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Predicting deterioration rate of culvert structures utilizing a Markov model

Chenguang Yang
Louisiana Tech University

PREDICTING DETERIORATION RATE OF CULVERT STRUCTURES UTILIZING A MARKOV MODEL

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Chenguang Yang, B.S., M.S.

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Supervisor of Dissertation Research

Head of Department

Department

Recommendation concurred in:

R. McKim

Advisory Committee

Approved:

Director of Graduate Studies

Dean of the College

Approved:

Dean of the Graduate School

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ABSTRACT

A culvert is typically a hydraulic passage, normally placed perpendicular to the road alignment, which connects the upstream and downstream sections underneath an embankment, while also providing structural support for earth and traffic loads. The structural condition of culverts continues to deteriorate due to aging, limited maintenance budgets, and increased traffic loads. Maintaining the performance of culverts at acceptable levels is a priority for the U.S. Department of Transportation (DOT), and an effective maintenance of culvert structures can be greatly improved by introducing asset management practices. A priority list generated by traditional condition assessment might not provide optimum solutions, and benefits of culvert asset management practices can be maximized by incorporating prediction of deterioration trends. This dissertation includes the development of a decision making chart for culvert inspection, the development of a culvert rating methodology using the Analytic Hierarchy Process (AHP) based on an expert opinion survey and the development of a Markovian model to predict the deterioration rate of culvert structures at the network level.

The literature review is presented in three parts: culvert asset management systems in the U.S.; Non-destructive Technologies (NDT) for culvert inspection (concrete, metal, and thermoplastic culvert structures); and statistical approaches for estimating the deterioration rate for infrastructure. A review of available NDT methods was performed to identify methods applicable for culvert inspection.

To identify practices currently used for culvert asset management, culvert inventory data requests were sent to 34 DOTs. The responses revealed that a relatively small number of DOTs manage their culvert assets using formal asset management systems and, while a number of DOTs have inventory databases, many do not have a methodology in place to convert them to priority lists. In addition, when making decisions, DOTs do not incorporate future deterioration rate information into the decision making process. The objective of this work was to narrow the gap between research and application.

The culvert inventory database provides basic information support for culvert asset management. Preliminary data analysis of datasets provided by selected DOTs was performed to demonstrate the differences among them. An expert opinion survey using AHP was performed to confirm the weight of 23 factors, which was believed to contribute to the hydraulic & structural performance of culvert structures, so as to establish the culvert rating methodology.

A homogenous Markov model, which was calibrated using the Metropolis-Hastings Algorithm, was utilized in the computation of the deterioration rate of culverts at the network level. A real world case study consisting of datasets of three highways inspected regularly by Oregon DOT is also presented. The performance of the model was validated using Pearson's chi-square test.

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CHAPTER 1

INTRODUCTION

This chapter outlines the motivation for the development of a deterioration rate prediction model for culvert structures. In this section, an overview, the objective and scope of this dissertation, as well as its layout, are introduced.

1.1 Overview and Objective

Culverts are pipes typically located under roadways, embankments, or service areas that allow passage of storm water. Culverts are built with straight horizontal alignment and a single grade (vertical alignment). Although the length of culverts is not restricted, most existing culverts are located under two-lane roadways and are no longer than 75 ft long. *The Status of the Nation's Highways, Bridges, and Transit: Conditions and Performance* (FHWA, 2004) reported a total of 118,394 culverts in the bridge inventory in the United States. This count refers to structures with no deck, superstructure, or substructure, but rather self-contained units under roadways, and constructed of concrete or corrugated steel. The National Bridge Inventory (NBI) only tracks culverts with a structural width 20 feet and larger, and this also can be multiple culverts that are placed adjacent to each other totaling 20 feet and greater. The total number of culverts in the U.S. is much larger than 118,394, and while a total count does not exist at the present time, estimates are in the order of several hundreds-of-thousands of culvert structures under the jurisdiction of DOTs, and at least an equal amount under the jurisdiction of local governments and other bodies, such as the U.S. Forestry Service.

Many culverts structures are in a deteriorated condition and reaching the end of their design life. When a culvert loses its structural integrity, it could lead to adverse impacts on the road surface above it in the form of surface depression, extensive cracking, and, in extreme cases, a collapse. However, to maximize the service life of these assets, an estimate of the deterioration rate of culvert structures is required so that future conditions can be predicted. The lack of tools for determining deterioration rate and enabling forecasting of the future conditions of culvert structures is a technical gap in many existing asset management systems. The research focus and objectives of this dissertation are presented as followed:

1. Culvert inspection technology. Identify available NDT evaluation methods and establish their suitability for the condition assessment of different culvert structures based on their ability to detect particular types of defects.
2. Culvert rating methodology. Develop a universally acceptable culvert rating methodology using AHP, based on an expert opinion survey for more efficient management of culvert assets.
3. Culvert deterioration rate prediction. Build a Markov model to evaluate the deterioration rate and service life of culverts at the network level for more appropriate budget allocation.

1.2 Motivation

In 1999, the FHWA Asset Management Office was established and was task with the incorporation of asset management concepts in transportation systems. However, there is still no universally accepted culvert condition assessment system used by DOTs. Consequences of culvert failures can be very severe especially in interstate highways. Table 1.1 lists selected culvert failures reported by media sources across the USA over the past 18 years.

Table 1.1 Culvert Failure-Case Histories

Number	Year	Location	Consequences
1	1983	Antwerp, Ohio	Five persons died, four injured
2	2001	Highway 401, Ontario, Canada	4 hours detour lasting 1 day
3	2003	Interstate 70, Colorado	Closure of I-70 lasting 7 days; the replacement costs $45,000
4	2003	SR-79, Ohio	20 minutes detour lasting 6 days
5	2003	SR-173, Ohio	20 minutes detour lasting 5 days
6	2003	Interstate 75, Michigan	20 minutes detour lasting 5 days; the replacement costs $95,000
7	2006	Interstate 88 Unadilla, NY	Two truck drivers died; closure of I-88 in both directions; the full replacement lasting 2 months
8	2008	Interstate 480, Ohio	Closure of lanes for 8 days; the replacement costs $384,000
9	2010	U.S. 138, Colorado	Closure of U.S. 138 lasting 24 days

Based on a questionnaire sent to FHWA division bridge engineers of U.S. DOTs in 2007, only 29 states use asset management software to manage their culverts, of which eight states use Pontis®. Pontis® is an asset management software developed by Cambridge Systematics, Inc. and Optima Inc, for transportation agencies to manage bridges and culvert as well as other transportation structures. Pontis® stores inspection data for bridges and culverts, and employs a deterioration prediction function to help transportation agencies to make optimal decisions in terms of preserving their assets. Thirteen states use in-house programs and eight states use a combination of Pontis® and in-house programs (FHWA, 2007a). The remaining DOTs that responded to this survey did not use culvert asset management software, indicating a gap between technology and application. Table 1.2 lists available culvert rating systems used by various DOTs.

Table 1.2 Condition Rating Methods for Culverts in the USA

Rating System	Agency	Year
PennDOT's System	PennDOT	2008
MN DOT's System	MN DOT	2006
ORITE'S System	ORITE[1]	2005
Meegode's System	NJ DOT	2004
Caltran's System	CA DOT	2003
ODOT's System	OH DOT	2003
Kurdziel's System	TRB	1988
Arnoult's System	FHWA	1986

[1]*ORITE: Ohio Research Institute for Transportation and the Environment*

The service lives of culvert structures largely depend on the supporting soil, local environment, and corrosive and abrasive properties of the transported fluid and solids (Meegoda, 2009). The California Test Method 643 uses pH of soil and water, and the minimum electrical resistivity to estimate the service life of corrugated metallic culverts.

This method is based on a testing of over 7,000 corrugated metallic culverts in California in 1959. The American Iron and Steel Institute (AISI) method is similar to the California Test Method 643, which uses the invert's service life to represent the culvert's durability. The Florida Method is also similar to California Test Method 643 and pH, and the minimum resistivity are the input parameters for predicting the service life of corrugated metal culverts. Table 1.3 summarizes the methods for service life estimation developed by different agencies across the USA.

Table 1.3 Service Life Estimation Methods

Estimation Methods	Agency	Year
California Test Method 643	CA DOT	1999
AISI[1] Method	AISI	1994
Florida Method	FL DOT	1993

[1]AISI: American Iron and Steel Institute Method

The main limitation of the California Test Method 643, the AISI Method and the Florida Method is their applicability to specific culvert materials that are located in the original areas where the corresponding methods were developed. For example, the Florida Method cannot be utilized in other states since deterioration rate of culverts are different at different states due to the climate, the construction material, and traffic loading and so on. The accuracies of three methods also change with time, so the prediction models need to be updated by additional validation. Advantages of these methods include fast evaluation, and limited possibility of human error and support of rapid decision making.

To sum up, the current technology for culvert asset management is not optimized in the U.S. in terms of gaining maximum benefit while minimizing disruption of traffic. A number of culvert failures have occurred in the past decades, resulting in the loss of lives, high economic loss and adverse social impact. In addition, culvert rating system is a bottleneck that supports decision making tasks such as prioritization and service life estimation as well as the final renewal plans. Thus, a proactive approach that aims at identifying culverts in structural distress in a timely manner to prevent collapses is needed. Currently, there is no unified rating system in the U.S., and the performance of current rating systems is difficult to be evaluated. Furthermore, service life estimation by statistical methods, an approach that provides future deterioration information of culverts at the group level, but has not been developed and applied by DOTs widely so far.

The objective of this work is to reduce the gap between current asset management theory and engineering applications, as to maximize the service life of culvert assets while minimizing the likelihood of culvert failure. In this research, technologies related to culvert asset management, including NDT inspection, condition rating, database management and deterioration prediction algorithms, are investigated. Successful application of culvert asset management can maximize the benefit of investment into culverts while minimizing the risk of catastrophic failures.

1.3 Scope and Organization

Chapter 1 presents an overview and the objectives of this research. Background knowledge about culverts and general information regarding culvert assets in the U.S. is provided. Case histories of culvert collapses, available culvert rating systems in the U.S. and culvert service life estimation methods are then presented and analyzed, supporting the need for this research work. The scope and organization of the thesis are introduced in the latter part of Chapter 1.

Chapter 2 provides a literature review of topics relevant to this research work, including an overview of culvert asset management in the U.S., NDT for culvert inspection and statistical approaches for predicting structural deterioration rate.

Chapter 3 presents the development of a culvert rating methodology. To investigate most of the recent technologies in data management, requests for culvert inventory data were sent to DOTs and the FHWA. After comparing the acquired inventory datasets, the Oregon DOT's inventory dataset was selected as the basis for developing a culvert rating methodology. An expert opinion survey was conducted to assist in establishing weights for each factor using AHP to rank the condition of all culverts.

Chapter 4 gives detailed description of utilizing the Markov model for culvert deterioration estimation at the network level. Datasets from three highways of the Oregon DOT were analyzed. Model calibration is the key for computing the unknown parameters of the Markov Model, which was computed by the Metropolis-Hastings Algorithm (MHA). Model validation was performed using the Pearson's chi-square test. Finally, a case study was provided. The results indicated that a Markov model based on the overall rating methodology did not pass the chi-square test, while the model based on the structural rating methodology passed the test. Possible reasons for that finding are investigated.

Chapter 5 concludes the research work of this dissertation, providing suggestions for future work.

CHAPTER 2

LITERATURE REVIEW

The following literature review provides background information regarding culvert asset management systems developed and/or utilized in the U.S., as well as an overview of culvert inspection technologies and deterioration estimation methods. Section 2.1 provides a state-of-the-art review for culvert asset management systems in the U.S. Section 2.2 examines the capabilities and limitations of Non-destructive Technologies (NDT) for different material types. Section 2.3 describes statistical approaches and their applications for predicting the deterioration of infrastructure elements.

2.1 Technologies for Culvert Asset Management in the U.S.–State of the Art Review

Culvert asset management is a strategic and systematic process which aims at maximizing benefits of the total asset inventory through optimizing resource allocation and utilization in business and engineering practices (FHWA, 2007b) while minimizing social and environmental impact. Significant research about culvert asset management has been performed. Publically available management technologies for culvert structures available in the U.S., which include inventory, inspection, assessment, maintenance, rehabilitation and replacement considerations, are indexed by *Culvert Technologies* published by the FHWA (2008).

Application of trenchless technologies for the comprehensive asset management of culverts and drainage structures was investigated and a decision support system for culverts was proposed (Salem and Najafi, 2008). The culvert management manual provides an efficient way to protect the public's investment in terms of inventory, inspection and maintenance technologies (Ohio DOT, 2003). A Culvert information management system (CIMS) including inspection, maintenance and replacement of corrugated steel culvert pipes was developed, which optimizes decision making, (i.e. budget allocation) (Meegoda, 2005). Trenchless lining techniques are a cost-effective solution compared with open-cutting when performing rehabilitation of existing culvert structures; Multi-criteria Decision Analysis (MCDS) is a robust way to maximize benefits by use of a customized decision aid model (FHWA, 2005). For evaluating the performance of culverts, a condition assessment system was developed to assist the Utah DOT to track the status of its culvert assets (McGrath, 2004). A state-of-the-practice review performed for condition assessment, rehabilitation and replacement of corrugated metal pipe culverts, culvert inspection and rating systems was compiled by Simicevic (2008). A decision making system for optimizing management of culvert repair, rehabilitation and replacement was developed, and enhancement for CIMS which included a culvert assessment module and optimization module were proposed for New Jersey DOT by Meegoda (2009).

A synthesis made by NCHRP reveals that it will be helpful for the DOTs to establish a proactive maintenance program and database for culverts (NCHRP, 2002). Case studies for culvert asset management (CMS) were developed to demonstrate how transportation agencies could apply CMS to improve the asset quality of culverts (FHWA, 2007b). A method for predicting the remaining service life of corrugated steel culvert pipes (CSCPs) utilizing the Markov model was proposed by Meegoda (2004). A material durability rating system for metal and concrete pipes was developed, which aimed at ensuring the different types of culvert's materials are uniformly rated (Kurdziel, 1988). Factors for a culvert condition rating system were analyzed, and 9 out of the 33 factors considered were found to be statistically significant to develop the new model which has a 1 to 5 rating scale (Cahoon, 2002).

2.2 Non-destructive Technologies (NDT) for Culvert Inspection and Condition Assessment

Condition assessment of culvert structures to establish their structural integrity is a common practice by many transportation agencies as part of their asset management and capital planning programs. There are many Non-destructive Technologies that could provide information regarding the presence, nature and severity of defects in different culvert types/materials. The challenge is to select the most appropriate NDT methods scheme so that the needed data can be acquired in a reliable and economic manner.

NDT assessment is a rapidly developing field with applications in many engineering disciplines including condition assessment of civil infrastructure systems and facilities such as roads, bridges, runways, waste and potable water conveyance and distribution systems and more. This section focuses on a subgroup of technologies that can be used to assess the service performance and structural integrity of culvert structures and the embedment around them without the need of intrusive or destructive means. The goal of this section is to identify available NDT evaluation methods and establish their suitability for the condition assessment of different culvert structures based on their ability to detect particular defect types. This database is expected to serve as the basis for a rational and systematic decision support matrix which ranks the suitability of various NDT methods for a particular project, based on their capabilities and limitations.

2.2.1 Defect Classification for Culvert

Most culverts can be classified as cementitious, thermoplastic or metallic in terms of materials. Specific defects are known to be associated with particular construction materials. Table 2.1 shows the relationship between defects and culvert materials. Culvert structures take various shapes including circular, pipe arch, rectangular, pear and more. It is acknowledged that specific defect types might be more prevalent in particular culvert geometries; however, this aspect is not considered in this research.

Table 2.1 Common Defects for Different Culvert Materials/Types

DEFECTS	CEMENTITIOUS		THERMO-PLASTIC	METALLIC	
	Cast-in-place	Pre-cast		Pipe	Structural plates
Cracks	√	√	√	×	×
Spalls	√	√	×	×	×
Delamination	√	√	×	×	×
Joint misalignment	×	√	×	√	√
Internal/External corrosion	√	√	×	√	√
Invert erosion	√	√	√	√	√
Abrasion/wall thinning	√	√	√	√	√
Encrustation/Debris	√	√	√	√	√
Pipe ovality	√	√	√	√	√
Footing defects	√	×	×	×	√
Slabbing	×	√	×	×	×
Defective joints	×	√	×	√	√

Lateral deflection	√	√	√	√	√
Crown Sag	×	×	√	√	√
Corroded reinf. bars	√	√	×	×	×
Dents & localized damage	×	×	√	√	√

2.2.2 Short Descriptions of Selected Methods

2.2.2.1 Laser Profiling. Three-dimensional laser profiling, also called the light-line method, uses a laser to generate a line of light around the pipe circumference that, when viewed by a camera, is capable of capturing the geometry of the inside wall of the culvert. Laser profiling can detect deformations, siltation and corrosion in culvert structures. A 3D wire-mesh model of the pipe can also be created and displayed. Laser inspection can be conducted only in drained pipes, and thus, the culvert must be taken out of service (Jason Consultants, 2008). Inaccurate readings might occur when the laser crosses the interface of materials with different densities.

Laser profiler systems can generate variety of reports and 2D or 3D models of the pipe. Information provided included the grade of the pipe, the location and magnitude of deflections, measurements of sediment and water depth. Laser profilers are commonly combined with Closed Circuit Television (CCTV) systems and mounted on modular robotic transporter platforms for creating enhanced data collection systems. Recent research efforts focused on the development of artificial intelligent (AI) software capable of automatic feature extraction from the raw data. Duran (2003) reported a system that combines image analysis techniques and Artificial Neutral Network (ANN) to automatically locate and classify defects in the pipe structure.

2.2.2.2 <u>Sonar.</u> Sonar is a NDT method that operates under water to detect the presence of debris and gross defects at the pipe's invert. Sonar scans can only be performed in partially or fully filled pipes. Due to the irregular edges caused by the brick-mortar interface, sonar cannot be used for the inspection of brick pipes. Sonar technology is commonly used as supplement to CCTV and laser profiler inspections.

2.2.2.3 <u>Ultrasonic.</u> High frequency sound waves that range between 50kHz to 10MHz are able to provide information regarding the presence and location of boundaries within the pipe wall that results from the presence of delimitations, voids and poorly dense/high corroded zones (Berriman, 2003). The travel speed of ultrasound waves changes depending on the density of the medium through which they travel. When the propagating wave encounters reflector surfaces such as the flaws, voids and boundaries between two different mediums, part of the acoustic energy is reflected back and received by a transducer, which also performs the signal transmitting function (Iyer, 2005). The presence and location of various targets can be obtained from the raw data using a time domain based analysis. The results of inspection are presented in 2D or 3D formats. Integrating data from complimentary NDT methods could result in a more reliable and accurate interpretation of the results via super-positioning algorithms (EPA, 2008).

2.2.2.4 <u>Ground Penetrating Radar (GPR).</u> The primary application of GPR in the utility industry is to identify the location and depth of buried pipes and conduits. A qualitative measure of the magnitude of deterioration behind a liner can be established using high frequency GPR units that are placed within the pipeline very close to its interior wall (Koo et al., 2006). GPR units were also reported to be used for locating concrete deterioration and voids behind concrete liner employing a 1 GHz frequency antenna mounted such that it nearly touches the inner wall of the tunnel is inner surface (Parkinson and Ekes, 2008).

The penetration depth of GPR is greatly affected by the dielectric characteristics of the underground medium and the wavelengths of the transmitted signal. Resolution is typically inversely related to the penetration depth. GPR consists of a transmitting antenna that emits radio waves into the ground. The waves penetrate through the medium until they reach a material which has a different conductivity and dielectric constant, causing part of the signal to reflect back at that interface. The reflected signal is detected by a receiving antenna. After analyzing the time it took the pulse to travel to the boundary interface and return, the presence of the target and its estimated depth features below the ground surface can be determined. The center frequency of the transmitted antenna ranges from 25 to 1500 MHz, depending on the application at hand (Bungey, 2004). GPR data can be presented using 2D and 3D surveys. In a 2D survey, the features are located and marked at the site using standard surveying techniques. The 3D survey is more flexible, and data can be post-processed at the office. The effectiveness of the GPR methods is affected by soil conductivity, depth of the target, the presence and proximity of other buried objects, moisture content and environmental electromagnetic noise.

2.2.2.5 Infrared Thermography. This method can be deployed for leak detection and component assessment, and has been successfully applied in practice for a number of years (Weil, 2004). Pulsed active infrared thermography (PAIRT) detects subsurface defects based on the principle that different defects can show different thermal properties; the thermal emission could then be detected by thermal sensors, namely an infrared camera capable of detecting the surface emissivity. By applying the PAIRT method, an approximate quantitative wall thickness evaluation can be made, based on the principle that a pipe area with thinner wall thickness will be affected by thermal energy first, using the expression given in Eq. 2.1,

$$t = \left(\frac{Z^2}{\delta} \right), \tag{2.1}$$

where t is the observation time, δ is the thermal diffusivity of the materials (m^2/s), and Z is wall thickness (in the case of pipes). If the wall of pipeline has its thickness reduced by a factor of 2 due to corrosion, a thermal disturbance will arrive to the outer surface of the corroded section four times faster compared with other sections of the pipeline (Maldagure, 1999). Thus, by measuring the observation time t, it is possible to calculate the thickness of the pipe wall. In this method, the thermal transient inside the pipe needs to be generated by changing the flow condition in the pipe, then by observing the temperature distribution on its outside surface. A qualitative evaluation of the wall thickness can be obtained using the above expression. In cases where it is difficult to change the flow inside the pipeline, an external heat source can be used to uniformly increase the temperature of the outer wall of the pipe. Next, an infrared camera is utilized to record the temperature distribution on outside surface. Recent development of high resolution, dual/wide-band, infrared thermographic imaging systems increased the effectiveness of this method, allowing it to detect with high reliability thermal anomalies associated with leaks and erosion voids caused by leaks.

