AN ANALYTIC HIERARCHY PROCESS AND MARKOV CHAIN BASED APPROACH FOR CONDITION RATING AND DYNAMIC SERVICE LIFE PREDICTION OF RETAINING WALL

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A Thesis Submitted to the Faculty of the University of
Tennessee at Chattanooga in Partial
Fulfillment of the Requirements of the
Degree of Master of Science: Engineering

The University of Tennessee at Chattanooga
Chattanooga, Tennessee

August 2021

ABSTRACT

Retaining walls are typically considered auxiliary assets within the global transportation asset management scheme. However, failure cases to this structure class have attracted more attention to retaining wall assets. The possibility of failure also helps validate Moving Ahead for Progress in the 21st Century (MAP-21) requirements that transportation agencies develop asset management plans.

Consequently, this thesis represents the development of a framework that combines the Analytic Hierarchy Process (AHP) and Markov Chain to rate and predict the future condition of retaining walls respectively. Based on the Field Survey of candidate retaining walls, the research uses AHP for hierarchical configuration and pair-wise comparison of retaining wall elements (and sub-elements) – to generate relative weights. This process of relative weighting ultimately lends towards individual wall condition rating scores. This score, together with transition probabilities derived from historical condition data forms the basis of the dynamic service life prediction using the Markov chain.

Keywords: Retaining walls, Markov chain, AHP, Asset Management, Transportation agencies

DEDICATION

This thesis is dedicated to my ever-loving and supportive parents.

ACKNOWLEDGEMENTS

First, I give all glory and adorations to Almighty Allah – the All-Knowing and the All-Wise. To my major advisor and PI, Dr. Weidong Wu - I cannot thank you enough. I appreciate your enduring patience, guidance, and support towards the success of this thesis, and by extension, throughout the duration of my program. In the same vein, I would like to extend my deepest appreciation to other members of the committee; Dr. Joseph Owino, Dr. Ignatius Fomunung, and Dr. Mbakisya Onyango. You all are the greatest pillars of support holding the department together, and it's been a great privilege serving as your student. I thank Dr. Endong Wang, who initially conceived this idea, and proposed it to TDOT. To Ms. Lomen Karen, thank you for being so accessible and always willing to help.

Within and outside the confines of the University, I have made friends who have in no small measure contributed to my growth as a graduate student, and as a person. To all these beautiful human beings that I so gladly have the honor of calling my friends, I appreciate you all. To my family, most especially my parents; Dr. Adefalu Lateef Lawal, and Mrs. Salamat Nike Lawal. Your support and prayers have kept me going through the most challenging period of my life, your wise counsels have all kept me grounded and helped me focus better. I can't possibly begin to enumerate everything, but I see it all, and I am eternally grateful.

Finally, I would like to recognize and appreciate the State of Tennessee Department of Transportation (TDOT) for funding this project.

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LIST OF RECURRENT ABBREVIATIONS

AADT	Average Annual Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
AHP	Analytic Hierarchy Process
ASCE	American Society of Civil Engineers
ERS	Earth Retaining Structure
FHWA	Federal Highway Administration
DOT	Department of Transportation
MAP-21	Moving Ahead for Progress in the 21st Century
MCDM	Multi-Criteria Decision Making
MR&R	Maintenance, Rehabilitation and Repair
NBI	National Bridge Inventory
NHI	National Highway Institute
NPS	National Park Services
RW	Retaining Wall
TDOT	Tennessee Department of Transportation
UAV	Unmanned Aerial Vehicle
WIP	Wall Inventory and Condition Assessment Program

CHAPTER 1

INTRODUCTION

1.1 Background

From time immemorial, there has always existed a viable relationship between the success and progress of human society and the availability of public physical infrastructure (Uddin et al., 2013). In the American case study within the global context, the situation is not any different. Hence, the battle to restore the long-lost glory in the infrastructure realm has never been direr considering the devastating effect on the country's economy and its ability to be globally competitive (ASCE 2017; Ellingwood 2005). According to the American Society of Civil Engineers (ASCE) infrastructure report card (2017), the country's physical infrastructure is fast aging, as at the last audit, it stands at D+. While this overall rating masks specific critical aspects, it presents America's infrastructure's general fast deteriorating condition as a system. However, this comprehensive rating does not accurately depict the exact picture as it is an aggregation of different infrastructure categories ranging from Bridges to Ports. Out of all these categories, a significant and often neglected category is missing – Earth Retaining Structures.

Based on the Moving Ahead for Progress in the 21st Century Act (MAP-21), there is a need for state Departments of Transportation (DOTs) and other agencies to develop strict and performance-based programs for transportation assets and other assets along transportation infrastructure corridors. As such, some transportation agencies are now beginning to incorporate

Retaining wall management, being one of the visibly missing assets from the periodical infrastructure report card in their asset management programs.

1.2 Retaining wall

As one typical type of asset along transportation corridors, retaining wall (RW) is defined, by the National Highway Institute (NHI), as "a wall which makes an angle of 70 degrees or more with the horizontal and retains earth" (Brutus and Tauber, 2009). Being a critical geotechnical asset of a functional transportation system, retaining walls resist the lateral or other forces from soil, rock, and other mass to assist in the transportation functions of roads and bridge networks. The possibility of failure of these structures due to age-induced deterioration and the attendant effect on the host transportation network underlines how important it is for them to feature in transportation asset management programs (AASHTO, 2011; Lawal, 2017). Such a program that seeks to understand, track, and monitor the static and dynamic patterns of retaining wall systems thus becomes imperative to be put in place to ensure the safe operation of transportation systems.

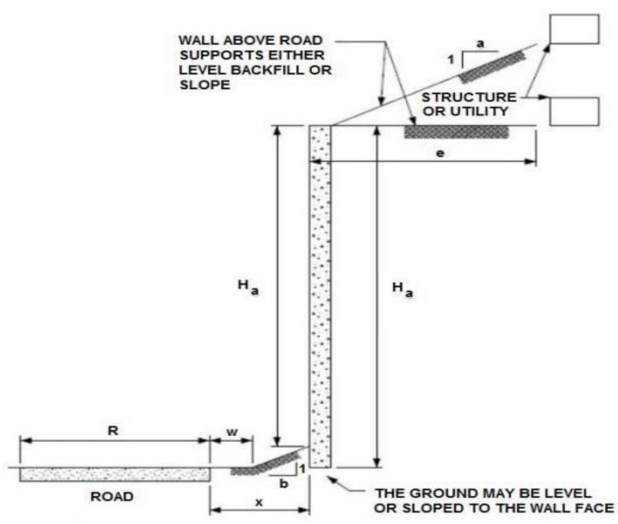

Figure 1.1: Typical retaining wall geometry (NYSDOT RW Inventory and Inspection Program)

Historically, retaining wall failures are relatively rare and are not often catastrophic (AASHTO, 2011), but recent incidents have called for the need for an effective management system (Hearn, 2003). The National Park Service, an agency of government responsible for maintaining thousands of miles of paved roads, oversees numerous subsidiary roadway features – including retaining walls. Retaining walls in this context are considered secondary assets but are nonetheless significant contributors to public safety and overall accessibility of the NPS road networks (DeMarco et al., 2010).

1.3 Condition rating

In the United States, transportation infrastructure asset management captures the development of modern data collection technologies, inspection techniques, and condition assessment methods of facilities (Schofer et al., 2010). There is no universally adopted condition rating technique, as the procedure varies for different agencies and departments of transportation. However, most transportation agencies assess structural performance through visual inspection-based structure condition states (Fragopol and Liu, 2007). There is also the anticipation that most of the agencies with inventory and inspection programs use a numerical rating that relies solely on a single-digit number to measure the overall condition of the retaining walls (Gabr et al., 2018). This single rating could potentially mask critical components of the retaining wall that are deficient and do not project the complete assessment of the condition of the earth retaining structures (Gabr et al., 2018). Notable examples are the 1- 7 system used by the New York City Department of Transportation (Brutus and Tauber, 2009) and Pennsylvania Department of Transportation (Gerber, 2012), the good, fair, poor system used by the Oregon Department of Transportation

(Brutus and Tauber, 2009), and the 1-10 rating scale utilized as a part of the Retaining Wall Inventory and Condition Assessment Program (WIP) of the National Parks Services (NPS) (DeMarco et al., 2010), the 1-4 rating system proposed by (Butler et al., 2016).

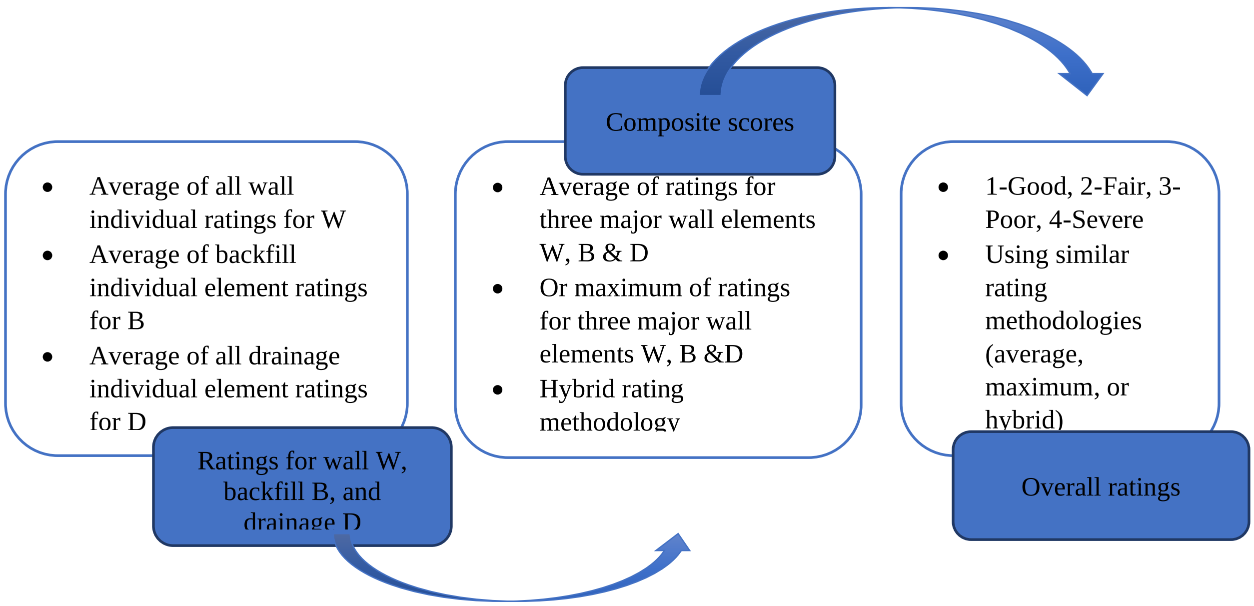

Figure 1.2: The earth retaining structure condition rating procedure (Butler et al., 2016)

1.4 Service life prediction

The growing degradation concern for retaining walls, just like other physical infrastructure systems, has encouraged the development of numerous computer-aided tools to predict the service life of structures (Marchand and Samson, 2009). Thompson et al. (2012) defined performance measures upon which infrastructure life prediction relies to include four distinct arguments. These are: when the asset is performing below agency standards, and rehabilitation seems to be the most viable alternative; when the asset is in a state where the risk of sudden failure is imminent; when the asset is living its extended life, after rehabilitation; and when each element that makes up the asset has its own set of preservation actions. With these in mind, coupled with the cost, labor-intensiveness, and subjectivity of visual inspection of structures such as bridges once every two years, there exist the need for a system that can effectively predict the dynamic condition and service life of civil structures (Chang et al., 2003).

1.5 Problem Statement

In September 2003, the retaining wall at the eastern end of the bridge on Jefferson Street on-ramp to I-40 West Davidson County, Tennessee, failed suddenly. Although there were no injuries or significant damage to approaching vehicles, the sudden collapse led to the closure of the existing ramp to traffic. The attendant effect of the closure led to the establishment of a detour and lost downtime. The post-failure assessment revealed that the last scheduled inspection was done two years prior - albeit to the overpass bridge alone. This event, though isolated, reveals the problem with the lack of systematic tally and rating of retaining wall components which are principal contributors to the safety and functionality of roadway systems. As a result, these structures' condition, performance, and reliability are mainly unknown, and eventually, the required preventive maintenance plans and associated budgets are difficult to schedule. These ultimately embed severe threats to public safety and roadway operation in Tennessee. This problem aligns with the realities of the tight maintenance and rehabilitation budget DOTs have to contend with yearly in the face of numerous projects.

Thus, there is the need for a system that can help identify and prioritize maintenance action of retaining walls, make in-state condition ratings, and predict the active service life. The result is an expectation of better decision-making, resource allocation, and overall improved asset management practices for transportation agencies.

1.6 Purpose of the Research

This thesis is part of a UTC team's effort to build a comprehensive, searchable inventory, rating, and performance prediction system of retaining walls for the State of Tennessee, a project funded by the Tennessee Department of Transportation. Therefore, the overarching goal of this thesis was to develop a model for retaining wall condition rating assessment and dynamic service life prediction based on the current state rating. It is essential for management that a retaining wall system can predict the future state based on its current condition.

The in-state condition rating forms the basis of future prediction efforts. The rating uses the Analytic Hierarchy Process – a technique that helps aggregate the ratings of the different components of a wall based on each element's relative weights. The prediction model uses the Markov chain to exhibit the stochastic nature of retaining wall condition changes.

The specific objectives identified in achieving this are:

1. To identify sample retaining walls in locations within Tennessee;
2. To provide an Analytic Hierarchy Process (AHP) based condition rating system for retaining walls considering key characteristics;
3. To develop a Markov Chain-based structure deterioration model to estimate the retaining walls' service life and dynamic condition (ii).

1.7 Scope of the Research

While part of the broader research aim involves developing a GIS-based mapping system, showing locations and attributes of retaining wall structures in Tennessee, this thesis focuses on condition rating and service-life prediction. The scope is realized in a step-wise manner through:

1. Field survey of identified retaining walls;

2. Using AHP multi-criteria decision-making tool in generating relative weight of RW attributes;
3. Applying the weighted attributes and field survey result in condition rating;
4. Subsequent stochastic modeling of the deterioration using the principles of the Markov chain.

1.8 Research Approach

The research aims to develop an integrated AHP and Markov Chain-based condition rating and deterioration model. Therefore, to achieve the broad research goal, the approach entails reviewing past literature and subsequent application of findings to retaining wall case studies within Tennessee.

Literature Review

A comprehensive review of literature in different areas of infrastructure asset management using varied sources, including journals, books, and the worldwide web. The review takes place to synthesize information related to best practices and current models in infrastructure asset management. More specifically, the literature review addresses the following areas in terms of past research work done as it relates to the topic:

1. Retaining wall types, defects, and failure modes;
2. Infrastructure Asset management;
3. Multi-criteria Decision Making (MCDM) in Asset Management;
4. Stochastic Modelling;
5. Analytic Hierarchy Process;
6. Markov-Chain for Stochastic Modeling of Civil Infrastructure.

Data Collection

Information on retaining wall history is sourced from Wall owners, primarily the Tennessee Department of Transportation, being the area under study. A questionnaire was designed and forwarded to engineers in the four regions within the State of Tennessee. This questionnaire helps in aggregating unavailable data relating to the construction and maintenance history of the surveyed walls. Retaining wall information is also collected from a geotechnical database provided by the Tennessee Department of Transportation, TDOT. This database serves as the first point of call. The location information is derived and subsequently plugged into google earth for additional pre-survey information such as geographical coordinates, height, and length.

Development of condition rating scale, AHP model, and Markov chain

This process begins with establishing rating criteria, condition rating scale and develops an Analytic Hierarchy Process model for weight assignments and eventual condition rating. The next stage is developing a Markov Chain-based deterioration model of the selected retaining walls for the dynamic service-life prediction.

1.9 Thesis Structure

This thesis consists of six chapters.

Chapter 1 represents the introduction and generally sets the tone for the entire body of work. The chapter's research background, problem statement, purpose, scope, and thesis structure are all defined.

Chapter 2 presents the results of a comprehensive review of past literature.

Chapter 3 explains the methodological approaches to achieving the research goals, with specific entries for equipment, case studies, and applied methods.

Chapter 4 discusses the results and outcomes of the research.

Chapter 5 contains the summary and conclusions drawn, the references used to prepare the thesis, and the appendices follow.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This research seeks to address the problems in retaining wall asset management as part of a broader transportation asset management plan using AHP and Markov chain concepts. While these separate approaches have been used extensively in modeling different transportation assets in terms of deterioration and resource prioritization, there has not been broad joint applicability of both methods for Retaining walls. Thus, this chapter summarizes the previous works that apply these concepts within the confines of infrastructure asset management.

