Network-Level Pavement Performance Prediction Modelling with Markov Chains
Predicting the Condition of Road Network for Rijkswaterstaat

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Network-Level
Pavement Performance Prediction Modelling
with Markov Chains
Predicting the Condition of Road Network for Rijkswaterstaat

by
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Preface

“If you are successful, it is because somewhere, sometime, someone gave you a life or an idea that started you in the right direction. Remember also that you are indebted to life until you help some less fortunate person, just as you were helped.” – Melinda Gates

In (hopefully) successfully finishing the thesis and my 2.5-year journey as a TU Delft mater’s student, I would like to express my gratitude to the people who have supported me intellectually, financially, and mentally.

Firstly, I would like to thank my graduation committee members: Ms. Sandra Erkens, Mr. Rob Schoenmaker, Mr. Frank Bouman from Rijkswaterstaat, and Mr. Wim Courage from TNO. Thank you for providing intellectually-stimulating discussions and detailed feedback from their busy schedules. Sometimes it is challenging to adapt to their different expertise and perspectives, but their guidance is very valuable. It is a pleasure to have the opportunity to write on this topic and to work with all of them. Thank you for providing me all the knowledge, input, correction, data, criticism, and support.

Next, I would like to thank my adorable friends for becoming my big brothers and sisters while I’m in the Netherlands. Also friends from CME and Pret-a-Loger for making my academic journey become memorable. All of the different characters, traits, and individuals that I have encountered are truly inspiring. Each of them has taught me a valuable lesson.

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It is also during the last few years I realize that distance is not an obstacle to provide emotional supports. My biggest gratitude to my mother, for teaching her children to live below our means, so that she can send us to study abroad. To my siblings, Bang Do and Kak Mira, thank you for the endless support. Their logical (and sometimes bitter) advice keeps me on the right track. To Bonang F Jusri, for always being there during my ups and downs. Finally, I would like to dedicate this thesis and this master’s degree to my late father. If someday I am able to achieve something, I owe it to him.

Delft, December 2015

Gini Arimbi
# Table of Contents

Summary .................................................................................................................................................. 1

Chapter 1: Introduction .......................................................................................................................... 3  
1.1 Background ...................................................................................................................................... 3  
1.2 Problem Statement ........................................................................................................................... 5  
1.3 Research Objectives ......................................................................................................................... 5  
1.4 Research Questions ......................................................................................................................... 5  
1.5 Research Methodology .................................................................................................................... 6  
1.5.1 Type of Research: Case Study .................................................................................................... 6  
1.5.2 Research Methodology ............................................................................................................... 7  
1.5.3 Validation of the Model .............................................................................................................. 7  
1.6 Thesis Outline ............................................................................................................................... 8  

Chapter 2: Literature Study .................................................................................................................. 11  
2.1 Maintenance Model in Pavement Network .................................................................................... 11  
2.1.1 Asset Management in Road and Pavement ............................................................................... 11  
2.1.2 Maintenance Optimization Model ............................................................................................ 11  
2.1.3 Condition-Based Maintenance ................................................................................................. 12  
2.1.4 Types of Maintenance ............................................................................................................... 14  
2.1.5 Maintenance Effectiveness Model ............................................................................................ 15  
2.1.6 Manual and Automated Inspection ......................................................................................... 16  
2.1.7 Pavement Distress and Types of Pavement Maintenance ....................................................... 17  
2.1.8 Summary .................................................................................................................................. 18  
2.2 Pavement Performance Prediction Models ..................................................................................... 19  
2.2.1 Definition and Classification of Performance Prediction Models ........................................... 19  
2.2.2 Deterministic Models ............................................................................................................... 20  
2.2.3 Stochastic Models ..................................................................................................................... 21  
2.2.4 Summary .................................................................................................................................. 25  
2.3 Markov Chains for Pavement Prediction ....................................................................................... 26  
2.3.1 Markov Chains Application and Assumption .......................................................................... 26  
2.3.2 Markov Mathematical Model ................................................................................................... 26  
2.3.3 Discussion on Markov Chains .................................................................................................. 28  
2.4 Conclusion .................................................................................................................................... 28
Chapter 3: Case Study and Calculation ................................................................. 30
  3.1 IVON and Pavement Inspection ........................................................................ 30
  3.1.1 Introduction to IVON .................................................................................. 30
  3.1.2 Pavement Evaluation in Rijkswaterstaat ....................................................... 31
  3.1.3 Scope of Research ...................................................................................... 32
  3.2 IVON Database ................................................................................................ 34
  3.2.1 Database Structure ..................................................................................... 34
  3.2.2 Filtering ..................................................................................................... 36
  3.3 Model Criteria and Classification ..................................................................... 37
  3.3.1 Model Criteria and Filtered Database .......................................................... 37
  3.3.2 Model Classification .................................................................................. 42
  3.4 Calculation and Results .................................................................................. 44
  3.4.1 Example of Calculation ............................................................................. 44

Chapter 4: Results and Analysis ............................................................................ 50
  4.1 Service Life Prediction .................................................................................... 50
  4.1.1 Service Life Prediction for Network with Maintenance .................................... 50
  4.1.2 Service Life Prediction for Network without Maintenance .......................... 53
  4.1.4 Maintenance Effectiveness ......................................................................... 56
  4.2 Validation of Service Life Prediction ............................................................... 58
  4.3 Predicted and Actual Performance .................................................................. 62
  4.4 Project and Network-Level Comparison .......................................................... 63
  4.5 Network-Level Performance Based on Markov Chains and Combined Project-Level .......... 65
  4.6 Markov Chains Feasibility ............................................................................. 68

Chapter 5: Conclusions and Recommendations ..................................................... 73
  5.1 Conclusions ..................................................................................................... 73
  5.1.1 Answers to Sub-Research Questions ............................................................ 73
  5.1.2 Summary of Main Research Question ......................................................... 76
  5.2 Recommendations for RWS .......................................................................... 77
  5.3 Significance .................................................................................................... 77
  5.4 Future Research ............................................................................................. 78

References ........................................................................................................... 79
APPENDICES ........................................................................................................ 83
# Table of Figures

Figure 1.1 Research Methodology ............................................................................................................ 7
Figure 1.2 The Modelling Process (Fellows & Liu, 2003) ................................................................. 8
Figure 1.3 Thesis Outline ......................................................................................................................... 9
Figure 2.1 Bathtub curve on time-based maintenance (Ahmad & Kamaruddin, 2012) ................. 12
Figure 2.2 Traditional Predictive Maintenance Cycle (Amari & McLaughlin, 2006) ..................... 13
Figure 2.3 Types of Maintenance (Mamlouk & Zaniekewski, 2001) ............................................... 14
Figure 2.4 Hypothetical Performance Jump and Trend After Maintenance (Labi et al., 2003) ....... 15
Figure 2.5 Short-term and Long-term Effectiveness (M. Ahmed et al., 2012) ................................. 16
Figure 2.6 Types of surface distress (Papagiannakis & Masad, 2008) ............................................. 18
Figure 2.7 Example of Raveling (Rijkswaterstaat, 2013) ................................................................ 18
Figure 2.8 The deterioration process of pavement (Haas & Hudson, 2015) ..................................... 19
Figure 2.9 Pavement condition uncertainty (Thom, 2014) .............................................................. 22
Figure 2.10 Survivor Curve (Lytton, 1987) ....................................................................................... 23
Figure 2.11 Markov Process (Lytton, 1987) .................................................................................... 23
Figure 2.12 Structure of Research ..................................................................................................... 29
Figure 3.1 Maintenance Intervention in IVON (Rijkswaterstaat, 2013) ............................................. 30
Figure 3.2 Flowchart for Pavement Evaluation with Manual Inspection ....................................... 31
Figure 3.3 Flowchart for Pavement Evaluation with Automated Inspection .................................. 32
Figure 3.4 Example of Repaired Pavement Section ......................................................................... 33
Figure 3.5 Structure of IVON Database ............................................................................................ 34
Figure 3.6 Example of Road Section ................................................................................................. 35
Figure 3.7 Example of Data for Modelling ....................................................................................... 35
Figure 3.8 The Filtering Criteria .......................................................................................................... 36
Figure 3.9 Filtering Procedure ............................................................................................................ 37
Figure 3.10 Modelling Algorithm ....................................................................................................... 38
Figure 3.11 State 1 ............................................................................................................................... 39
Figure 3.12 State 2 .............................................................................................................................. 40
Figure 3.13 State 3 .............................................................................................................................. 40
Figure 3.14 State 4 .............................................................................................................................. 40
Figure 3.15 Filtered Database ............................................................................................................. 41
Figure 3.16 Complete Modelling Classification ................................................................................ 43
Figure 3.17 Example of Probability over the Years ......................................................................... 47
Table of Tables

Table 2.1 Comparison between TBM and CBM (Ahmad & Kamaruddin, 2012) ................................................. 14
Table 2.2 Classification of Prediction Models (Mahoney, as cited by Haas, 1994) ........................................... 20
Table 2.3 Comparison of Probabilistic Models ................................................................................................. 25
Table 3.1 Average Service Life for Asphalt Surface Layers ........................................................................... 33
Table 3.2 Criteria for State Classification ........................................................................................................ 39
Table 3.3 Categories for Model Classification ................................................................................................. 42
Table 3.4 Classification for Maintenance ......................................................................................................... 43
Table 3.5 Example of Data Set ....................................................................................................................... 44
Table 3.6 Classification for Maintenance ....................................................................................................... 44
Table 3.7 Example of State Transition ........................................................................................................... 45
Table 3.8 Example of Years and State Probability .......................................................................................... 48
Table 4.1 Average Increase in Expected Service Life ...................................................................................... 58
Table 4.2 Summary of Markov Chains Feasibility ......................................................................................... 72
# List of Abbreviations