2.2.2.6 <u>Gamma-Gamma Logging.</u> This technology is used mainly for concrete pipe assessment, especially for vertical boreholes in the mining and oil and gas industries. Gamma radiation, such as cesium-137, is generated by Gamma-Gamma probes and scattered back to a shielded detector. The data logged can be used to evaluate the density of the concrete. A recent study at Karlstuhe University in Germany indicated that Gamma-Gamma probe could be used to locate and measure the voids and cavities in bedding materials. The technology might be applicable for evaluating the general condition of cementitious culverts pipes or detecting voids in their surrounding bedding (EPA, 2009).

2.2.2.7 Visual and CCTV. Visual and CCTV are most commonly used NDT for inspection. Man-entry visual inspection is only applicable to culverts that have sufficient working space (i.e., large diameter). For non-man-entry pipes, remote inspection technology, closed circuit television (CCTV), is the most commonly used method for examining the culvert barrel. A camera is mounted on a crawler or transporter, which is connected through a cable that provides power, thus enabling the crawler to travel along the pipe while capturing video images of the traveled section. The video is then reviewed by a certified inspector that documents the condition of the barrel. A pan-and-tilt camera enables to inspect the entire circumferences of the pipe, overcoming the limitations of front-viewing cameras. Although the accuracy of CCTV inspection results is highly dependent on the inspector's experience, it is still one of the most widely used NDT for inspection of culvert structures.

2.2.2.8 Other Emerging NDT and Monitoring Methods. There are a number of emerging non-destructive testing technologies that have demonstrated potential for providing valuable information regarding specific attributes of buried structures or pipes. Table 2.2 summarizes emerging NDT and monitoring methods that might be beneficial for culvert inspection programs (FHWA, 2006).

Table 2.2 Emerging NDT and Monitoring Methods

NDT Methods	Description
Smart Paint 1	Uses microencapsulated dye to outline fatigue cracks
Smart Paint 2	Uses resin layer attached to electrodes to monitor vibrations; used to support accurate fatigue calculations
Penetrating Dye	Detects extent and size of surface flaws in steel members, the test area needs to be cleaned and separated from structure
Radiographic Testing	X-rays or gamma rays are passed through the member and are absorbed differently by various flaws (IAEA, 2005)
Nuclear Methods	Measures chlorides in reinforced concrete to determine corrosion hazard
Magnetic Field Disturbance	Evaluates fatigue damage to steel reinforcement in concrete members
Pachometer	The magnetic device used to determine the position of reinforcement
Liquid Penetrant Testing	Evaluates cracks of mechanical parts such as gears
Magnetic Particle	Detects and locates the slight subsurface discontinuities or defects
Backscatter Tomography	Provides image of defects inside infrastructure elements using a single-side access (applicable to most materials)

2.2.3 Methods Selection of NDT for Culvert Inspection

Tables 2.3 - 2.5 represent the mapping of NDT methods to specific defect types for different culvert materials. These matrices can assist engineers in selecting the appropriate NDT method for their projects.

Table 2.3 Inspection of Concrete Culvert Structures

NDT Methods	Defect Type / Location													
	Cracks, Spalls	Joint defects/ mis-align.	Int. Corros.	Debris	Ovality	Infl.	Invert Erosion	Bedding Voids	Wall Thinning	Delam.	Ext. Corros.	Crown Sag	Corrod. Bars	Defect behind liner
Visual	√	√	√	√	×	√	√	×	×	×	×	√	×	×
Smoke	√	√	×	×	×	√	×	×	×	×	×	×	×	×
CCTV/ Optical scanning	√	√	√	√	×	√	√	×	×	×	×	√	×	×
Pigs	×	×	×	×	√	×	×	×	×	×	×	√	×	×
Laser Profiling[1]	×	√	√	√	√	×	√	×	×	×	×	√	×	×
Sonar/ Ultra-sonic[2]	×	×	×	√	×	×	×	×	√	×	×	√	×	×
Impact-echo	×	×	×	×	×	×	×	×	√	√	√	×	×	×
SAWS[3]	×	×	×	×	×	×	×	√	×	√	×	×	×	×
IRT[4]	×	×	×	×	×	×	×	√	×	×	×	×	×	×
GPR[5]	×	×	×	×	×	×	×	√	×	√	×	×	×	√
Gamma-Gamma	×	×	×	×	×	×	×	√	×	√	×	×	×	×
Dye Test	×	×	×	×	×	√	×	×	×	×	×	×	×	×

[1] unflooded condition; [2] flooded conditions; [3] spectral analysis of surface waves; [4] Infrared Tomography; [5] from inside the pipe.

Table 2.4 Inspection of Thermoplastic Culvert Structures

NDT Methods	Defect Type										
	Cracks	Debris	Ovality	Inflow	Joint defects/ misalignment	Abrasion/ wall thinning	Bedding Voids	Low density bedding	Dents & localized damage	Lateral Deflection	Crown Sag
Visual	√	√	×	√	√	×	×	×	√	√	√
Smoke	√	×	×	√	×	×	×	×	×	×	×
CCTV	√	√	×	√	√	×	×	×	√	√	√
Laser	×	√[1]	√	×	√	√	×	×	×	√	√
Sonar/ ultrasonic2	×	√	×	×	×	√	×	×	×	√	√
IRT[3]	×	×	×	×	×	×	√	×	×	×	×
GPR[4]	×	×	×	×	×	×	√	×	×	×	×

[1] unflooded condition; [2] flooded conditions; [3] Infrared Tomography; [4] from inside the pipe.

Table 2.5 Inspection of Metallic Culvert Structures

NDT Methods	Defect Type										
	Off-set joint	Internal Corrosion	Debris	Ovality	Inflow	Abrasion/wall thinning	Bedding Voids	External Corrosion	Lateral Deflection	Crown Sag	Low density bedding
Visual	√	√	√	×	√	×	×	×	√	√	×
Smoke	√	×	×	×	√	×	×	×	×	×	×
CCTV	√	√	√	×	√	×	×	×	√	√	×
Laser	√	√	√[1]	√	×	√	×	×	√	√	×
Sonar/ ultrasonic2	×	×	√	×	×	√	×	×	√	√	×
Mechanical impedance	×	×	×	×	×	×	√	×	×	×	√
IRT[3]	×	×	×	×	×	×	√	×	×	×	×
GPR[4]	×	×	×	×	×	×	×	×	×	×	×

[1] unflooded condition; [2] flooded conditions; [3] Infrared Tomography; [4] from inside the pipe.

2.3 Statistical Approaches for Deterioration Prediction

This section introduces statistical models for deterioration prediction, presents calibration methods for deterioration prediction models, and contrasts alternative prediction models.

2.3.1 Deterioration Models

Statistical approaches for deterioration prediction in the area of infrastructure management have been proven to be robust, not only at the network level, but also at the individual element level. Table 2.6 presents model suitability in deterioration predictions based on a literature review.

Table 2.6 Model Suitability for Deterioration Prediction

Statistical Approach	Serviceability Forecast		Structural Forecast	
	Network Level	Individual Level	Network Level	Individual Level
Markov Model	√		√	
Semi-Markov Model	√		√	
Ordered Probit Model		√		√
Probabilistic Neutral Network		√		√
Multiple Logistic Regression		√		√
Multiple Discrimination Analysis		√		√
Ordinal Regression Model		√		√

2.3.1.1 <u>Markov Model (MM).</u> A discrete time Markov chain $\{X_t\}$ is the Markov stochastic process that consists of countable state space T, in which T= (0,1,2, ...), for the probability of X_{t+1} in state j, given X_t in state i, one-step transition probability $P_{ij}^{n,n+1}$ can be denoted by Eq. 2.2 (Karlin 1972),

$$P_{ij}^{n,n+1} = P\{X_{n+1} = j | X_n = i\}. \tag{2.2}$$

In the Markov chain, next state X_{t+1} only depends on the current state X_t, not the history of the chain, which ranges from X_0 to X_{t-1} (Gilks 1996). Assuming the Markov chain is time homogeneous, a transition probability matrix, P_{ij}, describes the probability of transition from one state to another over a certain time (normally 1 year in infrastructural management). Future condition of infrastructure element I at any year can be predicted by the Chapman-Kolmogorov equation as shown in Eq. 2.3,

$$C_i^t = C_i^0 \cdot (P_{ij})^t, \tag{2.3}$$

where: C_i^t=probability of I at state i in t years; C_i^0=initial state of I; P_{ij}=transitional probability; i=condition states of I.

The semi-Markov model assumes the time spent in each state is not evenly distributed, which allows fitting a variety of statistical distributions to deterioration problems.

A significant amount of research has been done in the application of the Markov chain theory in the infrastructure area. Micevski et al. (2002) successfully modeled the deterioration of storm water pipes using the Markov model utilizing the Metropolis-Hastings Algorithm (MHA), one of the Markov chain Monte Carlo methods for calibration; the results were compared with the depreciation curve from Australia AAS27, which concluded that AAS27 highly exaggerated the depreciation of storm water pipes. Baik (2006) developed a Markov chain based deterioration model for wastewater systems, and its transition probabilities were computed by OPM. The results showed that OPM outperformed a nonlinear optimization-based deterioration model. In an integrated pavement management system application, pavement deterioration prediction was performed by applying a discrete-time Markov model (Abaza, 2004).

For modeling the deterioration of large combined sewers, Wirahadikusumah (2001) discussed how to improve the modeling of the sewer system by using a Markov chain based model with a nonlinear optimization. Kleiner (2006) simulated the deterioration of infrastructure assets using a semi-Markov model, which is a non-stationary, time-dependent transition process. Dirksen (2008) investigated the probabilistic modeling of sewer deterioration in the Netherlands, by applying the Markov model to sewer pipelines. A model was constructed of the "surface damage by corrosion" which was solely dependent on structural condition. After combining the states 3, 4, 5 to one state because of the characteristics of the data, a three states transition probability matrix was established and calibrated, which illustrated a robust performance in deterioration forecasting.

In predicting the remaining service life for corrugated steel culvert pipes, Meegoda (2004) proposed a novel half-life probability method to calculate the transitional probabilities for the Markov chain due to lack of historical data. Based on an expert opinion survey, Kathula (2000, 2001) developed a Markovian-based statistical model for Sanitary Sewer Management Systems (SSMS), to evaluate the future distress condition of concrete and clay sewer pipes. Tran (2009a) performed a structural deterioration prediction of storm water pipes at the network level using the Markov model, which aims to support the decision maker in allocating the budget and estimate the remaining service life. Tran (2008) investigated the applicability of the Markov model in predicting the serviceability deterioration of storm water pipe. Tran (2009b; 2010c) applied the Markov model to evaluate the structural deterioration of storm-water pipe assets. Sinha (2007) proposed a probability based Markov prediction model for performance estimation as part of a pipeline management system. Golroo (2009) investigated the application of the Markov chain process in modeling concrete pavement condition in cold climates. A semi-Markov approach was selected for modeling asset deterioration by Black (2005) based on the observed condition data for ground-mounted transformers.

2.3.1.2 Ordered Probit Model (OPM). The ordered probit model was introduced by Madanat (1995) to evaluate the deterioration of bridge decks which outperformed the common expected-value approach for estimation of transition probabilities in terms of accurate prediction and realistic reasoning. Madanat (1997) developed a random effects ordered probit model, which accounts for the heterogeneity in a sample, for evaluating bridge deck deterioration. The theory of OPM is given by Eq. 2.4 and Eq. 2.5,

$$log(S_i) = r_i + \varepsilon_i, \tag{2.4}$$

$$r_i = \sum_{k=1}^{K} \beta_k X_k, \tag{2.5}$$

where: S_i=continuous deterioration process that ranges from 0 to $+\infty$ for infrastructure I, where the log scale constrain the deterioration process to a positive value; r_i=linear formula denoting input factors X_k and corresponding coefficient β_k, ε_i=error of random events for i. Thresholoul d value θ divides the deterioration $log\,(S_i)$ to segments representing the conditions of the infrastructure element.

Assume ε_i follows the normal distribution N, I has 4 rating scales and 3 threshold values, so the probability that I stays in condition 1 is given by Eq. 2.6,

$$P_{I,i}\text{= probability } [log(S_i) < \theta_1]\text{=probability } [r_i + \varepsilon_i < \theta_1]\text{= probability } [\varepsilon_i < \theta_1 - r_i]. \quad (2.6)$$

Assigning F to be the cumulative distribution function of ε_i, Eq. 2.7, Eq. 2.8, Eq. 2.9 and Eq. 2.10 can be derived,

$$P_{1,i} = F(\theta_1 - r_i), \quad (2.7)$$

$$P_{2,i} = [\theta_1 < log(S_i) \le \theta_2] = F(\theta_2 - r_i) - F(\theta_1 - r_i), \quad (2.8)$$

$$P_{3,i} = [\theta_2 < log(S_i) \le \theta_3] = F(\theta_3 - r_i) - F(\theta_2 - r_i), \quad (2.9)$$

$$P_{4,i} = 1 - P_{1,i} - P_{2,i} - P_{3,i}\,, \quad (2.10)$$

where $P_{q,i}$=probability of segment i at condition q, ranges from 1 to 4; F=cumulative normal distribution of ε_i; θ_1, θ_2 and θ_3 are threshold values of the OPM.

Baik (2006) successfully applied the OPM to deterioration of a waste water collection system, and suggested that OPM outperformed a nonlinear optimization-based approach. To capture the deterioration of individual storm water pipe segments, Tran (2009a; 2010b) developed OPM for structural and hydraulic deterioration estimation of individual storm water drainage pipes. Tran (2008) proposed an ordinal regression model (ORM) based on OPM for evaluating the serviceability deterioration of storm water pipes.

2.3.1.3 <u>Probabilistic Neural Network (PNN).</u> Probabilistic Neutral Networks is a hybrid computation method based on a Neural Network platform which incorporates the Bayesian classification theory. The difference between NN and PNN is that NN, i.e. back-propagation neural networks, needs a long training process, while the PNN finds the best solution for each pattern of structural conditions by using the Parzen-Cacoullos theory.

PNN is constructed by four layers named the input layer, pattern layer, summation layer and output layer. Condition recognition is realized by a Bayesian classifier given by Eq. 2.11 (Tran, 2010c),

$$D(X) = C_i \ \ if \ l_i h_i f_i(X) \geq l_j h_j f_j(X) \ \ i,j = 1, \ldots, m, \tag{2.11}$$

where: X = K-dimensional vector which has k input factors; $D(X)$=projection of X in a group of m conditions; l=loss incurred by misclassifying the condition i to j; h=prior probability of occurrence for a condition; $f(X)$=PDF (probability density function) for a condition. l and h are assumed to be uniform for each condition in modeling, so pattern classifying only depends on which condition has the highest value of $f(X)$.

PDF is the core algorithm for the Bayesian classifier. Although there is no confident information to draw the PDF, it is still possible to estimate $f(X)$ based on given knowledge, such as observation data, through the Parzen-Cacoullos Method, which is given by Eq. 2.12,

$$f(X) = \frac{1}{N\sigma_1\sigma_2\cdots\sigma_K}\sum_{i=1}^{N} W\left(\frac{X-X_i}{\sigma}\right), \tag{2.12}$$

where: X=K-dimensional vector representing infrastructure with K input factors; σ=group of K smoothing factors denoting the standard deviation of each factor; N=number of available observations; $f(X)$=PDF; W=kernel density function. Eq. 2.13 is achieved after fitting the widely used Gaussian kernel density function into Eq. 2.12 as a substitute for W,

$$f(X) = \frac{1}{(2\pi)^{m/2} N\sigma^m} \sum_{i=1}^{N} exp\left[\frac{(X-X_n)^T(X-X_n)}{2\sigma^2}\right], \tag{2.13}$$

where: m is the vector number of X. In a four-layer PNN, the input layer consists of neurons, one for each input factor; the pattern layer is responsible for calculating the exponential part of Eq. 2.13 and sending it to the summation layer, in which $f(X)$ will be computed. At last, in the output layer, the pattern assigning will be performed by Bayesian classifier, to judge which pattern has the highest $f(X)$ value.

Tran did extensive work in the development of PNN for storm water pipe deterioration prediction not only in the structural aspect (Tran, 2006; Tran, 2007a; Tran, 2009b; Tran, 2009c), but also the hydraulic/serviceability performance (Tran, 2007b; Tran, 2010b).

2.3.1.4 Multiple Logistic Regression (MLR). Multiple logistic regression is a probabilistic approach that illustrates the deterioration of infrastructure by a logistic cumulative distribution function. The principle of MLR is simple; it segments the continuous deterioration curve of infrastructure I into four zones by three threshold values (assuming I has four conditions). The four segmented zones are corresponding with the four conditions of I. The condition of I can be identified by computing the highest value of the probabilities of I staying in each of the conditions.

The logistic function is presented by Eq. 2.14,

$$f(z) = \frac{e^z}{1+e^z}, \tag{2. 14}$$

where $f(z)$=latent deterioration curve ranging from 0 to 1; z=a factor including the thresholds and the linear function. $f(z)$ is a cumulative distribution function, assuming that the infrastructure I has four conditions from 1 (best) to 4 (worst), the probabilities of I staying in each of the conditions are expressed by Eq. 2.15, Eq. 2.16, Eq. 2.17 and Eq. 2.18, respectively,

$$P_1 = [f(z) \leq \theta_1] = \frac{e^{\theta_1+\sum_{i=1}^{k}\beta_i X_i}}{1+e^{\theta_1+\sum_{i=1}^{k}\beta_i X_i}}, \quad (2.15)$$

$$P_2 = [\theta_1 < f(z) \leq \theta_2] = \frac{e^{\theta_2+\sum_{i=1}^{k}\beta_i X_i}}{1+e^{\theta_2+\sum_{i=1}^{k}\beta_i X_i}} - \frac{e^{\theta_1+\sum_{i=1}^{k}\beta_i X_i}}{1+e^{\theta_1+\sum_{i=1}^{k}\beta_i X_i}}, \quad (2.16)$$

$$P_3 = [\theta_2 < f(z) \leq \theta_3] = \frac{e^{\theta_3+\sum_{i=1}^{k}\beta_i X_i}}{1+e^{\theta_3+\sum_{i=1}^{k}\beta_i X_i}} - \frac{e^{\theta_2+\sum_{i=1}^{k}\beta_i X_i}}{1+e^{\theta_2+\sum_{i=1}^{k}\beta_i X_i}}, \quad (2.17)$$

$$P_4 = 1 - P_1 - P_2 - P_3, \quad (2.18)$$

where: P_1, P_2, P_3 and P_4=probability of I in condition 1, 2, 3 and 4; θ_1, θ_2 and θ_3 = thresholds for $f(z)$; X_i=input factors relating to the deterioration process, k=total number of factors; β_i=coefficient of X_i. In predicting the deterioration rate of the storm water pipes, MLR was successfully applied, and its performance was compared with the PNN (Tran 2009c).

2.3.1.5 <u>Multiple Discrimination Analysis (MDA).</u> Multiple discrimination analysis can be used to perform pattern classification by using the discriminant function, which is determined by factors that affect the performance of the final output. Tran (2007b) applied the MDA to investigate the serviceability condition of storm water pipes.

In pattern classifying, MDA computes the Z scores of a set of linear discriminate functions which are used for defining the pattern zone in K-1 space, in which K is the total count of the pattern number. Calibration of the MDA is to maximize between-class variance relative to the within-class variance based on test data (Tran, 2007b). Pattern recognition of the MDA is realized by the testing infrastructure *I*, whose value will be compared with the centroid of the MDA; the pattern is assigned to the closest centroid. The centroid of the specific class can be achieved by averaging *Z* scores of each function coming from the sample data. The discriminant function is shown as Eq. 2.19,

$$D_k = B_{ko} + B_{kil}X_1 + B_{k2}X_2 + \cdots + B_{kj}X_j, \tag{2.19}$$

where: D_k =discriminant function; B_{ko} =constant; B_k =coefficients for discriminant function; X= vectors of input.

In summary, all deterioration models rely on high quality datasets but the models do not have tools to verify the accuracy of the datasets used. Other limitations include application area and dataset format requirements. For example, the Markov model is only applicable to deterioration prediction at the network level which can provide future information of infrastructure, and only age and condition of the culverts are needed to perform the deterioration prediction. The Markov model needs the preliminary process (sorting) of the datasets to get the target group that represent the regional deterioration characteristics. It is not optimized to apply the entire datasets to the Markov model, as it might result in inaccurate results. Thus, another limitation of Markov model is that the accuracy of the prediction results is highly related to the data sorting or data selecting.

OPM, PNN and MLR are models applicable to deterioration prediction at the individual level for infrastructure elements. Applying all factors from the inspection datasets to perform the calibration is not an optimized solution. Statistical significances between the factors and predicted results need to be evaluated.

Currently, there is no model that can perform all deterioration predictions for an infrastructure at the network level and the individual level. To take advantage of different deterioration models, Tran (2010a) proposed a conceptual framework for asset management decisions in sewer network which incorporates a network deterioration model, an individual condition classifying model, an individual deterioration model and a risk ranking model.