2.2 Retaining Wall Asset Management

A Retaining wall, otherwise known as Earth Retaining Structures (ERS), is any structure designed and constructed to offer stabilization to an otherwise unstable soil mass through the provision of lateral support (AASHTO, 2003). Retaining walls, just like other transportation assets, requires management in the form of inspection, maintenance, and repair to achieve its functional purpose and to ensure longevity. However, unlike bridges, pavements, and signages, there is no broad applicability of Asset Management techniques to ERS. Asset management broadly shares similar fundamental concepts and can be achieved through the three stages of Information collection, data analytics, and policy-making (Brutus & Tauber, 2009).

1. Informational stage: this consists of all the processes that enable asset managers to identify the assets that are most in need of action (maintenance, repair, or even closure) to avoid further deterioration or sudden failure. This stage also typically involves developing a comprehensive database where condition information and other data can show.

1. Analytical stage: This stage is where the data from the database can be analyzed to make reliable forecasts of cost, service life, and failure risk of the assets under consideration.
2. The policy-making stage essentially is the phase where information turns into data-driven policy actions. These actions could be in the form of a review of standard specifications or assessing conditions appropriate for using the different assets.

These stages, according to Brutus and Tauber (2009), can be shown in Figure 2.1 below:

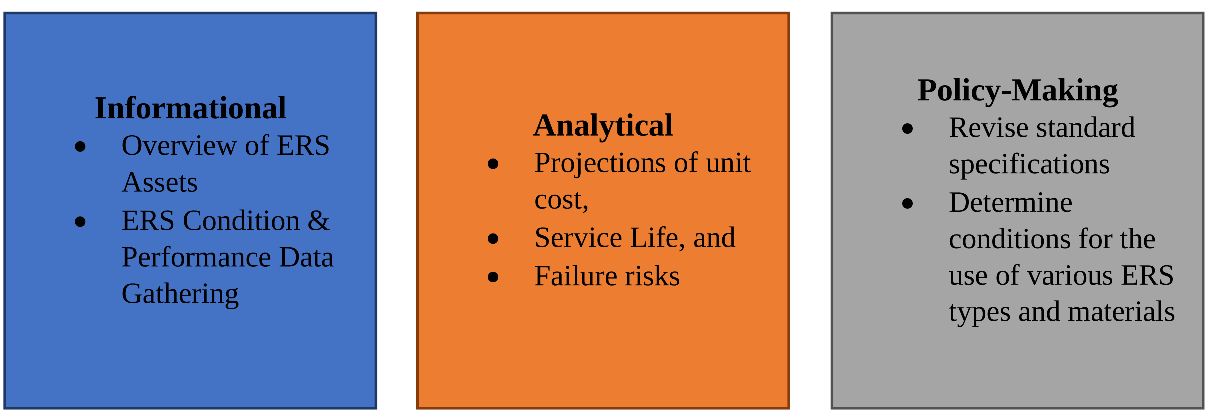

Figure 2.1: Stages of Asset Management of ERS (Brutus and Tauber, 2009)

Effective infrastructure asset management, while not a myth, remains challenging to achieve for public agencies. Development of infrastructure objectives, management of different stakeholders with varying interests, and establishment of a uniform alignment between set objectives, situation, and intervention represents some of the critical challenges associated with infrastructure asset management (Schraven et al. 2011). Uddin et al. (2013), in their book on Public Infrastructure Asset Management, talked about the lack of systemic planning for operational maintenance and rehabilitation of public infrastructure. He noted how important it is for life-cycle analysis through condition prediction and deterioration and performance management to ensure optimal treatment at the right time using the suitable method. Figure 2.2 shows the analysis below:

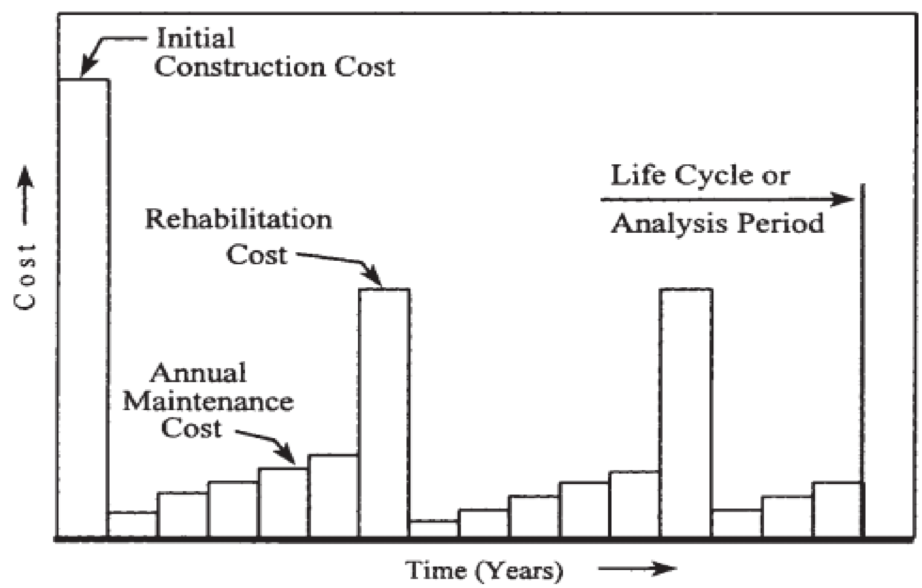

Figure 2.2: Life-cycle cost streams for infrastructure analysis (Brutus and Tauber, 2009)

Although it has been established that most of the asset management processes are applicable across the different transportation infrastructures, there exists a significant limitation of current systems in its consideration of geotechnical issues (Stanford et al., 2003). This leads us to analyze the current practice for retaining wall asset management through a review of associated literature.

2.3 Current State of Practice

Outside of Tennessee, many highway agencies have expanded their infrastructure asset management to accommodate earth retaining structures. Below is a synthesis of some DOTs regarding their current adaptability and approach regarding retaining wall management. There are about 18 of these agencies and DOTs with varying degrees of progress in their Inventory and Inspection. The summary is in a table, and an additional explanation is provided on each DOT's current state of practice.

Table 2.1: Agencies with Inspection Programs (Gabr et al. 2018; Brutus et al. 2011)

Agency	With inventory OR an inspection program	With inventory AND inspection program	With inventory AND inspection program in an asset management system	With only accessible guidance manuals AND/OR inspection forms	Rating scale
Alaska DOT	X	---	---	---	---
British Columbia Ministry of Transportation	X	X	X	---	---
California DOT	X	---	---	---	---
City of Cincinnati	X	X	X	---	---
Colorado DOT	X	---	---	---	---
FHWA and NPS	X	X	X	X	1-10
Kansas DOT	X	X	---	---	---
Maryland DOT	X	---	---	---	---
Minnesota DOT	X	---	---	---	---
Missouri DOT	X	---	---	---	---
New York City DOT	X	X	---	X	1-7
New York State DOT	X	X	---	X	1-7
Oregon DOT	X	X	---	---	Good/Fair/Poor
Pennsylvania DOT	X	X	X	---	2-8
VicRoads Technical Consulting for Victoria Australia	X	X	X	X	1-4
Nebraska Department of Roads	---	---	---	X	0-9
Ohio DOT	---	---	---	X	Yes/No
Utah DOT	---	---	---	X	Yes/No

Indiana Department of Transportation

Khedekar et al. (2019) "Creation of Statewide Inventory for INDOT's Retaining walls" developed geotechnical asset management, specifically focusing on retaining walls for the state. In doing this, it was necessary to identify the challenges that had to be overcome in building an inventory of the structures. For instance, many of the dated structures were not documented in terms of construction history and locations. Overcoming this database difficulty meant that a new system had to be developed that could smartly store the vital data - and this was achieved through the use of ArcGIS collectors. The data collection process included fieldwork where trained inspectors were deployed to identified locations to examine walls for defects, take pictures, and input defects and wall ratings in the database.

Alaska Department of Transportation

Thompson (2017), in the "Geotechnical asset management plan: technical report" for Alaska DOT, identified in line with federal regulations condition rating categories. While the FHWA (2017) broadly used the good, fair and poor system, the Alaska DOT utilizes a five-category condition rating system with two different fair and poor condition ratings, respectively, in addition to 'good'. Typically, a score of 100 is assigned to assets in condition 1, i.e., good, while 0 is assigned when the asset is in its worst possible state, i.e., condition state 5. Despite the dollar value of Alaska's soil slopes and earth retaining structure, the department does not have a comprehensive inventory of geotechnical assets, with significant performance gaps in the existing partial inventories.

Idaho Department of Transportation

MSE walls, predominantly used in bridges and along highways in Idaho, were surveyed as part of the state's overall asset management program. It was essential to preselect a list of attributes upon which the database would be built. These include location, wall dimensions, wall type and functionality, historical data, structural data, drainage. The wall information was generally difficult to locate owing to the lack of record-keeping, with predominantly most of the information available coming from a region known for the building of MSE walls in recent years. It was also realized that Unmanned Aerial Vehicle (UAV) could also help photograph areas that inspectors would otherwise not be able to reach (Sharma et al., 2019).

Colorado Department of Transportation

The Colorado Department of Transportation has a built asset management program for ancillary transportation assets, including retaining walls, sound walls, and other geotechnical assets. The program was formulated within a year to improve public mobility, safety, and performance through corrective actions. However, the retaining wall component of the asset management program was integrated with the state's bridge management program and cascaded to the National Bridge Inventory (NBI) system level. It is worth noting that the data collection and inventory development and overall management of the retaining wall assets were carried out using hand-held web-based mobile devices (Vessely et al., 2015).

North Carolina Department of Transportation

In 2014, North Carolina State DOT developed a retaining wall inventory and assessment system (NCDOT, 2015). This was eventually published as part of efforts towards incorporating retaining walls into inventory and inspection programs of all transportation agencies (Butler et al., 2016). NCDOT developed a systematic means of cataloging retaining wall assets along highways, including the condition assessment of the structures. This was done as part of the organization's efforts towards efficient retaining wall maintenance, rehabilitation, and replacement priorities supporting the "Moving Ahead for Progress in the 21st Century Act", MAP-21.

New York State Department of Transportation

In its Retaining wall inventory and inspection program, the New York State Department of Transportation (NYSDOT) established how essential asset inventory data is to maintain the validity of the asset management program. A vast majority of the approach taken by the DOT is similar to other state transportation agencies, including the types of data collected. However, the agency uses a different overall condition rating scale of 1-4, with 1 representing a wall in a new to a good state and 4 denoting a wall in a critical to severe condition. The inventory program also accommodates a risk rating component based on wall condition, age factor, failure consequence, AADT factor, and height factor. The risk score obtained from a simple multiplication of the listed input helps classify the walls of either low risk, moderate risk, or elevated risk (NYSDOT, 2018).

Minnesota Department of Transportation

The Minnesota Department of Transportation was one of the DOTs at the forefront of developing an inventory and inspection program for retaining wall asset management, catching the wave in 2013. Through a transportation research synthesis (TRS 1305), the agency sought to understand what other DOTs were doing and approaches taken to develop their different management plans. This was done to understand the needed inspection guidelines, essential attributes, criteria, methods, performance measures, and risk management strategies that could optimally serve the needs of MnDOT (TRS, 2013).

2.4 MCDM in Infrastructure Asset Management

Multi-Criteria Decision-Making methods have been in use since the 18th century (Zavadskas et al., 2015). In retaining wall management, just like other infrastructure asset management, there exists the need for critical decision-making, frequently coming in a multidimensional manner. Since all the retaining walls in a state cannot be surveyed, priorities would have to be set using specific criteria. The contribution of the different attributes to the condition rating is not equal, leading to the assignment of weights. In this vein, this section reviews practices related to how these multi-criteria decisions have been made scientifically over the years in infrastructure management, highlighting the options available with their strengths and limitations, respectively.

Kabir et al. (2014) reviewed different MCDM approaches as applied to different infrastructure class types (e.g., bridges and pipe), and prevalent intervention (e.g., repair and rehabilitate). The paper focused on such approaches as the Weighted sum model (WSM), Weighted product model (WPM), Compromise Programming, Analytical Hierarchy Process (AHP), etc. However, the different approaches shared similar underlying mathematical principles of assigning values for each criterion and alternative and ultimately outputting a total score of the multiplication of weights and assigned values. The application area trend showed AHP to be the most widely used approach among the considered methods for all application areas ranging from water resources to bridges and buildings.

Niekamp et al. (2015), in their paper titled "A multi-criteria decision support framework for sustainable asset management and challenges in its application," presented a case for analytical decision support for management of industrial assets in the face of multiple objectives. The research underscored the importance of factoring both Life cycle assessment and Life cycle costing in defining the sustainability criteria for asset management. It ultimately presented a framework that includes criteria and alternatives identification, choice of MCDM approach, alternatives scoring, and finally result in comparison, considering the input from major stakeholders. Again, among the considered approaches, Analytical Hierarchy Process remains the most prominent.

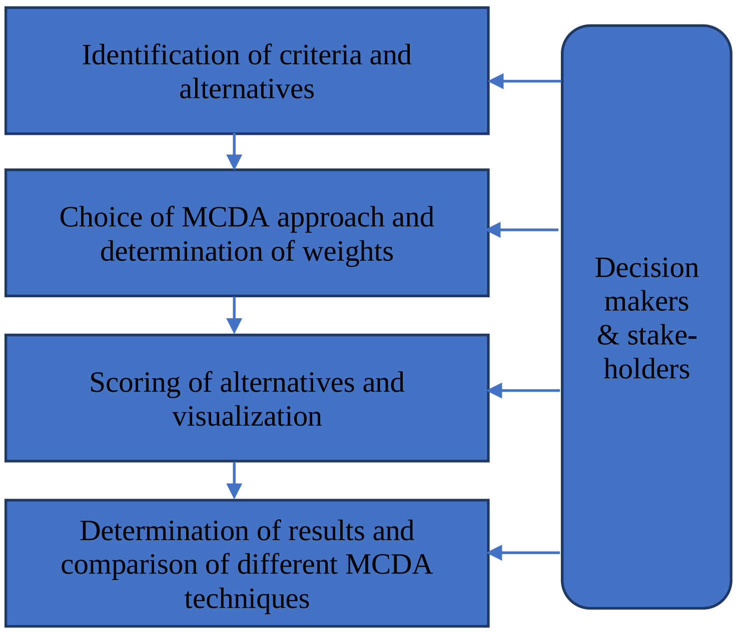

Figure 2.3: MCDA framework (Niekamp et al. 2015)

Niekamp et al. (2015) further x-rayed the challenges associated with the application of MCDM frameworks. Data availability and formatting mainly manifests in inconsistent data or even sometimes an absolute lack of it. Criteria and weighting resulting from different stakeholders' involvement can pose a challenge due to subjectivity and difficulty to agree on some overall consents.

Schraven et al. (2011), in their case study of the Dutch provincial agency, showed that infrastructure objectives are at the heart and core of achieving effective asset management. Specifically, this devolved to mean evaluation criteria are derived from the goals of the infrastructure management program. Ultimately, it is shown that infrastructure objectives need to be monitored and evaluated based on prevailing changes in the infrastructure situation. The paper also revealed the decision-making challenges in infrastructure asset management, citing cases relating to aligning decision areas, difficulty articulating objectives, and challenges of managing multiple stakeholders.

Torres-Machi et al. (2015) analyzed the different economic, technical, and environmental considerations in Pavement management decision-making. With sustainability being the theme, it becomes essential for pavement managers to integrate these factors in evaluating available maintenance alternatives over the pavement's life cycle. The research shows the different methods explored to assist transportation agencies and researchers in incorporating sustainability into pavement management. Similarly, varying forms were considered with their inherent merits and disadvantages. Strikingly, Analytic Hierarchy Process (AHP) seems to be encouraged when the alternatives being considered are small (a threshold of seven or eight advised). The choice of AHP is due to the complexity that results from the pair-wise comparison of large alternative sets.

MCDM was used to analyze the taxi fleet's sustainable strategies in Beijing based on economic, policy, and environmental factors within a life-cycle analysis framework. In the research carried out by Cai et al. (2017), results showed the Multi-criteria Decision Analysis (MCDA) capability for taxi implementation utilizing available technologies as applied explicitly to Beijing. This research was conducted using data collection and questionnaire survey, life-cycle assessment, impact assessment, and ultimately multicriteria decision analysis. The MCDA considered three suitable methods for analyzing the data based on best to worst scenario rankings. These methods, namely, Technique for Order of Preference by Similarity to Ideal Solution

(TOPSIS), Simple Additive Weighting (SAW), and Elimination and Choice Expressing Reality III (ELECTRE III).