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>APDS</td>
<td>Automated Pavement Distress Survey</td>
</tr>
<tr>
<td>CBM</td>
<td>Condition Based Maintenance</td>
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<tr>
<td>CI</td>
<td>Cracking Indicator</td>
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<td>IRI</td>
<td>International Roughness Index</td>
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<tr>
<td>IVON</td>
<td>Information System for Maintenance of Pavements (Dutch: Informatiesysteem Verhardings Onderhoud)</td>
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<td>LCMS</td>
<td>Laser Crack Measurement System</td>
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<td>PCI</td>
<td>Pavement Condition Index</td>
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<td>PMB</td>
<td>Polymer Modified Bitumen</td>
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<td>RI</td>
<td>Roughness Index</td>
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<tr>
<td>RWS</td>
<td>Rijkswaterstaat</td>
</tr>
<tr>
<td>SHM</td>
<td>Structural Health Monitoring</td>
</tr>
<tr>
<td>TBM</td>
<td>Time Based Maintenance</td>
</tr>
<tr>
<td>TPM</td>
<td>Transition Probability Matrix</td>
</tr>
<tr>
<td>ZOAB</td>
<td>Porous Asphalt Concrete (Dutch: Zeer Open Asfaltbeton)</td>
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<tr>
<td>ZOABTW</td>
<td>Porous Asphalt Concrete with Two Layers (Dutch: Zeer Open Asfaltbeton Twee L a a g s)</td>
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<tr>
<td>ZOAB+</td>
<td>Porous Asphalt Concrete Plus (Dutch: Zeer Open Asfaltbeton Plus)</td>
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Summary

Background and Research Objectives

The road network is an essential component of infrastructure and contributes to economic activities of a nation. The increasing demand for the optimal use of maintenance budgets has become a significant issue in road network industry due to limited funding resource, especially for most industrialized countries (Worm & van Harten, 1996; OECD, 2011; Nasir, 2000). Road authorities need to monitor the performance of pavement condition for maintenance and budget planning purposes (Thom, 2014). Since funding levels for road maintenance are not likely to significantly increase, road agencies need to seek more cost-effective methods of pavement maintenance optimization that can extend the service life of pavement (Labi et al., 2003). However, one of the issues on the current maintenance optimization model is the lack of information provided regarding the effectiveness of maintenance treatments. A good connection between the network and project-level performance is also required to plan properly the investment required for pavement preservation.

One of the essential components of pavement maintenance optimization model is the prediction model (Weninger-Vycudil, 2008). For predicting pavement performance, road agencies need a prediction model that can accommodate uncertainty and randomness due to load and environment. Researches have shown that probabilistic models are suitable and it enable strategic assessment for funding and policy decisions (Costello, 2005). One of the examples of probabilistic models is Markov chains, where the future condition of pavement is built based on its existing condition and it integrates both pavement deterioration and improvement rates (Abaza, 2004; Black, 2005).

In developing prediction models, the characteristic of pavement distress needs to be considered. In the Netherlands, the dominant distress mechanism for asphalt wearing course is raveling or stone loss. Raveling is a progressive mechanism, and the period until raveling is initiated and the early development is varied. Because there are many variables that influence pavement performance, a mechanistic model is difficult to develop and calibrate. As a result, there is still a lack of standard performance curves to assist road agencies in building a reliable pavement performance models on network level. Thus, the main research question that will be answered is “How to develop a network-level performance prediction model for raveling in open graded wearing courses with Markov chains?”

The main objective of this research is to develop a pavement performance prediction model for maintenance optimization model based on Markov chains. It is applied for Porous Asphalt Concrete (in Dutch: ZOAB) wearing courses on network-level. Additional objectives are measuring maintenance effectiveness and comparing project and network-level performance. The Markov chains use historical data from inspection database from the year 2004 to 2013. The case study is based on pavement maintenance program IVON from Rijkswaterstaat (RWS) in the Netherlands.

Findings

Pavement performance prediction models for raveling distress can be built with Markov chains. The algorithm utilizes two things: the data of intervention year and the data of the construction year. The data of intervention year are converted into the states, reflecting the condition of pavement sections. State 1 represents the best or the initial condition while state 4 represents the worst condition, where maintenance is urgently needed. The difference among the states lies on the damage level and the quantity of stone loss. The transition between the states in two consecutive years (year $t$ and $t + 1$) is
captured in the transition probability matrix (TPM). With vector of state probabilities, the future performance can be obtained by having multiplication of the initial condition and TPM raised to the power of prediction year \( t \). This research focuses on obtaining the future probability of pavement sections to be in good condition (state 1) or the service life prediction. The initial condition starts from 2013 to predict the performance of the next ten years. In addition, construction year data are converted into age of asphalt to create two prediction scenarios: with and without maintenance.

This research investigates the influence of several variables toward the pavement performance, which are types of wearing course, number of carriageways, and traffic levels. The models show that ZOAB+ has the highest quality, followed by ZOAB and ZOABTW. The performance of the single carriageway networks shows a higher probability to be in good condition compared to multiple carriageways networks. The possible reasons for this finding are the difference in the number of the actual data that is taken into account, amount of maintenance, and the difference in the actual traffic levels.

This research classifies two categories according to the traffic levels, which are the category of high traffic (road number A2, A15, A16, A67) and low traffic (A7, A31, and A32). In general, there is no significant difference that can be found. A possible explanation for this finding is the actual number of low traffic pavement sections is much higher than a number of high traffic pavement sections.

The comparison between the project and predicted network-level performance indicates several differences. In the first few years, predicted performance underestimates the probability of pavement sections in the good condition. In the later phase, it shows the opposite. The project-level performance also reveals that a sudden performance drop can be found due to inspection change and road accidents.

In this research, maintenance effectiveness is difficult to be determined since corrective maintenance data are not recorded on the in the given database. However, there are some measures to evaluate the effect of renewal or rehabilitative maintenance. It is found out that the average increase of the expected service life due to surface layer renewal are 7 to 8 years for ZOAB, ZOABTW, and ZOAB+.

Markov chains offer good flexibility for the road agencies to create various performance prediction models. The accuracy of the prediction model has an average difference of 2.4% between the actual and the prediction, and it shows a slightly pessimistic predictions. A comparison between the project and network-level performance is beneficial to indicate a deviation of pavement section performance. Markov chains prediction models are also easy to understand and do not require special software. However, the reliability and the simplicity of replicating the model depend on the data variation.

There are several recommendations to improve the results of the research. First, state classification should consist of evenly distributed populations. Second, the higher the number of data points, the better the accuracy of the performance prediction models. Third, RWS should record corrective maintenance data explicitly and improve the consistency of the database records.

In conclusion, Markov chains enable the development of pavement performance prediction models on network level for open graded wearing courses. By obtaining a better estimation of pavement condition in the future, road agencies can use it as a decision support to build a more reliable maintenance planning for asphalt wearing course preservation. Road agencies can also have a better understanding of the benefit of their maintenance planning, which can contribute to the improvement of the pavement maintenance optimization model.
Chapter 1: Introduction

1.1 Background

The road network is an essential component of the infrastructure and contributes to the economic activities of a nation. The increasing demand for the optimal use of maintenance budgets has become a significant issue in road network industry (Worm & van Harten, 1996). Road authorities need to monitor the performance of pavement condition not only for maintenance planning based on safety and comfort considerations but also for budget planning purposes, especially when the political constraints are tight (Thom, 2014). Other challenges in managing road network are the increasing demand for improved levels of road service combined with limited funding resource (Ford, Arman, Labi, Sinha, & Lafayette, 2011; OECD, 2001). Failure to maintain the service level of road network will reduce economic efficiency, create user safety and comfort issues, and increase maintenance requirements and social costs (Zouch & Courage, 2014).

In most industrialized countries, the importance of effective road maintenance has replaced the need for building new roads (Bjornsson, 2000). As a consequence, road agencies need to re-evaluate their management system that results in shifting from system expansion to system preservation (FHWA, 2012). Since funding levels for road maintenance are not likely to significantly increase, road agencies need to seek more cost-effective methods of pavement maintenance optimization that can extend the service life of pavement (Labi et al., 2003; Mamlouk & Zaniewski, 2001).

Problems in Maintenance Optimization Model

In the last few decades, researchers have developed various maintenance programming optimization techniques such as linear, non-linear, and dynamic programming to achieve the required road performance under financial limitation. Despite the success of these optimization techniques, many road agencies still prefer to adopt the traditional methods. The traditional methods are mostly based on subjective ranking and prioritization rules, derived from economic and engineering criteria. However, one of the disadvantages of these methods is that they do not ensure the best possible maintenance strategies for long planning time spans (Harvey, 2012). Furthermore, there is a difficulty in formulating maintenance optimization from mathematical computation because of the complexity of large size networks (Dekker, 1996; Morcous & Lounis, 2005).