2.3.2 Calibration and Validation Methods

Model calibration is aimed at inferring the unknown parameters in the proposed model. For the Markov model, the unknown factor is the transition probability P_{ij}. For OPM, model calibration is to find out the coefficients and thresholds, etc. This section summarizes commonly used calibration methods, including expert opinion, maximum likelihood function, and half-life probability. The Metropolis-Hastings Algorithm will be introduced in Section 4.3.

2.3.2.1 Expert Opinion. Expert opinion should be considered when the engineering problem is hard to solve by soft computation modeling. It is nearly impossible to use soft computation methods to develop a culvert rating methodology based on the Analytic Hierarchy Process (AHP) because the weight of rating factors needs to be confirmed by expert opinion. In the deterioration rate estimation of sanitary sewers, an expert opinion survey was applied in the development of the Structural Condition Matrix (SCM) for clay pipes and concrete pipes, each one consisting of five structural distresses named "open crack," "open joint," "displaced joint," "corrosion" and "deformation" (Kathula, 2000).

2.3.2.2 Maximum Likelihood Technique. Maximum likelihood technique is a robust approach in inference of unknown parameters by maximizing the joint probability of observations. In a model consisting of unknown parameters θ and observation d, when assuming θ is a fixed value, the function $f(d|\theta)$ will be a likelihood function. In a series of observations, the maximum likelihood technique is used to compute the joint probability density for all observations and find the maximum one. In engineering applications, the log-likelihood is more convenient to use. The likelihood function is given by Eq. 2.20,

$$L(\theta|d_1, d_2, d_{3,...,}d_n) = f(d_1|\theta) \cdot f(d_2|\theta) \cdots f(d_n|\theta), \tag{2.20}$$

where $L(\theta|d_1, d_2, d_{3,...,}d_n)$ is the likelihood of observing facts d and $f(d|\theta)$=probability of observing d which consists of $d_1, d_2, \ldots, d_n$. In infrastructure management, the maximum likelihood method was applied widely in a variety of deterioration estimation models, such as OPM (Madanat, 1995; Baik, 2006; Tran, 2009a; Tran, 2010b), ORM (Tran, 2008) and MLR (Tran, 2009c) etc.

2.3.2.3 Half-life Probability. The half-life probability method was originally developed by Meegoda (2004) for predicting the remaining service life of a corrugated steel culvert pipe (CSCP) due to lack of the historical data. By assuming the average corrosion rates is 3 mil/year for urban (1.5 mil/year for rural), 50% of the cross section reduction for gauge 18 (0.052") will take 8.7 years, so the probability that CSCP remained at condition 1 after one year is calculated by Eq. 2.21,

$$(P_{11})^{8.7} = 50\%, \tag{2.21}$$

where P_{11} denotes the transition probability that the CSCP stays in condition 1 after one year of service. The transition matrix P_{ij} is established in a similar way to compute P_{11}.

The Half-Life Probability method provides the flexibility to estimate deterioration when there are insufficient datasets. However, assumptions need to be made based on generally accepted knowledge. The suitability of the assumptions affects the accuracy of the predictability performance of the model.

2.3.3 Comparison of Model Performances

The performance of deterioration prediction models can be compared at the same level. For example, it is possible to compare the performance of PNN and OPM at the individual element level; but it is impossible to compare the PNN with the Markov model, because the Markov model is used for network level prediction. Table 2.7 presents comparisons of the above discussed statistical models.

Table 2.7 List of Models for Performance Comparison

Network Level	MM	Standards
Individual Level	PNN	MDA
	NN	MDA
	PNN	BPNN
	PNN	MLR
	OPM	NN
	OPM	PNN

Model performance testing can provide a clear understanding of the advantages and limitations of the model's applications. Table 2.8 lists the results of the model performance comparisons.

Table 2.8 Comparison of Model Performance in Deterioration Estimation

Compared Models/Standards A	Compared Models/Standards B	Reference	Comparison Method	Performance/Remark
Markov Model	AAS27[1] Curve	Micevski 2002	Curve comparison	AAS27 overestimates actual STR deterioration.
PNN	MDA	Tran 2006	Performance rate	A outperforms B in STR[2] deterioration modeling.
NN	MDA	Tran 2007b	Performance rate	A outperforms B in SERV[3] deterioration modeling .
PNN	BPNN[4]	Tran 2007a	Chi-square test False negative rate Fraction correction rate	For STR deterioration modeling, in training dataset: A outperforms B but in test dataset: B outperforms A.
PNN	MLR	Tran 2009c	False negative rate Overall success rate	A is more suitable than B in STR deterioration modeling.
OPM	NN	Tran 2009a	Chi-square test False negative rate Fraction correction rate	A is less suitable than B in STR deterioration modeling.
OPM	PNN	Tran 2010b	Chi-square test False negative rate Overall success rate Agreement test	A is more suitable than B in hydraulic deterioration modeling.

[1]AAS27 is the Depreciation Requirements of Australia Accounting Standards; [2]STR=Structural; [3]SERV=Serviceability; [4]BPNN=Back Propagation Neural Networks.

2.3.4 Summary of Statistical Approaches for Infrastructure Deterioration Prediction

Based on the above presented literature review of deterioration prediction models, Table 2.9 summarizes statistical approaches that have been applied in the infrastructure field. It is impossible to apply only one model to solve all deterioration issues of infrastructures systems due to the limitations of each model. To perform a systematic renew, a conceptual framework which incorporates multiple deterioration models could be more beneficial for asset management (Tran, 2010a).

Table 2.9 Statistical Approaches in Buried Infrastructure Deterioration Prediction

Category	Reference	Infrastructure	Calibration / Software	Testing
Markov Model for Network Level				
STR[1]	Kathula 2001	Sanitary Sewers	Expert Opinion	Risk Ratio Test
STR	Micevski 2002	Storm-water Pipes	M-H[2] Algorithm	Chi-Square Test
STR	Meegoda 2004	Culverts	Half-Life Probability	*
STR	Sinha 2007	Pipelines	Expert Opinion	*
STR	Dirksen 2008	Sewer Pipelines	Max.[3] Likelihood Function	*
SERV[4]	Tran 2008	Storm-water Pipes	Bayesian inference; MCMC[5] Simulation	Chi-Square Test Performance Rate
STR	Tran 2009b	Storm-water Pipes	M-H Algorithm MATLAB®	Confusion Matrix Chi-Square Test
Semi-Markov Model for Network Level				
STR	Kleiner 2001	Large Buried Assets	Monte Carlo Simulation	*
STR	Black 2005	Transformers	Weibull Distribution	*

Ordered Probit Model for Individual Level				
STR	Madanat 1995	Bridges	Max. Likelihood	t-statistic Chi-Square Test
STR	Baik 2006	Sewer pipes	Max. likelihood	t-statistic P^2-statistic
STR	Tran 2009a	Storm-water Pipes	Max. Likelihood	Confusion Matrix Chi-Square Test
HYDR[6]	Tran 2010b	Storm-water Pipes	Max. Likelihood	Confusion Matrix Chi-Square Test Agreement Test
Probabilistic Neural Network Model for Individual Level				
STR	Tran 2006	Storm-water Pipes	MATLAB®	Chi-Square Test Performance Rate
SERV	Tran 2007b	Storm-water Pipes	Bayesian MCMC Simulation	Performance Rate
STR	Tran 2007a	Urban Drainage Pipes	Bayesian Approach	Chi-Square Test FNR[7] and FCR[8]
STR	Tran 2009c	Storm-water Pipes	MATLAB®	Confusion Matrix Chi-Square Test
HYDR	Tran 2010b	Storm-water Pipes	MATLAB®	Confusion Matrix Chi-Square Test Agreement Test
Multiple Logistic Regression for Individual Level				
STR	Tran 2009c	Storm-water Pipes	Max. Likelihood Calibration	Confusion Matrix Chi-Square Test
Multiple Discrimination Analysis for Individual Level				
SERV	Tran 2007b	Storm-water Pipes	SPSS®	Performance Rate
Ordinal Regression Model for Individual Level				
SERV	Tran 2008	Storm-water Pipes	Bayesian inference; MCMC Simulation	Performance Rate Chi-Square Test

[1]STR=Structural; [2]M-H=Metropolis-Hastings; [3]Max.=Maximum; [4]SERV=Serviceability; [5]MCMC= Markov chain Monte Carlo; [6]HYDR=Hydraulic; [7]FNR=False Negative Rate; [8]FCR=Fraction Correction Rate; * = N/A.

CHAPTER 3

DEVELOPMENT OF CULVERT RATING METHODOLOGY

Utilizing a culvert rating methodology is crucial for building the prioritization list in condition assessment (current information) and estimating the service life of culverts (future deterioration information). In this chapter, Section 3.1 summarizes rating systems in the U.S.; Section 3.2 includes culvert inventory datasets acquired from DOTs based on official requests; Section 3.3 explores AHP based on expert opinion survey to establish rating methodology for datasets from Oregon DOT; and Section 3.4 describes the rating methodologies based on overall rating opinion and structural rating opinion.

3.1 Culvert Rating Systems in U.S.

In the U.S., there are different types of rating systems to evaluate the performance of culverts, but no universally accepted one is available. Based on a literature search, rating systems used in the U.S. were identified.

The *Culvert Inspection Manual* describes how to rate a culvert based on severity of defects (Arnoult, 1986). The Recording and Coding Guide for Structure Inventory and Appraisal of the Nation's Bridges (FHWA, 1995) applied inspection and ratings developed in 1986 and added item No. 62 to evaluate the settlement, joints and structural condition and other aspects of the culvert structure. For metal culverts, Kurdziel (1988) developed a 10-scale condition rating system ranging from failure condition to excellent condition.

The Pennsylvania DOT established a culvert rating system based on physical condition, structural condition, flow condition and roadway deflection, in which the physical condition was selected for the overall condition score expressed as a single digit.

The California DOT developed a rating system for metal culvert barrels which is compatible with inventory datasets; rating factors include the waterway adequacy, shape, seams, joints and culvert material which were standardized in comparison charts.

The Oregon DOT developed a systemic culvert rating dataset including twenty-three factors. Measurement of each of the factors range from good to no rating, but no overall condition rating method was yet developed.

The Minnesota DOT evaluated structural condition of culverts based on the HydInfra management system, and the overall score ranges from 0 to 4. Yes/No are the only parameters used during rating in an effort to minimize human error.

The Ohio DOT's rating system has 16 factors which are evaluated from nine to zero ranging from excellent to fail. Cahoon (2002) proposed a rating system that includes nine factors which are selected from 33 parameters found to be statistically significant for the final rating. The Ohio Research Institute for Transportation and the Environment (ORITE) developed a new rating system for culverts based on a survey; the overall score was computed by adding scores of selected items (Mitchell et al, 2005).

The literature review provides the general background of rating systems in the United States. To investigate details of rating systems, culvert inventory datasets are needed which will be introduced in Section 3.2.

3.2 Culvert Inventory Data Collection

Data requests were sent to 28 agencies including the FHWA and the state DOTs, of which 12 agencies provided datasets. A sample of the inventory dataset request was presented in Appendix A. Acceptable formats of the inventory dataset includes, but are not limited to, DVD, CD, printout hardcopy and electronic files. Table 3.1 shows the agencies that provided the culvert inventory dataset and the corresponding formats.

Table 3.1 Agencies Providing Inventory Datasets

No.	Agencies	Formats
1	FHWA	Online Database
2	California	Electronic File (Email)
3	Colorado	Electronic File (Email)
4	New York	Electronic File (Email)
5	North Carolina	Electronic File (Email)
6	Ohio	Electronic File (Email)
7	Oregon	Electronic File, FTP & DVD
8	Utah	DVD (Photos & Reports)
9	Vermont	Electronic File (Email)
10	Wisconsin	Electronic File (Email)
11	Shelby County	Electronic File (Email) & CD
12	Maryland	Printout Copies (Mail)

Based on the datasets acquired, comparisons in terms of the number of culvert datasets, the number of rating factors and the number of description factors among transportation agencies were made. The aim of the comparison is to identify the objective for this research work; basic facts of datasets collected are given in Table 3.2.

Table 3.2 General Information of Data Acquired

Agency	Culvert Datasets	Rating Factors	Description Factors[1]
Oregon DOT	758	23	15
MN DOT	16,237	18	18
Caltrans	53,797	7	10
Ohio DOT	9313	15	34
Utah DOT	47.059	16	26
NC DOT	5,042	14	18
NYS DOT	11357	66	41
Shelby County	198	21	82
WI DOT	3662	NA	22
Colorado DOT	8455[2]	NA	NA

[1] Factors used for recording basic information of culvert, such as culvert ID, span, etc.

[2] National Bridge Inventory (NBI) datasets.

The Maryland DOT provided a sample of the inspection report; Utah DOT provided photos and reports of a finished project which is about the condition assessment of highway culverts. Shelby County provided not only the culvert inspection datasets, but also the software of Culvert Management System (CMS). The decision making for the preferred research objective was made based on following aspects:

- The completeness of datasets and data format.
- The number of rating factors.

- The number of datasets provided.
- The benefit of this research to the transportation agency.
- The year of system was developed.
- Rating scale of culverts.

After the preliminary screening, further comparison for rating factors was made among four DOTs, namely Oregon DOT, Ohio DOT, North Carolina DOT and Caltrans. Since there is no available standard to compare rating systems of culverts, the criteria should be carefully established. For a more precise comparison, the rating factors were divided into two groups, namely structural integrity and waterway condition. Normally, there are more factors to describe the structural aspect which can be further expanded to three categories called "barrel," "inlet and outlet structural," and the "roadway." Table 3.3 shows the comparison of rating factors made among the four rating systems.

Table 3.3 Comparison of Rating Factors among Four DOTs

Category	Oregon DOT	Ohio DOT	Caltrans	North Carolina DOT
Factors for Structural Integrity				
	Misalignment	Culvert Alignment	Alignment	Sufficiency Rating
	Abrasion	Slab	Material	Remaining Life
	Gen Brrl Damage	Abutment	Seams and joints	Pipe Condition
	Cracking	Protection	Shape	Top Slab
	Invert Dam	General	Piping	Bottom Slab
Barrel	Open Joints	Seams or Joints		Structure Alignment
	Out of Round	Shape		
	Settlement			
	Piping			
	Drift			
	Vegetation			
Inlet/Outlet Structures	Embankment Popouts	Embankment	Embankment	Wingwalls

	Embankment Seeps	End Structure	Flared End Section	Headwalls
	Embankment Erosion	Headwalls	Headwall	EXT & INT Walls
	Inlet Embankment Protection			
	Outlet Embankment Protection			
Roads	Pavement Cracking	Pavement	Roadway	Roadway Condition
	Roadway Sag			
	Guardrail Dip	Guardrail		
Factors for Water Way/Chanel				
Water Way	Inlet Channel Scour	Channel	Waterway adequacy	Waterway
	Outlet Channel Scour	Scour	Streambed Scour	Channel Alignment
	Steambank Erosion	Waterway Blockage		Scour
	Blockage			BC[1] Drain Systems

[1] Box Culvert.

Based on Table 3.3, the rating system from the Oregon DOT was selected to be the research objective since it has relatively more rating factors and meets more aspects of the selecting criteria. It is difficult to apply datasets to compare four rating systems; the decision about selecting the datasets from Oregon DOT is based on previous experience.

The rating system of the Oregon DOT consists of 23 factors, and the rating scale is from 0 to 4, a typical scale used by many DOTs. In this rating system, 4 indicates the best, 3 means fair, 2 means poor, 1 denotes worst and 0 means no rating. Currently, the Oregon DOT does not have an approach to compute the overall scores for each culvert, but definitions and ratings for 23 factors are well developed. The objective of Section 3.3 is to develop an algorithm to compute the overall score for culvert inventory datasets.

The following work, including the development of a culvert rating methodology and deterioration rate prediction, is based on the culvert inventory datasets provided by the Oregon DOT.

3.3 Analytic Hierarchy Process (AHP) Based on Expert Opinions

The Analytical Hierarchy Process (AHP) based on an expert opinion survey is used to establish weights of each factor. AHP is an algorithmic procedure wherein both data and experience play equally important roles. In this research, AHP used a three-level hierarchy-based model that reflects the goals and concerns of the decision-maker. The hierarchy was arranged in a descending order from the overall focus to the criteria, sub criteria, and alternatives. The hierarchy was then systematically evaluated using pairwise comparison of various criteria, matrix manipulation and eigenvalue computations, to obtain a final score for each alternative. AHP provided a systematic methodology to organize tangible and intangible factors and provided a structured, yet relatively simple, analysis algorithm to the decision-making problem (Yang and Allouche, 2010).

Based on characteristics of the factors, level 1 of AHP consisted of two parts: the culvert structural integrity and the water way. The structural integrity category included three parts as level 2, namely Barrel, Embankment and Roadway. No level 2 was assigned for water way since there are only 3 factors. Level 3 was formed by 23 factors from the inventory datasets. Figure 3.1 shows the structure of AHP including abbreviations for each factor.

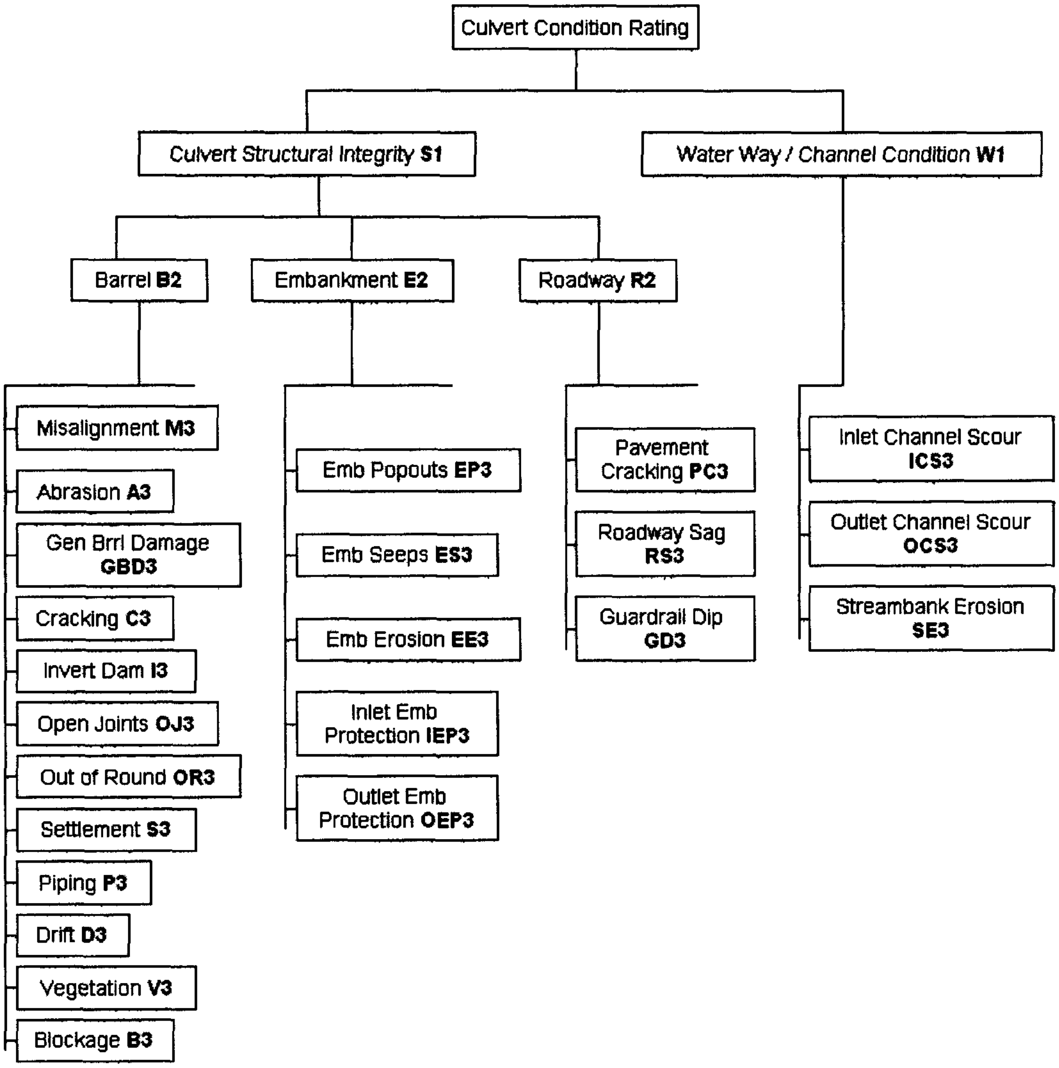

Figure 3.1 AHP for Culvert Rating Methodology

Table 3.4 shows the definitions of rating factors for the AHP, in which the rating scores range from 0 to 4 depending on the actual conditions of culverts when performing inspections.