Tscheikner-Gratl et al. (2017) compared side-by-side five MCDM methods (ELECTRE, AHP, WSM, TOPSIS, and PROMETHEE) in an integrated rehabilitation management system using a case study. Given the inherent differences between the methods, the results obtained were not equal. Results also revealed that criteria definition and score scaling influence the results far greater than the choice of the MCDM method. Consequently, the decision of the method to use for rehabilitation planning is more dependent on the available resources and data. Thus, serving to say that in cases where data quality is low and available resources in terms of the workforce are greatly limited, analysts should defer the choice to the most straightforward method. AHP and WSM are usable without any advanced programming skills and are quickly advised in this case.

The Analytic Hierarchy Process

Amongst the MCDM processes, the AHP is one of the most straightforward and most widely adopted approaches (Belton 1986; Velasquez & Hester 2013; Mulliner et al. 2016;). The Analytic Hierarchy Process, AHP, as Saaty (1987) explored, focuses on modeling different problem structures that could achieve a hierarchic configuration through pair-wise comparisons. Thus, there is an overarching objective for every hierarchy from which the criteria and sub-criteria descend. The author sampled different examples in the paper ranging from an application to politics, as in the case of the Finland parliament, to decide on a college for a prospective undergraduate student. The case studies considered were based on a fundamental scale, as shown in Table 2.2.

Table 2.2: The Fundamental Scale (Saaty, 1987)

Intensity of importance on an absolute scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one activity over another
5	Essential or strong importance	Experience and judgment slightly favor one activity over another
7	Very strong importance	An activity is strongly favored and its dominance demonstrated in practice
9	Extremely important	The evidence favoring one activity over another is the highest possible order of affirmation
2,4,6,8	Intermediate values between the two adjacent judgments	When compromise is needed
Reciprocals	If activity *i* has one of the above numbers assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared with *i*	
Rationals	Ratio arising from the scale	If consistency were to be forced by obtaining n numerical values to span matrix

In a study conducted by Smith et al. (1997), AHP was used to select bridge materials as part of the decision-making process for some states. Different project stakeholders ranging from state DOT Engineers to local highway officials were interviewed to find their material preferences and ultimately model these individual choices to give an overall decision. The team achieved the evaluation through the succinct definition of objective, decision-makers, criteria such as maintenance requirements to the material's lifespan, and material options ranging from steel to reinforced concrete. Results ultimately affirmed how decision modeling using AHP could be used in representing material choices of a select group of decision-makers.

Wang, Liu et al. (2008), in its paper titled "An integrated AHP-DEA methodology for bridge risk assessment," used a fusion of the technique with Data Envelopment Analysis (DEA) in evaluating bridge risks for hundreds of thousands of bridge structures in the United Kingdom. The author used AHP in projecting the different bridge priorities in terms of their overall risk scores based on Multiple Criteria Decision Making (MCDM). The criteria considered were:

- Safety of the general public concerning its continued use.
- The functionality of the bridge structures is based on how well it serves the public.
- Sustainability of both expenditure and workload.
- Effect of the systems on the environment.

These criteria were subsequently assigned weights determined by a top manager in charge of bridge maintenance projects, with a total of 20 bridges making the shortlist as alternatives (Wang, Liu, et al. 2008).

A sequel to bridge infrastructure risk assessment is the possibility of replacement action for select defaulting candidates. As a result, Saito (1987) examined the application of the Analytic Hierarchy Process to making priorities on bridge replacement projects. In his paper, the author used the technique to rank bridges based on specific criteria such as structural condition, remaining service life, road narrowing, deck width, service/cost, and approach condition. It is essential to carry out qualitative risk and reliability evaluation on case study structures to see the physical extent of defects (Lawal, Jimoh, et al., 2017). The six criteria were compared and assigned values based on perceived relative importance. These were then followed by ranking the project alternatives based on the defined criteria and comparing them. However, to apply this method on a larger scale, judgments and preferences of more decision-makers would have to be incorporated as against that of a single researcher (Saito 1987).

AHP was used in network-level infrastructure maintenance decision-making in determining the weighting of some preselected decision-making factors in a study conducted by (Li, Ni et al., 2018). The technique was explicitly applied to network-level pavement maintenance decision-making, considered five maintenance-related factors: pavement performance, pavement structure strength, traffic loads, pavement age, and road grade. The research selected these factors were through a review of past literature, a survey of experts' opinions, and an analysis of database information. All of the results from the decision-making process were subsequently subjected to sensitivity analysis to determine the factors with the most significant effects on the decision from both cost and service-life perspectives.

Analytic Hierarchy Process has, over time, proven to be a multicriteria decision-making tool in different spheres and has found its applicability in supporting both subjective and objective-based choices in infrastructure projects with social impact (Álvarez, Moreno, et al., 2013). According to the authors, AHP offers an excellent technique in assessing the effects of different stakeholders' participation in civil infrastructures projects.

The AHP, according to (Saaty 1987), is thus a "structured technique for organizing and analyzing complex decisions based on mathematics and psychology". This multicriteria decision-making tool affords individuals and organizations a systematic way to allocate and strategically solve a wide array of problems. The technique employs an approach that is divided into three categories, namely

- hierarchic design,
- methodology for the establishment of priorities, and
- pair-wise comparisons of the different possible outcomes or alternatives.

2.5 Stochastic Modeling in Infrastructure Asset Management

Mathematical modeling represents the quantitative description of a natural phenomenon, and can either be deterministic or probabilistic (Pinksy and Karlin 2010; Bender 2012). The term "stochastic" originates from the Greek language, and means "random or probable". Directly opposite this is "certain or deterministic". To put things into perspective, a "*deterministic model predicts a single outcome from a set of circumstances, while a stochastic model predicts a set of possible outcomes weighted by their likelihoods, or probabilities*" (Pinsky and Karlin 2010). Consider the case of a classical statistical theory with random variables X_0,......, X_n, i.e.

$$\mathrm{P}\ (X_0 \epsilon A_0, \ldots\ldots, X_n \epsilon A_n) = \prod_{i=0}^{n} \mathrm{P}\ (X\ \epsilon A_i),$$

where X is defined as a generic random variable with the same distribution as the X_i(Guttorp 2018). "A stochastic process is thus a family of random variables X_t, where t is a parameter running over a suitable index set T" (Pinksy and Karlin 2010).

$$\mathrm{P}\ (X_0 \epsilon A_0, \ldots\ldots, X_n \epsilon A_n)$$

$$= \mathrm{P}\ \{X_0 \epsilon\ A_0\} \prod_{i=1}^{n} \mathrm{P}\ (X_i\ \epsilon A_i |\ X_0 \epsilon A_0, \ldots.. X_{i-1} \epsilon A_{i-1}),$$

Stochastic models and processes can be grouped into different categories and differ majorly based on their mathematical properties. Amongst the various types of these random processes, discrete and continuous-time Markov chains are the most commonly used in modeling randomly evolving systems (Latouche and Ramaswami 1999).

Andrews et al. (2014) developed a stochastic model for railway track asset management. Given that the research found the geometry degradation process to be dependent on the maintenance history of the track, this becomes a problem that can model mathematically. The paper focused on predicting the present state of the track geometry and life-cycle costs using the Petri net method. The model was built off deterioration, inspection, intervention, and renewal processes, respectively. The model represented the deterioration process empirically to reflect the geometry's condition ranging from its pristine state to its worst possible form. Transition rate data are generated and executed to analyze deterioration time distribution through a Monte Carlo simulation of the model.

Morcous and Akhnoukh (2006) applied stochastic modeling to infrastructure deterioration, specifically concrete bridge decks. Since stochastic modeling can be either state-based or time-based (Mauch and Madanat 2001), the paper presented a close comparison between a state-based (using Markov chain) model and a non-parametric time-based model to guide decision making. Due to traffic loads, the reinforced concrete (RC) decks were selected as the most impacted part of a bridge structure. Based on the database condition rating system, bridge decks were assigned an initial condition vector P (0) and are assumed to have a future condition $P(t)$ after (t) number of transition periods (Collins 1972).

$$P(t) = P(0) * P^t$$

where, P =

$$
\begin{matrix}
p_{66} & 1-p_{66} & 0 & 0 & 0 & 0 \\
0 & p_{55} & 1-p_{55} & 0 & 0 & 0 \\
0 & 0 & 0 & 1-p_{44} & 0 & 0 \\
0 & 0 & 0 & p_{33} & 1-p_{33} & 0 \\
0 & 0 & 0 & 0 & p_{22} & 1-p_{22} \\
0 & 0 & 0 & 0 & 0 & 1
\end{matrix}
$$

For the state-based (Markov chain) deterioration model,

- P represents the Transition Probability Matrix (TPM) of order *(n x n)* where *(n)* is the number of condition ratings, with transition probabilities for all likely condition changes over a given period, based on the governing deterioration parameters.
- This model assumes that the future condition of the deck only depends on its initial/most current state.

On the contrary, the time-based model reflects the probability distribution of facility transition times based on set deterioration criteria. Ultimately, the research shows that choosing which type of data is used relies heavily on the kind of data available and the degree of accuracy decision-makers require.

Straub (2009) developed a generic framework for stochastic modeling of deterioration processes using Bayesian networks. The developed model was then applied to case studies of fatigue crack growth involving time-variant random variables and fatigue crack growth as a stochastic process. Results revealed that the Bayesian framework could provide a computationally robust approach to stochastically monitor the condition and reliability of structural members that are prone to deterioration. However, the limitation of this method is in the number of random variables it could take in and the intense computation time required.

Mishalani and Madanat (2002) presented a stochastic approach that considers the limitations of causal variables in developing a time-based discrete-state model. The most crucial assumption in the model is a probabilistic relationship between deterioration indicators and the actual deterioration process. The transition probability is determined from the duration model.

Markov Chain

Performance and Uncertainty modeling represents an essential aspect of asset management. Quantitative models could determine overall condition performance and life expectancies based on quantitative models (Thompson et al., 2012). These condition performance measures could be continuous, meaning condition changes on a smooth scale, or discrete, meaning condition changes on a step-wise scale. The next level is only dependent on the current status and independent of every other level (Thompson et al., 2012).

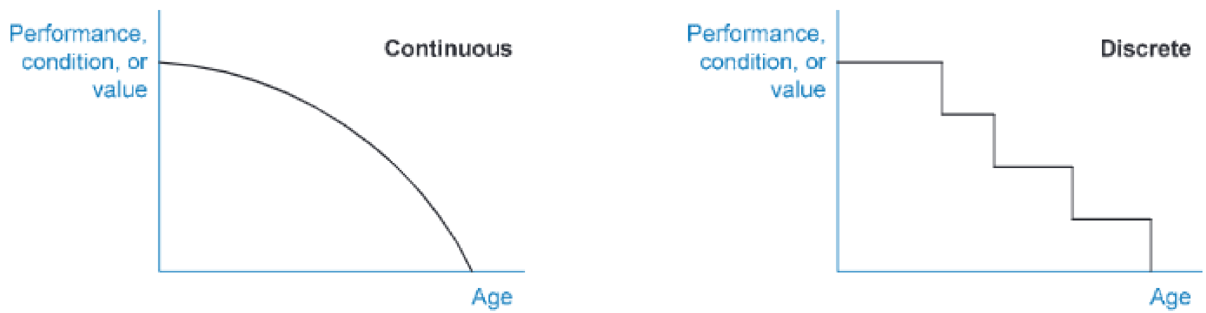

Figure 2.4: How asset performance changes over time (Thompson et al.,2012)

For simplicity, discrete models are often adopted, where uncertainty is estimated based on a constant transition probability from one condition state to the other in a year. This type of model is referred to as a Discrete Markov model or simply a Markov model (Thompson et al., 2012). Markov models are applied extensively in deterioration modeling due to their ability to capture the uncertainty and time-dependence of the deterioration process (Morcous and Mirza 2003).

The Markov chain approach represents the most popularly adopted stochastic modeling technique for dynamic condition prediction of infrastructure facilities (Agrawal 2009). It has been applied extensively to a host of different civil infrastructure deterioration modeling ranging from bridge management (Jiang and Sinha 1989; Cesare et al. 1992; Scherer and Glagola 1994; Madanat and Ibrahim 1995; Ng and Moses 2014); to pavement management (Camahan et al., 1987; Butt et al., 1994, Kidando et al., 2017); to railway assets management (Wellalage 2015); similarly, to wastewater systems (Jeong et al., 2005; Baik et al., 2006).

Markov Chain for Service Life Prediction

Markov chain, being an advanced statistics method, is a widely adopted method for modeling deterioration and predicting the remaining life of civil structures (Cesare et al. 1993, Li et al. 2014). In its simplest form, a Markov process describes a system in multiple states, with the likelihood of each state moving to the next state based on fixed probabilities (Li et al., 2014). These probabilities are termed as Transition probabilities, within the context of a finite Markov process, and given a trial t $(t = 1, 2..., T)$ depends only on the outcome of the preceding trial $(t\text{-}1)$ in every stage within the process (Lee et al. 1965).

Service life represents one of the most critical factors for infrastructure asset managers to predict (Thompson et al. 2012), evidently in bridge asset management (Jiang & Sinha 1989); water distribution network management (Sempewo and Kyokaali 2016); wastewater systems management (Baik et al. 2006). In all of these, there are shared commonalities in the development of a typical Markov model framework. These include:

States Definition

Markov chain as applied to performance prediction is hinged on defining states in terms of condition rating and obtaining the probabilities of these conditions to transition from one state to the other (Jiang and Sinha, 1989). Typically, the Markov chain (Discrete Markov) assumes that the conditional probability does not change over time (Baik et al., 2006).

Therefore, for all states *i* and *j* and all *t*, $P\ (X_{t+1} = j \mid X_i = i)$ is independent of *t* as expressed in Eq.:

$$P\ (X_{t+1} = j \mid X_i = i) = p_{ij}$$

where p_{ij} = transition probability given the system is in State *i* at time *t*, it will be in a state *j* at time *(t+1)*.

Madanat and Ibrahim (1995) explored the statistical appropriateness of the Markov chain process for deterioration modeling, as it applies to bridges.

Transition Probabilities

These probabilities are typically represented in a m *x m* matrix form termed transition probability matrix, *P*, where *m* is the number of condition states (Lee et al. 1965; Jiang and Sinha, 1989; Baik et al., 2006). Estimation of transition probabilities typically requires historical condition assessment data for existing systems (Baik et al., 2006). However, in building the deterioration model of a system without historical condition rating data, safe assumptions can be made, and a fixed transition probability matrix can be used (Morcous et al., 2003; Thompson et al., 2012). In defining transition probabilities, the following assumptions are made:

- That discrete transition time intervals exist through a constant population, i.e., transition probabilities do not vary with age) (Collins 1972);

- That probability of transition only depends on the current facility condition and not on the previous condition states (Collins 1972);
- Transition probabilities assume that the condition can either stay the same or deteriorate to the next stage directly following only, e.g., an asset's condition can stay in condition state four or decline to 3 only. This also means that an asset cannot possibly go from a bad condition state to a good condition state, barring rehabilitation (Madanat et al. 1997);

In the NYSDOT bridge inspection case study, condition ratings of 7 to 1 were defined, translating to seven Markovian states with each number corresponding to a condition state. Based on the assumptions of transition probabilities, the bridge system's condition rating would decrease with an increase in bridge age (Agrawal et al., 2008).

If each condition rating represents a condition state, i.e., condition rating 7 represents state 1, and rating 5 represent state 3; therefore, the transition probability matrix, P for this bridge system, is defined by the Equation (Agrawal et al. 2008):

$$P = \begin{matrix} p(1) & q(1) & 0 & 0 & 0 & 0 & 0 \\ 0 & p(2) & q(2) & 0 & 0 & 0 & 0 \\ 0 & 0 & p(3) & q(3) & 0 & 0 & 0 \\ 0 & 0 & 0 & p(4) & q(4) & 0 & 0 \\ 0 & 0 & 0 & 0 & p(5) & q(5) & 0 \\ 0 & 0 & 0 & 0 & 0 & p(6) & q(6) \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{matrix}$$

In the above equation, p (1) is the probability of transition from state 1 (condition rating 7) to state 1 (condition rating 7), i.e., the bridge remains in the same state. Similarly, q (1) is the probability of transition from state 1 (condition rating 7) to state 2 (condition rating 6). Since based on the assumptions, the bridge could only either remain in the same state or transition to the next state, q (1) = 1 - p (1). This is subsequently extended to all of the possible changes.

Service Life Prediction

After estimating the transition probabilities, the service life prediction can then be conducted using Eq. and Eq. (Jiang and Sinha 1989).

$$Q_t = Q_0 * P^t$$

where Q_t can be obtained by multiplying the initial state vector Q_0 and the transition probability matrix *P* raised to the power of *t*, i.e., after year 1, *t* = 1.

$$E\ (t, P) = Q_t * R'$$

Here, *R* can be the vector of condition ratings, and R' is the transform of *R*, therefore the estimated condition rating by Markov chain is defined by *E* (*t, P*) (Jiang and Sinha 1989).