Another prominent issue in the road network is the importance to understand the integration of project-level predictions into the network-level management, that can offer cost-effectiveness through system optimization (Aktan, 2000; Thom, 2014). However, network-level prediction can be too aggregated to provide practical decision support at the road section level (Fallah-Fini, Rahmandad, & Triantis, 2009). A good connection between network and project-level evaluation is required to help road agencies in properly planning the investment required for pavement preservation.

Pavement Prediction Models

In maintenance optimization models, there are two important issues that have been widely discussed in previous researches. The first issue is the need for a reliable pavement performance prediction models and the second issue is the ability to measure the maintenance effectiveness. Performance
prediction models are the essential component of pavement maintenance optimization model (Dekker, 1996; Li et al., 1996; Weninger-Vycudil, 2008). Pavement prediction models are typically classified into deterministic and probabilistic models.

In general, pavement deterioration results from several factors such as traffic loads, weather, construction techniques, type of soil, and materials. High uncertainties in weather and traffic loads contribute to the low predictability of pavement performance (Camahan, 1987). Hence, road agencies require a prediction model that is able to accommodate uncertainty and randomness due to load and environment factors.

So far, previous studies have pointed out that probabilistic models can assist the road agencies in predicting medium to long-term performance. Probabilistic models are able to accommodate uncertainties of the environment and enable strategic assessment for funding and policy decisions (Camahan et al., 1987; Costello, Snaith, Kerali, Tachtsi, & Ortiz-Garcia, 2005).

One of the examples of probabilistic models is Markov chains, where the condition of pavement is built based on its existing condition and it is able to integrate both pavement deterioration and improvement rates (Black, Brint, & Brailsford, 2005; Haas, Hudson, & Zaniewski, 1994). At the moment, a number of researches in United States, Australia, Canada, UK, and Finland have achieved success in utilizing Markov chains to predict the future performance of infrastructure systems (Austroads, 2012; Li, Xie, & Haas, 1996; Weninger-Vycudil, 2008). Therefore, this research will utilize Markov chains in building the pavement performance (or degradation) prediction model.

Another issue with the maintenance optimization model is the lack of information provided regarding the effectivity of maintenance treatments toward the overall condition of pavement network (Mamlouk & Zaniewski, 2001). Currently, road agencies are reported to find difficulties in formulating maintenance schedule and budget. Labi (2003) mentioned several reasons behind this: the inconsistency of maintenance treatments, lack of reliability of pavement decision from software, and lack of information on the optimal timing of maintenance (Mamlouk & Zaniewski, 2001). Since different options on maintenance treatments can highly affect the required maintenance budget, there is a need for a model that can explain the relationship between maintenance effectiveness and the extension of pavement service life.

Based on the previous reasons, this research will develop a pavement performance prediction model for maintenance optimization model by using Markov chains. It will provide a prediction model for the average performance of Porous Asphalt Concrete (in Dutch: ZOAB) wearing courses and measure the maintenance effectiveness. The Markov chains utilizes historical data from the inspection database. Thus, it is expected to be better in representing the current and future condition of the pavement.

The case study of a pavement maintenance program is based on the data from IVON program (Dutch: Informatiesysteem Verhardings Onderhoud) in Rijkswaterstaat (RWS). RWS is a Ministry of Infrastructure and Environment in the Netherlands, which serve as the road agency for Dutch highways. The performance prediction models will be built based on the existing inspection database. The Markov chains model is expected to predict the service life of pavement wearing courses on the network level for year 2014 to 2023. Furthermore, it should be able to indicate the effectiveness of various maintenance methods. Because of the data availability from IVON, the study focuses on porous (or open graded) wearing courses from 2004 through 2013. Specifically, the study focuses on the dominant failure mechanism in these wearing courses, which is raveling or stone loss.
1.2 Problem Statement

The maintenance planning of asphalt wearing course by RWS is based on condition monitoring. Since raveling is a progressive mechanism, deterioration of the wearing course becomes faster over time. As such, the actual maintenance moment can be predicted relatively accurate. However, the period until raveling is initiated and the early development is much more variable.

To study the causes of early or late raveling, a standard or average raveling development model is needed. Because of the many variables that influence pavement performance, a mechanistic model is difficult to develop and calibrate. As a result, there is still a lack of guidelines or standard performance curves to assist road agencies in building a reliable pavement performance models on network-level that can accommodate uncertainty and is able to describe the maintenance effectiveness.

1.3 Research Objectives

The main objective of this research is to provide an average performance model for porous asphalt wearing courses on network-level. Additional objectives that are addressed are developing a method to measure the effectiveness of maintenance treatments and to compare project and network-level performance.

The focus of this study is on raveling, which is the dominant distress criteria for open graded asphalt in the Netherlands, with the observation time of 10 years (2004 to 2013). The ten years observation is chosen since it is sufficient to capture the long-term performance. These limitations are based on the available data set from the inspection database for raveling distress on porous asphalt wearing courses.

1.4 Research Questions

The main research question that will be answered is “How to develop a network-level performance prediction model for raveling in open graded wearing courses with Markov chains?”

To answer the main research question, the following sub-questions will be explored.

1. What are the factors that influence the existing performance prediction model for raveling in IVON?

The first question will analyze the current practice of pavement maintenance planning within the selected road agency. It will investigate the inspection methodology and the existing algorithms to obtain intervention (maintenance) years. Furthermore, it will identify the physical and environmental factors that are taken into account for the current calculation of this intervention year. This question will also discuss the challenges and limitations of the current methodology.
2. Can an algorithm for pavement performance prediction for raveling be built, based on Markov chains?

The current intervention years in the maintenance program from sub-question number 1 will be used as a database to build a new prediction model for the case study. This sub-question will elaborate the procedures to build the performance prediction models, also defined as pavement service life prediction, from the available database.

3. What is the expected performance of pavement on network-level with Markov Chains performance prediction model?

This sub-question will focus on analyzing the results of the pavement performance prediction models. It will be evaluated if the expected performance of pavement network under various conditions. The models will be validated by experts so that its accuracy can be evaluated.

4. How to assess the effectiveness of maintenance treatments on network level?

An attempt will be made to measure the maintenance effect on network performance. It will be done by creating two sets of prediction models, which are prediction models with maintenance and without maintenance. These two prediction models will be compared to observe the overall effect of maintenance in extending the service life of pavement.

5. What is the feasibility of using Markov chains for building pavement performance prediction models?

Finally, this question will evaluate the feasibility of using Markov chains in developing a pavement prediction model on the network-level.

1.5 Research Methodology

1.5.1 Type of Research: Case Study

A case study research is classified as practice-oriented research which aims to contribute an intervention in order to change an existing situation (Verschuren & Doorewaard, 2010). In this case, the intervention is defined as improving the optimization of the pavement maintenance model for the road agency. This research is expected to produce a predictive model for the degradation of Porous Asphalt wearing courses on the network level, which is a step towards further optimization of maintenance.

By choosing a case study as the research strategy, several benefits can be obtained since it focuses more on the depth rather than the breadth of the research. It is also argued that the case study can provide an in-depth investigation of a particular phenomenon within a given context. It can result in general ideas on the topic, providing an overall picture (Verschuren & Doorewaard, 2010).

This thesis chooses road agency in the Netherlands as a case study with the focus on building pavement performance model for ravelling distress. The results of the research can be applied to other pavement management systems in different countries.
1.5.2 Research Methodology

The research methodology used in this research consists of the following steps:

(i) Study literature on maintenance optimization models, pavement prediction models, and Markov chains method
(ii) Perform interviews with stakeholders from the road agency regarding the existing methodology on maintenance program and factors that influence the deterioration process
(iii) Gather data from the road agency (Rijkswaterstaat) inspection database for the pavement maintenance program
(iv) Develop a pavement prediction model for Porous Asphalt Concrete wearing course with Markov chains

![Research Methodology Diagram]

Figure 1.1 Research Methodology

1.5.3 Validation of the Model

Model verification involves determining the correctness of the structure of the model by examining the output results. External validity will measure the ability to create generalization from the findings (Fellows & Liu, 2003). Validation of the model needs to be aligned with the objectives and criteria from the selected road agency in the case study.
In this research, the validation procedure will consist of comparing the predictions from the model with the actual data. Conceptual validation will also be conducted by interview with a team of experts to evaluate whether the model reflects the real conditions of pavement network.

1.6 Thesis Outline

This report is divided into 5 chapters. The first chapter explains the background, research objectives, research questions, and structure of the research. Chapter 2 discusses relevant observations from literature. In chapter 3, the case study is introduced. The existing pavement evaluation method used by RWS is described. The structure and the current issues with the IVON database are explained. In this Chapter also, criteria to obtain intervention years are proposed.