Table 3.4 Definition of Rating Factors in AHP Structure (Oregon DOT 2010)

Title	Definition
Abrasion Rating	Wearing or grinding of the barrel material due to the sediment

	or debris working against the barrel.
Blockage Rating	Rating value of the blockage inside the structure.
Channel Scour - Inlet	Has the channel been deepened by scour at the inlet.
Channel Scour - Outlet	Has the channel been deepened by scour at the outlet.
Cracking Rating	Inspection rating of the impact of cracking on the structure.
Drift Rating	Debris that drifts on or near the water surface that passes though the culvert.
Embankment Protection - Inlet	Condition of the bank protection in place at the inlet of the culvert.
Embankment Protection - Outlet	Condition of the bank protection in place at the outlet of the culvert.
Erosion Rating	Rating value given to the impact of embankment erosion.
General Damage Rating	Rating value of the barrel/structure for general damage.
Guardrail Dip Rating	Rating value for deformation of guardrails.
Invert Damage	Rating value of damage to the invert. Bottom portion of the culvert/structure.
Open Joints Rating	Ratings value of open joints.
Out of Round Rating	Percentage rating of deformity to the barrel of the culvert from its original geometry.
Pavement Crack/Patch Rating	Cracks or patches observed in the pavement.
Piping Damage Rating	Rating the condition of fill material removed by seepage along a culvert barrel, forming a void adjacent to the culvert.
Popouts Rating	Rating value of the impact of noticeable outward/downward displacements of parts of the embankment.

Roadway Sag Rating	Rating value of roadway deviation from its original grade.
Seeps Rating	Inspection rating value given to the impact of any seeps in the embankment.
Settlement Rating	Rating value of embankment settlement.
Vegetation Obstruction Rating	Rating value for vegetation obstructing the inlet or outlet.

A survey form aiming to identify weights of each factor was sent to DOTs (see Appendix B). The general response rate was 41%. Respondents are professional engineers who have experience with culvert inspection and management. Table 3.5 shows responses from the survey.

Table 3.5 Responses from Survey

Response	14
No Response	18
Declined	2

3.4 Culvert Rating Methodology

Based on the questionnaires, the pairwise computation was applied to process the received data, weights of each factor in AHP is shown in Table 3.6. The overall rating represents opinions for weights of 23 factors while the structural rating only focuses on 20 factors, excluding the 3 factors from the water way condition. The structural rating only focuses on structural factors, which was easily achieved by simply setting the weight of the structural rating as 100%. Table 3.6 presents the definitions of factors for the culvert rating system, and it also lists weights of each factor in the AHP in terms of the overall rating methodology and the structural rating methodology. Table 3.6 provides two ways to rate a culvert; the overall rating represents the condition of the culvert based on all 23 factors, while the structural rating shows the condition of the culvert based on 20 factors which focuses on structural aspects. The survey report is included in Appendix C.

Table 3.6 Definition of Factors for Culvert Rating System and Weight of Factors in AHP

AHP Levels	Factors	Definition	Overall	Structural
Sample Size			14	14
Level 1	S1	Culvert Structural Integrity	56.79%	100%
	W1	Water Way Condition	43.21%	0%
	Total		**100%**	
Level 2	B2	Barrel	23.19%	40.83%
	E2	Embankment	15.61%	27.48%
	R2	Roadway	17.99%	31.68%
	Total		**56.79%=S1**	**100.00%=S1**
Level 3	M3	Misalignment	1.73%	3.05%
	A3	Abrasion	1.36%	2.39%
	GBD3	Gen Barrel Damage	1.85%	3.25%
	C3	Cracking	2.04%	3.60%
	I3	Invert Damage	2.05%	3.61%
	OJ3	Open Joints	2.27%	4.00%
	OR3	Out of Round	1.77%	3.12%
	S3	Settlement	2.42%	4.26%
	P3	Piping	2.79%	4.90%
	D3	Drift	1.44%	2.53%
	V3	Vegetation	1.22%	2.16%
	B3	Blockage	2.25%	3.97%
	Total		**23.19%=B2**	**40.83%=B2**
	EP3	Embankment Pop-outs	2.53%	4.45%
	ES3	Embankment Seeps	2.84%	5.01%
	EE3	Embankment Erosion	3.17%	5.59%
	IEP3	Inlet Embankment Protection	3.38%	5.95%
	OEP3	Outlet Embankment protection	3.68%	6.49%
	Total		**15.61%=E2**	**27.48%=E2**
	PC3	Pavement Cracking	3.54%	6.24%

R S3	Roadway Sag	7.34%	12.93%
GD3	Guardrail Dip	7.11%	12.52%
Total		**17.99%=R2**	**31.68%=R2**
ICS3	Inlet Channel Scour	14.88%	0
OCS3	Outlet Channel Scour	15.50%	0
SBE3	Stream Bank Erosion	12.83%	0
Total		**43.21%=W1**	**0%=W1**

Eq. 3.1 shows the algorithm for the computation of overall scores of culverts based on the overall rating,

$$Condition\,Score\,for\,General\,Rating = (0.0173 \times M3 + 0.0136 \times A3 + 0.0185 \times GBD3 + 0.0204 \times C3 + 0.0205 \times I3 + 0.0227 \times OJ3 + 0.0177 \times OR3 + 0.0242 \times S3 + 0.0279 \times P3 + 0.0144 \times D3 + 0.0122 \times V3 + 0.0225 \times B3) + (0.0253 \times EP3 + 0.0284 \times ES3 + 0.0317 \times EE3 + 0.0338 \times IEP3 + 0.0368 \times OEP3) + (0.0354 \times PC3 + 0.0734 \times RS3 + 0.0711 \times GD3) + (0.1488 \times ICS3 + 0.1550 \times OCS3 + 0.1283 \times SBE3). \quad (3.1)$$

Eq. 3.2 shows the algorithm for the computation of overall scores of culverts based on the structural rating,

$$Condition\,Score\,for\,Structural\,Rating = (0.0305 \times M3 + 0.014 \times A3 + 0.0239 \times GBD3 + 0.0360 \times C3 + 0.0361 \times I3 + 0.040 \times OJ3 + 0.0312 \times OR3 + 0.0426 \times S3 + 0.0490 \times P3 + 0.0253 \times D3 + 0.0216 \times V3 + 0.0397 \times B3) + (0.0445 \times EP3 + 0.0501 \times ES3 + 0.0559 \times EE3 + 0.0595 \times IEP3 + 0.0649 \times OEP3) + (0.0624 \times PC3 + 0.0734 \times RS3 + 0.0711 \times GD3). \quad (3.2)$$

The datasets are in the format of a Microsoft® Excel file; thus, the above two equations can be easily added as two extra columns into original files. Overall scores, computed from the Eq. 3.1 and the Eq. 3.2, include one decimal, which have to be converted to the scale currently used by the Oregon DOT that ranges from zero to four.

Table 3.7 shows the conversion chart for the overall scores that are computed by Eq. 3.1 and Eq. 3.2. In this chart, the condition four includes the culverts scored from 3.5 to 4.0, which is a conservative approach to guarantee the safety of the culvert asset. The condition one has a wider range, from 0.1 to 1.4, which aims to address more culverts in severe conditions.

Table 3.7 Rating Score Conversion Chart

Conditions	Description	Range	
		From	To
4	Good	3.5	4.0
3	Fair	2.5	3.4
2	Poor	1.5	2.4
1	Critical	0.1	1.4
0	No Rating	0	0

When computing the overall scores of culverts, there are factors showing no rating, which means the inspection score of this factor is zero. The existence of factors having no rating has a significant influence to the overall score. There are two opinions regarding this issue at the time of developing this rating system. The first opinion is that including an unrated factor score may create a false score; another opinion is that assuming zero in lack of an assigned value results in a conservative overall score.

In this research, the Oregon DOT suggested employing the second opinion, in which all factors in datasets rated as zero will be applied for the overall score computation. The reasons explained by the Oregon DOT use real cases. For example, due to the high flow or if the barrel is backwatered, especially in coastal environments, the invert and other barrel field cannot be rated which will be assumed as a worst case scenario to issue a score zero. In turn, the project team, dive team, or maintenance can go back out in better conditions and more accurately rate the barrel fields. There is an exception for factor guardrail. If there was no guardrail, zero was issued when inspections were performed since four may be misleading to indicate the existence of culvert. In this research, guardrails rated as zero, were suggested to adjust to four by the Oregon DOT, which would give a better representative picture of the condition of the culvert.

CHAPTER 4

DEVELOPMENT OF MARKOV MODEL FOR CULVERT DETERIORATION PREDICTION

Deterioration prediction for culvert structures utilizing the Markov model aims to provide reliable future information to optimize decision making so as to maximize the service life of culvert assets. Section 4.1 gives the basic theory of the deterioration prediction for culverts using the Markov model. Section 4.2 analyzes the data source applied for the deterioration prediction. Section 4.3 discusses the model calibration technique utilizing the MHA. Section 4.4 presents the programming and running for the model calibration and the service life estimation. Section 4.5 includes the model validation performed by a Pearson's chi-square test. Section 4.6 describes the field calibration method which is based on inspection photos.

4.1 Markov Model in Deterioration Prediction for Culverts

The Markov model has been introduced in Section 2.3.1.1, and its calibration method, the MHA, is presented in Section 4.3. To apply the Markov model to the culvert deterioration problem, it is necessary to adjust the parameters based on characteristics of datasets. Parameters of the Markov model include the size of the transition matrix, homogenous or non-homogenous, and the time interval which is based on the developed rating methodology in Chapter 3.

The Markov model, also called the Markov chain, is a stochastic process that in a space which consists of a sequence of discrete random variables, $\{X_0, X_1, X_2, \ldots\}$, at each time when $t \geq 0$, the next state X_{t+1} depends only on the current state X_t. This statement means X_{t+1} does not depend on the history states $\{X_0, X_1, \ldots, X_{t-1}\}$ (Gilks, 1996). In this study, since the culvert rating has 4 states, which are 4 (good), 3 (fair), 2 (poor) and 1 (critical), so the transition matrix for X_t is a four by four matrix P, see Eq. 4.1, which shows the probability of changing state within one year (Micevski, 2002),

$$P = \begin{bmatrix} p_{44} & p_{43} & p_{42} & p_{41} \\ 0 & p_{33} & p_{32} & p_{31} \\ 0 & 0 & p_{22} & p_{21} \\ 0 & 0 & 0 & p_{11} \end{bmatrix}, \tag{4.1}$$

where p_{ij}=the transition probability from the state i to the state j over a time interval, which in this research, was assumed to be one year.

For example, p_{43} denotes the probability that the culvert moves from condition 4 (good) to condition 3 (fair) in 1 year. For $i < j$, $p_{ij} = 0$, means the culvert cannot change from one condition to another condition that is better than before without maintenance. For example, p_{14} denotes the probability is 0 for the culvert to move from condition 1 (critical) to 4 (good), which matches with engineering experience.

Given the transition matrix from the Markov model, the condition of a culvert after t years can be obtained by Eq. 4.2, the Chapman-Kolmogorov formula,

$$C_k^t = C_k^0 \cdot \left(P_{ij}\right)^t, \tag{4.2}$$

where C_k^t=the probability of a culvert in state k at year t; C_{ik}^0=the initial state of I; P_{ij}=the transitional probability; k=condition states of culvert ranging from 1 to 4. Eq. 4.2 can be expanded to Eq. 4.3 as following,

$$[c_4^t \quad c_3^t \quad c_2^t \quad c_1^t] = [c_4^0 \quad c_3^0 \quad c_2^0 \quad c_1^0] \cdot \begin{bmatrix} p_{44} & p_{43} & p_{42} & p_{41} \\ 0 & p_{33} & p_{32} & p_{31} \\ 0 & 0 & p_{22} & p_{21} \\ 0 & 0 & 0 & p_{11} \end{bmatrix}^t, \qquad (4.3)$$

where: $C_i^t = [c_4^t \quad c_3^t \quad c_2^t \quad c_1^t]$=the probability distribution of four conditions to the culvert at year t; $C_i^0 = [c_4^0 \quad c_3^0 \quad c_2^0 \quad c_1^0]$ =initial state of culvert, of which $C_i^0 = [1 \quad 0 \quad 0 \quad 0]$ in this study.

4.2 Data Source

The datasets are acquired from culvert inventory datasets developed and managed by the Oregon DOT. The datasets were input when performing field inspection; Table 4.1 gives the background information of inventory datasets for this research.

Table 4.1 Data Source

Road ID	Culverts Number	Built Years	Inspection Years	Geography
Hwy 053 (U.S. 26)	216	1935	June 2007	Hood River/Wasco County (North Central Oregon)
Hwy 009 (U.S. 101)	108	1930	May 2009	Clatsop County (Northwestern Oregon)
Hwy 045 (OR 38)	434	1931	April 2009	Douglass County (Southwestern Oregon)

The term "highway" followed by the three digit index is a designation that is only used internally by the Oregon Department of Transportation. The State highway index number is used to identify State highways and set the mile posts along the highway system. The highway index number is different than the signs and routes along the highway and those listed on the Oregon official state highway map.

Warms Springs Highway 053 makes up a segment of U.S. 26. The Highway begins at mile point 57.45; datasets include 63 to 86 that travel off the east slope of the Cascade Mountain Range which has a lot of snow and rain. Mile point 86 to 113 are within the high desert with an annual rainfall average around 12 to 16 inches. For the Highway 053, a major realignment of this highway took place in the 1940s. Highway 053 between Mt. Hood and Madras has not seen many changes recently. No construction plans before the reconstructions were found, so the built year was estimated as 1920s to 1930s. Figure 4.1 shows the sections of Highway 053 in the datasets.

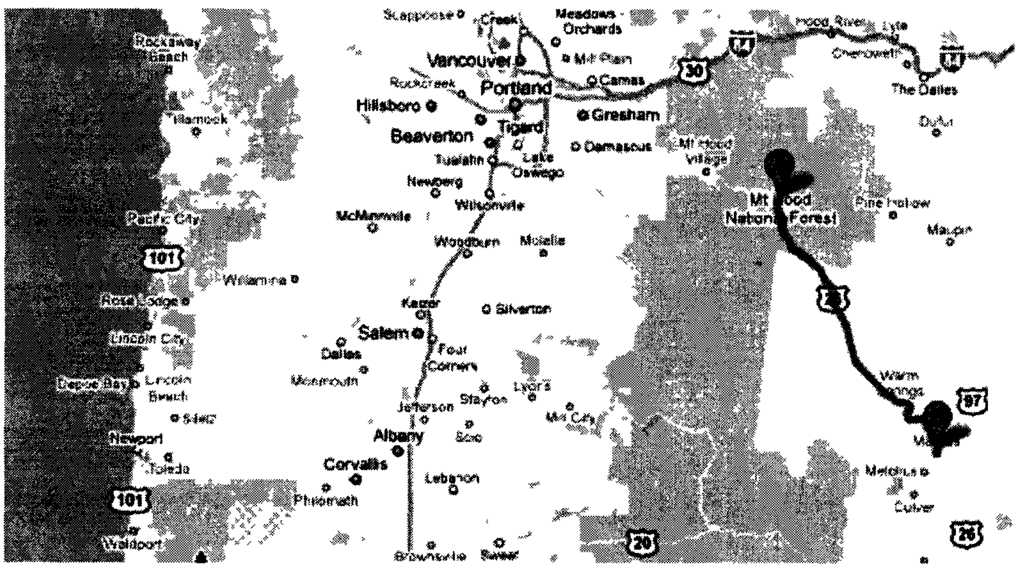

Figure 4.1 Section of Hwy 053 Shown from Points A to B (Google Map)

Oregon Coast Highway 009 (U.S. 101) is a highway that runs adjacent to the Pacific Ocean along the entire Oregon coast; datasets include the sections basically from the City of Astoria/Warrenton, south to just past the town of Cannon Beach. Mile points start north and increase to the south. Highway 009 has gone through many changes, as most of the highway was built in the 1930s. Figure 4.2 shows the sections of Highway 009 in the datasets.

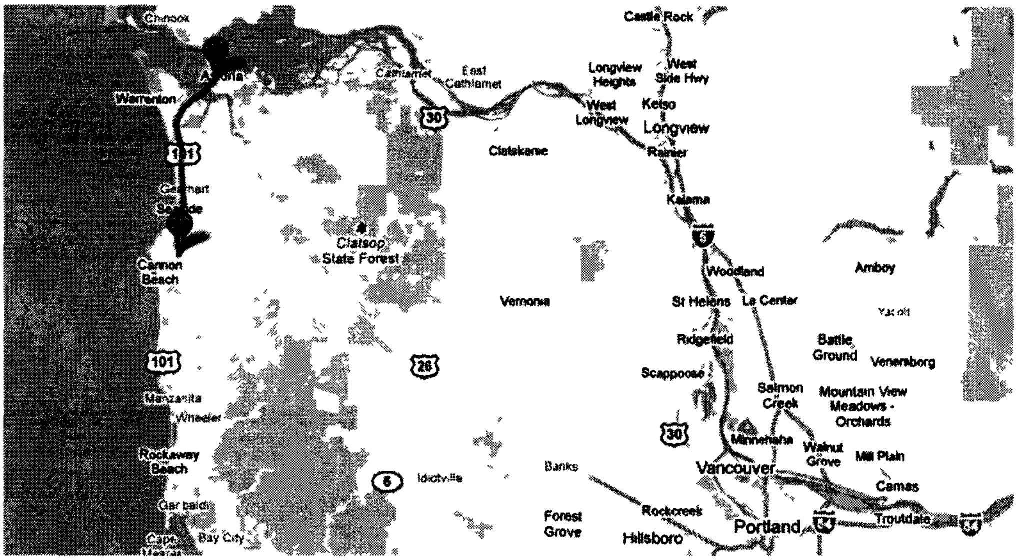

Figure 4.2 Section of Hwy 009 Shown from Points A to B (Google Map)

The Umpqua Highway 045 (OR 38) was built in the 1930s of which datasets include the section from Reedsport on the coast to Interstate 5. The mile points start at the coast and increase heading east. A portion of Highway 045 is located near the Pacific Coast and the tidal estuaries. Culverts located along this section are influenced from the salt environment and water, which are up to mile point 10. The remaining section of Highway 045 travels through the coastal mountains to Interstate 5. Figure 4.3 shows the sections of highway 045 in the datasets.

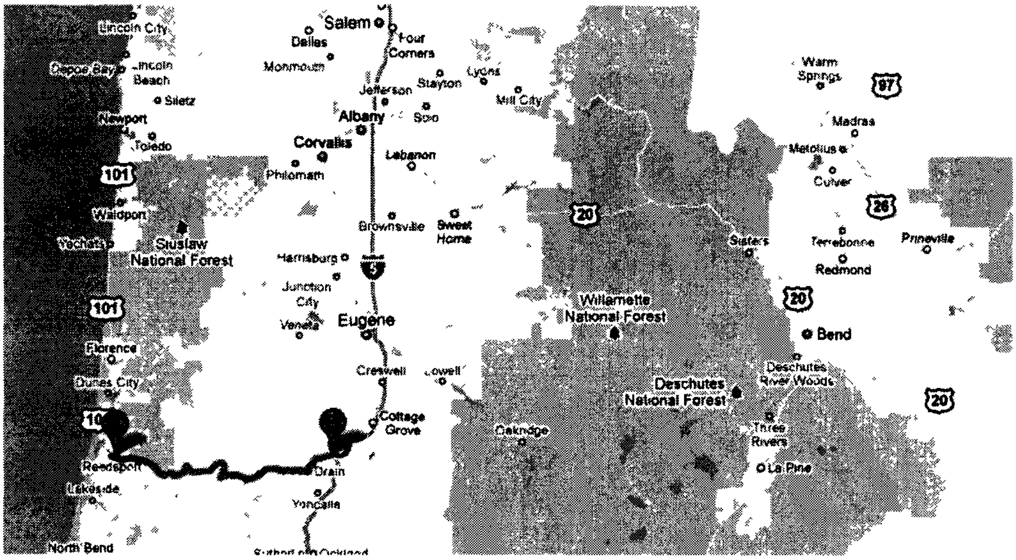

Figure 4.3 Section of Hwy 045 Shown from Points A to B (Google Map)

Since no information about the year the culverts were built was available in the culvert inventory datasets, three assumptions to infer ages of culverts were made. The estimation of age information was based on construction plans of highways which include the rehabilitation and replacement of culverts dating back to 1930s. The first assumption was that when the construction of the highway was initiated, the culvert was considered as a new culvert with an age of zero.

Secondly, if renewal actions were initiated on whole road sections, the previous ending conditions of culverts will be considered as condition 2. Finally, the percentage of culverts at condition 4 in the datasets was considered to be high following 60 years of service, which necessitate reduction to match engineering experience.

Based on these three assumptions, Table 4.2 shows the processed datasets for the overall rating methodology, and Table 4.3 shows the processed datasets for the structural rating methodology.

Table 4.2 Datasets (Overall)

Age	Culvert Condition			
	4	3	2	1
7	8	1	0	0
8	54	0	0	0
10	17	10	1	0
18	11	0	0	0
19	17	14	0	0
32	1	2	0	0
33	2	0	0	0
34	1	0	0	0
37	8	3	0	0
41	0	0	10	0
50	3	1	0	0
59	0	0	54	0
60	2	12	0	0
62	0	1	0	0
72	3	0	0	0
78	1	16	1	2
79	1	2	0	0
Subtotal	129	62	66	2
			Total	259

Table 4.3 Datasets (Structural)

Age	Culvert Condition			
	4	3	2	1
7	2	7	0	0
8	53	1	0	0
10	6	21	1	0
18	11	0	0	0
19	11	19	1	0
32	1	2	0	0
33	0	2	0	0
34	1	0	0	0
37	1	10	0	0
41	0	0	10	0
50	1	3	0	0
59	0	0	54	0
60	2	19	0	0
62	0	1	0	0
72	3	0	0	0
78	1	2	8	2
79	1	2	0	0
Subtotal	94	89	74	2
			Total	259

The datasets were randomly split into two parts, 80% for the calibration and 20% for the validation. Model calibration is discussed in Section 4.3, and model validation is presented in Section 4.5.