CHAPTER 3

METHODOLOGY

3.1 Overview

This research aims at providing a framework for retaining wall in-state condition rating and future condition prediction during its service life. It was necessary to comb through past literature to develop rating criteria for the different retaining wall types. Based on the developed criteria, the condition rating of the walls is carried out. This rating subsequently forms the input for the dynamic condition prediction part. The flowchart of activities is presented in Figure 3.1.

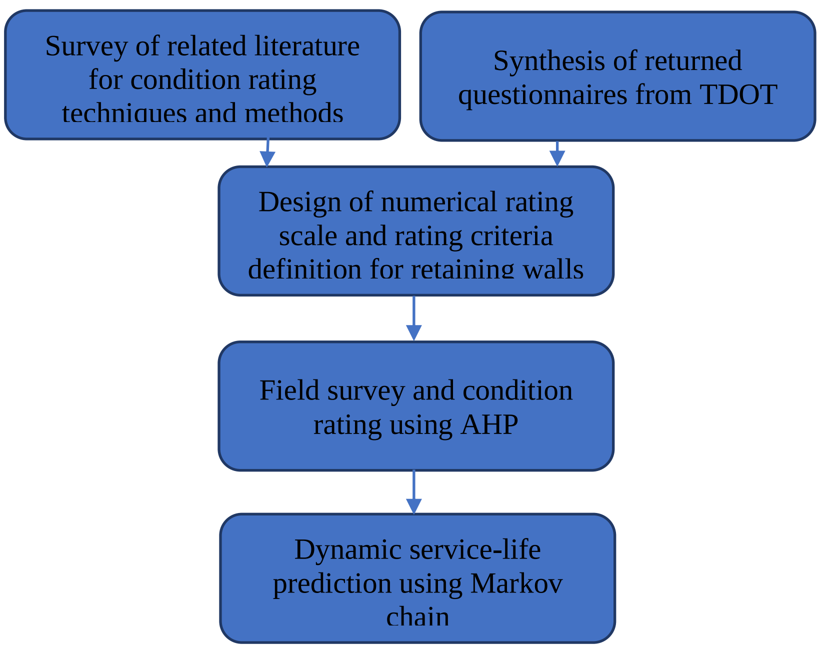

Figure 3.1: Diagram showing the activity process flow

3.2 Case Study and Scope

In recognition of the inherent limitation of surveying all the walls in the state, it was necessary to develop screening criteria to aid the selection of candidate walls for the research aim. With this in mind, the walls selected for the survey were based on such factors as:

1. Route: Wall should be along State routes or Paved Tennessee interstate;
2. Accessibility: Wall should be easily accessible and should not pose a significant hazard to the survey team;
3. RW dimensions: The height of the wall must be greater than or equal to 6ft.;
4. Relation to TN transportation asset: Wall should be of interest to TN Department of Transportation, which effectively eliminates the need to survey privately-owned walls;
5. Importance: Potential wall failure should significantly affect TN roads through damage to highway assets and injury or death to the patronizing public.

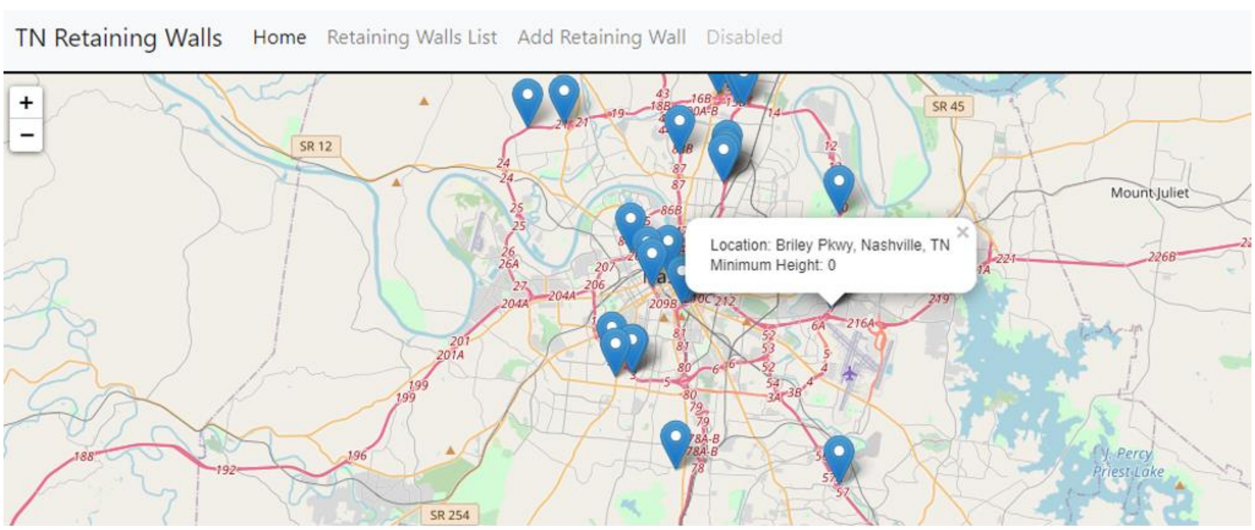

Figure 3.2: Sample retaining wall locations are taken from ArcGIS

3.3 Equipment

The DJI Phantom 4 drone (Figure 3.3) is primarily used for data collection in this study. Considering the exposure of the data collection team to traffic hazards, traffic control safety gear such as cones, stop/slow signs, as well as reflectors are used in controlling traffic during the entire process. Hand-held measuring tape and electronic distance meter were also available to collect measurement data relating to dimensions.

Figure 3.3: DJI Phantom 4 drone

The data collected are in picture and video formats, with a complimentary side of visual inspection.

3.4 Computational Tool

R statistical package is used in implementing the Analytic Hierarchy Process and Markov Chain simulation components of the thesis.

3.5 Data Collection Sites

The study includes 31 data collection locations across the different regions in the state of Tennessee. Even though about 92 locations were identified during the preliminary data mining process using TDOT geotechnical database and google earth, most of these locations were left out due to data collection limitations and traffic control challenges. These locations are reflected in Table 3.1.

Table 3.1: Some Data Collection Sites with geographical coordinates and other wall data

S/No.	Location	Geographical coordinates	Length (ft)	Average height (ft)	Maximum height (ft)	Retaining wall type
1	308 Ashland Terrace, Chattanooga, TN	35°07’13” N 85°17’07” W	215’4”	7’9”	9’8”	Mortared Stone Gravity wall, GM
2	7244-7254 E Brainerd Rd., Chattanooga, TN	35°01’01” N 85°10’01” W	149’2”	5’9”	8’7”	Concrete Block, GB
3	TN-153, Off Bonny Oaks Dr., Chattanooga, TN	35°04’52” N 85°12’18” W	692’5”	14’9”	22’4”	Concrete Cantilever Wall, CL
4	1301 Washington Avenue, Knoxville, TN	35°59’03” N 83°54’50” W	192’2”	7’2”	11’3”	Mechanically Stabilized Modular Block Facing, MS
5	Hall of Fame Dr. , Knoxville, TN	35°59’07” N 83°55’07” W	144’5”	7’1”	10’7”	Concrete Block, GB
6	James White Pkwy, Knoxville, TN	35°57’54” N 83°54’10” W	1173’ 10”	15’7”	27’3”	Concrete Cantilever Wall, CL
7	N Broadway Ramp to I40, Knoxville, TN	35°58’52” N 83°55’07” W	952’7”	16’9”	24’9”	Mechanically Stabilized wall, MS
8	Briley Pkwy, Nashville, TN	36°08’04” N 86°49’13” W	723’6”	15’6”	23’9”	Prefabricated Modular Geosynthetic Facing Wall, MG
9	Northpoint Boulevard, Chattanooga, TN	35°07’47” N 85°14’03” W	235’	7.3’	13.5’	Concrete Block, GB
10	Riverside Dr, TN-58, Chattanooga, TN	35°03'04.53"N 85°17'52.89"W	272’8”	7’11”	12’2”	Concrete Gravity, CIP
11	Signal Mountain Rd., Chattanooga, TN	35°05'02.25"N 85°19'26.56"W	978’4”	16’5”	21’7”	Prefabricated Modular Gravity Walls
12	1727 Dayton Blvd, Chattanooga, TN	35°04'51.44"N 85°19'08.19"W	198’4”	7’6”	10’2”	Concrete Block, GB
13	222, Baker Street, Chattanooga, TN	35°03'44.78"N 85°17'59.94"W	110’2”	13’5”	17’2”	Concrete Cantilever, CL
14	918-988 Cherokee Blvd, Chattanooga, TN	35°03'44.78"N 85°17'59.94"W	80’4”	15’4”	19’3”	Concrete Cantilever, CL
15	Elm Hill Pike, Nashville, TN	36°09'02"N 86°41'34"W	197’	12’3”	14’7”	Prefabricated Modular Gravity Wall

3.6 General Framework Development

Several data sources are required to develop an effective deterioration model for retaining walls. These data sources range from aggregated historical inspection data, weather data, and construction record data. (Davies et al. 2001). However, due to the dearth of historical records, alternative data sources had to be sought. The process employed in achieving this is presented in the flowchart shown in Figure 3.4.

For the deterioration model, condition rating data and information related to the history of each retaining wall asset are needed. Condition rating data are typically sourced through field surveys and subsequent utilization of AHP. Although the quality of this data is subjective, the research team underwent thorough training to optimize the output of the field survey and visual inspection.

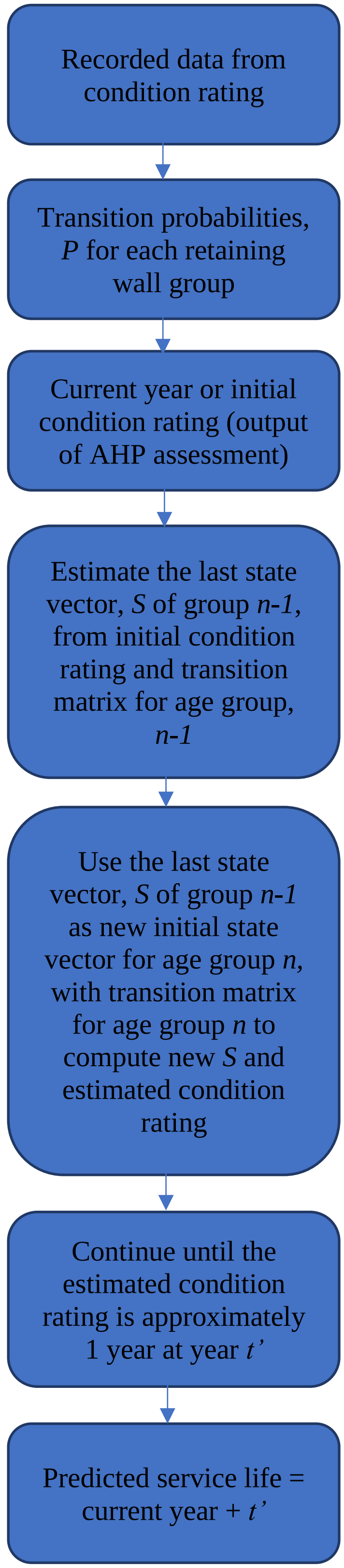

Figure 3.4: Flow chart of the dynamic service life prediction process using Markov chain

Development of Rating Criteria

Retaining walls vary in type, and thus the specific metrics upon which their condition rating would be based might slightly differ. In recognition of this, different rating criteria were developed for the different types of retaining walls identified. These rating criteria provide the much-needed detailed guidelines for each wall element's rating scores under consideration. For instance, the rating criteria for a Concrete gravity wall will not be the same as Dry stone gravity wall, owing to the difference in elements. However, minimum retaining wall elements have to be incorporated in defining rating criteria (Brutus and Tauber, 2009). This, together with the standard structure of a typical retaining wall (RW) rating criteria, is shown in the following tables:

Table 3.2: Minimum primary elements to include in wall condition ratings (FHWA NPS WIPG)

WALL TYPE	Piles and Shafts	Lagging	Anchor heads	Wire Geosyn. Facing	Bin	Concrete	Shortcrete	Mortar	Brick	Wall foundation materials
Anchor, Tie back	x	x	x							X
Anchor Micropile	x		x							X
Anchor, Sheet Pile	x		x							X
Bin, Concrete					x					X
Bin, Metal					x					X
Cantilever, Concrete						X				X
Cantilever, Soldier Pile	x	x								X
Cantilever, Sheet Pile	x									X
Crib, Concrete					x					X
Crib, Metal					x					X
Crib, Timber					x					X
Gravity, Brick								x	x	X
Gravity, Concrete						X				X
Gravity, Dry Stone										X
Gravity, Gabion				x						X
Gravity, Mortared Stone								x		X
MSE, Geosyn				x						X
MSE, Precast						X				X
MSE, Segmental Block									x	X
MSE, Wire Face				x						X
Soil Nail							x			X

Where x = wall elements that should always be rated for a given wall type

Table 3.3: Minimum primary elements to include in wall condition ratings (FHWA NPS WIPG)

WALL TYPE	Wall drains	Architectural facing	Traffic Barrier	Road/Sidewalk	Slope	Vegetation	Other Secondary elements	Performance
Anchor, Tie back	x		o	O	O			x
Anchor Micropile	x		o	O	O			x
Anchor, Sheet Pile	x		o	O	O			x
Bin, Concrete	x		o	O	O			x
Bin, Metal	x		o	O	O			x
Cantilever, Concrete	x		o	O	O			x
Cantilever, Soldier Pile	x		o	O	O			x
Cantilever, Sheet Pile	x		o	O	O			x
Crib, Concrete	x		o	O	O			x
Crib, Metal	x		o	O	O			x
Crib, Timber	x		o	O	O			x
Gravity, Brick	x		o	O	O			x
Gravity, Concrete	x		o	O	O			x
Gravity, Dry Stone	x		o	O	O			x
Gravity, Gabion	x		o	O	O			x
Gravity, Mortared Stone	x		o	O	O			x
MSE, Geosyn	x		o	O	O			x
MSE, Precast	x		o	O	O			x
MSE, Segmental Block	x		o	O	O			x
MSE, Wire Face	x		o	O	O			x
Soil Nail	x		o	O	O			x

Where o = 1 of 2 primary elements required depending on location observed

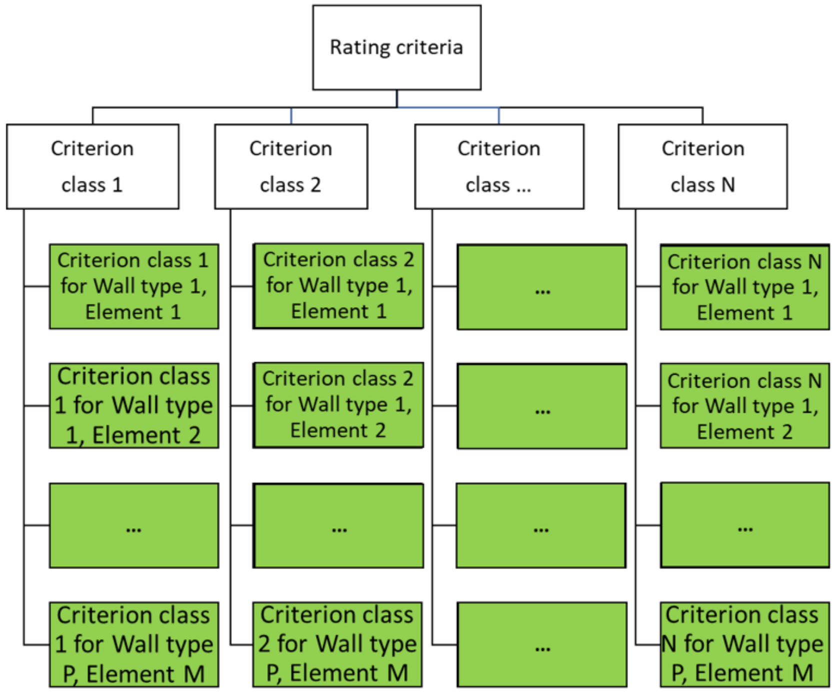

Figure 3.5: Typical Structure for RW rating criterion narrative (Brutus and Tauber, 2009)

After reviewing the different rating criteria adopted by different agencies and transportation agencies and considering the specific need of this research, a 1-4 rating scale was adopted. This is summarized in Table 3.2 below.

Table 3.4: Retaining wall element rating scale

Rating number	Narrative
1	Severe- wall element is in a deplorable state and action is highly recommended
2	Poor- wall element’s function is impaired
3	Fair- wall element is in a fair condition
4	Good - wall element is in an overall good state

Development of Field Survey Form

It is imperative that a field survey form reflects the developed rating criteria and allows condition ratings of individual elements to be achieved.