Chapter 4 provides the results the pavement performance prediction model (or service life prediction) based on Markov chains, analyzes the results of the models, and describes the feasibility of using Markov chains for building a prediction model for porous asphalt wearing courses. In chapter 5, conclusions and recommendations are presented.
<table>
<thead>
<tr>
<th>Chapter 1. Introduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Background</td>
</tr>
<tr>
<td>- Problem Statement</td>
</tr>
<tr>
<td>- Research Objectives</td>
</tr>
<tr>
<td>- Research Questions</td>
</tr>
<tr>
<td>- Research Methodology</td>
</tr>
<tr>
<td>- Thesis Outline</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter 2. Literature Study</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Maintenance Models in Pavement Network</td>
</tr>
<tr>
<td>- Pavement Performance Prediction Models</td>
</tr>
<tr>
<td>- Markov Chains for Pavement Prediction</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter 3. Case Study and Calculation</th>
</tr>
</thead>
<tbody>
<tr>
<td>- IVON and Pavement Inspection</td>
</tr>
<tr>
<td>- IVON Database</td>
</tr>
<tr>
<td>- Model Criteria and Classification</td>
</tr>
<tr>
<td>- Calculation and Results</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter 4. Results and Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Service Life Prediction</td>
</tr>
<tr>
<td>- Validation of Service Life Prediction</td>
</tr>
<tr>
<td>- Predicted and Actual Performance</td>
</tr>
<tr>
<td>- Project and Network-Level Comparison</td>
</tr>
<tr>
<td>- Network-Level Performance Based on Markov Chains and Combined Project-Level</td>
</tr>
<tr>
<td>- Markov Chains Feasibility</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Chapter 5. Conclusions and Recommendations</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Conclusions</td>
</tr>
<tr>
<td>- Recommendations for RWS</td>
</tr>
<tr>
<td>- Significance</td>
</tr>
<tr>
<td>- Future Research</td>
</tr>
</tbody>
</table>

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Figure 1. 3 Thesis Outline
Chapter 2: Literature Study

This chapter presents a summary from the literature studies done for this thesis. Chapter 2 begins by explaining the overview of maintenance model in pavement network. Next, literature studies related to maintenance optimization models are discussed. The differences between using probabilistic and deterministic methods to build pavement prediction models are described. Lastly, mathematical models based on Markov chains are presented.

2.1 Maintenance Model in Pavement Network

2.1.1 Asset Management in Road and Pavement

Limited government funding and the increase in infrastructure maintenance have raised the growing interest in strategic asset management (OECD, 2001; Volker, Scharpf, Weerdt, Herder, & Weerdt, 2012). In this thesis, asset management (AM) is defined as a complex task that can be applied to achieve the desired level of an asset’s performance level throughout time. Institute of Asset Management (2014) defines AM as ‘the coordinated activity of an organization to realise value from assets’. In the case of infrastructure industry, asset management has distinctive features such as long lifespan of assets and no resale value (Volker et al., 2012). Therefore, complex uncertainties can be easily found in managing infrastructure assets compared to other forms of asset management (Altamirano, 2010).

In the context of road sector, asset management can be defined as ‘a systematic process of maintaining, upgrading and operating assets, combining engineering principles with sound business practice and economic rationale, and providing tools to facilitate a more organised and flexible approach to making the decisions necessary to achieve the public’s expectations’ (OECD, 2001). Failure to provide and maintain vital communication links, which is road network, might impacts on traveling time, mounting cost, vehicle damage, and accident costs (Atkinson, 1997).

One of the methods to improve asset management practices in pavement management is by the development of strategic performance objectives for the highway system (FHWA, 2010). Pavement management system is defined as a ‘set of tools or methods that assist decision makers in finding optimum strategies for providing and maintaining pavements in a serviceable condition over a given period’ (Haas, Hudson, & Zaniewski, 1994). The objective of pavement management system is to produce cost-effective pavement program, connect maintenance and operation through the analysis of pavement preservation program, and provide pavement performance data (FHWA, 2010; Haas et al., 1994). One of the components of pavement management system is the maintenance prediction and/or planning model, which is what this thesis focuses on.

2.1.2 Maintenance Optimization Model

Maintenance is a crucial activity to keep the function and performance of road network. In general, maintenance can be defined as the combination of all technical and associated administrative actions intended to retain an item or system in, or restore it to, a state in which it can perform its required
function (British Standard Institution, 1984). Dekker (2007) defined four maintenance functions: ensuring the system function (availability, efficiency, and product quality), ensuring system life (asset management), ensuring safety, and ensuring human well-being. From the perspective of road agencies, ensuring the system life of road asset becomes a priority.

To ensure the performance of road network, a maintenance optimization model is needed. Dekker (1996) defined maintenance optimization models as ‘mathematical models whose aim is to find the optimum balance between the costs and benefits of maintenance while taking all kinds of constraints into account’ (Dekker, 1996). Vasili (2011) proposed a definition of maintenance optimization model as a ‘mathematical model that aims to quantify the costs and to find the optimum balance between the cost of maintenance on one side, and the associated cost (benefit) on the other.’ A maintenance optimization model consists of four aspects (Dekker, 1996):

(i) Description of a technical system.
(ii) A modelling of the deterioration of the system in time and possible consequences of the system.
(iii) Description of the available information about the system and the actions to open management.
(iv) An objective function and an optimization technique which helps in finding the best balance.

Prediction models are an essential part of good road management (Aijo, 2005). With prediction models, road agencies can obtain information in prioritizing maintenance measures. Therefore, this research will focus on (ii): developing a model which can describe the deterioration of the pavement system, specifically the deterioration of Porous Asphalt wearing courses in the right hand lane of Dutch highways.

2.1.3 Condition-Based Maintenance

Maintenance models can be classified into two categories: time based maintenance (TBM) and condition based maintenance (CBM). TBM is based on the bathtub curve and assumes that the failure of a system depends entirely on the age of a component. In the bathtub curve, the hazard rate will increase in a predetermined way. Two components with the same type and age will have the same failure rate despite of the events that have occurred during operations (Amari & McLaughlin, 2006).

![Bathtub curve on time-based maintenance](Ahmad & Kamaruddin, 2012)
CBM, also known as predictive maintenance, is developed by detecting causes or symptoms of a future failure so that the failure can be handled in a most cost effective way before its occurrence. CBM is a maintenance program that provides maintenance actions based on information collected from monitoring processes (Ahmad & Kamaruddin, 2012). Because of the many variables in construction, use of pavements, and the resulting variation in lifetimes, typically CBM is the method of choice for pavement maintenance.

![Traditional Predictive Maintenance Cycle](image)

**Figure 2.2 Traditional Predictive Maintenance Cycle (Amari & McLaughlin, 2006)**

CBM is developed by making predictions based on the measures of physical parameters against predetermined engineering limits. The measurement of the physical parameters can be recorded periodically depending on the characteristics of the system. If the measurement exceeds the established limit, maintenance actions need to be taken (Amari & McLaughlin, 2006).

There are four stages of CBM requirements that were described by Amari (2006):

(i) Identify failure mechanisms, causes, detection and prevention methods.
(ii) Identify the deterioration model associated with the system.
(iii) Determine the costs and effects associated with the various kind of failures.
(iv) Develop an optimal CBM policy that involves optimal inspection schedules for condition monitoring and the optimal maintenance decisions.

This research seeks to identify component (ii), which is translated as building pavement performance prediction models from pavement deterioration process. The result of the models can help building and determining the optimal maintenance decisions. In Chapter 3, the data from road inspection will be used to develop the deterioration model.

The difference between CBM and TBM is explained in the following table. For pavement networks, failure rates behave differently from one component to another. Therefore, a specific deterioration modelling is required which can be built based on the physical measures of the pavement.
Table 2. Comparison between TBM and CBM (Ahmad & Kamaruddin, 2012)

<table>
<thead>
<tr>
<th>Comparison criteria</th>
<th>TBM</th>
<th>CBM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data required and collection</td>
<td>Theory/principle</td>
<td>Uses failure time/user-based data</td>
</tr>
<tr>
<td></td>
<td>Practical issues</td>
<td>• The recording of failure time data is not always available</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Very sensitive due to incorrect recording and censoring effects</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• A set of adequate failure data (time to failure) for the modelling process is difficult, time-consuming, and may be expensive to gather (Bekier &amp; Scarf, 1998)</td>
</tr>
<tr>
<td>Data analysis/ modelling</td>
<td>Theory/principle</td>
<td>Uses the reliability theory based on Bathrub curve assumption</td>
</tr>
<tr>
<td></td>
<td>Practical issues</td>
<td>• Unrealistic assumptions</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Operating conditions are assumed constant (e.g., environmental effects)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Only effective for equipment in deteriorating state (increasing failure rate)</td>
</tr>
<tr>
<td>Decision process</td>
<td>Theory/principle</td>
<td>Use of the optimisation approach</td>
</tr>
<tr>
<td></td>
<td>Practical issues</td>
<td>• Difficult to model and interpret</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Decision model is not always stable</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Time-consuming in model development</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Is more of a mathematical exercise most of the time rather than a practical application</td>
</tr>
</tbody>
</table>

2.1.4 Types of Maintenance

Preventive maintenance has become an important subject due to its potential in improving cost effectiveness through pavement preservation (Mamlouk & Zaniewski, 2001). In general, pavement maintenance is divided into three classes: preventive, corrective, and rehabilitation.

Preventive maintenance is defined as the treatments that are performed to reduce the rate of deterioration and preserve the pavement integrity, such as cleaning of the emergency lanes and the application of rejuvenators. Corrective maintenance refers to treatments that maintain the characteristics and structural integrity of an existing pavement for continued serviceability. In the case of flexible pavements, several types of corrective maintenance are crack treatment, thin overlays, microsurfacing, slurry seals and chip seals. Rehabilitation or restorative maintenance is a wearing course replacement that restore the pavement structure to its initial condition, such as wearing course replacement.