Table 4.4 shows calibration datasets for the overall rating; Table 4.5 shows calibration datasets for the structural rating.

Table 4.4 Calibration Datasets (Overall)

Age	Culvert Condition			
	4	3	2	1
8	54	0	0	0
10	17	10	1	0
19	17	14	0	0
59	0	0	54	0
60	2	12	0	0
72	3	0	0	0
78	1	16	1	2
79	1	2	0	0
Subtotal	95	54	56	2
			Total	207

Table 4.5 Calibration Datasets (Structural)

Age	Culvert Condition			
	4	3	2	1
8	53	1	0	0
10	6	21	1	0
19	11	19	1	0
59	0	0	54	0
60	2	19	0	0
72	3	0	0	0
78	1	2	8	2
79	1	2	0	0
Subtotal	77	64	64	2
			Total	207

Table 4.6 shows validation datasets for the overall rating; Table 4.7 shows validation datasets for the structural rating.

Table 4.6 Validation Datasets (Overall)

Age	Culvert Condition			
	4	3	2	1
7	8	1	0	0
18	11	0	0	0
32	1	2	0	0
33	2	0	0	0
34	1	0	0	0
37	8	3	0	0
41	0	0	10	0
50	3	1	0	0
62	0	1	0	0
Subtotal	34	8	10	0
			Total	52

Table 4.7 Validation Datasets (Structural)

Age	Culvert Condition			
	4	3	2	1
7	2	7	0	0
18	11	0	0	0
32	1	2	0	0
33	0	2	0	0
34	1	0	0	0
37	1	10	0	0
41	0	0	10	0
50	1	3	0	0
62	0	1	0	0
Subtotal	17	25	10	0
			Total	52

4.3 Model Calibration Technique

Model calibration is used to infer the transition matrix P for the Markov model, which is performed by the Markov chain Monte Carlo (MCMC) method. The theoretical support of the Bayesian inference is needed for the MCMC, see Eq. 4.4,

$$P(\theta|D) = \frac{P(D|\theta) \cdot P(\theta)}{P(D)}, \qquad (4.4)$$

where: θ=unknown parameters; D=observed fact; $P(\theta|D)$= the posterior distribution of θ; $P(D|\theta)$=the likelihood to observe D based on the known θ provided by the sampling; $P(\theta)$=the prior knowledge about θ; $P(D)$=constant value.

Next, Eq. 4.4 was applied to the deterioration prediction problem for culverts which utilizes the Markov model. Then $P(\theta|D)$ is the posterior distribution of the transition matrix P; $P(D|\theta)$ is the likelihood to observe culvert conditions, given P from the sampling algorithm. The objective of the Bayesian inference is to evaluate the $P(\theta|D)$ based on the prior distribution of θ and the observed fact, D. In theory, the posterior expectation is possible to be evaluated by generating samples from posterior distribution π utilizing Monte Carlo integration, which can approximate to a very accurate result by increasing the sample size. Normally, it is impossible since there is no standard expression for π, but drawing samples from a process that is proportional to π is feasible, if this process is performed through the Markov chain which has a stationary distribution that is equal to π, then it is called Markov chain Monte Carlo (Gilks, 1996).

In this study, the MHA, a member of MCMC methods, was selected to construct a Markov chain that has the expected posterior distribution as its stationary distribution. The theory of MHA was used to generate the candidate (transition matrix) based on a fixed sampling algorithm. The qualified candidates will pass the testing and the chain keeps moving to the optimum point, where the chain converges.

The candidate point X_{t+1} is generated by the proposed symmetric distribution q, a multivariate normal distribution, and the variance-covariance matrix $\sum$. Comparing the random variable U that is uniformly sampled from (0, 1) with α (see Eq. 4.5), if $U \leq \alpha(X_t, X_{t+1})$, the proposed X_{t+1} is accepted, and the chain moves; or it will be rejected, and the chain stays at current point. The MHA runs a large number until the chain converges to the stationary based on the optimum setting of the proposed distribution q and the $\sum$. Since q is a symmetric distribution, so $q(X_t|X_{t+1}) = q(X_{t+1}|X_t)$, Eq. 4.5 can be simplified to Eq. 4.6. For Eq. 4.7, derived from Eq. 4.4, π_0 is fixed, so π is proportional to L, therefore $\frac{\pi(X_{t+1})}{\pi(X_t)}$ can be easily obtained by computing $\frac{L(X_{t+1})}{L(X_t)}$,

$$\alpha(X_t, X_{t+1}) = min\left(1, \frac{\pi(X_{t+1})q(X_t|X_{t+1})}{\pi(X_t)q(X_{t+1}|X_t)}\right), \tag{4.5}$$

$$\alpha(X_t, X_{t+1}) = min\left(1, \frac{\pi(X_{t+1})}{\pi(X_t)}\right), \tag{4.6}$$

$$\pi(\theta|D) \propto L(D|\theta) \times \pi_0(\theta), \tag{4.7}$$

where $\pi(\theta|D)$ =the posterior distribution of P; $\pi(\theta|D)$ =the likelihood function; $\pi_0(\theta)$=the prior distribution of P. The likelihood function is presented in Eq. 4.8; for the convenience of programming, the logarithm format is applied, see Eq. 4.9,

$$L(D|\theta) = \prod_{t=1}^{T} \prod_{k=1}^{4} (C_k^t)^{M_k^t}, \tag{4.8}$$

$$log[L(D|\theta)] = \sum_{t=1}^{T} \sum_{k=1}^{4} M_k^t \cdot log(C_k^t), \tag{4.9}$$

where: t=culvert age (years); T=the largest age of culvert from inspection datasets; k=the conditions of culvert; M_k^t=the number of culvert in the condition k at the year t; C_k^t=the probability in the condition k at year t calculated by the C-K formula.

If the $\sum$ is too large, the acceptance rate will decrease and the chain is hard to converge to the stationary. If the $\sum$ is too small, the acceptance rate will increase but the chain converges slowly. The common rule to pick the optimum $\sum$ is that the acceptance rate of the algorithm should be close to 0.234 (Roberts, 2001).

4.4 Programming and Calibration

The MATLAB$^{@}$ R2007b software was selected to program the model calibration based on the MHA. The codes are presented in Appendix D. The program was run 5,000 times to make sure Markov chain converged to the stationary. Accepted iterations completed at final 1,500 running were used for calculating the average value of P.

The variance-covariance matrix is critical for the convergence of the Markov model, which affects the acceptance rate; trial running has to be performed to make sure the acceptance rate can be close to the optimum value of 0.234. Table 4.8 shows the variance-covariance matrixes for the model calibration. Table 4.9 shows the final acceptance rates for the MHA based on two rating methodologies, which are 0.234 for the overall rating and 0.235 for the structural rating.

Table 4.8 Variance-covariance Matrices for Model Calibration

Overall Rating				Structural Rating			
0.45	0.00	0.00	0.00	0.42	0.00	0.00	0.00
0.00	0.30	0.00	0.00	0.00	0.31	0.00	0.00
0.00	0.00	0.35	0.00	0.00	0.00	0.25	0.00
0.00	0.00	0.00	0.3	0.00	0.00	0.00	0.30

Table 4.9 Acceptance Rates for MHA

Rating Methodology	Total Running	Accepted Iteration	Acceptance Rate

Overall Rating	5000	1170	0.234
Structural Rating	5000	1175	0.235

To monitor the MHA running and the convergence of the Markov model, the norm of the matrix was introduced. The norm of matrix is a scalar which describes the magnitude of the elements in the matrix. Norm in MATLAB® has different types. In this study, the maximum value of the singular value decomposition (SVD) was returned as the norm value.

The norm of transitional matrix indicates the magnitude of acceptance, P; the norm of $(P_{\text{new}} - P_{\text{old}})$ indicates the magnitude changes of the adjacent P. If the Markov chain converges well, the norm of transitional matrix should be stable and norm of $(P_{new} - P_{old})$ will be close to 0. Figure 4.4 demonstrates the norm of P for overall rating datasets; Figure 4.5 demonstrates the norm of $(P_{new} - P_{old})$ for overall rating datasets.

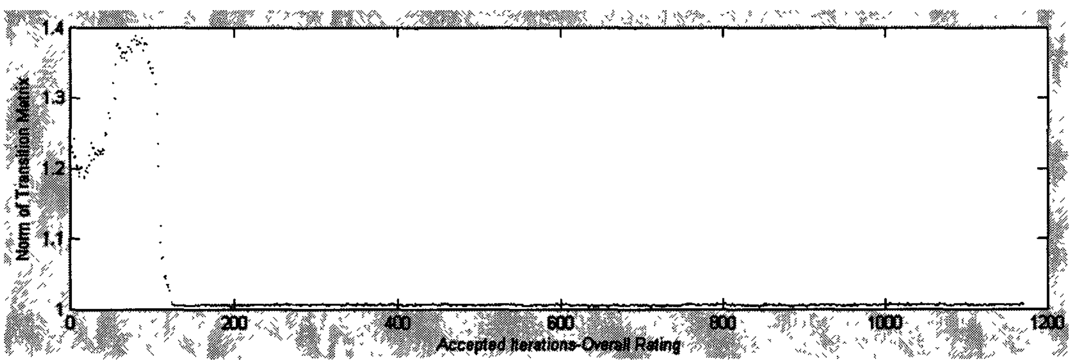

Figure 4.4 Norm of Transition Matrices for Overall Rating

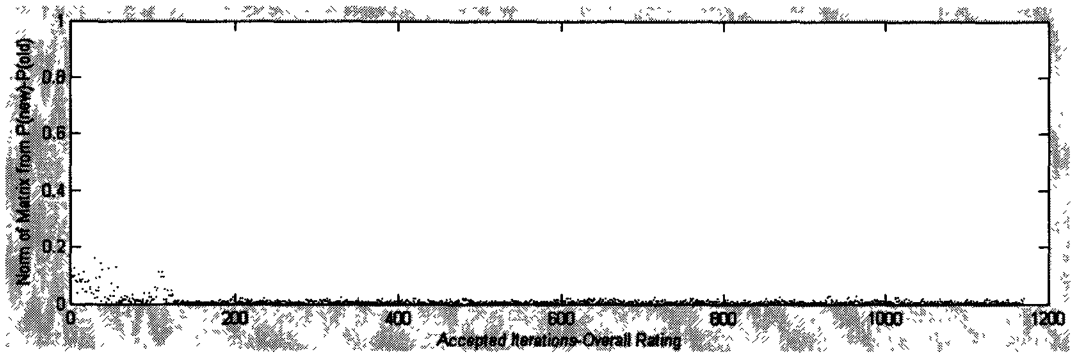

Figure 4.5 Norm Error for Transition Matrices for Overall Rating

Figure 4.6 demonstrates norm of P for the structural rating; Figure 4.7 demonstrates norm of $(P_{new} - P_{old})$ for the structural rating.

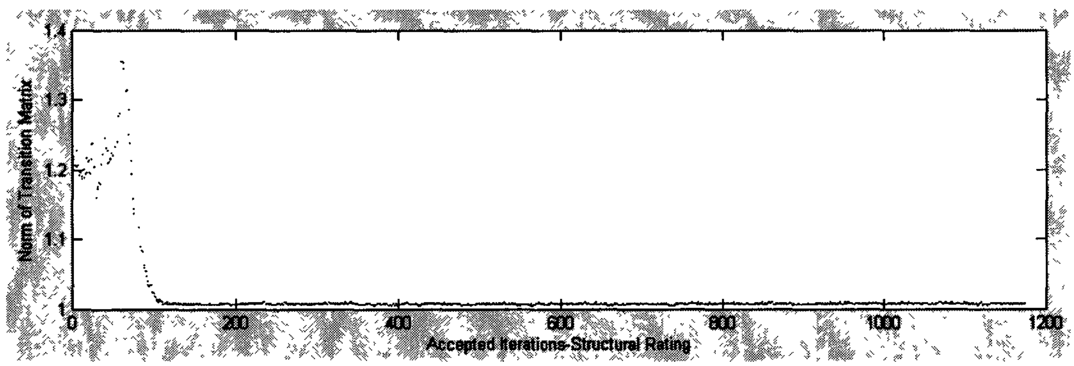

Figure 4.6 Norm of Transition Matrices for Structural Rating

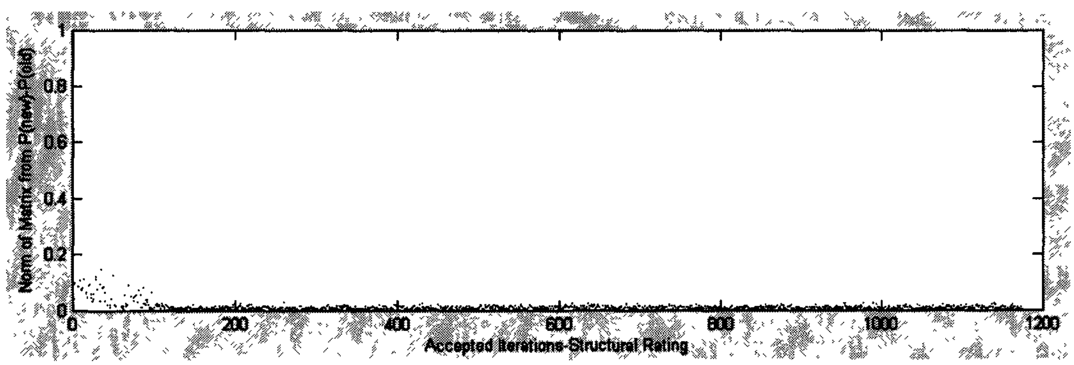

Figure 4.7 Norm Error for Transition Matrices for Structural Rating

Figure 4.4 and Figure 4.6 indicate that the Markov model converged to stationary after less than 200 iterations (accepted running).Transitional matrixes computed by the MHA are presented in Table 4.10 in terms of the overall rating and the structural rating.

Table 4.10 Transition Matrices from Calibration Datasets

Overall Rating				Structural Rating			
0.9684	0.0316	0.0000	0.0000	0.9583	0.0413	0.0003	0.0001
0.0000	0.9759	0.0238	0.0004	0.0000	0.9716	0.0284	0.0000
0.0000	0.0000	0.9994	0.0006	0.0000	0.0000	0.9995	0.0005
0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	1.0000

By applying transition matrices to the C-K formula, see Eq. 4.3, the deterioration trend of culverts at the network level and service life of the culvert at the individual level can be achieved. The result of Eq. 4.2, $[c_4^t \quad c_3^t \quad c_2^t \quad c_1^t]$, at the network level can be a proportion of culverts in condition k at year t. At the individual level, it indicates the condition of culvert (group average) at year t.

For example, for the overall rating at year 19, $[c_4^{19} \quad c_3^{19} \quad c_2^{19} \quad c_1^{19}] = [0.5433 \quad 0.3614 \quad 0.0938 \quad 0.0019]$, which means 54.33% of culverts are in condition 4 (network level). For an individual level, it means the probability of culvert to stay in condition 4 is 54.33%, then this culvert will be recognized as condition 4 since 54.33% is the largest value in $[c_4^{19} \quad c_3^{19} \quad c_2^{19} \quad c_1^{19}]$. Figure 4.8 shows deterioration curves for culverts based on overall rating; Figure 4.9 shows deterioration curves for culverts based on structural rating.

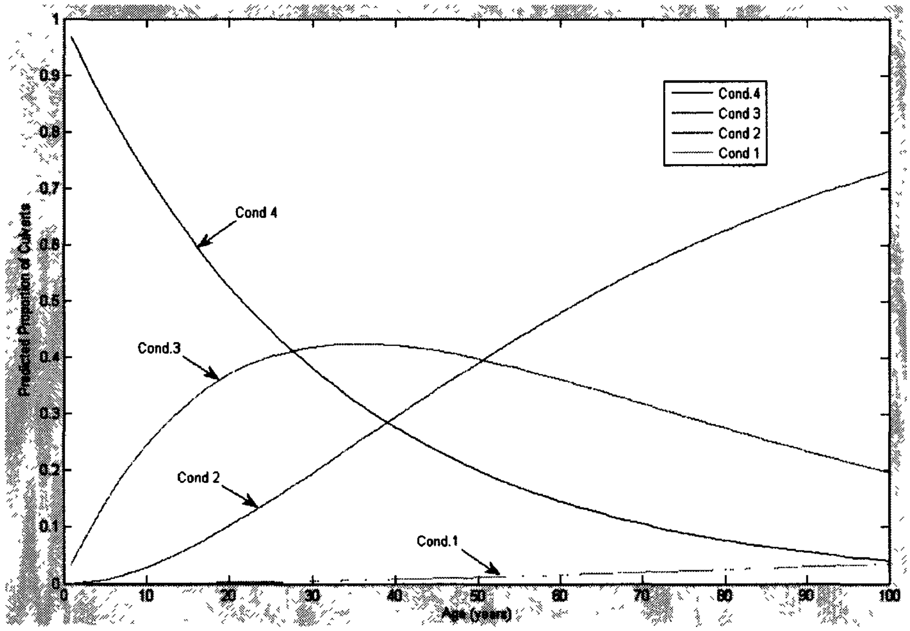

Figure 4.8 Deterioration Curves for Culverts from Overall Rating

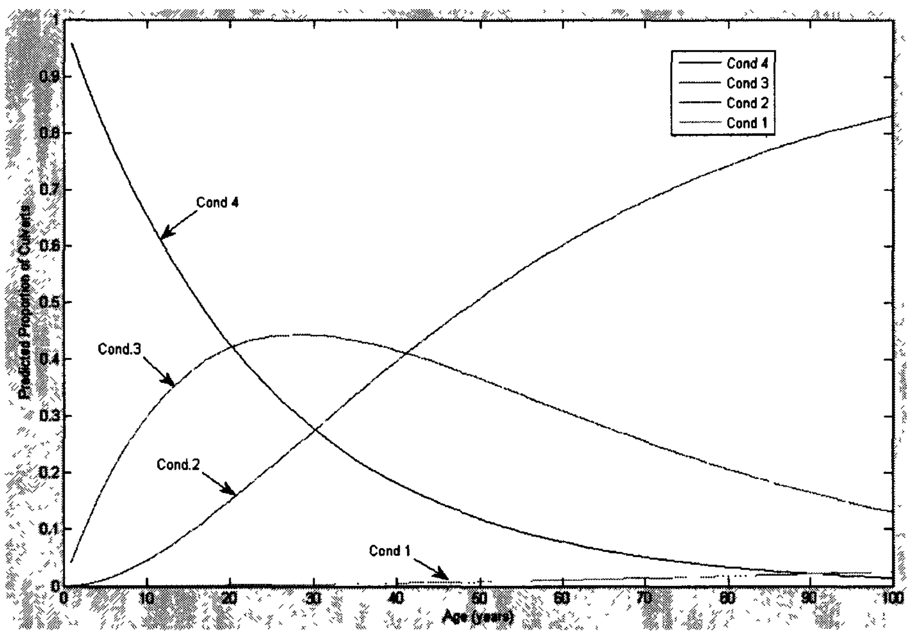

Figure 4.9 Deterioration Curves for Culverts from Structural Rating

The service life estimation is based on applying $[c_4^t \quad c_3^t \quad c_2^t \quad c_1^t]$ to culverts at the individual level, which represents the average service life of the culvert group (see Table 4.11). Figure 4.10 and Figure 4.11 are derived based on Table 4.11.

Table 4.11 Culvert Service Life Prediction

Culvert Condition	4 Good	3 Fair	2 Poor	1 Critical*
Overall Rating Methodology (years)	0	28	52	77
Structure Rating Methodology (years)	0	21	42	63

* Computed by curve fitting, see Fig. 4.10 and Fig. 4.11

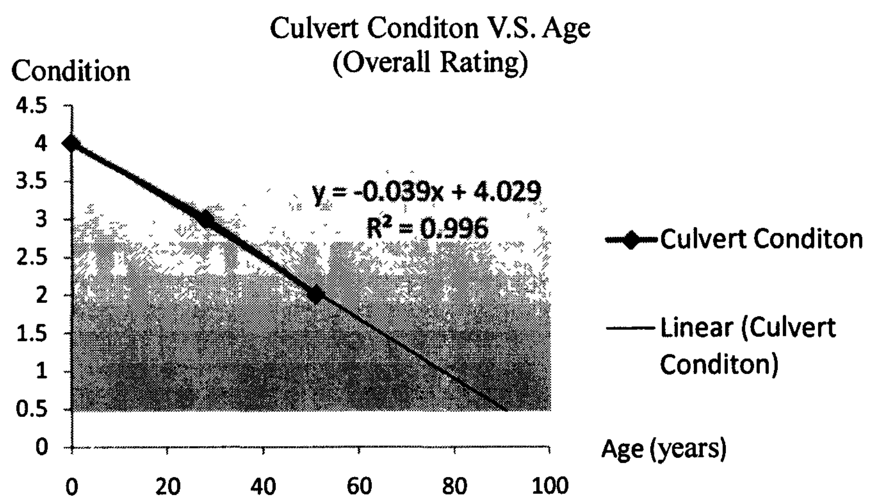

Figure 4.10 Service Life Curve for Culvert based on Overall Rating

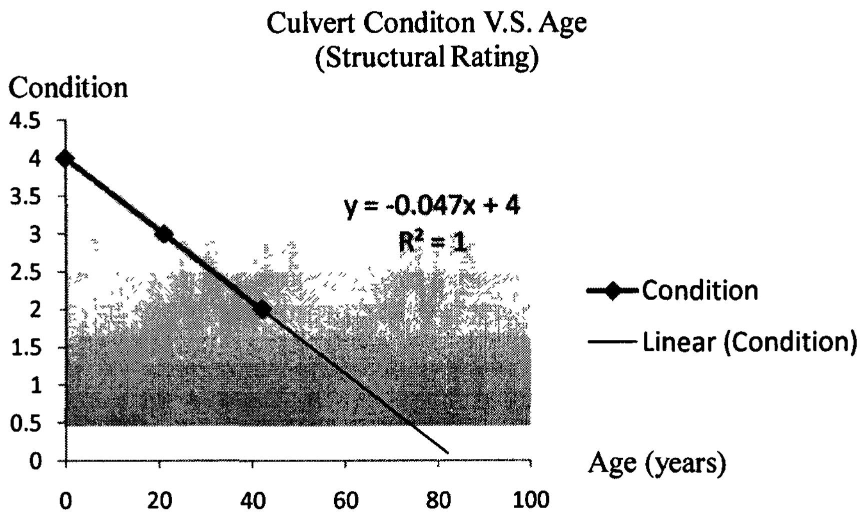

Figure 4.11 Service Life Curve for Culvert based on Structure Rating

Equations in Figure 4.10 and Figure 4.11 are constructed based on datasets of condition 4, 3 and 2, which fit curves for the service life of culverts. Eq. 4.10 and Eq. 4.11 are obtained by transformation of the regression equations shown in Figure 4.10 and Figure 4.11,

$$t = -25.5 * C_{General} + 102.83, \tag{4.10}$$

where: $C_{General}$=culvert condition at year t based on overall rating; t=culvert age (years),

$$t = -21 * C_{Structural} + 84, \tag{4.11}$$

where: $C_{Structural}$=culvert condition at year t based on structural rating; t=culvert age (years).