3.7 AHP Development Methodology

Analytic Hierarchy Process method is proposed in this study, where pair-wise comparison values are assigned based on the collected field data from ten different retaining walls within different regions in Tennessee, USA. A typical AHP implementation is shown in Figure 3.7 below

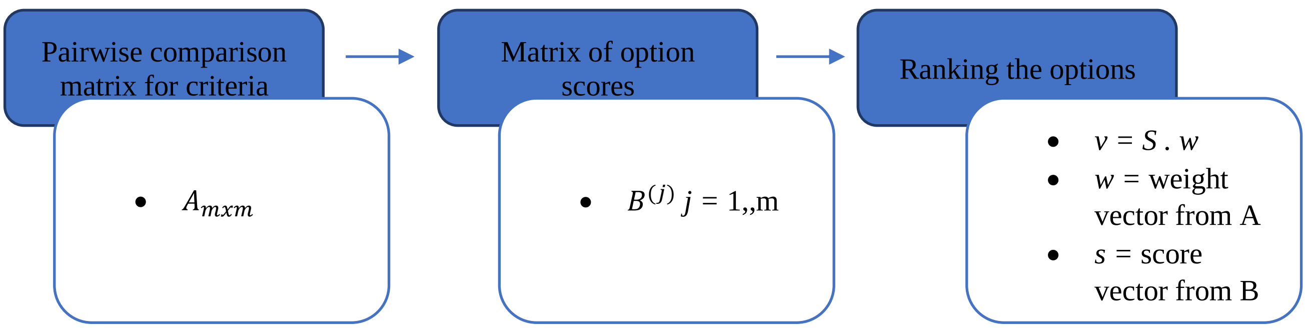

Figure 3.6: AHP implementation steps

Description of Steps

- Creating a pair-wise comparison matrix: where *m* is the number of evaluation criteria considered. For this case, the primary evaluation criteria are Structure, Auxiliary, Surrounding settings, and Service Functionality/Wall Overall performance. Therefore, *m* is 4. Similarly, sub-criteria are defined, and a pair-wise comparison is applied. Based on the criteria and sub-criteria involved, there is the need to calculate their relative weights. Therefore, the criteria weight vector, *w*, is estimated for all the evaluation criteria. This is calculated using the Equation.

$$w = \frac{\sum_{i=1}^{m} \bar{a}_{jk}}{m}, \text{ where } \bar{a}_{jk} = \frac{a_{jk}}{\sum_{l=1}^{m} a_{lk}}$$

a_{jk}= preference level of two compared criteria based on Saaty (1987).

m = number of evaluation criteria

- Computing the matrix of option scores: The option score matrix represents a matrix *S* of dimension *n x m*. Here, *n* represents the number of options used in the two-part rating system. For every entry of matrix *S*, the score of the *i*th option is taken relative to the *j*th criterion.
- Option Ranking: This is based on Equation.

$$v = S.\, w$$

where *v* represents the global score assigned by the AHP to the *i*th option.

In this research, the system used is two-part, which essentially entails individual wall element rating and an aggregated overall rating. This is further shown in the Figure below.

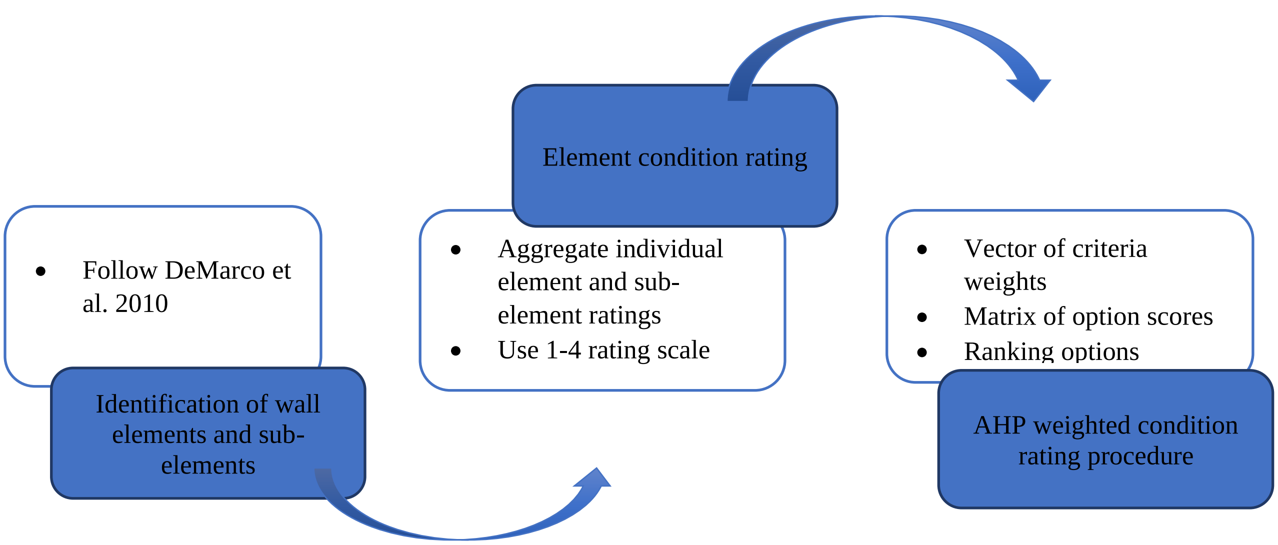

Figure 3.7: AHP-weighted two-part rating system used in the study

The AHP hierarchy is developed in Figure 3.9 to show the goal, the set criteria, and the attributes.

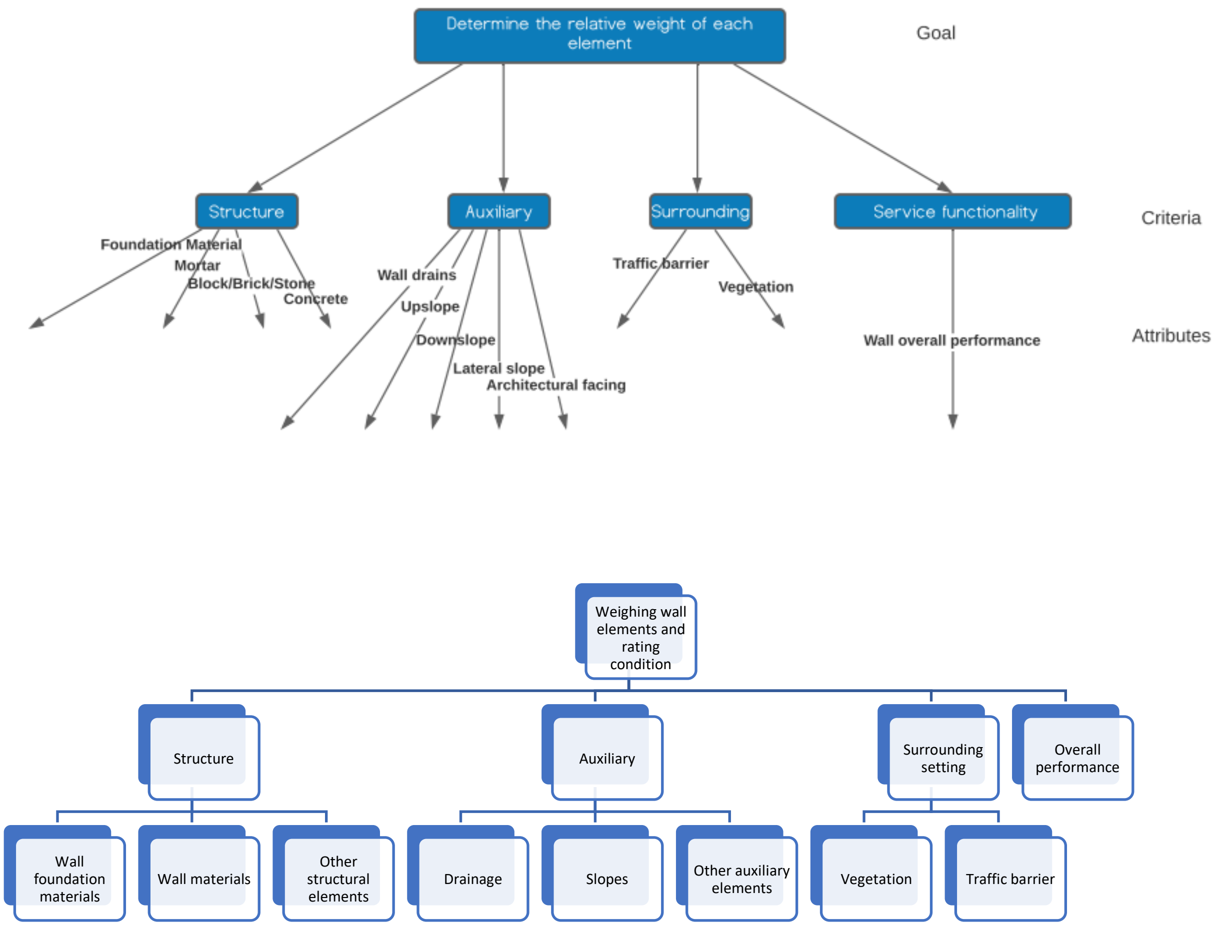

Figure 3.8: The AHP hierarchy for element importance weighting of retaining wall

3.8 Markov Chain Approach to Dynamic Service Life Prediction

The Markov chain as applied to retaining wall dynamic service life prediction is based on concepts of defining states in terms of retaining wall condition ratings and obtaining the probabilities of the wall condition changing from one state to another. These probabilities are defined in a matrix form called the probability matrix or transition probability matrix of the

Markov chain. This is thus incumbent upon knowing the present state of the retaining walls. These states represent the initial state by which future conditions can be predicted through multiplications of transition probability matrix and initial state vector.

$$P\ (X_{t+1} = i_{t+1} \,|\, X_t = i_t, X_{t\;\,1} = i_{t\quad 1}, \ldots\ldots, X_1 = i_1, X_0 = i_0)$$
$$= P\ (X_{i+1} = i_{t+1} \,|\, X_t = i_t\ )$$

Since the probability of moving to the next state only depends on the present state, irrespective of the previous states, the Markov chain transition is shown in figure 3.10 below.

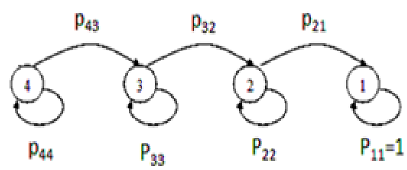

Figure 3.9: Markov chain state transitions (Wang & Shen, 2013)

Markov chain-based structure deterioration modeling is used to estimate the service life of the retaining wall systems identified. Based on the defined targeted condition, the resulting time point for the target is estimated. This time point ultimately makes way for the prediction of the remaining service life of the retaining walls. Pictorially, this is depicted by way of Figure 3.11.

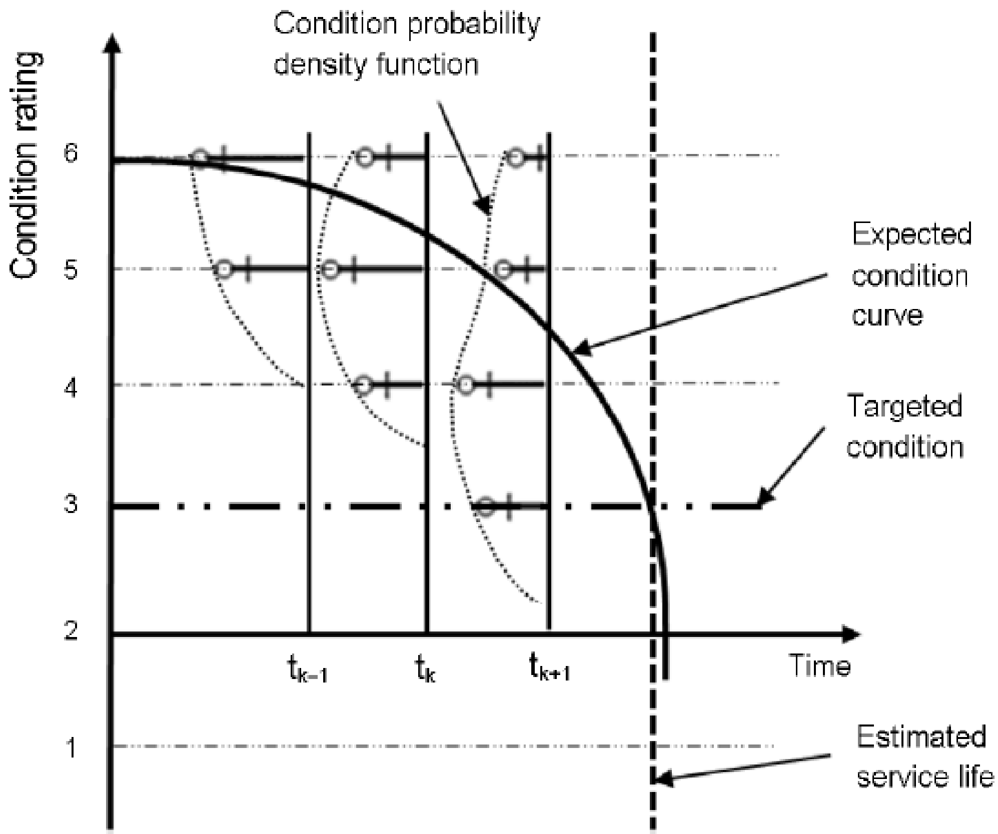

Figure 3.10: Service life prediction using Markov Chain (Lounis et al., 1998)

Development of Transition Matrix

Jiang and Sinha (1989) proposed a non-linear programming objective function to estimate transition probabilities for different age group categories. The programming function is shown in the Equation below:

$$\min \sum_{t=1}^{N} \left| Y(\mathrm{t}) - E(t, P) \right|$$

where N = the number of years in one age group,

I = number of unknown probabilities

P = a vector of length I equal to [p (1), p (2), …., p (I)]

$Y(t)$ = average of condition ratings at time t, based on regression function

$E(t, P)$ is derived through multiplication of the state vector at any time, t $\left(Q_{(t)}\right)$ by the transform of vector of the condition ratings (R'), i.e., $E(t, P) = Q_{(t)} * R'$

Similarly, $Q_{(t)}$ is estimated by multiplying Initial state vector $Q_{(0)}$ by the transition probability matrix raised to the power t i.e., $Q_{(t)} = Q_{(0)} * P^t$

Description of Steps

- Initial Condition Data: Based on the result of the field survey element rating and AHP, final condition rating data are obtained, which serves as the basis for dynamic service life prediction of the retaining walls.
- Transition probabilities: This represents the percentage of the retaining walls that will transit from the current condition state to a worse condition state, say within one year. For the research, the condition rating scale used is a 4-1 system, where 4 represents the best possible start, and 1 is the state just before rehabilitation will be required.

  Therefore, P's transition probability matrix is a 4 *x* 4 matrix based on this four-point scale.

$$P = \begin{matrix} p_{44} & p_{43} & p_{42} & p_{41} \\ p_{34} & p_{33} & p_{32} & p_{31} \\ p_{24} & p_{23} & p_{22} & p_{21} \\ p_{14} & p_{13} & p_{12} & p_{11} \end{matrix}$$

Under a normal circumstance, i.e., without maintenance or rehabilitation action, the retaining wall condition can only stay the same or deteriorate for every given year within the useful life of the wall. Therefore, and are all equal to 0. This effectively reduces the matrix to:

$$P = \begin{matrix} p_{44} & p_{43} & p_{42} & p_{41} \\ 0 & p_{33} & p_{32} & p_{31} \\ 0 & 0 & p_{22} & p_{21} \\ 0 & 0 & 0 & p_{11} \end{matrix}$$

Also, part of the founding assumptions was that since the deterioration conditions are considered yearly (1year interval), it would be an anomaly for a retaining wall in a condition state, say 4, to jump to 2 after a year. This thus means that, are all equal to zero. The resulting matrix is:

$$P = \begin{matrix} p_{44} & p_{43} & 0 & 0 \\ 0 & p_{33} & p_{32} & 0 \\ 0 & 0 & p_{22} & p_{21} \\ 0 & 0 & 0 & p_{11} \end{matrix}$$

However, given the lack of historical data on retaining wall condition, reasonable assumptions had to be made, consistent with relevant literature (Morcous et al., 2003; Morcous et al., 2006) and the NCHRP Report 713 on *Estimating the Life Expectancies of Highway Assets*, for which retaining wall assets are a part of (Thompson et al., 2012).

The transition probabilities, are given in Table 3.3

Table 3.5: Markov Transition Probability Matrix

	State probability in one year (i.e., *t* = 1)			
State Today (i.e., *t* = 0)	4	3	2	1
4	0.93	0.07	0	0
3	0	0.92	0.08	0
2	0	0	0.9	0.1
1	0	0	0	1

This table shows that after year 1, there is a 93% probability of the retaining walls in condition state four as of today, i.e., year 0, remaining in state 4. Similarly, from basic probability, = 1- = 7% (i.e., there is a 7% probability that the retaining walls in condition state four as of today will transition to the next lower condition state, 3. This same principle applies to retaining walls in condition states 3, 2, and 1 today and is the logic behind the populated transition probability matrix.