The effect of maintenance type toward the pavement condition can be observed in the following figure.

![Figure 2.3 Types of Maintenance (Mamlouk & Zaniewski, 2001)](image-url)
Without any maintenance treatment, pavement condition will gradually deteriorate according to its service life. Near the end of the service life, the deterioration rate has a steeper slope than the one in the early phase. Preventive maintenance is usually done in the early phase to avoid the declined pavement condition. When the pavement is in the worse condition (indicated by the steeper slope of deterioration rates), maintenance treatment will have less capacity in maintaining the good condition. When maintenance treatment is applied near the end of pavement’s service life, the required maintenance effort will be bigger.

2.1.5 Maintenance Effectiveness Model

Theoretically, pavement preventive maintenance is an important measure that needs to be done to extend the service life of the pavement. However, there is still limited numbers of road agencies that incorporate preventive maintenance due to: 1) lack of information on the long-term benefits of preventive maintenance; 2) lack of information on the optimal timing for maintenance to make it more cost-effective (Mamlouk & Zaniewski, 2001). Since the results of delaying preventive maintenance do not directly affect the quality of the road, it is often become the most cut activity when maintenance budget is limited. Therefore, a measure of effectiveness is needed to determine the optimal timing to do maintenance. However, there are still very few studies on pavement deterioration prediction that utilize pavement maintenance as an explanatory variable.

A model that able to measure the maintenance effectiveness can help the road agencies in determining the impact of maintenance treatments toward the extension of pavement service life. It will help the road agencies to schedule maintenance or reconstruction activities at individual pavement sections.

One of the methods to measure the maintenance effectiveness is to quantify the effect of treatments on extending pavement life or increasing ride quality, both in the short and long-term (M. Ahmed, Haas, & Haas, 2012). Several indicators to measure the maintenance effectiveness are: sudden elevation of pavement condition upon treatment, often referred to as ‘performance jump’, and area bounded by the pavement performance curve. The explanation on these indicators is elaborated in the next section.

**Short Term Effectiveness**

Short-term effectiveness focuses on the improvement of pavement performance after one year of applying the maintenance treatments. Performance jump measures the short-term effectiveness of the rehabilitation treatments, denoted by the jump in the condition index upon application of the treatment.
Long Term Effectiveness

In reality, pavement will receive various treatments over its life cycle. Long-term effectiveness focuses on finding the extension of service life due to treatment over period years of life. Long-term effectiveness measure can be more useful since it involves longer time span of the analysis.

Several measures to describe the long-term effectiveness are described by Labi (2003) as treatment service life, increase in the area bounded by performance curve, or increased average pavement condition over treatment service life.

The area bounded by performance curve is able to evaluate the effectiveness of rehabilitation treatments by combining service life and improvement in average pavement condition (A. Ahmed, Labi, Li, & Shields, 2012). The following figure shows pavement performance over time. The area bounded by performance curve is indicated by the integral of the improvement due to maintenance over time. The time starts from the time of maintenance treatment to the time when pavement needs to be maintained. Thus, the area bounded by performance curve shows the “quality time” resulted from the maintenance treatments.

![Performance Curve](image)

Figure 2. 5 Short-term and Long-term Effectiveness (M. Ahmed et al., 2012)

2.1.6 Manual and Automated Inspection

One of the key components of maintaining infrastructure is the inspection. Traditionally, asset owners rely on visual inspection to detect damage and predict failure of structural damage (Huston, 2010). However, visual inspection has several limitations, such as biased results from human errors (Zhang, Keoleian, & Lepech, 2013), labour-intensive, and time consuming (B. K. C. P. Wang, 2000). The personnel in charge of inspection activities are also subjected to hazardous conditions if traffic intensity increases (M. Ahmed et al., 2012; Timm & McQueen, 2004). This condition has been a growing problem on the Dutch highways.
Over the last two decades, automated pavement distress survey (APDS) has been developed with various success rates (Ouyang & Xu, 2013). Successful automation of surface distress survey could reduce the survey cost and develop more objective and standardized results for rehabilitation management (B. K. C. P. Wang, 2000). In general, APDS is classified into two types. The first type is the imaging of the pavement surface through photographing, videotaping, or digitalizing. The second type is the measurement of pavement longitudinal and transverse profile through the use of various noncontact sensors (Di Mascio, 2007).

Regardless the ongoing technical development of APDS technology, road agencies have started to incorporate APDS in their pavement management system to gradually replace the manual inspection. These cases can be found in the United States (Transportation Research Board, 2004), the Netherlands (Aalst, 2015), and Finland (Aijo, 2005).

Up to now, there is still a lack of publications regarding the successful complete transition from manual inspection to APDS. However, several attempts have been made by US Department of Transportation in comparing the results of manual and automated pavement surveys. Rijkswaterstaat has followed a similar approach in their development of the Laser Cracking Measurement System (LCMS), which was calibrated using experienced inspectors and which is now used to automatically detect ravelling in Porous Asphalt.

Studies indicated that the results from manual and automated inspection are quite consistent with an acceptable degree of random error. Several researches agreed that the results are faster, safer, and eliminate human error (Cline, Shahin, & Burkhalter, 2003; K. C. P. Wang et al., 2003). However, Smith (2014), Timm (2004), and Mullis (2005) found that the results are not always consistent between manual and automated inspection. In addition, there has been little discussion about the successful transitions from manual to automated data collection (Timm & McQueen, 2004). So, although the transition is still far from complete, road authorities will increasingly use automated inspection techniques to get their performance information. That information will be similar to the information obtained from visual inspections and it needs to be transformed into maintenance predictions.

### 2.1.7 Pavement Distress and Types of Pavement Maintenance

Pavement distress is defined as the manifestation of construction defects, as well as the damaging effects of the traffic, environment, and their interaction. Pavement distress in asphalt concrete pavement is categorized into three categories: cracking, surface deformation, and surface defects (Papagiannakis & Masad, 2008). A complete classification of pavement distress can be found in Appendix A.

One of the dominant types of surface distress that is often found in the Netherlands is raveling of asphalt’s wearing course (Aalst, 2015). Raveling is the wearing away of the pavement surface caused by the dislodging of aggregate particles and loss of asphalt binder that leads to a rough and pitted surface with obvious loss of aggregates (Laurent et al., 2009). Figure 2.6 illustrates the mechanism of distress on asphalt pavement.
2.1.8 Summary

There is a need to optimize the maintenance models in the pavement management system and to compare the effects of various maintenance strategies. One of the important components of a maintenance optimization model is a deterioration or performance prediction model.

A maintenance model can be classified as time-based and condition-based. Pavement structures have unique characteristics that require their own deterioration models. The influence of construction and environment results in variation of pavement lifetimes. Therefore, condition-based maintenance will be an appropriate choice to observe the failure mechanism on pavement structures.
Maintenance types are divided into preventive, corrective, and rehabilitation treatments. The value of preventive maintenance cannot be measured directly, hence creating a resistance within road agencies toward the use of preventive maintenance techniques. Several attempts have been made to measure maintenance effectiveness, which are: performance jump, area bounded by the performance over time curve. The performance over time is the basis to produce performance prediction models and it is explained in the next section.

2.2 Pavement Performance Prediction Models

2.2.1 Definition and Classification of Performance Prediction Models

2.2.1.1 Definition and Objectives

Pavement performance is defined as how pavement changes its condition or serve its intended function with accumulating use. Pavement performance modelling has often been described as a very important aspect of the pavement management system. The objective of monitoring pavement performance is to determine objectively the current condition of pavements and then use historical trends to develop a management plan (Lytton, 1987). Pavement prediction influences the quality of other components of pavement management such as rehabilitation years, types of treatment, and selecting cost-effective maintenance alternatives (Li et al., 1996).

From Figure 2.8, it can be seen that deterioration can be measured in distress parameter such as Present Serviceability Index (PSI). Over the time, the condition of pavement will decline due to aging factors and accumulated axle loads. The monitoring process will capture the condition over the time so that the deterioration rate can be calculated. From the deterioration rate, the remaining service life can be calculated. Several maintenance or rehabilitation alternatives can be chosen to increase the condition parameters. Different maintenance techniques produce different complexity, cost, and effect for the future condition of the pavement.

![Figure 2.8 The deterioration process of pavement (Haas & Hudson, 2015)](image)

2.2.1.2 Network and Project Level Evaluation

According to its scope, pavement evaluation can be divided into the project-level and network-level evaluation. Project-level evaluation has a high level of detail and is used in designing and analysing
the life-cycle cost of pavements. Network-level is less detailed but is used for the estimation of overall maintenance and rehabilitation needs and budgets (Haas & Hudson, 2015; Lytton, 1987). There is an interface issue between network and project-level evaluation since the maintenance budget can only be properly budgeted if the magnitude of maintenance requirements is known (Thom, 2014). For the purpose of maintenance and budget planning, pavement evaluation in network-level becomes critical.

2.2.1.3 Prediction Models

Pavement performance models can also be classified into deterministic and probabilistic models. According to Robinson (as cited in Ortiz-García, Costello, & Snaith, 2006), a deterministic model is a model for which the condition is predicted as a precise value based on mathematical functions from observed deterioration.

