2	GR
688	624	19	0	2.01	Miller Road West 226-3	1.994	50	8	8	8	8	7	1	2	2	GR
689	625	19	0	4.07	Rabou Road	4.032	60	8	8	8	8	7	1	3	3	GR

690	626	19	0	1.01	West Romsa Road	1.005	50	8	8	7	8	6	1	3	3	GR
691	627	19	0	1.89	Sorenson Road	1.936	50	8	8	7	7	7	1	3	3	GR
692	628	19	0	2.55	Strube Road	2.563	50	8	8	8	8	7	1	3	3	GR
693	629	19	0	2.02	A-160-3	2.001	50	7	8	8	8	7	1	3	3	GR
695	630	19	0	6.06	Malm Road	5.997	40	7	8	7	7	7	1	2	2	NE
697	631	20	0	2.56	McLees Road	2.560	45	8	8	8	8	8	1	3	3	NE
698	632	21	0	5.5	A-238-4	5.634	45	5	8	7	8	7	2	3	3	NE
699	633	21	0	1	Bliss Rd	1.066	40	7	8	8	8	8	2	3	3	GR
702	634	21	0	2.76	Bear Creek/Marsh Road	3.016	35	6	8	5	9	7	3	3	3	NE
703	635	22	0	9.72	Moffett Road	9.654	60	8	8	8	8	8	1	3	3	GR
706	636	23	0	0.576	150-6	0.577	50	8	8	7	8	7	1	3	3	GR
707	637	23	0	1.27	Beet Dump Road	1.267	40	7	8	7	7	6	1	3	3	GR
712	638	24	0	0.86	Person Road	0.833	40	8	8	7	7	7	1	2	2	NE
11	639	1	6.9	11.1	120-1_Seg_4	4.200	40	8	8	8	8	8	2	2	2	GR
98	640	3	1.3	2.3	Oline Road_Seg_2	1.000	45	8	8	8	8	7	1	2	3	NE
99	641	3	0	0.5	A-205-1_Seg_1	0.500	30	7	8	7	8	7	3	2	2	NE
100	642	3	6	9.11	Pulver Road_Seg_2	3.110	60	9	8	8	8	8	1	3	3	GR
111	643	3	11	17.18	Arcola Road_Seg_3	6.180	60	8	8	6	7	6	1	2	3	NE
117	644	3	1	1.7	A-201-Seg1	0.700	45	8	8	8	8	8	1	3	3	GR
119	645	3	0	10	Plambeck Road_Seg_1	10.000	60	9	8	8	8	6	1	3	3	GR
119	646	3	10	16.1	Plambeck Road_Seg_2	6.100	60	8	8	7	8	8	1	3	3	GR
119	647	3	16.1	19.1	Plambeck Road_Seg_3	3.000	60	7	8	8	7	7	1	3	3	GR
123	648	3	0	1	Soppe Road_Seg_1	1.000	50	9	8	8	8	8	1	3	3	NE
123	649	3	1	4.7	Soppe Road_Seg_2	3.700	60	9	8	8	8	8	1	3	3	GR
132	650	4	0	8	154-1_Seg1	8.000	60	8	8	8	8	6	1	3	3	GR
144	651	5	0	0.7	Ferguson Road_Seg_1	0.700	40	8	8	8	8	6	2	3	2	GR
151	652	5	4.3	8.2	Gilchrist Road_Seg2	3.900	50	8	8	8	7	7	3	3	3	GR/TR
151	653	5	8.2	9.4	Gilchrist Road_Seg3	1.200	50	8	8	8	8	7	4	3	3	GR
517	654	8	0	1	Old Highway Burns West_Seg1	1.000	60	8	8	8	8	7	1	3	3	GR
517	655	8	1	2	Old Highway Burns West_Seg2	2.000	60	8	8	8	8	8	1	3	3	GR