4.5 Model Validation by Pearson's Chi-square Test

Pearson's chi-square test is applied to the validation of datasets, and is capable of evaluating goodness-of-fit to the developed model. The 95% confidence level and $(n-1)$ degree of freedom are parameters for testing, in which n means total conditions of the culverts. Based on developed rating methodologies, n is 4, so the critical value will be 7.81. If the chi square value, computed from validation dataset, is lower than the critical value, the model passes testing. Chi-square value indicates the fitness level between the predicted frequency of culvert conditions and the observed frequency of culvert conditions. Eq. 4.12 shows the Pearson's χ^2 statistic, and testing results are listed in Table 4.12,

$$\chi^2 = \sum_{i=1}^{4} \frac{(O_i - P_i)}{P_i}, \tag{4.12}$$

where O_i means the observed number of culverts in condition i, P_i denotes the predicted number of culverts in condition i, and i ranges from 4 to 1 indicating the condition of the culverts.

Table 4.12 Pearson's Chi-square Test for Deterioration Prediction Models

Overall Rating Methodology (Failed)				Structural Rating Methodology (Passed)			
Condition	Observed	Predicted	$\frac{(O_i-P_i)}{P_i}$	Condition	Observed	Predicted	$\frac{(O_i-P_i)}{P_i}$
1	0	1	0.00	1	0	1	0
2	10	10	0.00	2	10	14	1.14
3	8	19	6.37	3	25	20	1.25
4	34	22	6.55	4	17	18	0.06
$\chi^2 = 12.91 > \chi^2_{(0.05,3)} = 7.81$				$\chi^2 = 2.45 < \chi^2_{(0.05,3)} = 7.81$			

The Markov model based on overall rating failed the χ^2 testing, while the model based on structural rating passed the test, indicating the latter exhibits better performance for the dataset considered in this study.

For further validation of the model calibration, the datasets were randomly split two additional times, with 80% of the data used for calibration and 20% for validation. Table 4.13 summarized the characteristics of the datasets used in the three runs.

Table 4.13 Data Splitting Based on Structural Rating Methodology

Culvert Ages	First Splitting[1]		Second Splitting		Third Splitting	
	Calibration 80%	Validation 20%	Calibration 80%	Validation 20%	Calibration 80%	Validation 20%
7		√	√		√	
8	√		√		√	
10	√		√			√
18		√	√		√	
19	√			√	√	
32		√	√			√
33		√		√	√	
34		√		√	√	
37		√	√		√	
41		√		√	√	
50		√	√		√	
59	√		√		√	
60	√		√			√
62		√		√	√	
72	√			√	√	
78	√		√		√	
79	√			√	√	

[1] Given by Table 4.5 and Table 4.7.

Model calibration was performed using the program described in Section 4.4. Transition matrices, calibrated by the MHA algorithm, for second and third data splits are listed in Table 4.14, while the transition matrix for first splitting is presented in Table 4.10.

Table 4.14 Transition Matrices for Second and Third Data Splitting

Second Splitting				Third Splitting			
0.9556	0.0442	0.0000	0.0002	0.9630	0.0364	0.0002	0.0004
0.0000	0.9724	0.0276	0.0000	0.0000	0.9564	0.0436	0.0000
0.0000	0.0000	0.9998	0.0002	0.0000	0.0000	0.9999	0.0001
0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	1.0000

The acceptance rate is 0.262 for the second splitting, 0.264 for the third splitting. Deterioration curves for second and third splitting generated based on the transition matrices in Table 4.14, are presented in Appendix E.

Pearson's chi-square test for the second and third splits was performed; and the results are summarized in Table 4.15.

Table 4.15 Pearson's Chi-square Test for Deterioration Prediction Models

2nd Data Splitting (Passed)				3rd Third Data Splitting (Failed)			
Condition	Observed	Predicted	$\frac{(O_i-P_i)}{P_i}$	Condition	Observed	Predicted	$\frac{(O_i-P_i)}{P_i}$
1	0	1	0.00	1	0	0	0
2	11	14	0.64	2	1	17	15.06
3	24	21	0.43	3	42	12	75.00
4	16	16	0.00	4	9	22	7.68
$\chi^2 = 1.07 < \chi^2_{(0.05,3)} = 7.81$				$\chi^2 = 97.74 > \chi^2_{(0.05,3)} = 7.81$			

Table 4.16 summarized the service life prediction for the three data splits for the structural rating methodology.

Table 4.16 Service Life Prediction for the Data Splitting Exercises

Culvert Condition	4 (Good)	3 (Fair)	2 (Poor)	1 (Critical)*
First Time Data Splitting	0	21	42	NA
Second Time Data Splitting	0	19	42	NA
Third Time Data Splitting	0	30	30	NA

* Curve fitting is not applied this time; Table 4.11 presents the curve fitting method.

The three randomly data splitting exercises provided a mean to evaluate the deterioration rate of culvert structures. If the model passed the Pearson's chi-square test, the deterioration rate prediction results were similar. For example, calibration results for first and second data splits exhibited consistent results. If the model failed the Pearson's chi-square test, the deterioration rate prediction results are unlikely to match real engineering experience. Ways to improve the prediction performance of the proposed algorithm include increasing the size of the datasets, increasing the accuracy of the culvert inspection and choosing a more relined culvert rating methodology.

The dramatic change of the values of transition matrices that were acquired from model calibrations by three times data splits. shows the considered datasets are noisy. If the data was consistent, a change in the different data split would not impact the value of transition ratio greatly. The Markov model is capable of generating the best matrix that matches the deterioration facts (the inspection datasets). Culvert structural deterioration rate for a certain region is very stable unless the climate or the traffic load experiences a huge change. Noisy level of datasets, which represents the matching degree between datasets and culvert structural deterioration rate from real world, is impossible to be evaluated so far. However, the engineering experiences and the Pearson's chi-square test provide a way to screen the model calibration results, the transition matrices.

4.6 Field Calibration

Field calibration for the culvert rating was performed to evaluate the effectiveness of the established rating methodology. Several factors affect the accuracy of the rating methodology.

1. Human factors when performing the rating. After checking photos taken by the site engineer, several ratings had to be corrected based on the opinion of the professional engineer from the Oregon DOT. For example, Figure 4.12 and Figure 4.13 show the culvert at mile point 16.93 along OR 58. This culvert pipe is concrete with a corrugated metal pipe extension that is very common; the ratings of defects of piping and open joints are four. After correction, piping was adjusted to two, and open joints was issued three.

Figure 4.12 Culvert Photo at MP16.93

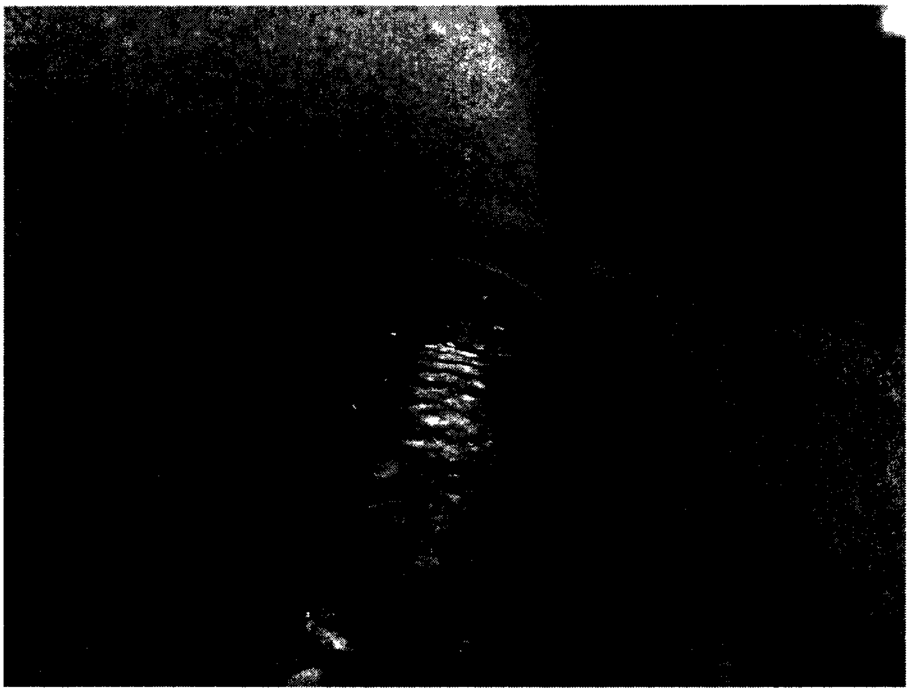

Figure 4.13 Culvert Photo at MP16.93

2. Inexperienced rating. Figure 4.14 is the view looking into the culvert; defects include open joints, settlement and ponding of water.

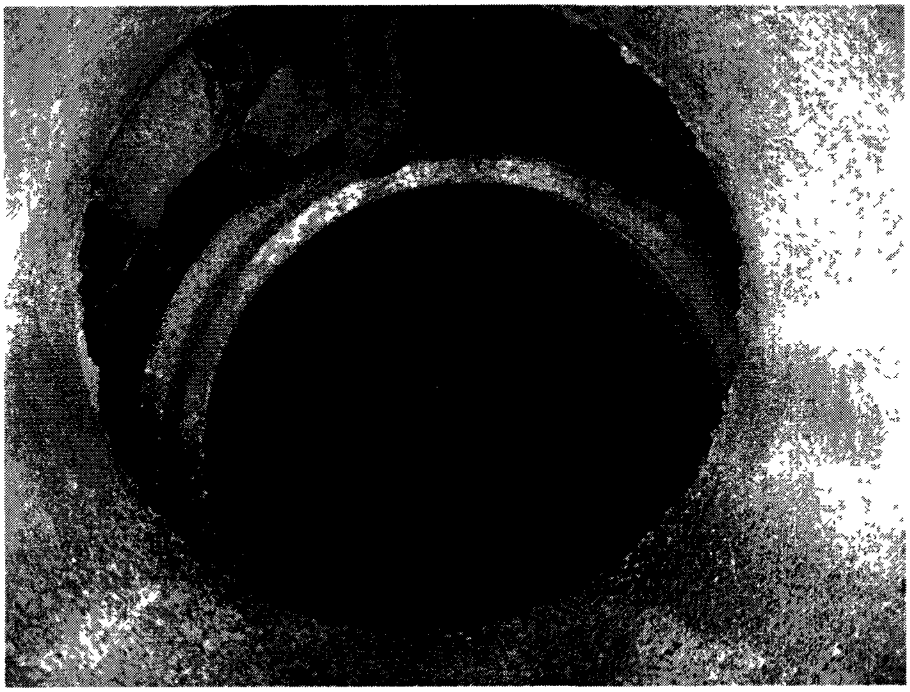

Figure 4.14 Culvert photo at MP 45.57

Figure 4.15 is the view looking into culvert; defects include major cracking at the crown and open joints. Figure 4.16 shows the view of looking into the culvert; defects include settlement, open joints and ponding of water. In Figure 4.16, the infiltration can be easily neglected by the inspector, which might create voids in the roadway embankment during rain events.

Figure 4.15 Culvert photo at MP1.21

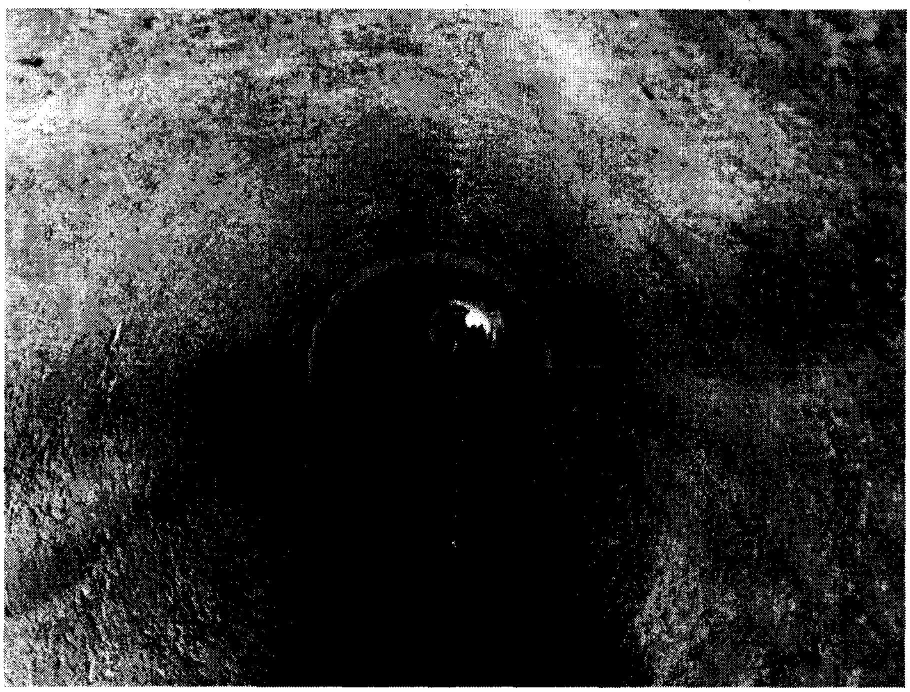

Figure 4.16 Culvert photo at MP 31.14

Figure 4.17 shows severe settlement at the joint while Figure 4.18 shows open joints and light-to-moderate joint settlement. Figure 4.19 shows typical open joints in a pre-cast concrete culvert.

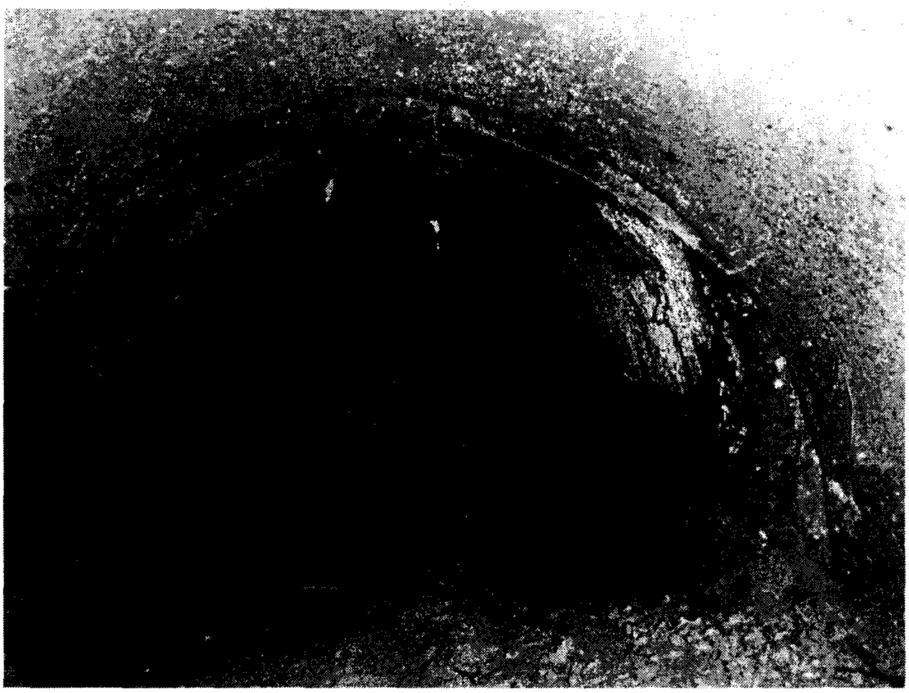

Figure 4.17 Culvert photo at MP 40.58

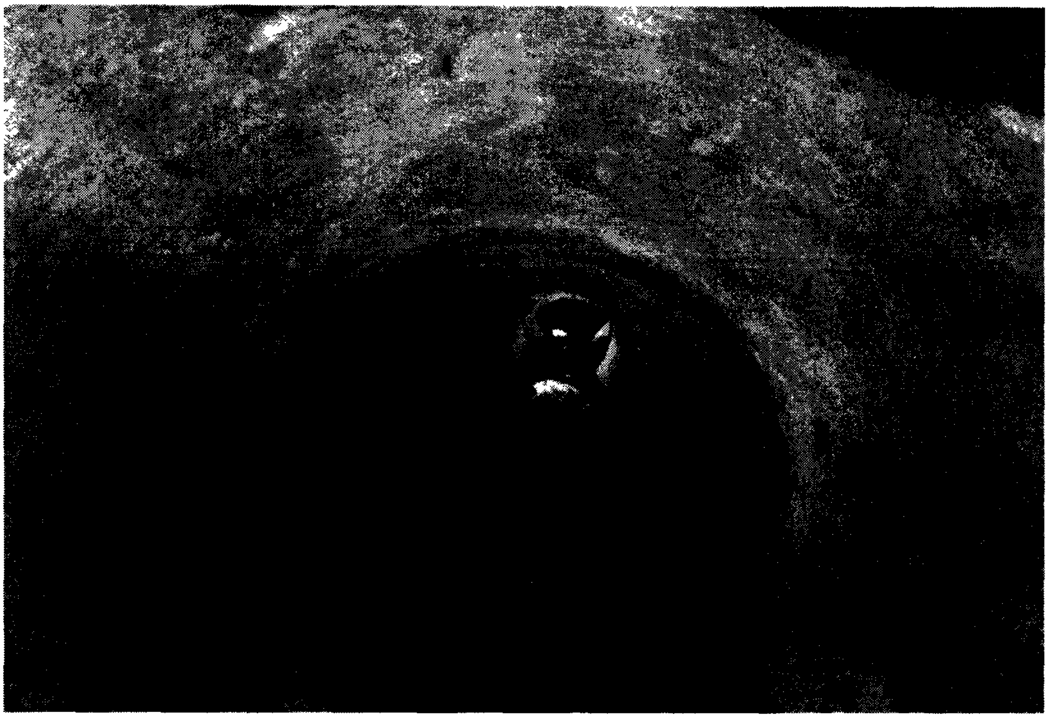

Figure 4.18 Culvert photo at MP 40.58

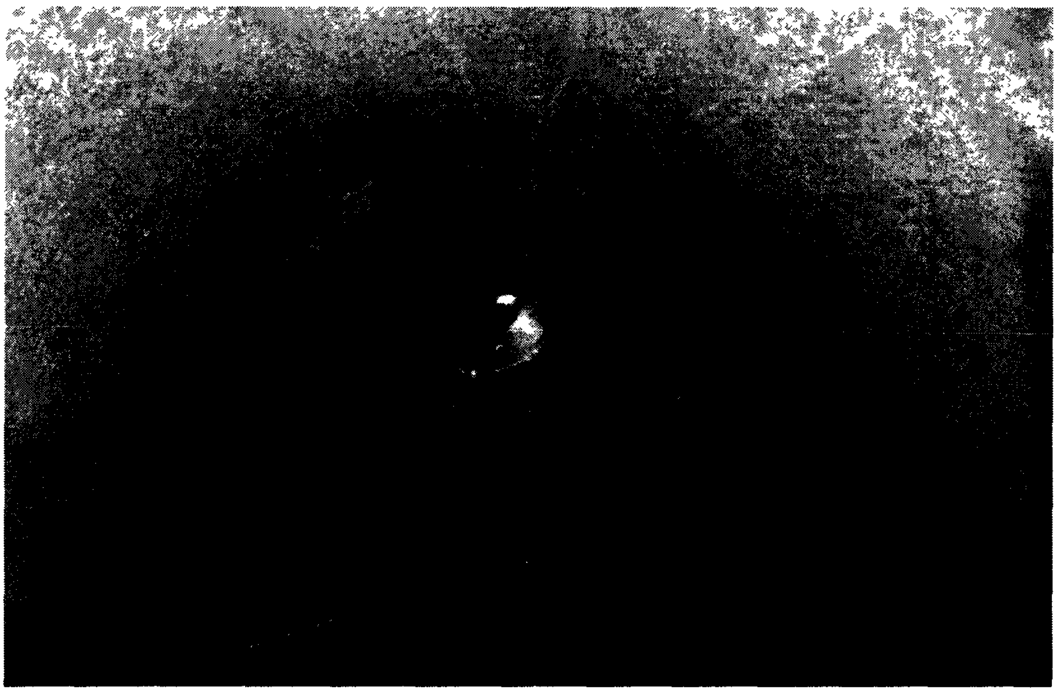

Figure 4.19 Culvert photo at MP 23.70

CHAPTER 5

DISCUSSIONS, CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

Deterioration prediction for culverts utilizing the Markov model provides future information when initiating an asset management aimed at maximizing the benefit of investment and the service life of culvert structures. Chapter 5 concludes the dissertation with discussion (Section 5.1), conclusion (Section 5.2) and recommendation for future research (Section 5.3).