Probabilistic models predict the pavement condition as the probability of occurrence of a range of possible outcomes (Ortiz-García et al., 2006). Pavement evaluation in network-level uses probabilistic models since network-level evaluation involves a high number of variables and variations. Each type of the model will be explained in the next section.

Classification of prediction models has been suggested by Mahoney (1990, as cited by Haas, 1994). From the table 2.2, it can be seen that deterministic model is only suitable for project-level performance.

Moreover, Haas (1994) stated that Markov chains are an excellent way to create performance models since the future state of the model element is estimated solely for the current state of the element.

Table 2.2 Classification of Prediction Models (Mahoney, as cited by Haas, 1994)

<table>
<thead>
<tr>
<th></th>
<th>Deterministic</th>
<th>Probabilistic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Primary</td>
<td>Probabilistic</td>
</tr>
<tr>
<td></td>
<td>Structural</td>
<td>Transition Process</td>
</tr>
<tr>
<td>Deflection Stress</td>
<td>PSI</td>
<td>Markov</td>
</tr>
<tr>
<td>Strain</td>
<td>Pavement Safety</td>
<td>Semi Markov</td>
</tr>
<tr>
<td>Structural Stress</td>
<td>Damage Survivor</td>
<td></td>
</tr>
<tr>
<td>Functional Distress</td>
<td>Load Equivalent</td>
<td></td>
</tr>
</tbody>
</table>

2.2.2 Deterministic Models

Deterministic models are classified into three types (Lytton, 1987):

(i) Primary response models
Predicts primary response of pavement to imposed loads and climatic conditions such as deflection, stress, strain, thermal stress, temperature.

(ii) Structural performance models
Predicts pavement distress and composite measures of pavement condition such as the pavement condition index.

(iii) Functional performance models
Predicts the present serviceability index, pavement surface friction, and wet-weather safety index.

Another classification of deterministic models is proposed by Harvey (2002). Deterministic models can be categorized into mechanistic, empirical, and mechanistic-empirical models.

The mechanistic models utilize fundamental theories of pavement behaviour to model deterioration trends and produce models that are applicable for different pavements conditions. Empirical models rely on statistical analysis of locally observed deterioration trends. Compared to the mechanistic models, empirical models are less structured. However, it may not be transferrable to other pavement with different conditions. Mechanistic-empirical models are the combination of both mechanistic and empirical models. It can produce models with moderate data requirements and can be applicable in the different pavement with different conditions with changed calibration parameter (Harvey, 2012).

By nature, pavement deterioration has a probabilistic behaviour and not deterministic. Pavement deterioration contains many unpredictable factors such as quality of the materials, characteristics of sub-grade, and vehicle loading. Li (1996) also argued that applying only deterministic models to pavement management will be inadequate due to: the uncertainties in pavement behaviour under changeable traffic and environmental conditions, difficulties in quantifying influencing factors, and error from the subjective evaluation of pavement condition.

Therefore, deterministic models do not take into account the variability that might be expected in the future (Camahan, Davis, Shahin, Keane, & Wu, 1987). Moreover, deterministic prediction models only provide an average estimate to a future condition that is not necessarily likely to be achieved given the variability of pavement performance.

2.2.3 Stochastic Models

A stochastic process is a process that has an unpredictable nature due to the influence of random variables. A random variable is defined in statistical terms as one of the possible outcomes of an experiment, together with its associated probability of occurrence (Costello, Snaith, Kerali, Tachtsi, & Ortiz-Garcia, 2005). In pavement deterioration, a random variable is the pavement condition at that location coupled with the associated probability of finding it in that condition.

Compared to the deterministic models, probabilistic models are useful in two situations; (i) when the prediction has to be made based on limited or non-existing information, and (ii) when the uncertainty of the predicted performance needs to be clearly revealed (Austroads, 2012). The latter application is particularly beneficial for decision-makers, as it may influence the allocation of funds and risk management. A probabilistic approach can assign various probabilities to the future conditions of a pavement.
The accuracy of a probabilistic model is not defined by a single value. Since a probabilistic model predicts a range of the performance, the accuracy is defined as a distribution. The distribution within that range indicates the likelihood of the predicted number within the range (Austroads, 2012).

The practitioners with a preference for probabilistic deterioration models can incorporate this model into a life-cycle costing analysis with quantitative risk assessment for treatment selection. The range of pavement conditions that is produced by probabilistic models is able to accommodate uncertainties in pavement condition. In addition, road agencies also need to adjust their maintenance planning based on available budget, which usually depends on many political factors. The flexibility of probabilistic models of having a range of planning would improve decision making for maintenance and rehabilitation treatment timing and selection. From this requirement, it was inferred that the probabilistic deterioration models would be more likely to be adopted in a network-level rather than at a project-level.

The use of probabilistic prediction models recognises the random nature of pavement performance, and it is particularly suitable where the existing performance data is limited in both quantity and range. Types of well-known probabilistic models for pavement prediction are survivor curves, Markov chains, and semi-Markov.

### 2.2.3.1 Survivor Curve

A survivor curve is a graph of probability versus time that can be used to make a performance prediction model. Developing survivor curves requires observational time series of data consisting of construction, maintenance, and rehabilitation histories recorded by the road agencies (Austroads, 2012; Lytton, 1987).

The probability drops off with time from value 1 to 0 and it expresses the percentage of pavement sections that remain in service after a number of years. The slope of the survival is the probability density of survival which is built from historical data by determining the percentage of pavements that need to be maintained each year after its most recent major repair or new construction.

A probability distribution function (PDF) is usually defined by a Weibull distribution especially when the pavement conditions are approaching failure. Survivor curves can be built to estimate the PDF.
based on observational time series of data. The PDFs can be used as input for other probabilistic approaches in performance prediction modelling (Austroads, 2012).

Any maintenance activity that occurred in the given pavement sections will influence the pavement performance and may require a redefinition of the survivor curves. Once the pavement condition at failure is defined, the data requirements to build survivor curves become less extensive. Complex calculation is less needed to build the survivor curves, but it requires reliable data.

![Survivor Curve](image1)

**Figure 2. 10 Survivor Curve (Lytton, 1987)**

### 2.2.3.2 Markov Chains

One of the probabilistic models that has been extensively utilized to build pavement performance model is Markov chains. Markov process describes a probable “before” and “after” condition of the pavement. The probabilities are shifted downward to lower condition states that are described by ranges of serviceability index. In Figure 2.9, it can be observed that the probability of pavement sections in state 4 in “before” condition equals to 0.1. In “after” condition, the number is reduced to zero and probability in new states appear. Hence, it creates a shift in the PDF.

![Markov Process](image2)

**Figure 2. 11 Markov Process (Lytton, 1987)**
Both the Markov and semi-Markov approaches require transition probability matrices (TPM) to define the transition from one pavement condition state to another. A Markov TPM expresses the probability that a group of pavements of similar age or traffic level will transition from one state of distress to another within a specified time period (Lytton, 1987).

The most important aspect is to determine the probability of changing from one condition state to another. The probability is determined by expert opinion or based on the analysis of available information such as survivor curves. Theoretically, TPM is used to predict future performance without any explanatory power and thus contain inherent inaccuracy (Austroads, 2012).

In Markov chains, the condition of a pavement is based on its existing condition. The Markov approach assumes that the probability of changing one state to another is independent of an item’s earlier condition history (Austroads, 2012; Black, Brint, & Brailsford, 2005). In addition, performance prediction models from Markov chains are also able to integrate both deterioration rates and improvement rates (Abaza, Ashur, & Al-Khatib, 2004). However, in some cases, the assumption of time independence on Markov chains creates a disadvantage since it ignores non-load or environmental effects. In this case, a semi-Markov approach is used.

2.2.3.3 Semi-Markov

Semi-Markov is a modification to the Markov approach to overcome the independence of time assumption used when changing from one pavement condition state to another (Lytton, 1987). It recognizes that changing conditions (weather, traffic) create a variation in the transition process. Semi-Markov allows a state’s transition probability to depend on the time spent in that state (Black et al., 2005). In predicting pavement performance, the transition process in the TPMs is usually applied at time intervals of one year to allow for time-related and other unexpected effects on pavement performance.

2.2.3.4 Comparison of Probabilistic Models

The following table summarizes the differences between the three probabilistic models.
Table 2.3 Comparison of Probabilistic Models

<table>
<thead>
<tr>
<th>Type</th>
<th>Assumption</th>
<th>Sample Required / Data Needed</th>
<th>Advantages</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Survivor Curves</td>
<td>Not extensive but</td>
<td>Requires reliable data</td>
<td>Less complex calculation</td>
<td>Requires historical data</td>
</tr>
<tr>
<td></td>
<td>requires reliable</td>
<td></td>
<td></td>
<td>Influenced by the maintenance history</td>
</tr>
<tr>
<td></td>
<td>data</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Markov</td>
<td>Independent of time</td>
<td>No need historical data for prediction</td>
<td>- More extensive than survivor curve</td>
<td>Independent of variables</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>- Able to incorporate improvement and deterioration into single entity</td>
<td>Inherent inaccuracy from expert judgement</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>- Only requires data from the present state for prediction</td>
<td>Large variations of models</td>
</tr>
<tr>
<td>Semi-Markov</td>
<td>Dependent on Time</td>
<td>No need historical data</td>
<td>Take into account the ‘dependence on time’</td>
<td>Requires more time to gain accuracy</td>
</tr>
</tbody>
</table>

2.2.4 Summary

Pavement prediction models can be divided into deterministic models and stochastic or probabilistic models. The output of deterministic models is a single value while the output of probabilistic models is a range of probability. The examples of probabilistic models are survivor curves, Markov chains, and semi-Markov. The nature of pavement performance contains high uncertainties due to the influence of traffic and environment. Thus, it requires probabilistic models.