- Markov chain simulation: The Markov chain simulation follows the derivation of Transition Probability Matrix, TPM. The codes used are linked in the Appendix section of this thesis.

- Statistical analysis with regression model: Following Jiang and Sinha (1989), a regression model showing the performance curve of the retaining walls is generated. The objective of this is to serve as a means to validate the Markov chain predicted values and also to show on its own the relationship between retaining wall age and their corresponding condition rating.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Relative weighting of wall elements

The AHP technique is applied to estimate the different weights of the wall elements' performance. The hierarchical structure is shown in Figure 4.1 below.

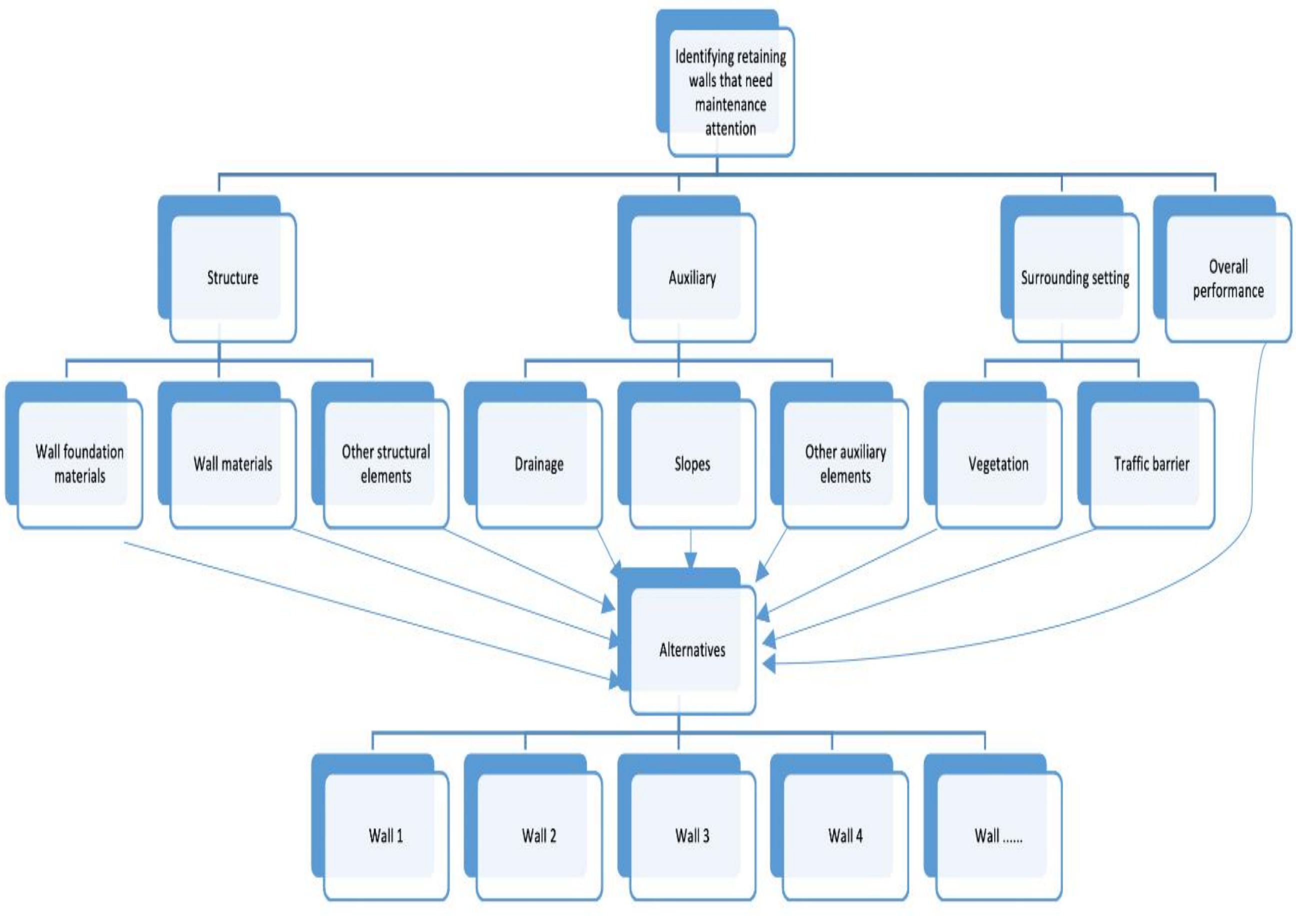

Figure 4.1: Hierarchical Structure utilized in Relative weighting

The primary contributors (attributes) to the overall condition rating of the individual walls are defined at the topmost level, just beneath the objective of the Analytic Hierarchy Process. Based on the Analysis, the pair-wise comparison of these attributes (namely structure, auxiliary, surrounding setting, and service functionality) are presented in Table 4.1.

Table 4.1: Pairwise Comparison of Main criteria

	pairwise comparison matrix A				normalized matrix *A* norm				criteria weight vector *w*
Structure	1.00	5.00	9.00	3.00	0.608	0.547	0.409	0.662	0.556
Auxiliary	0.20	1.00	7.00	0.33	0.122	0.109	0.318	0.074	0.156
Surrounding setting	0.11	0.14	1.00	0.20	0.068	0.016	0.045	0.044	0.043
Service functionality	0.33	3.00	5.00	1.00	0.203	0.328	0.227	0.221	0.245
sum	1.64	9.14	22.00	4.53	1	1	1	1	1

The pairwise comparison matrix from the table above is then modified and presented in Table 4.2.

Table 4.2: Modified Pairwise Comparison Matrix of Main Criteria

	pairwise comparison matrix *A*				normalized matrix *A* norm				criteria weight vector *w*
Structure	1.00	5.00	9.00	3.00	0.608	0.547	0.409	0.662	0.556
Auxiliary	0.20	1.00	7.00	0.33	0.122	0.109	0.318	0.074	0.156
Surrounding setting	0.11	0.14	1.00	0.20	0.068	0.016	0.045	0.044	0.043
Service functionality	0.33	3.00	5.00	1.00	0.203	0.328	0.227	0.221	0.245
sum	1.64	9.14	22.00	4.53	1	1	1	1	1

Subsequently, each wall element's components are compared in a pairwise manner, forming the basis of the third-level of the hierarchy shown in figure above.

For Structure, the pairwise comparison matrix for the sub-elements are presented in Table 4.3:

Table 4.3: Pairwise Comparison Matrix for Criterion Structure

	Pairwise comparison matrix			Normalized matrix B_1			Option scores s_1	Weight sub-elements according to main criteria
Wall foundation material	1.00	3.00	7.00	0.600	0.600	0.600	0.600	0.334
Mortar	0.33	1.00	5.00	0.200	0.200	0.200	0.200	0.111
Block/Brick & Concrete	0.14	0.20	1.00	0.200	0.200	0.200	0.200	0.111
sum	1.48	4.20	13.00	1	1	1	1	0.556

For Auxiliary, the sub-elements are also compared in a pairwise manner and the matrix is presented in Table 4.4.

Table 4.4: Pairwise Comparison Matrix for Criterion Auxiliary

	Pairwise comparison matrix			Normalized matrix B_2			Option scores s_2	Weight sub-elements according to main criteria
Drainage	1	1	9	0.474	0.474	0.474	0.474	0.074
Slope	1	1	9	0.474	0.474	0.474	0.474	0.074
Architectural facing	0.11	0.11	1.00	0.053	0.053	0.053	0.053	0.008
sum	2.11	2.11	19.00	1.00	1.00	1.00	1.000	0.156

For surrounding settings, the sub-elements are compared and the pairwise comparison matrix is shown in Table 4.5.

Table 4.5: Pairwise Comparison Matrix for Criterion Surrounding Settings

	Pairwise comparison matrix		Normalized matrix B_3		Option scores s_3	Weight sub-elements according to main criteria
traffic barrier	1.00	0.20	0.17	0.17	0.167	**0.007**
vegetation	5.00	1.00	0.83	0.83	0.833	**0.037**
sum	6.00	1.20				0.044

Overall, the summary of the relative weights as obtained from the AHP analysis is displayed in the table 4.6 below.

Table 4.6: Summary of Relative Weight for all elements

	Relative Weight
Performance rating	100% (1)
Structure	0.556
Wall foundation material	0.334
Mortar	0.0556
Block/Brick/Stone	0.0555
Concrete	0.111
Auxiliary	0.156
Drainage	0.074
Slope	0.074
Architectural facing	0.008
Surrounding settings	0.043
Vegetation	0.007
Traffic Barrier	0.037
Service Functionality	
Wall Overall Performance	0.245

Overall Condition Rating = Sum of (Relative weight of each element * element condition rating)

4.2 Retaining wall field inspection

The team embarked on series of field inspections to collect the needed data for retaining wall condition rating. As described in the methodology, an Unmanned Aerial Vehicle UAV was used to ensure the effectiveness of the process, considering areas that are difficult to access for visual assessment. The result of a typical retaining wall inspection as obtained for this thesis is recorded in the field survey form in the form of wall description data, wall measurement data, wall location data, and the condition assessment of the wall elements. The condition assessment part, being the most important, is designed to reflect the research objectives and carry the elements assessed and the ratings assigned. A sample of the inspected retaining walls are included to demonstrate and further shed more light on the process that leads to the overall condition rating.

Retaining wall case study

The retaining wall on North Broadway Ramp, located in Knoxville, TN, is about 3.4 miles away from the University of Tennessee, Knoxville. The wall, being along a ramp leading to a major highway, is on a relatively busy route, and safety control gears had to be mounted to ensure the safety of the inspection crew.

Condition assessment of Wall elements

Based on the AHP, relative weights generated are combined with element rating to generate a weighted score for each element. An overall score, which represents the wall condition rating at this time, is calculated by summating all the weighted scores. These relationships are shown in the form of Equation.

$$s' = w * s$$

$$S = \sum_{a}^{j} s'$$

Where a = the first element assessed, and j = the last element assessed

Table 4.7: Condition rating assessment table for retaining wall along N Broadway Ramp

Element	Relative weight, w	Assigned rating (1-4), s	Weighted score, s'
Wall foundation material	0.334	1	0.334
Mortar	0.0556	1	0.0556
Block/Brick	0.0555	1	0.0555
Concrete	0.111	1	0.111
Drainage	0.074	2	0.148
Slope	0.074	2	0.148
Architectural Facing	0.008	3	0.024
Vegetation	0.007	3	0.021
Traffic Barrier	0.037	2	0.074
Overall Performance	0.245	2	0.49
Overall condition rating, S			1.4611

The condition assessments are based on the picture data collected using UAV and judgments from visual inspection. To corroborate the judgments, the following figures are attached

Figure 4.2: Concrete spalling observed on the base of the wall

Figure 4.3: Drain at the base of the wall partially clogged

Figure 4.4: Upslope with a decently vegetated top

Figure 4.5: Drainage channel at the top of the wall clearly defined, albeit with little to no blockage

Figure 4.6: Concrete Block elements of the wall with significant obvious weathering effect

Figure 4.7: Noticeable presence of efflorescence and moderate-to-wide cracks

Figure 4.8: Aerial view of wall showing adjoining traffic and no traffic barrier

4.3 Condition Rating

It is necessary to classify the retaining walls surveyed into groups, and this is done based on age, using the Age group classification defined in Table 4.8. The output of condition ratings for the candidate retaining walls is presented in Table 4.9.

Table 4.8: Age group classification for retaining walls

Age group #	Age
1	0-6
2	7-12
3	13-18
4	19-24
5	25-30
6	31-36
7	37-42
8	43-48
9	49-54
10	55-60
11	61-66
12	67-72
13	73-78
14	79-84
15	85-90

Table 4.9: Overall condition states of the 31 surveyed walls, classified by age group

No.	Retaining wall locations	Retaining wall age (yrs)	Overall condition rating	Age group #
1	Northpoint Boulevard, Chattanooga, TN	13	2	3
2	7244-7544 E Brainerd Chattanooga, TN	14	4	3
3	N Broadway Ramp to I40, Knoxville, TN	15	1	3
4	1727 Dayton Blvd, Chattanooga, TN	16	3	3
5	Signal Mountain Road, Chattanooga, TN	18	3	3
6	6312 Fisk Ave, Chattanooga, TN	16	4	3
7	6828 Northside Dr. Chattanooga, TN	17	4	3
8	9303 E Brainerd Rd. Chattanooga, TN	15	4	3
9	Hall of Fame Drive, Knoxville, TN	19	2	4
10	TN-153, Off Bonny Oaks Dr., Chattanooga, TN	21	3	4
11	1301 Washington Avenue, Knoxville, TN	21	3	4
12	308 Ashland Terrace, Chattanooga, TN	22	2	4
13	918-998 Cherokee Blvd, Chattanooga, TN	22	3	4
14	222 Baker Street, Chattanooga, TN	24	3	4
15	Elm Hill Pike, Nashville, TN	24	2	4
16	SR-153 S, Chattanooga, TN	22	3	4
17	US-27 N, Chattanooga, TN	23	3	4
18	Riverside Drive, TN-58, Chattanooga	27	2	5
19	1201-1261 Dayton Blvd, Chattanooga, TN	27	3	5
20	US-27 S, Chattanooga, TN	29	3	5
21	US-27 S, Chattanooga, TN	26	3	5
22	US-27 N, Chattanooga, TN	25	3	5
23	James White Pkwy, Knoxville, TN	31	2	6
24	Briley Pkwy, Nashville, TN	35	2	6
25	I-75 N, Chattanooga, TN	35	2	6
26	I-75 S, Chattanooga, TN	36	2	6
27	SR-153 S, Chattanooga, TN	38	2	7
28	1701-1899 Meharry Dr, Chattanooga, TN	45	1	8
29	6401 Lee Hwy, Chattanooga, TN	47	1	8
30	4177 Willard Dr. Chattanooga, TN	48	1	8
31	Birmingham Highway, Chattanooga, TN	49	1	9

4.4 Service Life Prediction

Regression Models

Regression Statistical Analysis (both Linear and Exponential) is used to derive the relationship between the two variables, i.e., Condition rating and Retaining wall age. Based on the generated models, the statistical significance of the estimated relationship is assessed. This value gives the degree of confidence to which the estimated relationship is close to the actual relationship. This analysis is carried out using the MS Office Excel tool.

The field data is combined with the AHP-generated weights to estimate the condition rating of each of the retaining walls. The age of the considered retaining walls is estimated using Google Earth Pro's combined resources and the Letting Data history collected from TDOT. While the age of the walls could not be ascertained perfectly, this method gives an approximate estimation of the age. The Excel output is shown in the figures below and explained:

1. The coefficient of determination represents a good measure of the overall goodness of fit. For the Linear regression model, = 0.5107, which means 51.07% of the variation of the independent variable (condition rating) around its mean is explained by the dependent variable (age). This simple linear regression plot determined that after approximately 56 years, the condition state becomes 1 (which is at the point the Retaining wall requires major rehabilitation, repair or replacement action to function optimally).

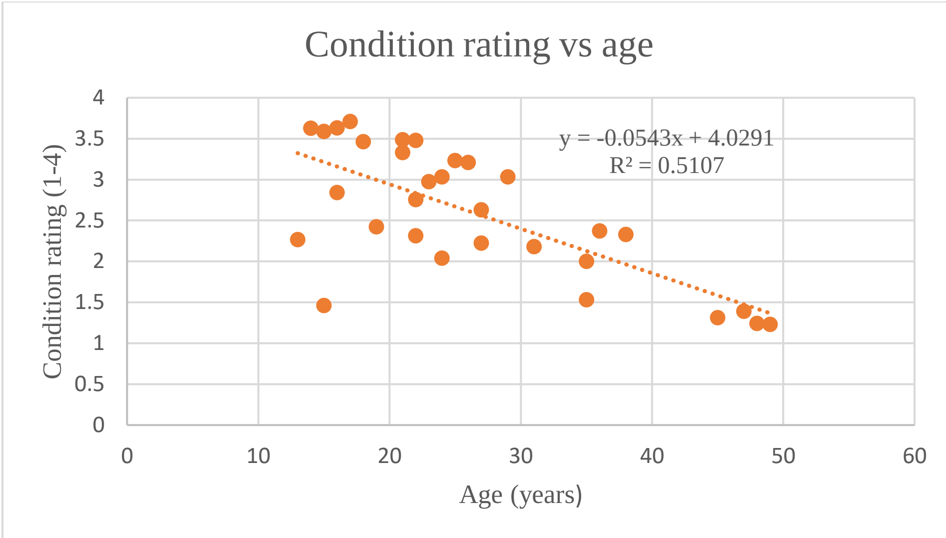

Figure 4.9: Simple Linear Regression Fitting

2. Conversely, for the exponential regression model, the coefficient of determination = 0.469. This coefficient means 46.9% of the variation of the independent variable (condition rating) around its mean is explained by the dependent variable (age). This exponential plot shows that the retaining wall will take approximately 62 years to reach condition state 1 (i.e., requires major rehabilitation, repair, or replacement action).