5.1 Discussions

The Markov model is a robust way to predict the deterioration rate of culverts, synergizing the effectiveness of the renewal plan that based only on the condition assessment. Data quality is crucial for the Markov model to provide useful information, but the effect is hard to examine. Pearson's χ^2 statistic is a robust way to evaluate the prediction performance of the Markov model in this study. Pearson's χ^2 testing results can be affected by many factors: error from culvert inspection, culvert rating methodology, quality and size of inspection datasets. Therefore, the meaning of passing the Pearson's χ^2 testing is only limited to predicting the performance of the Markov model that has statistical significance for selected datasets which can only support the decision making for the data source region.

A culvert rating methodology was developed in this study using the AHP based on expert opinions, derived to overall rating and structural rating. It is hard to judge which one is better because there is no universally acceptable way to validate results. Based on deterioration estimation results, structural rating was found to be more conservative than the overall rating. More culverts will be addressed for maintenance and replacement actions if the structural rating method is used, which will increase the safety of total culvert asset but raise the cost. In addition, the Markov model based on structural rating passed the χ^2 testing, a positive indication for the performance of the culvert asset management system. Age data plays a fundamental role in predicting future condition of culverts; thus, adding age information to culvert inventory datasets is proposed by the author.

5.2 Conclusions

1. A method selection process for choosing suitable NDT methods for performing a culvert inspection was developed.
2. A culvert rating methodology using the AHP based on expert opinions from DOTs was developed and expressed in mathematical form.
3. A Markov model for predicting the deterioration rate of culverts at the network level and the service life at the individual level was developed based on culvert inspection datasets from three highways in the state of Oregon.
4. The norm of matrix was introduced as an effective way to monitor the running of the MHA for the model calibration.

5. Model validation was performed via the Pearson's χ^2 testing; results show that the Markov model based on the structural rating methodology passes the test and is the recommended procedure for calculating the overall score for culverts.
6. Datasets were split three times at the ratio of 80%-20% (calibration-validation), wide variations of the calibration results for the transition matrices show that the datasets exhibit a certain level of noise, which is unable to be evaluated so far.

5.3 Suggestions for Future Research

Suggestions for the future work related with this research are presented.

1. NDT methods as a selection tool for culvert inspection can be expanded to a decision making tool to assist engineers to find the optimal solution for a particular project.
2. The culvert rating methodology is based on an expert opinion survey, which includes two versions in this work, the overall rating including 23 factors and the structural rating including 20 factors. Case studies to evaluate the effectiveness of these rating methodologies are critical for further evaluation and validation of these approaches. The method to isolate a culvert when a field has a critical rating, but the AHP score shows the culvert is performing fair to good (i.e. if invert damage and general barrel damage are critical and all other fields are fair to good), should be investigated.
3. Model calibration highly relies on the quality of the datasets; the model can be more accurate if more datasets are acquired. Since the Markov model is group level based, impact of regional weather conditions for deterioration should be

evaluated. The noise level of datasets should be evaluated using appropriate methodologies.

APPENDIX A

DATA REQUEST FORM

LOUISIANA TECH
UNIVERSITY

To: **Mr. Manuel Morales**
Sr. Transportation Engineer
Culvert Inspection Program Coordinator
California Department of Transportation
1120 N. Street, MS 31
Sacramento, CA 95814

Date: Aug.18, 2009

Re: Culverts Inspection/Inventory Data Requesting

Trenchless Technology Center (TTC) is currently undertaking a research project titled "Culvert Rehabilitation to Maximize Service Life While Minimizing Direct Costs and Traffic Disruption" (Proj. 14-19) on the behalf of the Transportation Research Board (TRB).

The TTC is requesting your assistance in collecting culverts inspection/inventory data (including condition rating scores for individual culverts, if available). We will be happy to accommodate whatever format the data is available at (e.g., hard copies, pdf, electronic database files). The TTC will use the data provided to develop a new methodology for asset management of culvert structures. The requested data will be used only in support of this research project. At no point in time will the TTC share or disclose the information to another party, or disclose the source of the data, without a written permission from California DOT.

We would like to thank you in advance for your assistance.

Sincerely,

Erez Allouche, Ph.D., P.E.
Technical Director of Trenchless Center
599 W. Arizona Ave.
Louisiana Tech University
Ruston, LA 71272
Phone: 318-257-2852

Chenguang Yang
Ph.D. Student in Civil Engineering
599 W. Arizona Ave.
Louisiana Tech University
Ruston, LA 71272
Phone: 318-257-3091

TRENCHLESS TECHNOLOGY CENTER

A MEMBER OF THE UNIVERSITY OF LOUISIANA SYSTEM

APPENDIX B

SURVEY FOR CULVERT RATING METHODOLO

To: **Whom it may concern** Date: Feb.09, 2010

Re: Expert Opinion Survey for Condition Rating of Culvert Structures

The Trenchless Technology Center (TTC) is currently undertaking a research project aiming at the development of a rehabilitation design guideline for culvert structures. As part of this work, the TTC is looking to develop a new methodology for asset management of culvert structures.

We are requesting your assistance in completing the attached questionnaire. It should take approximately 15 minutes to complete this survey. The information provided will be used only in support of this research project. All participants will receive a summary report describing the findings of the study (names of participants to remain anonymous).

Please fax the completed questionnaire to 318-257-2777, email a scanned electronic copy to cya003@latech.edu

OR mail to

Sandi Perry (to Chenguang Yang)

599 W Arizona Ave, TTC Office 201

Louisiana Tech University

Ruston, LA 71272

We would like to thank you in advance for your assistance.

Sincerely,

Erez Allouche, Ph.D., P.Eng.

Technical Director, Trenchless

Technology Center

Chenguang Yang

Ph.D. Student in Civil Engineering

The goal of this survey is to identify the weight of each of the factors in Figure B.1 so as to calculate an overall score for the culvert's condition using the Analytic Hierarchy Process (AHP) based on expert opinions.

A review of field inspection reports used by various DOTs across the country revealed twenty-three factors used to describe deficiencies in culvert structures. The objective of this survey is to conduct a pair-wise computation to determining the relative weight of each of these factors. The structure of an AHP process is shown in Figure B.1. Table B.1 provides the definitions of the various rating factors.

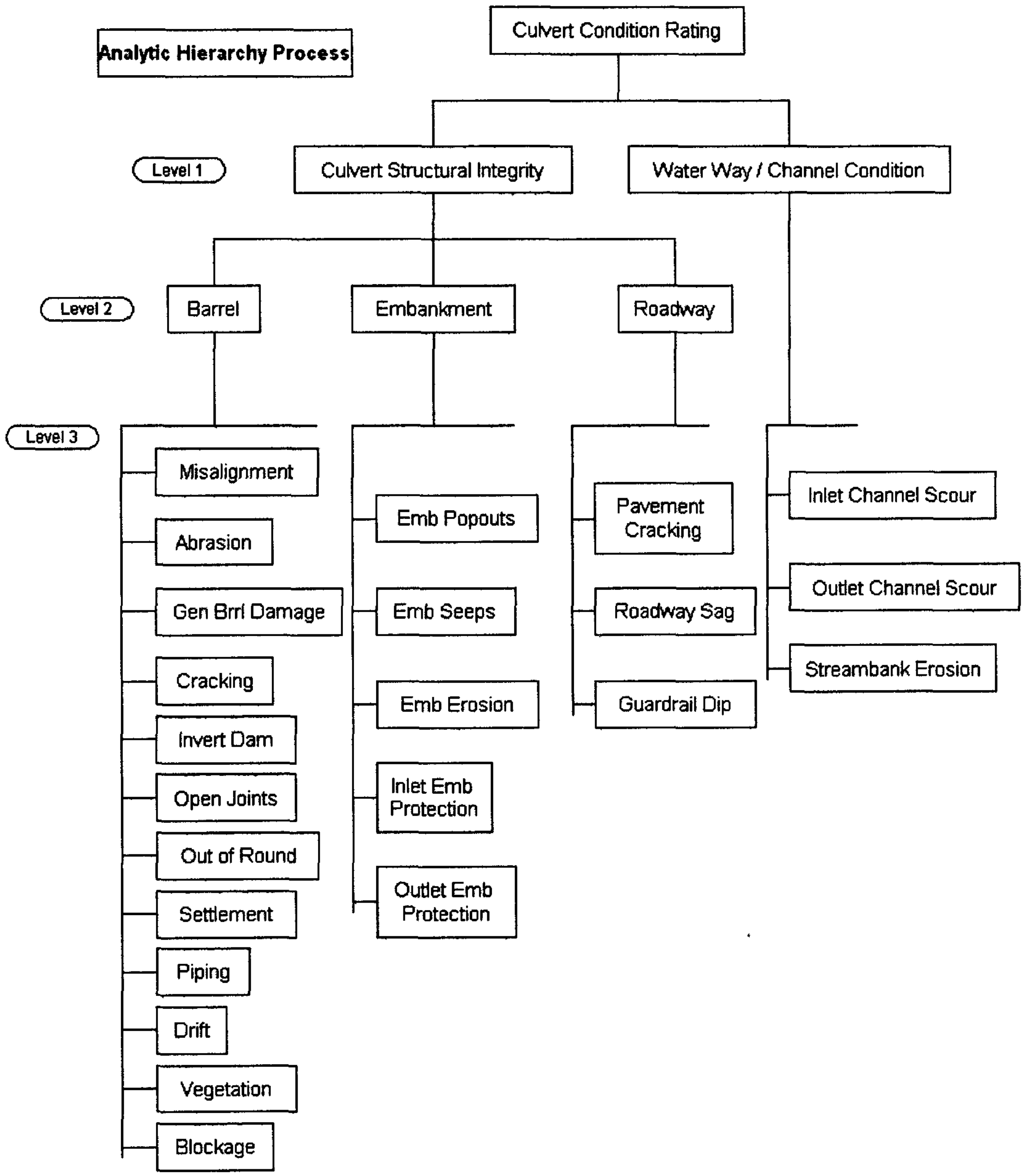

Figure B.1 Three Level AHP Structure for Culvert Condition Rating

Table B.1 Definition of Rating Factors in AHP Structure

Title	Definition
Abrasion Rating	Wearing or grinding of the barrel material due to sediment or debris working against the barrel.
Blockage Rating	Rating value of the blockage inside the structure.
Channel Scour - Inlet	Has the channel been deepened by scour at the inlet.
Channel Scour - Outlet	Has the channel been deepened by scour at the outlet.
Cracking Rating	Inspection rating of the impact of cracking on the structure.
Drift Rating	Debris that drifts on or near the water surface that passes though the culvert.
Embankment Protection - Inlet	Condition of the bank protection in place at the inlet of the culvert.
Embankment Protection - Outlet	Condition of the bank protection in place at the outlet of the culvert.
Erosion Rating	Rating value given to the impact of embankment erosion.
General Damage Rating	Rating value of the barrel/structure for general damage.
Guardrail Dip Rating	Rating value for deformation of guardrails.
Invert Damage	Rating value of damage to the invert. Bottom portion of the culvert/structure.
Open Joints Rating	Ratings value of open joints.
Out of Round Rating	Percentage rating of deformity to the barrel of the culvert from its original geometry.
Pavement Crack/Patch Rating	Cracks or patches observed in the pavement.
Piping Damage Rating	Rating the condition of fill material removed by seepage along a culvert barrel, forming a void adjacent to the culvert.

Popouts Rating	Rating value of the impact of noticeable outward/downward displacements of parts of the embankment.
Roadway Sag Rating	Rating value of roadway deviation from its original grade.
Seeps Rating	Inspection rating value given to the impact of any seeps in the embankment.
Settlement Rating	Rating value of embankment settlement.
Vegetation Obstruction Rating	Rating value for vegetation obstructing the inlet or outlet.

INSTRUCTIONS:

To complete the survey, select the level of preference of each factor as compared to the factors listed in the first column of the relevant table by circling the right relationship between each pair of parameters. For example, in the first table below, if one were to select 4 **(Equally Important)**, one is suggesting that **"Water Way Condition"** is **"Equally Important"** to **"Structural Integrity"** in terms of the culvert's overall condition rating.

Example:

AHP Level 1- Culvert Structural Integrity

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Water Way Condition	1	2	3	4	5	6	7

Survey Starts:

AHP Level 1- Culvert Structural Integrity

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Water Way Condition	1	2	3	4	5	6	7

AHP Level 2 – Barrel

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Embankment	1	2	3	4	5	6	7
Roadway	1	2	3	4	5	6	7

AHP Level 2 – Embankment

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Roadway	1	2	3	4	5	6	7

AHP Level 3 – Misalignment

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Abrasion	1	2	3	4	5	6	7
Gen Brrl Damage	1	2	3	4	5	6	7
Cracking	1	2	3	4	5	6	7
Invert Damage	1	2	3	4	5	6	7
Open Joints	1	2	3	4	5	6	7
Out of Round	1	2	3	4	5	6	7
Settlement	1	2	3	4	5	6	7
Piping	1	2	3	4	5	6	7
Drift	1	2	3	4	5	6	7
Vegetation	1	2	3	4	5	6	7
Blockage	1	2	3	4	5	6	7

AHP Level 3 – Abrasion

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Gen Brrl Damage	1	2	3	4	5	6	7
Cracking	1	2	3	4	5	6	7
Invert Damage	1	2	3	4	5	6	7
Open Joints	1	2	3	4	5	6	7
Out of Round	1	2	3	4	5	6	7
Settlement	1	2	3	4	5	6	7
Piping	1	2	3	4	5	6	7
Drift	1	2	3	4	5	6	7
Vegetation	1	2	3	4	5	6	7
Blockage	1	2	3	4	5	6	7

AHP Level 3 – Gen Brrl Damage

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Cracking	1	2	3	4	5	6	7
Invert Damage	1	2	3	4	5	6	7
Open Joints	1	2	3	4	5	6	7
Out of Round	1	2	3	4	5	6	7
Settlement	1	2	3	4	5	6	7
Piping	1	2	3	4	5	6	7
Drift	1	2	3	4	5	6	7
Vegetation	1	2	3	4	5	6	7
Blockage	1	2	3	4	5	6	7

AHP Level 3 – Cracking

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Invert Damage	1	2	3	4	5	6	7
Open Joints	1	2	3	4	5	6	7
Out of Round	1	2	3	4	5	6	7
Settlement	1	2	3	4	5	6	7
Piping	1	2	3	4	5	6	7
Drift	1	2	3	4	5	6	7
Vegetation	1	2	3	4	5	6	7
Blockage	1	2	3	4	5	6	7

AHP Level 3 – Invert Damage

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Open Joints	1	2	3	4	5	6	7
Out of Round	1	2	3	4	5	6	7
Settlement	1	2	3	4	5	6	7
Piping	1	2	3	4	5	6	7
Drift	1	2	3	4	5	6	7
Vegetation	1	2	3	4	5	6	7
Blockage	1	2	3	4	5	6	7

AHP Level 3 – Open Joints

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Out of Round	1	2	3	4	5	6	7
Settlement	1	2	3	4	5	6	7
Piping	1	2	3	4	5	6	7
Drift	1	2	3	4	5	6	7
Vegetation	1	2	3	4	5	6	7
Blockage	1	2	3	4	5	6	7

AHP Level 3 – Out of Round

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Settlement	1	2	3	4	5	6	7
Piping	1	2	3	4	5	6	7
Drift	1	2	3	4	5	6	7
Vegetation	1	2	3	4	5	6	7
Blockage	1	2	3	4	5	6	7

AHP Level 3 – Settlement

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Piping	1	2	3	4	5	6	7
Drift	1	2	3	4	5	6	7
Vegetation	1	2	3	4	5	6	7
Blockage	1	2	3	4	5	6	7

AHP Level 3 – Piping

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Drift	1	2	3	4	5	6	7
Vegetation	1	2	3	4	5	6	7
Blockage	1	2	3	4	5	6	7

AHP Level 3 – Drift

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Vegetation	1	2	3	4	5	6	7
Blockage	1	2	3	4	5	6	7

AHP Level 3 – Vegetation

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Blockage	1	2	3	4	5	6	7

AHP Level 3 – Emb Popouts

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat Important	More Important	Significantly More Important
Emb Seeps	1	2	3	4	5	6	7
Emb Erosion	1	2	3	4	5	6	7
Inlet Emb Protection	1	2	3	4	5	6	7
Outlet Ebm Protection	1	2	3	4	5	6	7

AHP Level 3 – Emb Seeps

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Emb Erosion	1	2	3	4	5	6	7
Inlet Emb Protection	1	2	3	4	5	6	7
Outlet Ebm Protection	1	2	3	4	5	6	7

AHP Level 3 – Emb Erosion

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Inlet Emb Protection	1	2	3	4	5	6	7
Outlet Ebm Protection	1	2	3	4	5	6	7

AHP Level 3 – Inlet Emb Protection

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Outlet Ebm Protection	1	2	3	4	5	6	7

AHP Level 3 – Pavement Cracking

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Roadway Sag	1	2	3	4	5	6	7
Guardrail Dip	1	2	3	4	5	6	7

AHP Level 3 – Roadway Sag

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Guardrail Dip	1	2	3	4	5	6	7

AHP Level 3 – Inlet Channel Scour

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat More Important	More Important	Significantly More Important
Outlet Channel Scour	1	2	3	4	5	6	7
Stream bank Erosion	1	2	3	4	5	6	7

AHP Level 3 – Outlet Channel Scour

	Significantly Less Important	Less Important	Somewhat Less Important	Equally Important	Somewhat Important	More Important	Significantly More Important
Stream bank Erosion	1	2	3	4	5	6	7

APPENDIX C

SURVEY REPORT

Trenchless Technology Center

Louisiana Tech University

2010

Survey Report for Culvert Rating Methodology

PREPARED FOR

PREPARED BY

Chenguang Yang, Ph.D. Student

Erez N. Allouche, Ph.D. P.Eng.

December 2010

C.1 BACKGROUND

Culvert condition rating methodology is an important element in culvert asset management. A proactive decision making process in culvert asset management has been proven to provide significant economic benefits, not only in direct cost savings but also in reduced social costs. The Federal Highway Administration (FHWA) and U.S. Department of Transportation (DOT) indentified the need for new rating methodologies for more efficient management of culvert assets.

Currently there is no universally accepted culvert rating system that can be used to prioritize culvert maintenance and rehabilitation needs. As one of the tasks in the development of asset management system for culvert structures, the Trenchless Technology Center (TTC) at Louisiana Tech University conducted a survey aimed at the development of such a rating methodology. The survey was sent to transportation professionals in 34 DOTs knowledgeable in the culvert asset management practices. Analytic Hierarchy Process (AHP) was used to compile and analyze collected responses from the survey. The algorithm used is described in Section 3. The method was used to evaluate the importance of various factors ("the weight") in culvert condition rating.

C.2 SUMMARY OF RESPONSES

A questionnaire was distributed to a total of 34 DOT offices with a response rate of 41%. The respondents consisted of engineering staff from the various DOTs offices. Table C.1 and Figure C.1 provide the general information about responses.

Table C.1 Responses of Survey

Response	14
No Response	18

Declined	2

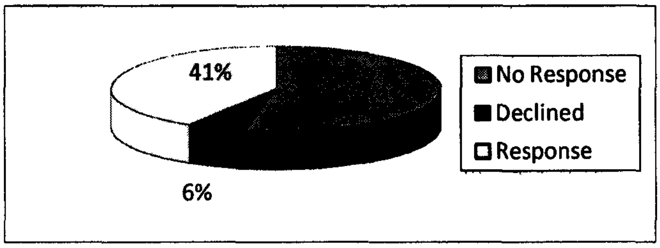

Figure C.1 Feedback from Survey

C.3 COMPUTATION METHODS AND RESULTS

Figure C.2 displays the structure of the three-level Analytic Hierarchy Process (AHP) used to develop the expression for calculating the aggregated score for each culvert structure. Two factors were assigned to the first level of the AHP, which were structural integrity and waterway condition. For structural integrity, assigned second level factors included barrel, embankment and roadway condition. As fewer factors are used to describe waterway condition, no second level factors were used. The third level of the AHP included 23 factors. The survey aimed at identifying the relative weight of each factor, which would then be used in the final computation of the overall culvert score, thus providing support information to decision makers tasked with generating a priority list for the maintenance and rehabilitation of culvert structures.