One of the methods that has been widely used to predict pavement performance is Markov-chains model. Chapter 2.3.2 will explain further the application and mathematical model of Markov chains in predicting pavement performance.
2.3 Markov Chains for Pavement Prediction

2.3.1 Markov Chains Application and Assumption

Markov chains have been widely used in predicting performance for infrastructure system. Markov process allows a partial inclusion of physical knowledge by specifying the parameters in the expectation of the process, which is a power law function (Kallen, 2007). In maintenance optimization model, Markov chains have been widely used (Kallen & van Noortwijk, 2006; Morcous & Lounis, 2005; Srinivasan & Parlikad, 2013; Worm & van Harten, 1996). In pavement management, it is used to build pavement deterioration or performance prediction models (Austroads, 2012; Camahan et al., 1987; Li et al., 1996; Ortiz-García et al., 2006; Weninger-Vycudil, 2008). A number of network level pavement management systems have also incorporated Markov chains in their system: NOS, NETCOM, MicroPAVER, and STRAT-2 (Ortiz-García et al., 2006).

Markov Assumption

Lytton (1987) and Costello (2005) describe the assumption for Markov Model process:

(i) There are a finite number of states which describe a range of distress or serviceability index.
(ii) The probability of making a transition from one state to another depends only on the present state
(iii) The transition process is stationary. The probability of changing from one state to another is independent of time. However, this assumption is generally not true for pavement conditions, since changes can occur in weather condition or heavy traffic.
(iv) The stochastic process should be discrete in time. It means that the time interval to build TPM should be in measureable unit. In the case of pavement performance prediction models, the time is usually measured by years.
(v) The stochastic process should have a countable or finite state space. A number of state to define pavement condition should be countable.

2.3.2 Markov Mathematical Model

Markov chains are a sequence of random variables. A state is one of the possible values that the random variable can have. The state space is denoted by $E = \{1, 2, \ldots, N\}$. A point in time is denoted by $t = 0, 1, 2, \ldots, n$. The random variable $X_t$ represents the state of the chains at time $n$. For a pavement prediction model, the damage is represented by state vector $E$, where each component of $E$ corresponds to a certain condition. The value assigned to a characteristic damage variable has the interpretation of the most probable remaining lifetime for the feature in question (Sheskin, 2011).

To model the deterioration process, it is necessary to establish a transition probability matrix (TPM) denoted by $P$. A transition probability matrix $P$ consists of transition probability $p_{ij}$.
The transition probability $p_{ij}$ indicates the probability of the portion of the network in the state $i$ moving to state $j$ in one duty cycle. For example, a duty cycle refers to 1 year of degradation. In addition, the sum of the entries in each row in the transition probability matrix $P$ should be equal to one and the value of all entries should be positive.

$$p_{ij} = P(X_{t+1} = j | X_t = i) = P(X_1 = j | X_0 = i)$$

The transition probability $p_{ij}$ is built from the historical data. For building pavement performance prediction models, $p_{ij}$ is calculated with the following formula.

$$p_{ij} = \frac{N_{ij}}{N_i}$$

$N_{ij}$ = number of pavement sections in the network that moved from state $i$ to state $j$ during one duty cycle

$N_i$ = total number of pavement sections in state $i$ at the starting year $t$

To predict the future condition, an initial vector needs to be established. This initial vector shows the probability or distribution of pavement section to be in certain conditions or states. If there are four states to explain the condition of pavement section, the initial state is described as an initial vector $a_0 = (p_1, p_2, p_3, p_4)$. As an example, $p_1$ shows the probability of pavement condition to be in state 1 at time 0 or initial year.

The performance of pavement network in the future (year $t$) can be predicted with the following equation of the vector-state probabilities:

$$a_t = a_0 P^t$$

$a_t$ = distribution of pavement condition at prediction year $t$

$a_0$ = distribution of pavement condition at year 0 (initial condition)

$P^t$ = transition probability matrix raised to the power $t$. 

\[ \begin{array}{c|cccc} X_t \backslash X_{t+1} & 1 & 2 & \ldots & n \\ \hline 1 & p_{11} & p_{12} & \ldots & p_{1n} \\ 2 & p_{21} & p_{22} & \ldots & p_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ n & p_{n1} & p_{n2} & \ldots & p_{nn} \end{array} \]
The Markov property assumes a dependency where given the present state of a random process, the conditional probability of the next state depends only on the present state and is independent of the past history of the process. As the number of transition increases, the behaviour of the chain changes from transient (short-term) to steady state, showing a stationary probability vector in the long run.

2.3.3 Discussion on Markov Chains

Li (1996) and Amin (2015) investigated three major disadvantages on the application of Markov chains:

1. assumptions of dealing with external variables such as weather and traffics;
2. the methods to build the TPMs for pavements;
3. large variations of TPM models that must be established.

Homogeneous Markov assumes that variables that affecting pavement performance (such as growth rate, volume) and environmental conditions (weather, soil subgrade) are constant throughout the analysis period. However, this is not the actual situation.

The TPM is usually developed by using the expert opinions. It is known that the method is subjective and contains human error. Alternatively, pavement performance data can be used, but the data collection process is also time-consuming and costly.

Other disadvantages are that pavement sections must be grouped into a large number of roughly homogenous families based on pavement characteristics. This classification results in fewer samples of pavement sections in each family and thus reduces the reliability and validity of the TPMs generated for each family (Amin, 2015). However, the validity of the prediction per family is ultimately improved with respect to the situation where information from various types of pavements is used to predict the behaviour of all types.

2.4 Conclusion

The following figure describes the summary of the problems and the structure of this research. Budget limitations for pavement preservation, which in most Western countries is exacerbated by aging infrastructure with an increasing need for maintenance, have triggered the improvement of maintenance optimization models.

One of the components of the optimization model is the pavement performance prediction model. Due to the nature of high uncertainty from environment and traffic loading, pavement performance prediction models need to be able to accommodate these uncertainties. For budget planning purposes, it is also important to provide the integration between project and network level performance. Moreover, maintenance effectiveness is still difficult to measure. Thus, maintenance works have often not been prioritized by the road agencies.
There are many types of mathematical models that are suitable to predict pavement performance. However, in this case, Markov chains are chosen since it establishes transition relations that can be used to predict developments in performance, regardless the available data for the initial condition. Markov chains are also able to integrate both pavement deterioration rates and improvement rates. Moreover, it has higher accuracy compared to other probabilistic models such as Survivor Curves.

The results of the prediction model can serve as decision support for road agency in creating a more reliable maintenance planning, as well as to study those pavements that deviate from the overall performance.
Chapter 3: Case Study and Calculation

This chapter elaborates on the case study done, using data from the IVON pavement management system in the Netherlands. Firstly, the inspection methods in IVON is explained. The structure of the database and the filtering method are discussed, and the scope of the case study and the model criteria are explained. Finally, the calculation example of pavement prediction models is presented.

3.1 IVON and Pavement Inspection

3.1.1 Introduction to IVON

In the Netherlands, IVON is used by Rijkswaterstaat (RWS) for maintenance on highway networks. IVON is a program that generates an optimal maintenance plan on network level by predicting maintenance needs based on the current state of the network, with its associated cost. It estimates the expenditure for maintaining bituminous pavements over a number of years and it concentrates on providing the best possible grouping of actions representing one project in view of “economies of scale” (Worm & van Harten, 1996). IVON treats the various pavement distress types independently and distinguishes among others raveling, skid resistance, and cracking. There is no weighted or combined value such as Pavement Condition Index (PCI) or Roughness Index (RI) to identify the threshold of failure year.

IVON utilizes intervention year to describe the end of service life of a pavement section. The same section of pavement can have different intervention years for different distress mechanisms (raveling, cracking, unevenness). The nearest intervention year (first distress type that is expected to reach the intervention level) determines the intervention year for that section. Intervention years on all distress type are calculated for every 100 meter pavement section. This is shown in Figure 3.1, where the horizontal axis shows 100m pavement sections (between the green dotted lines) and the vertical axis shows intervention years.

![Figure 3.1 Maintenance Intervention in IVON (Rijkswaterstaat, 2013)](image-url)
There are several types of distress shown, such as RAF (ravelling), KRK (cracking) and LVL (longitudinal unevenness). The second set of 100 meter sections has the intervention year 2001 for ravelling and 2003 for longitudinal unevenness. Although ravelling determines the intervention year, the need to also address the unevenness may lead to a larger reconstruction a little later in time. Thus, when the pavement section reaches the intervention year, maintenance is required to be done in that particular section and the type of maintenance depends on the distress type.

Asphalt behaviour is difficult to model on the network level due to the high variations of data. Many factors contribute to this problem such as the high variation in asphalt quality and traffic load. Thus, at the moment, RWS mainly relies on the annual performance monitoring to predict the future need for pavement performance.