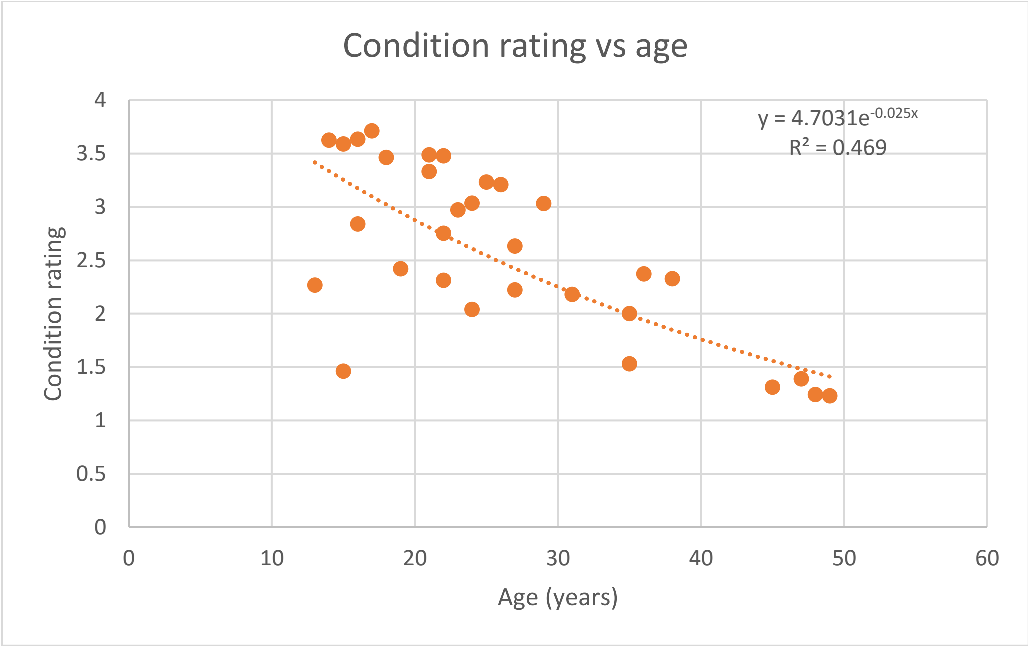

Figure 4.10: Exponential least-square fitting

3. The residuals versus independent variable, i.e., Retaining wall age, is plotted to evaluate the normality, linearity, independence of errors, and homoscedasticity assumptions. There is no clear pattern from the plot, and most of the points are symmetrically distributed, tending to cluster towards the middle of the plot. Hence, these assumptions are generally not seriously violated.

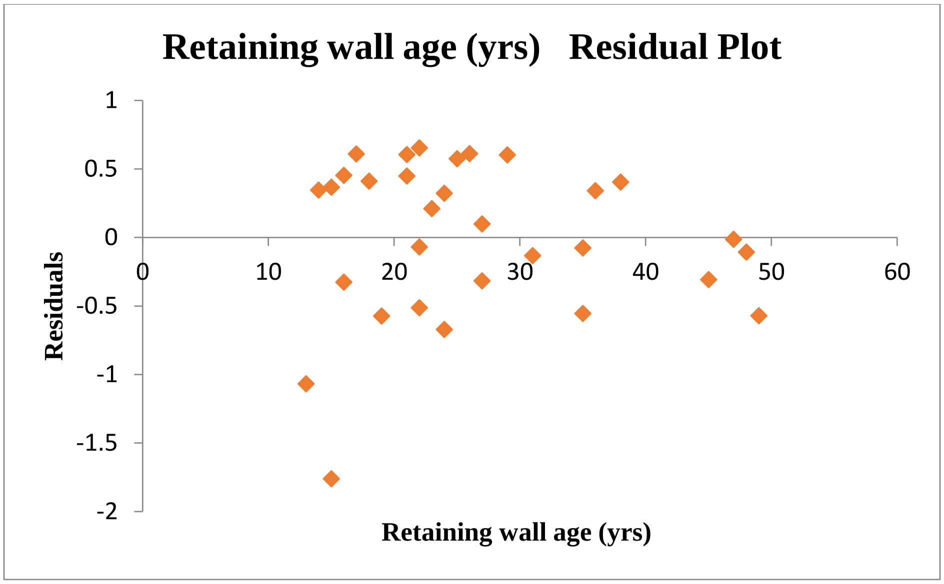

Figure 4.11: Residual versus age plot

4. The data distribution is approximately normal, as reflected by the Normal probability plot. The data is neither totally skewed to the left nor right and can be easily approximated by a straight, diagonal line.

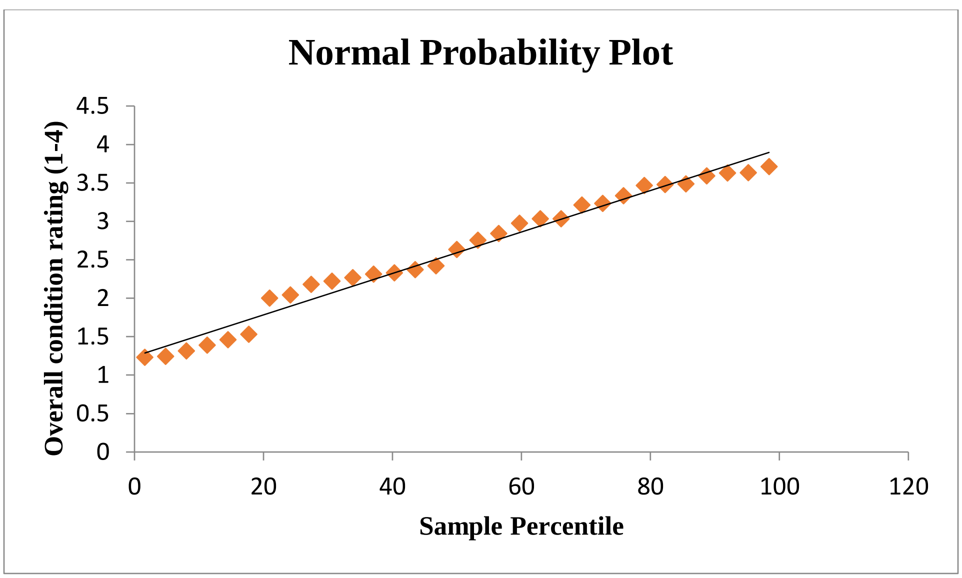

Figure 4.12: Normal Probability Plot

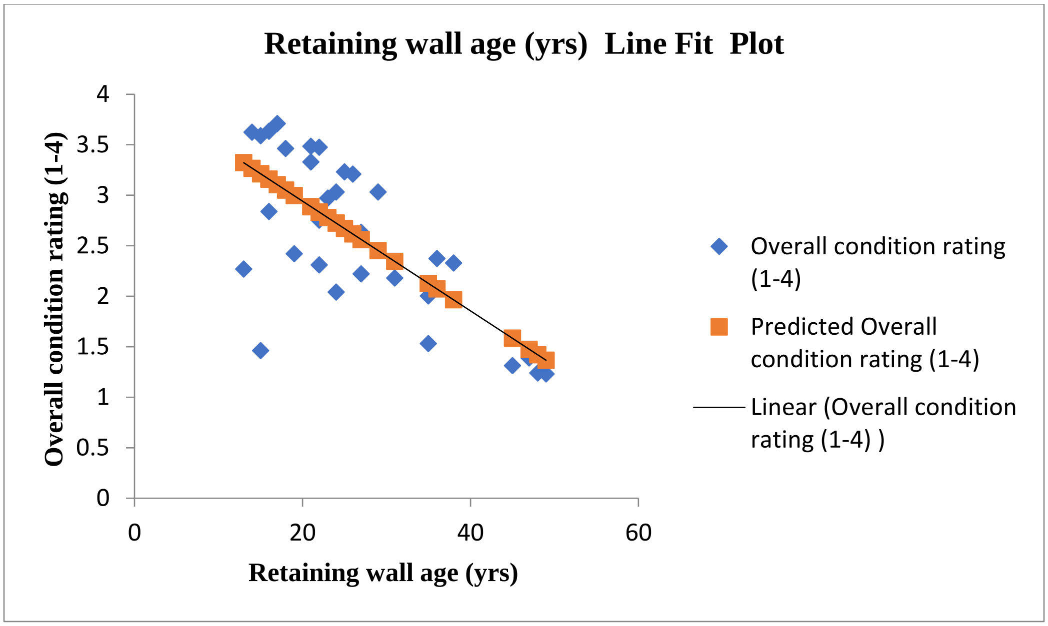

Figure 4.13: Line Fit Plot Showing Observed and Predicted values

Table 4.10: Summary Statistic

Regression Statistics	
Multiple R	0.714651125
R Square	0.51072623
Adjusted R Square	0.49385472
Standard Error	0.568630118
Observations	31

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	9.788	9.788	30.2715	6.29272E-06
Residual	29	9.37687	0.32334		
Total	30	19.1649			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	4.029073152	0.280469	14.3655	1.01874E-14	3.455449477	4.6027
Retaining wall age (yrs)	-0.054332644	0.009875	-5.502	6.29272E-06	-0.07452959	-0.0341

Markov Model

The future condition forecast used in the Markov model is based on the equation

$$y_k = \sum_j x_j \, p_{jk}$$

Where y_k is the probability of state *k* in the next year?

j = condition state in this year, i.e., *j* = 4, 3, 2, 1

p_{jk} = transition probability from state *j* to state *k*

i.e., for a wall currently in condition state 4, the probability that it will stay in condition state 4 is

$$y_4 = x_4 * p_{44} + x_3 * p_{34} + x_2 * p_{24} + x_1 * p_{14}$$

where p_{14}, p_{24}, and p_{34} are zeroes, based on the assumption that the retaining wall could only either stay in the same condition, or transit to the next lower condition in any one year. As explained in the methodology, the transition probability matrix estimated is shown in Table 4.11

Table 4.11: Markov Transition Probability Matrix used for all wall age group

	State probability in one year			
State Today	4	3	2	1
4	0.93	0.07	0	0
3	0	0.92	0.08	0
2	0	0	0.9	0.1
1	0	0	0	1

Based on this, and using the equation above, the future condition forecast is generated and shown in Table 4.12:

Table 4.12: Future Condition Forecasts Result using the Markov model

Year	Percentage by condition state			
	4	3	2	1
0	1	0	0	0
1	0.930	0.070	0.000	0.000
2	0.865	0.130	0.006	0.000
3	0.804	0.180	0.015	0.001
4	0.748	0.222	0.028	0.002
5	0.696	0.256	0.043	0.005
6	0.647	0.284	0.059	0.009
7	0.602	0.307	0.076	0.015
8	0.560	0.325	0.093	0.023
9	0.520	0.338	0.110	0.032
10	0.484	0.347	0.126	0.043
11	0.450	0.353	0.141	0.056
12	0.419	0.357	0.155	0.070
13	0.389	0.357	0.168	0.085
14	0.362	0.356	0.180	0.102
15	0.337	0.353	0.190	0.120
16	0.313	0.348	0.200	0.139
17	0.291	0.342	0.207	0.159
18	0.271	0.335	0.214	0.180
19	0.252	0.327	0.220	0.201
20	0.234	0.319	0.224	0.223
21	0.218	0.310	0.227	0.246
22	0.203	0.300	0.229	0.268
23	0.188	0.290	0.230	0.291
24	0.175	0.280	0.230	0.314
25	0.163	0.270	0.230	0.337
26	0.152	0.260	0.228	0.360
27	0.141	0.250	0.226	0.383
28	0.131	0.240	0.224	0.406
29	0.122	0.230	0.220	0.428
30	0.113	0.220	0.217	0.450

31	0.105	0.210	0.213	0.472
32	0.098	0.201	0.208	0.493
33	0.091	0.192	0.203	0.514
34	0.085	0.183	0.198	0.534
35	0.079	0.174	0.193	0.554
36	0.073	0.166	0.188	0.573
37	0.068	0.157	0.182	0.592
38	0.063	0.150	0.177	0.610
39	0.059	0.142	0.171	0.628
40	0.055	0.135	0.165	0.645
41	0.051	0.128	0.159	0.662
42	0.047	0.121	0.154	0.678
43	0.044	0.115	0.148	0.693
44	0.041	0.109	0.142	0.708
45	0.038	0.103	0.137	0.722
46	0.035	0.097	0.131	0.736
47	0.033	0.092	0.126	0.749
48	0.031	0.087	0.121	0.761
49	0.029	0.082	0.116	0.774
50	0.027	0.078	0.111	0.785
51	0.025	0.073	0.106	0.796
52	0.023	0.069	0.101	0.807
53	0.021	0.065	0.097	0.817
54	0.020	0.061	0.092	0.827
55	0.018	0.058	0.088	0.836
56	0.017	0.055	0.084	0.845
57	0.016	0.051	0.080	0.853
58	0.015	0.048	0.076	0.861
59	0.014	0.046	0.072	0.868
60	0.013	0.043	0.069	0.876
61	0.012	0.040	0.065	0.883
62	0.011	0.038	0.062	0.889
63	0.010	0.036	0.059	0.895
64	0.010	0.034	0.056	0.901
65	0.009	0.032	0.053	0.907
66	0.008	0.030	0.050	0.912
67	0.008	0.028	0.047	0.917
68	0.007	0.026	0.045	0.922
69	0.007	0.025	0.043	0.926
70	0.006	0.023	0.040	0.930

71	0.006	0.022	0.038	0.934
72	0.005	0.020	0.036	0.938
73	0.005	0.019	0.034	0.942
74	0.005	0.018	0.032	0.945
75	0.004	0.017	0.030	0.948
76	0.004	0.016	0.029	0.952
77	0.004	0.015	0.027	0.954
78	0.003	0.014	0.026	0.957
79	0.003	0.013	0.024	0.960
80	0.003	0.012	0.023	0.962
81	0.003	0.011	0.021	0.964
82	0.003	0.011	0.020	0.966
83	0.002	0.010	0.019	0.968
84	0.002	0.009	0.018	0.970
85	0.002	0.009	0.017	0.972
86	0.002	0.008	0.016	0.974
87	0.002	0.008	0.015	0.975
88	0.002	0.007	0.014	0.977
89	0.002	0.007	0.013	0.978
90	0.001	0.006	0.012	0.980
91	0.001	0.006	0.012	0.981
92	0.001	0.006	0.011	0.982
93	0.001	0.005	0.010	0.983
94	0.001	0.005	0.010	0.984
95	0.001	0.005	0.009	0.985
96	0.001	0.004	0.009	0.986
97	0.001	0.004	0.008	0.987
98	0.001	0.004	0.008	0.988
99	0.001	0.003	0.007	0.989
100	0.001	0.003	0.007	0.989

From the table, at approximately 50% (i.e., 0.493) highlighted in yellow, the fraction in the severe state reaches 50%. This means approximately 50% would have reached condition state 1, and the wall would require rehabilitation, repair, or replacement action to function optimally. This coincides with the year 32.

For instance, the retaining wall along *1301 Washington Avenue, Knoxville, TN*, has a condition of 3, and the current age is 21 years. Based on the Markov chain simulation, the retaining wall would reach condition state one after approximately 60 years.

Service life = Current age + age as at condition rating 1

This means the service life of the said retaining wall is predicted to be 81years.