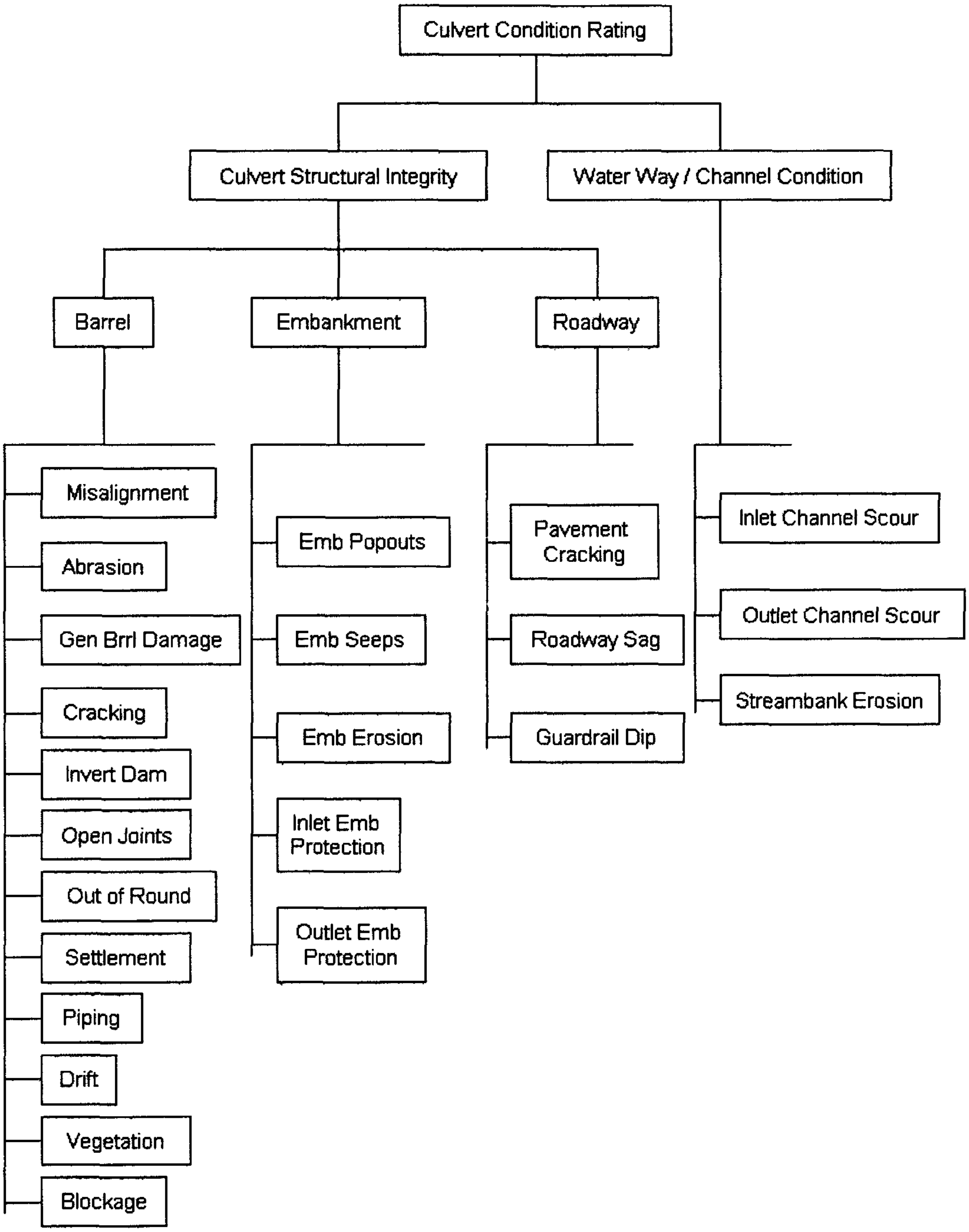

Figure C.2 Analytic Hierarchy Process for Culvert Rating Methodology

Analytic Hierarchy Process (AHP) is an algorithmic procedure where both data and experience play equally important roles. AHP uses a three-level hierarchy-based model that reflects the goals and concerns of the decision-maker. The hierarchy is arranged in a descending order from the overall focus to the criteria, sub-criteria and alternatives.

The hierarchy is then systematically evaluated using pairwise comparison of various criteria, matrix manipulation and eigenvalue computations to obtain a final score for each alternative. AHP provides a systematic methodology to organize tangible and intangible factors and provides a structured, yet relatively simple, analysis algorithm to the decision-making problem.

Table C.2 lists the definition of the factors used in the development of the culvert rating system and shows the computation results based on the respondents' opinion.

Table C.2 Definition of Factors for Culvert Rating System and Weight of Factors in AHP

AHP Levels	Factors	Definition	Respondents Opinion
Sample Size			14
Level 1	S1	Culvert Structural Integrity	56.79%
	W1	Water Way Condition	43.21%
	Total		**100%**
Level 2	B2	Barrel	23.19%
	E2	Embankment	15.61%
	R2	Roadway	17.99%
	Total		**56.79%=S1**
Level 3	M3	Misalignment	1.73%
	A3	Abrasion	1.36%
	GBD3	Gen Barrel Damage	1.85%
	C3	Cracking	2.04%
	I3	Invert Damage	2.05%
	OJ3	Open Joints	2.27%
	OR3	Out of Round	1.77%

S3	Settlement	2.42%
P3	Piping	2.79%
D3	Drift	1.44%
V3	Vegetation	1.22%
B3	Blockage	2.25%
Total		**23.19%=B2**
EP3	Embankment Pop-outs	2.53%
ES3	Embankment Seeps	2.84%
EE3	Embankment Erosion	3.17%
IEP3	Inlet Embankment Protection	3.38%
OEP3	Outlet Embankment protection	3.68%
Total		**15.61%=E2**
PC3	Pavement Cracking	3.54%
RS3	Roadway Sag	7.34%
GD3	Guardrail Dip	7.11%
Total		**17.99%=R2**
ICS3	Inlet Channel Scour	14.88%
OCS3	Outlet Channel Scour	15.50%
SBE3	Stream Bank Erosion	12.83%
Total		**43.21%=W1**

Based on Table C.2, Eq. C.1 was developed to compute condition scores of culvert based on the respondents' opinions.

$$Condition\,Score = 0.568 \times S1 + 0.432 \times W1 \tag{C.1}$$

The first level parameter S1 consists of second level parameters B2, E2 and R2. The first level parameter W1 only consists of second level parameters ICS3, OCS3 and SBE3. Thus Eq. C.1 can be expanded to include second level parameters, yielding the following expression.

$$Condition\,Score = (0.232 \times B2 + 0.156 \times E2 + 0.180 \times R2) + (0.149 \times ICS3 + 0.155 \times OCS3 + 0.128 \times SBE3) \tag{C.2}$$

Eq. C.2 could be further expanded to include third level parameters. Eq. C.3 is the final equation which accounts for all 23 parameters.

$$Condition\,Score = (0.017 \times M3 + 0.014 \times A3 + 0.019 \times GBD3 + 0.020 \times C3 + 0.021 \times I3 + 0.023 \times OJ3 + 0.018 \times OR3 + 0.024 \times S3 + 0.028 \times P3 + 0.014 \times D3 + 0.012 \times V3 + 0.023 \times B3) + (0.025 \times EP3 + 0.028 \times ES3 + 0.032 \times EE3 + 0.034 \times IEP3 + 0.037 \times OEP3) + (0.035 \times PC3 + 0.073 \times RS3 + 0.071 \times GD3) + (0.149 \times ICS3 + 0.155 \times OCS3 + 0.128 \times SBE3) \quad (C.3)$$

While looking somewhat cumbersome, Eq. C.3 can be easily incorporated into a spreadsheet program. Table C.3 shows a sample implementation of Eq. C.3 for an actual data set obtained from a highway, located in the northwest part of the USA. The lowest scoring culverts are highlighted.

Table C.3 Sample Implementation of Eq. C.3

Culvert ID	W1	S1	B2	E2	R2	Final Score
1	1.11	1.46	0.60	0.40	0.46	2.57
2	1.20	1.58	0.65	0.43	0.50	2.78
3	1.32	1.74	0.71	0.48	0.55	3.06
4	1.24	1.64	0.67	0.45	0.52	2.88
5	1.54	2.02	0.83	0.56	0.64	3.56
6	1.30	1.71	0.70	0.47	0.54	3.01
7	1.41	1.85	0.76	0.51	0.59	3.26
8	1.40	1.85	0.75	0.51	0.58	3.25
9	1.25	1.65	0.67	0.45	0.52	2.90
10	1.40	1.84	0.75	0.50	0.58	3.23
11	1.49	1.97	0.80	0.54	0.62	3.46
12	1.58	2.07	0.85	0.57	0.66	3.65

13	1.03	1.36	0.55	0.37	0.43	2.39
14	1.19	1.57	0.64	0.43	0.50	2.76
15	1.23	1.62	0.66	0.44	0.51	2.85
16	1.37	1.80	0.74	0.50	0.57	3.17
17	1.26	1.65	0.68	0.45	0.52	2.91
18	1.52	2.00	0.82	0.55	0.63	3.52
19	1.27	1.67	0.68	0.46	0.53	2.93
20	1.19	1.56	0.64	0.43	0.49	2.75
21	1.32	1.73	0.71	0.48	0.55	3.05
22	1.56	2.05	0.84	0.56	0.65	3.61
23	0.87	1.14	0.46	0.31	0.36	2.00
24	1.40	1.85	0.75	0.51	0.59	3.25
25	1.46	1.91	0.78	0.53	0.61	3.37
26	1.25	1.64	0.67	0.45	0.52	2.89
27	1.45	1.90	0.78	0.52	0.60	3.35
28	1.35	1.77	0.72	0.49	0.56	3.11
29	1.36	1.79	0.73	0.49	0.57	3.16
30	1.18	1.55	0.63	0.43	0.49	2.74

C.4 SUMMARY

The Analytic Hierarchy Process (AHP) method was used to establish the weight of 28 factors as part of the developed culvert rating system using expert opinions solicited from 14 U.S. state Department of Transportation agencies.

In Level 1, the weight of structural integrity was found to be 57%, and the weight of waterway condition was calculated to be 43%. In the category of structural integrity, barrel was identified as the most important factor, followed by roadway condition as the second most important factor.

Twelve factors were used for describing barrel condition, with the three most important factors being piping, settlement and open joints. Detailed information about relative weights of each factor is given in Table C.2. An equation that relates all 23 relevant factors for calculating the overall rating for a given culvert structure was derived based on the results of the survey.

Additional comments were offered by survey participants. One participant reported that implications to the riding surface is the most important factor in rating hierarchy of structural integrity, and that both piping and roadway sag present threats to the roadway.

Another participant had difficulty in determining whether culvert conditions were supposed to address either (A) The structure's current ability to function or (B) a long-term prognosis. For example, a blocked culvert may not operate at all, but the remedy (unblocking) might be easy and inexpensive to implement, making this factor less important than other factors such as piping, cracking or erosion for which the culvert may need to be rehabilitated or replaced.

The goal of the inspection is to determine if and when an action is needed. Blockage is a serviceability related failure and the collapse is a structural criterion related failure. Preventing imminent collapse precedes unblocking the culvert, but clearing the culvert might precede a rehab operation (in fact it has to). These actions are not mutually exclusive.

C.5 ACKNOWLEDGEMENTS

We would like to thank all participants in this survey for their professional views, suggestions, and support for this project. We also sincerely appreciate the help from Mr. Robert E. Trevis. Comments and feedback are welcome.

APPENDIX D

CODES FOR PROGRAMMING

D.1 Code for MHA

Software: MATLAB R 2007b, Version 7.5.0.342

Main Program

```
clear all;
D = load ('data.txt');  % read input from overall or structural rating, subprogram 1
[m,n] = size (D);   % m year, n value
iter = 0;        % accept iteration number
maxstep = 0;     % total loop number
px = init_p (n);     % create p, subprogram 4
sigma = init_s (n); % create sigma, subprogram 5
p_sumation = zeros (4,4);
accept = 0;
for step = 1:5000
   pxnew = getp (px, sigma, n);  %get new px from old px and sigma, subprogram 3
   u = rand (); % u uniformly distribute from 0,1
   pxold = px;
   pold = f (px); % subprogram 2
   pnew = f (pxnew); % subprogram 2
   l_old = likely (pold, D);  % likelyhood function, subprogram 6
  l_new = likely (pnew, D); % likelyhood function, subprogram 6
   t = l_new - l_old;
   alpha = min (0,t);
   if u <= exp (alpha)
      err = norm (pnew - pold);
      if step > 5000 - 500
         p_sumation = p_sumation + p;
         accept = accept + 1;
      end
      px = pxnew;
```

```
      p = pnew;
      iter = iter + 1;
    else
      px = pxold;
      p = pold;
      iter = iter + 0;
    end
    maxstep = maxstep + 1;
    [iter, maxstep, iter/maxstep, err]
    disp (p);
    subplot (2,1,1);
    plot (iter,norm (p) );
    hold on;
    subplot (2,1,2);
    plot (iter,err);
    hold on;
    drawnow;
end
p_ave = p_sumation / accept
s = iter / maxstep
```

Subprograms:

```
1. D = load('data.txt')
% For overall rating:
[54, 0, 0, 0; 17, 10, 1, 0; 17, 14, 0, 0; 0, 0, 54, 0;
2, 12, 0, 0; 3, 0, 0, 0; 1, 16, 1, 2; 1, 2, 0, 0]
% For structural rating:
[53, 1, 0, 0; 6, 21, 1, 0; 11, 19, 1, 0; 0, 0, 54, 0;
2, 19, 0, 0; 3, 0, 0, 0; 1, 2, 8, 2; 1, 2, 0, 0]
```

```
2. pold = f (px); pnew = f (pxnew);
```

```
function out = f (x)
n = length (x);
out = (exp (x) ) / (1+exp (x) );
for j = 2:n
        for k = 1 : j-1
                out (j,k) = 0;
        end
end
b = out * ones (n,1);
for j = 1:n
        for k = 1:n
                out (j,k) = out (j,k) / b (j,1);
        end
end
```

3. pxnew = getp (px, sigma, n)

```
function out = getp(px, sigma, n)
out = px + randn(n)*sigma;
```

4. px = init_p (n)

```
function out = init_p(n)
out = zeros(n,n);
for j = 1:n-2
        out(j,j) = 0.9;
        out(j,j+1) = 0.1;
        out(j,j+2) = 0.1;
end

out(n-1,n-1) = 0.8;
out(n-1,n) = 0.2;
out(n,n) = 1;
```

```
5. sigma = init_s (n);
% For overall rating:
function out = init_s (n)
out = zeros(n);
out (1,1) = 0.45; out (2,2) = 0.30; out (3,3) = 0.35; out (4,4) = 0.3;
end
% For structural rating:
function out = init_s (n)
out = zeros(n);
out (1,1) = 0.42; out (2,2) = 0.31; out (3,3) = 0.25; out (4,4) = 0.3;
end

6. l_old = likely (pold, D);  l_new = likely (pnew, D);
function out = likely(p, D)
year = [8,10,19,59,60,72,78,79];
[m,n] = size(D);
l = 0;
for j = 1:m
        s0 = p ^ (year (j) );
        s = s0 (1,:);
        for k = 1:n
                l = l + log (s (k) ) * (D (j,k) );
        end
end
out = l;
```

D.2 Code for Service Life Prediction Based on C-K Formula

Software: MATLAB R 2007b, Version 7.5.0.342

```
% For Overall Rating:
K = [0.9684, 0.0316, 0.0000, 0.0000;
        0.0000, 0.9759, 0.0238, 0.0004;
        0.0000, 0.0000, 0.9994, 0.0006;
        0.0000, 0.0000, 0.0000, 1.0000];
I = [1.00, 0.00, 0.00, 0.00];
N = 100;
Result = I*K;
for n = 2:N
   Result = [Result;I*(K^n)];
end
Result2 = zeros(N,1);
for n = 1:N
   Result2(n,1) = max(Result(n,:));
End

% For Structural Rating:
K = [0.9583, 0.0413, 0.0003, 0.0001;
      0.0000, 0.9716, 0.0284, 0.0000;
      0.0000, 0.0000, 0.9995, 0.0005;
      0.0000, 0.0000, 0.0000, 1.0000];
I = [1.00,0.00,0.00,0.00];
N = 100;
Result = I*K;
for n = 2:N
   Result = [Result;I*(K^n)];
end
Result2 = zeros(N,1);
```

```
for n = 1:N
   Result2(n,1) = max(Result(n,:));
end
```

APPENDIX E

DETERIORATION CURVES

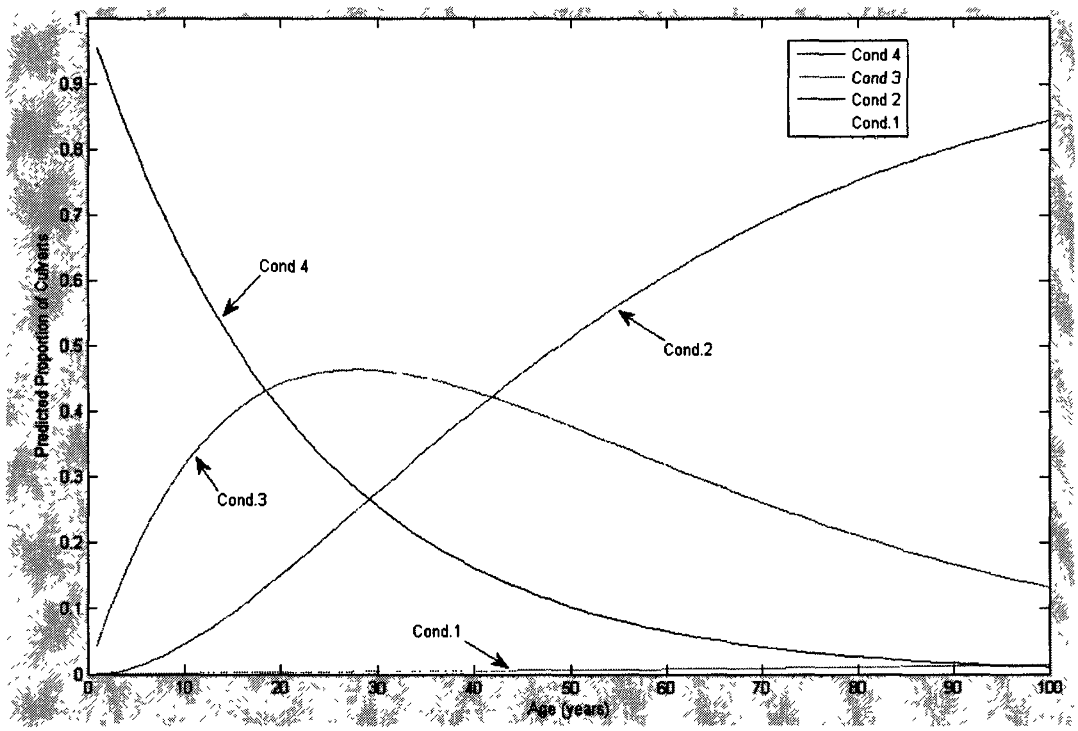

Figure E.1 Culvert Deterioration Curves for Second Data Splitting

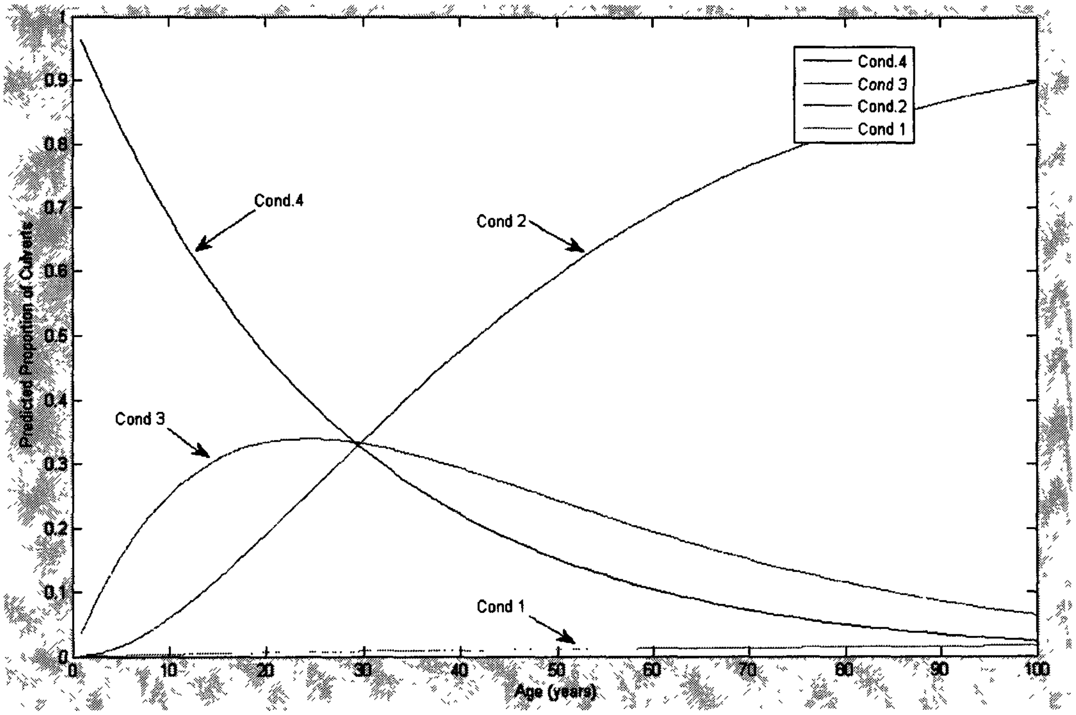

Figure E.2 Culvert Deterioration Curves for Third Data Splitting

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