532	656	8	5	11	Tremble Road_Seg_2	6.000	50	7	8	8	8	6	2	1	2	GR
540	657	8	0	5	Mikesell Road_Seg_1	5.000	60	9	8	8	8	6	1	3	3	NE
540	658	8	5	10	Mikesell Road_Seg_2	5.000	60	8	8	7	7	8	2	3	3	GR
572	659	9	0	4	A-161-3_Seg1	4.000	50	8	8	7	8	7	1	3	3	NE
589	660	11	0	3.6	Holmes Road_Seg_1	3.600	55	7	8	8	8	8	1	3	3	GR
614	661	12	0	3.05	Jay Road_Seg_1	3.050	45	6	8	8	8	7	1	3	3	GR
619	662	12	14.3	16.51	Indian Hill Road 128-2_Seg_4	2.210	35	8	8	7	8	8	2	2	2	GR
630	663	13	0	3	Lyons Road_Seg1	3.000	60	8	8	7	7	6	1	3	3	NE
657	664	14	4.3	6.2	158-4_Seg3	1.900	40	8	8	7	8	6	1	1	1	NE
663	665	16	4.5	9.9	Lewis Ranch/Indian Hill Road-Seg_3	5.400	25	3	8	3	8	7	3	2	3	NE
664	666	16	0	7.78	Bristol Ridge/Hirsig Road- Seg1	7.780	60	8	8	8	7	6	1	3	3	GR
664	667	16	15.28	19.08	Bristol Ridge/Hirsig Road- Seg3	3.800	60	8	8	8	7	7	2	3	3	GR
667	668	17	0	5	Kirkbride Road_Seg_1	5.000	50	8	8	8	8	7	1	3	3	GR
668	669	17	1	4	Indian Hill Road 131-3_Seg_2	3.000	60	7	8	8	8	7	1	3	3	GR
700	670	21	0	1	Chalk Hill/Bliss Road_Seg_1	1.000	30	7	8	6	8	6	3	1	1	GR
3	671	0	0	0.75	Jenny Lynn Road	0.761	35	6	9	8	7	6	3	3	3	GR
5	672	0	0	1.57	Chimney Rock Loop	1.566	30	8	9	8	8	7	3	3	3	GR
24	673	1	0	0.12	N. Avenue B-4	0.127	30	8	9	8	8	8	3	3	1	GR
27	674	1	0	0.25	Gopp Court	0.252	30	8	9	8	8	7	3	3	3	GR
46	675	1	0	0.12	David Court	0.105	30	8	9	8	9	8	3	3	3	GR
147	676	5	0	1.95	Latigo Loop	1.943	45	8	9	7	9	8	3	3	3	TG
157	677	5	0	2	Hyde Merritt Road	1.996	50	9	9	9	8	8	3	3	3	TG
184		6	0	0.08	Pharmond Trail	0.071	20	9	9	9	9	8	3	3	3	GR
189		6	0	0.13	Hodahlee Trail	0.126	20	8	9	8	9	7	4	3	3	GR
205		6	0	0.1	Evan Place	0.099	10	9	9	8	9	8	4	2	3	GR
206		6	0	0.36	E. Idaho Street	0.365	20	9	9	8	9	9	4	3	3	GR
207		6	0	0.46	Iowa Street	0.451	25	8	9	7	9	7	4	3	3	GR
224		6	0	0.4	Mount Meeker Road	0.389	30	8	9	9	9	6	3	3	3	GR
227		6	0	0.28	Sherman Mountain Road	0.269	30	8	9	8	8	7	3	3	3	GR
231		6	0	0.42	Stoneridge Drive	0.409	30	9	9	8	9	8	3	3	3	GR

242		6	0	0.12	Brimmer Road	0.126	15	5	9	7	9	5	4	2	3	GR
251		6	0	0.33	Sherman Mountain Loop	0.335	25	9	9	9	9	9	4	3	3	GR
252		6	0	0.38	Fox Ridge Drive	0.383	25	9	9	8	9	9	3	3	3	GR
253		6	0	0.1	Barrett Road	0.098	20	9	9	8	9	8	3	2	2	GR
263		6	0	0.18	Santa Marie Drive	0.173	30	9	9	8	9	8	3	3	3	GR
269		6	0	0.9	Tranquility Road	0.889	30	8	9	7	8	8	4	3	3	TG
281		6	0	0.1	Little Ridge Court	0.101	30	9	9	8	9	8	3	3	3	GR
293		6	0	0.51	Delware Street	0.503	25	9	9	9	9	9	4	3	3	TR
301		6	0	0.24	Buffalo Avenue	0.236	30	8	9	8	9	6	3	3	3	GR
302		6	0	0.39	Green Mountain Road	0.382	30	8	9	8	9	6	3	3	3	GR
303		6	0	0.49	Laughlin Road	0.472	30	8	9	8	8	7	2	3	3	GR
306		6	0	0.48	W. Wrangler Road	0.473	30	8	9	8	9	6	3	3	3	GR
307		6	0	0.87	Chisholm Trail	1.000	30	8	9	7	8	8	3	3	3	GR
582		10	0	0.95	Mountain Shadow Dr	0.960	35	7	9	9	7	6	3	3	3	GR
585		10	0	2.03	Mountain Shadow Ln	2.028	35	7	9	9	8	5	3	3	3	GR
608		11	0	0.25	Century Road	0.250	35	9	9	8	9	8	3	3	3	GR
132		4	12	15	154-1_Seg3	3.000	60	7	7	7	6	7	1	3	3	GR