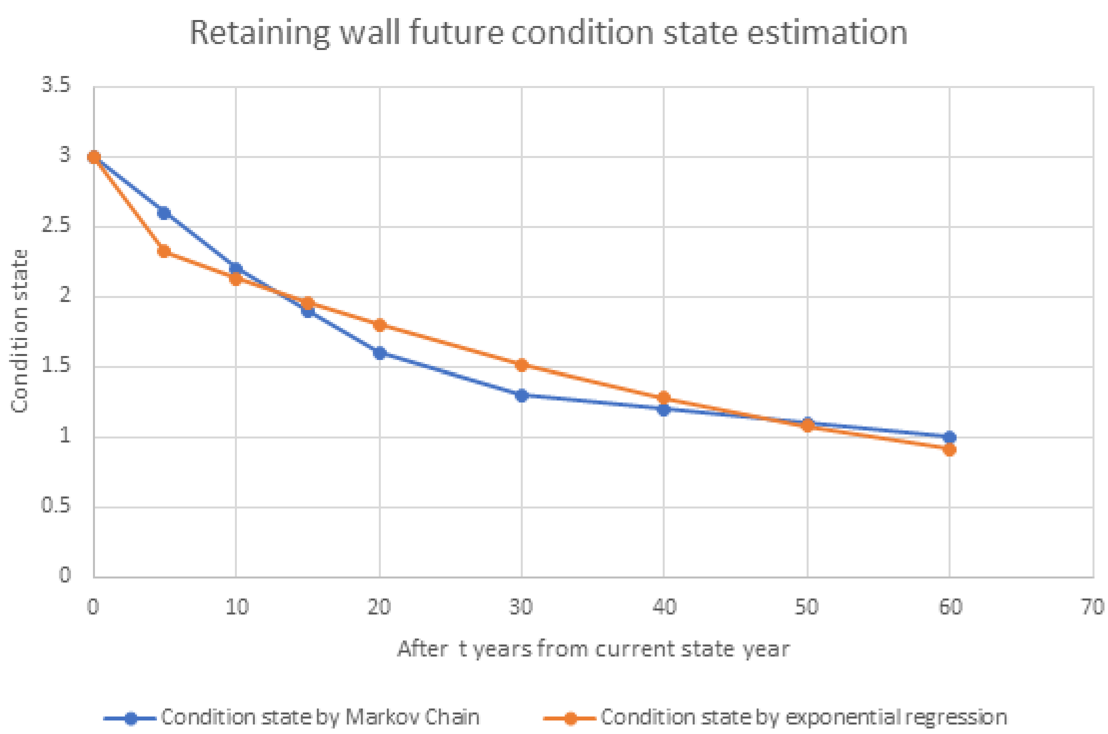

Figure 4.14: Condition state estimation and service life prediction

CHAPTER 5

SUMMARY AND CONCLUSION

5.1 Summary

Retaining walls typically protect highways through slope retention and grade transition, an important asset class in transportation asset management. It suffices to say that when retaining wall assets sneeze, the host transportation network catches a cold. This applies because a failure to a critical retaining wall along a highway corridor directly affects the highway through the obstruction to traffic and even possible damage to the pavement structure. This underlines, in part, the need for proper attention to be paid to this class of structure by transportation agencies and other concerned stakeholders.

This thesis proposed a framework primarily implemented in R statistical software, adopting Analytic Hierarchy Process and Markov Chain simulation techniques to solve this problem. This, together with a complementary field inspection process, forms the basis of the methodology for this research. The thought process behind the AHP part of the methodology is that all elements do not contribute equally to the overall rating of a wall, as some elements are weightier than others. Thus, AHP was used in generating relative weights for all of the elements based on sound judgment, literature reviews, and questionnaires.

The relative weights, combined with the element ratings obtained from the field survey process, form the condition rating. These condition rating values are then passed to the Markov chain simulation model to estimate the time in years, *t*, when the condition rating of the wall reaches a poor/severe state, i.e., condition state 1. This knowledge, together with the current age of the walls, presents the 'how' to the service life prediction objective of the thesis.

It was necessary to carry out statistical analysis, and this was done by generating regression models (both simple linear and exponential), and comparing the outputs with that of the Markov model. Considering the closeness in the values of the service life prediction obtained from the models, the result is believed to be fairly accurate for the data size used.

5.2 Conclusion

This thesis has achieved its objectives in developing a framework for retaining wall service life prediction through the defined methodology. However, it is still noteworthy to point out that the estimations were performed under certain assumptions. These include:

- That it is reasonable to estimate transition probability matrix for retaining wall with no historical condition data available (Morcous et al., 2003; Thompson et al., 2012).
- That the same transition probability matrix exists for all the retaining wall age groups, which sometimes is not the case. Although, for the asset class under consideration (retaining walls) being without historical condition data, this would fly.
- The data set obtained and utilized are not large and thus manifested through very low coefficient of determination, $r2$ in the regression models.
- The age of the retaining walls was estimated through Google Earth historical imagery.

Nevertheless, the framework proposed in this work is readily applicable to future condition and service life prediction of retaining walls.

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APPENDIX A

YAML CODE FOR AHP STRUCTURE

```
# Version: 2.0

  ########################
 # Alternatives Section
 #

   Alternatives: &alternatives
 # Here, we list all the alternatives, together with their attributes.
 # We can use these attributes later in the file when defining
 # preferenceFunctions. The attributes can be quantitative or
 # qualitative.
   Scenario A :
     wall foundation materials: 4
     mortar: 3
     block/brick/stone: 3
     concrete: 2
     wall drains: 3
     upslope: 3
     downslope: 2
     lateral slope: 3
     architectural facing: 2
     traffic barrier: 3
     vegetation: 3
     wall overall performance: 4
   Scenario B :
     wall foundation materials: 1
     mortar: 1
     block/brick/stone: 1
     concrete: 2
     wall drains: 2
     upslope: 3
     downslope: 2
     lateral slope: 2
     architectural facing: 2
     traffic barrier: 2
     vegetation: 3
     wall overall performance: 3
   Scenario C :
     wall foundation materials: 1
     mortar: 2
     block/brick/stone: 2
     concrete: 2
     wall drains: 2
     upslope: 1
```

```
     downslope: 2
     lateral slope: 2
     architectural facing: 1
     traffic barrier: 2
     vegetation: 2
     wall overall performance: 2
## #
## # End of Alternatives Section
## #####################################
##
## #####################################
## # Goal Section
## #
##
##
 Goal:
## # The goal spans a tree of criteria and the alternatives
  name: Rating and identifying retaining wall that needs attention
   description:>
     This is a classic single decision maker problem. It models
     the situation facing by a family that wants to buy a new car.
  author: Abdulazeez Lawal
  preferences:
     # preferences are typically defined pairwise
     # 1 means: A is equal to B
     # 9 means: A is highly preferrable to B
     # 1/9 means: B is highly preferrable to A
     pairwise  :
       - ["Structure", "Auxiliary", 5]
       - ["Structure", "Surrounding setting", 9]
       - ["Structure", "Wall overall performance", 3]
       - ["Auxiliary", "Surrounding setting", 7]
       - ["Wall overall performance", "Surrounding setting", 5]
       - ["Wall overall performance", "Auxiliary", 3]
   children:
      Structure:
       preferences:
         pairwise:
           - ["wall foundation material", "mortar", 5]
           - ["wall foundation material", "block/brick/stone", 3]
           - ["Wall foundation material", "concrete", 1]
           - ["concrete", "mortar", 1]
           - ["concrete", "block/brick/stone", 1]
           - ["block/brick/stone", "mortar", 1]
```

```
      children:
        wall foundation material:
          preferences:
            pairwise:
              - ["Scenario A", "Scenario B", 1]
              - ["Scenario A", "Scenario C", 1]
              - ["Scenario B", "Scenario C", 1]
          children: *alternatives
        mortar:
          preferences:
            pairwise:
              - ["Scenario A", "Scenario B", 1]
              - ["Scenario A", "Scenario C", 1]
              - ["Scenario B", "Scenario C", 1]
          children: *alternatives
        block/brick/stone:
          preferences:
            pairwise:
              - ["Scenario A", "Scenario B", 1]
              - ["Scenario A", "Scenario C", 1]
              - ["Scenario B", "Scenario C", 1]
          children: *alternatives
        concrete:
          preferences:
            pairwise:
              - ["Scenario A", "Scenario B", 1]
              - ["Scenario A", "Scenario C", 1]
              - ["Scenario B", "Scenario C", 1]
          children: *alternatives
    Auxiliary:
       preferences:
        pairwise:
          - ["drainage", "slope", 1]
          - ["drainage", "architectural facing", 9]
          - ["slope", "architectural facing", 9]
      children: *alternatives
        drainage:
          preferences:
            pairwise:
              - ["Scenario A", "Scenario B", 1]
              - ["Scenario A", "Scenario C", 1]
              - ["Scenario B", "Scenario C", 1]
          children: *alternatives
        slope:
```

```
          preferences:
            pairwise:
              - ["Scenario A", "Scenario B", 1]
              - ["Scenario A", "Scenario C", 1]
              - ["Scenario B", "Scenario C", 1]
          children: *alternatives
        architectural facing:
          preferences:
            pairwise:
              - ["Scenario A", "Scenario B", 1]
              - ["Scenario A", "Scenario C", 1]
              - ["Scenario B", "Scenario C", 1]
          children: *alternatives
    Surrounding setting:
      preferences:
        pairwise:
          - ["vegetation", "traffic barrier", 1]
      children: *alternatives
        vegetation:
          preferences:
            pairwise:
              - ["Scenario A", "Scenario B", 1]
              - ["Scenario A", "Scenario C", 1]
              - ["Scenario B", "Scenario C", 1]
          children: *alternatives
        traffic barrier:
          preferences:
            pairwise:
              - ["Scenario A", "Scenario B", 1]
              - ["Scenario A", "Scenario C", 1]
              - ["Scenario B", "Scenario C", 1]
          children: *alternatives
    Overall performance:
      preferences:
        pairwise:
          - ["Scenario A", "Scenario B", 1]
          - ["Scenario A", "Scenario C", 1]
          - ["Scenario B", "Scenario C", 1]
      children: *alternatives
#
```

APPENDIX B

AHP R STUDIO CODE

```
# loading ahp file that is stored in a text file in yaml format
library(ahp)
wallAHP <- Load("wallmac.txt")

# print the data tree structure
library(data.tree)
print(wallAHP,filterFun = isNotLeaf)

# Calculate priorities
Calculate(wallAHP, pairwiseFun = PrioritiesFromPairwiseMatrixEigenvalues,
        scoresFun = PrioritiesFromScoresDefault)

# Visualize and display results
print(wallAHP, priority = function(x) x$parent$priority["Total", x$name])
Visualize(wallAHP)
Analyze(wallAHP)
AnalyzeTable(wallAHP,
          variable = "priority",
          sort = "orig",
          pruneFun = function(node, decisionMaker) PruneByCutoff(node, decisionMaker, 0.05),
          weightColor = "skyblue",
          consistencyColor = "red",
          alternativeColor = "green")
```

The AHP hierarchy data tree structure for the retaining wall printed using the R statistics codes is given in the following:

```
1 Rating and identifying retaining wall that need attention
2  ¦--Structure
3  ¦   ¦--wall foundation material
4  ¦   ¦--wall materials
5  ¦   °--other structural elements
6  ¦--Auxiliary
7  ¦   ¦--drainage
8  ¦   ¦--slope
9  ¦   °--other auxiliary elements
10 ¦--Surrounding setting
11 ¦   ¦--vegetation
12 ¦   °--traffic barrier
13 °--Overall performance
```

Sample results of priority for each wall elements and walls to be ranked are shown below:

```
                            levelName   priority
1 Rating and identifying retaining wall        NA
```

```
2  ¦--Structure                    0.56192181
3  ¦  ¦--wall foundation material     0.74705283
4  ¦  ¦  ¦--wall1                  0.65864419
5  ¦  ¦  ¦--wall2                  0.18517401
6  ¦  ¦  °--wall3                  0.15618181
7  ¦  ¦--wall materials             0.13355863
8  ¦  ¦  ¦--wall1                  0.65864419
9  ¦  ¦  ¦--wall2                  0.18517401
10 ¦  ¦  °--wall3                  0.15618181
11 ¦  °--other structural elements    0.11938853
12 ¦     ¦--wall1                  0.65864419
13 ¦     ¦--wall2                  0.18517401
14 ¦     °--wall3                  0.15618181
15 ¦--Auxiliary                    0.14593100
16 ¦  ¦--drainage                  0.47368421
17 ¦  ¦  ¦--wall1                  0.65864419
18 ¦  ¦  ¦--wall2                  0.18517401
19 ¦  ¦  °--wall3                  0.15618181
20 ¦  ¦--slope                     0.47368421
21 ¦  ¦  ¦--wall1                  0.65864419
22 ¦  ¦  ¦--wall2                  0.18517401
23 ¦  ¦  °--wall3                  0.15618181
24 ¦  °--other auxiliary elements     0.05263158
25 ¦     ¦--wall1                  0.65864419
26 ¦     ¦--wall2                  0.18517401
27 ¦     °--wall3                  0.15618181
28 ¦--Surrounding setting            0.04058678
29 ¦  ¦--vegetation                 0.66666667
30 ¦  ¦  ¦--wall1                  0.65864419
31 ¦  ¦  ¦--wall2                  0.18517401
32 ¦  ¦  °--wall3                  0.15618181
33 ¦  °--traffic barrier             0.33333333
34 ¦     ¦--wall1                  0.65864419
35 ¦     ¦--wall2                  0.18517401
36 ¦     °--wall3                  0.15618181
37 °--Overall performance            0.25156041
38    ¦--wall1                     0.65864419
39    ¦--wall2                     0.18517401
40    °--wall3                     0.15618181
```

APPENDIX C

MARKOV CHAIN CODE

```
# This script is for prediction of service life of retaining wall
# in the state of Tennessee by using Markov chain model

library(readxl)
library(markovchain)
library(heemod)
library(diagram)

# automatically set the working directory
WD <- getwd()
if (!is.null(WD)) setwd(WD)

# using available dataset to estimate transition matrix
#read history condition data from Excel file
states<-read_excel("states.xlsx")

#estimate transition matrix
#default Maximum likelihood (ML)estimation method used
#other methods that may be used include
#"map", "Bootstrap" or "Laplace"
estTransMat<-markovchainFit(data = states$conditions,
                        name = "condStates" )$estimate

#the following commands reverse rows and columns
estTransMat<-estTransMat[nrow(estTransMat):1, ]
estTransMat
estTransMat<-estTransMat[,ncol(estTransMat):1 ]
estTransMat

#the transition probability matrix estimated based on dummy history data

#          4-Good       3-Fair       2-Poor        1-Severe
#
# 4-Good      0.930000    0.07000     0.000000       0.00000000
# 3-Fair     0.000000    0.920000     0.080000       0.00000000
# 2-Poor      0.00000000 0.00000000 0.900000       0.100000
# 1-Severe    0.00000000    0.0000000     0.0000000    1.0000000


# The state values
# 4-Good 3-Fair 2-Poor 1-severe
conditionsRatings <- c("4","3","2","1")
as.numeric(conditionsRatings)
#
# The transition matrix used below carry over from the estimation results above
# the estimated transition matrix "estTransMat" will be automatically transferred
```

```
# to the object "predState" in the next report

byRow <- TRUE
transMatrix <- matrix(data=c(0.930000 ,0.07000,0.000000,0.00000000,
0.000000, 0.920000,0.080000,0.00000000, 0.25000000, 0.00000000,0.00000000, 0.900000,
0.100000, 0.00000000, 0.0000000, 0.0000000 ,1.0000000 ),
                  byrow=byRow,nrow=4,
                  dimnames = list(conditionsRatings,conditionsRatings))

predState <- new("markovchain",states=conditionsRatings,byrow=byRow,
              transitionMatrix=transMatrix, name="Retaining Wall Condition")


# Make predictions
t <- 2

# initial state vector,
# assume initial state is 3 prob1 corresponding to rating 3
initialState <- t(as.matrix(c(0,1,0,0)))

# estimated state after t years
estState <- initialState*(predState^t)
estState


# estimated condition ratings by Markovchain at time t
numRatings <- t(t((as.numeric(conditionsRatings))))
# estimated condition ratings after t years
estRatings<-estState %*% numRatings
estRatings
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VITA

Abdulazeez Remilekun Lawal, son of Dr. Adefalu Lateef Lawal and Mrs. Nike Salamat Lawal was born in Ilorin, Nigeria in November 1996. He attended University Staff School Ilorin and then proceeded to University of Ilorin Secondary School between 2006 and 2012, graduating as the Overall best student (boy). Abdulazeez had his Bachelor of Engineering degree in Civil Engineering from the University of Ilorin graduating with a First-class honors degree, best graduating student in the structures option, and second-best graduating civil engineering student in 2017. After his undergraduate degree, he joined the services of Ariosh Limited, an Engineering, Procurement, Construction, and Installation Services company in Lagos, Nigeria as a Civil/Structural Engineer. He served in this role until August 2019.

In August 2019, he moved to the United States, having accepted a Graduate Research Assistantship Position at the University of Tennessee at Chattanooga for a Master's of Science in Engineering (Civil) degree program. During this period, Abdulazeez was recognized for a Dean's Merit Scholarship Award at the College of Engineering, as well as a National Society of Black Engineers (NSBE) Graduate Scholarship Award. He enjoyed a rare opportunity of Interning with the Tennessee Department of Transportation (TDOT) during the Summer of 2020. Together with graduating with a perfect GPA, all of these culminated in a relatively successful graduate program experience.

Abdulazeez will be proceeding to Iowa State University, Institute of Transportation as a Graduate Research Assistant in Fall 2021. He will be in this position while he pursues his Ph.D.