### 3.1.2 Pavement Evaluation in Rijkswaterstaat

In RWS, there are two methods to obtain intervention years for raveling distress:

1. **Manual or Visual Inspection**

   Inspection data from the visual inspection will be converted into intervention years by expert judgement from the inspectors. They determine the intervention year based on a given guideline that regulates specific types of distress. The main factors to determine intervention year are the distress level, average service life, and construction year. Another factor such as traffic level is also taken into account. If the expected service life is less than or equal to five years, the inspectors will directly determine the number. Next, the number of expected service life become the input for IVON program.

   If the inspectors determine that the expected service life is more than 5 years, it will be calculated by the IVONLANG program. The IVONLANG program calculates the long-term intervention year based on factors such as average service life for that type of wearing course, type of soil, traffic level, and climate. However, the dominant factor for the calculation is the average service life of that particular type of the asphalt wearing course. The program also classifies the intervention year into two parts: right hand lane and carriageways. The difference between the intervention years between the two parts is approximately 5 to 7 years.

![Flowchart for Pavement Evaluation with Manual Inspection](image-url)
2. Automated Inspection with LCMS

Since two years ago, RWS has opted to switch from the manual inspection to the automated inspection with Laser Crack Measurement System (LCMS). In the Netherlands, LCMS is utilized to measure cracking and raveling (Rijkswaterstaat, 2013). LCMS compares the actual distress photo taken from the field with a library that consists of a huge data set of distress photos. Then, the LCMS will automatically calculates the intervention year.

The use of LCMS will reduce the inspection cost, reduce the inspection time, increase the objectivity of the inspection data, and increase the safety level for the inspection personnel.

In LCMS, the 3D laser profiler is able to extract types of distress such as cracks, macro-texture, and raveling. For raveling inspection, it measures the volume of aggregate loss per unit of surface area (Laurent et al., 2009). The LCMS is producing photos that will be linked to the damage level and determine the intervention years. A special algorithm is designed to detect the amount of the aggregate loss.

![Flowchart for Pavement Evaluation with Automated Inspection](image)

Figure 3. 3 Flowchart for Pavement Evaluation with Automated Inspection

3.1.3 Scope of Research

Raveling is the dominant failure mechanism for porous asphalt in the Netherlands. It accounts for more than 90% of failure (Aalst, 2015). It is difficult to model the effect of raveling to the reduced service life in asphalt due to variables such as the asphalt quality, soil condition, and construction quality. Raveling is a progressive mechanism where the deterioration becomes faster over the time and difficult to be predicted. The current LCMS is not tailored-made for raveling distress. RWS is currently developing a new model to predict raveling in the LCMS. Meanwhile, it is interesting to observe the effect of raveling from the existing procedure in RWS.

Therefore, the focus of this research is to develop the performance prediction model with a probabilistic approach for the raveling distress. The observation time from the inspection is 10 years, from 2004 to 2013. The data that will be used is on the right hand lane in all regions in the Netherlands. The reason to choose right hand lane is due to the fact that it is the most heavily loaded with traffic compared to other lanes.

In this thesis, there are three types of porous asphalt that are discussed, which are ZOAB, ZOABTW, and ZOAB+. Porous asphalt has the biggest percentage of all, and it accounts for roughly more than 85% of the highways in the Netherlands (Aalst, 2015). The average life of asphalt wearing course is 11 years with the life range from 5 to 23 years depends on types of the wearing course.
ZOAB is the standard porous asphalt concrete and it is the most common type in Dutch highways. ZOAB+ is the improved version of ZOAB which has been built since 2008. It has more bitumen than ZOAB, therefore it has longer average service life. ZOABTW is specially designed for noise reduction purposes. It contains special type of polymer-modified bitumen (PMB). However, the expected average service life of ZOABTW is the shortest among the three surface layer. Table 3.1 shows the average service life for asphalt surface layers. Since right hand lane is the most loaded with traffic, it has the shortest average service life compared with the rest of the road.

<table>
<thead>
<tr>
<th>Surface Layer</th>
<th>Characteristics</th>
<th>Average Service Life (Years)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Right Hand Lane</td>
</tr>
<tr>
<td>ZOAB</td>
<td>Porous asphalt concrete</td>
<td>10</td>
</tr>
<tr>
<td>(Dutch: Zeer Open</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asfaltbeton)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ZOABTW</td>
<td>Porous asphalt with two layers</td>
<td>9</td>
</tr>
<tr>
<td>(Dutch: Zeer Open</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asfaltbeton Twee</td>
<td></td>
<td></td>
</tr>
<tr>
<td>L a a g s )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ZOAB+</td>
<td>Improved porous asphalt concrete</td>
<td>11</td>
</tr>
<tr>
<td>(Dutch: Zeer Open Asfaltbeton Plus)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.1 Average Service Life for Asphalt Surface Layers

Figure 3.4 Example of Repaired Pavement Section
3.2 IVON Database

3.2.1 Database Structure

The following table illustrates the structure of IVON Database. All of the surface layers (ZOAB, ZOAB+, ZOABTW) are built with different composition of material and affects their average service life. Hence, the prediction models are going to be built individually for the 3 surface layers. Sections 3.3 and 3.4 describe the example of using IVON database to build performance prediction models with Markov chains.

<table>
<thead>
<tr>
<th>Surface Layer</th>
<th>n=3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Road Number</td>
<td>n=52; 40; 24</td>
</tr>
<tr>
<td>Carriageway</td>
<td>n=3</td>
</tr>
<tr>
<td>Lane</td>
<td>n=6</td>
</tr>
<tr>
<td>Inspection Year</td>
<td>n=11</td>
</tr>
<tr>
<td>Location</td>
<td>0-0.1, 0.1-0.2, ...</td>
</tr>
</tbody>
</table>

In IVON database, the ‘road number’ data show different regions of road networks and are represented with road number from 1 to 838. ZOAB has the highest number of regions, which is 52 regions, followed by ZOAB+ with 40 regions and ZOABTW with 24 regions.

Each ‘road number’ consists of a different set of carriageways. Mainly, there are 3 different carriageways: 0HRM, 1HRR (right side), and 1HRL (left side). 0HRM is a single carriageway which consists of at least two lanes with traffic moving in opposite directions. On the other hand, 1HRR or 1HRL can consist up to 6 lanes.
In this thesis, the duration of inspection years which are taken into account to build the model is ten years, from the year 2004 to 2013. Data from the year 2014 will be used for validation procedure. For each location, the database shows the intervention year which describes the performance level of a pavement section. Each of the location also contains construction year data so that the age of asphalt can be calculated. The intervention year and the age of asphalt are the two main criteria in building the pavement performance prediction models.
3.2.2 Filtering

One of the most challenging issues in building the prediction models is on the filtering process of the database. Building a transition probability matrix in Markov chains requires comparing the intervention year and age from the exact pavement section for two consecutive years. However, comparing the data on a network level, where it consist of approximately 350,000 data points, is not a straight forward procedure.

Figure 3. 8 The Filtering Criteria

In general, the filtering process can be divided into three phases. The first phase is to figure out the structure of the database. It is done by comparing the same consistent variables for the 10 years of inspection for all three surface layers. Variables in the road, carriageway, and lanes were investigated in detail to discover the consistency among them. Another complication arises due to the code of the right hand lane. New right hand lanes were built throughout the years. Thus, in some cases, the codes in the database are also changing. Some of the new right hand lanes are indicated by the higher number of lanes.

The second phase is to filter the location of pavement sections. Unfortunately, the inspection data on the location are not recorded consistently from one year to another. A significant amount of the pavement location data were missing in the middle of the inspection years. Due to that reason, the database should be filtered for every two consecutive years to obtain pavement sections from the same location that have the same properties.

The third phase of the filtering process is to filter the maintenance and renewal process. In the middle of the observation years, it was found that some parts of the ‘age’ data (obtained from the construction year) are reduced drastically. The reason behind this is that RWS has renewed the surface layer on that particular pavement section. However, to build the prediction models without maintenance activities, the data that containing maintenance need to be removed. One way to do this is by comparing the ‘age’ data for two consecutive years and remove the data containing age difference. It was found out that the data with maintenance activities accounts for 10% of the data. Detail explanation of the filtering process can be found in Appendix B.
The example of the filtered database can be found in Figure 3.15.

### 3.3 Model Criteria and Classification

#### 3.3.1 Model Criteria and Filtered Database

The intervention year and age of asphalt from IVON are used as the input for the prediction models. The following flowchart explains the algorithm to obtain pavement performance prediction model from the age and intervention year in IVON.
Figure 3. 10 Modelling Algorithm
The state classification shows the asphalt performance based on the distress level. For RWS, it shows how many years ahead when they need to maintain the particular pavement section. The intervention year is classified into 4 classes. State 1 is the condition where asphalt was evaluated to be in the best condition. Intervention or maintenance would not be needed for more than 5 years. On the other hand, state 4 indicates that the pavement is in the worst condition with immediate intervention required within 0 to 1 year.

State 2, 3, and 4 represent the intervention years evaluated from the visual inspection. State 1 represents the intervention years from the automated calculation from the IVONLANG program.

Table 3. 2 Criteria for State Classification

<table>
<thead>
<tr>
<th>State</th>
<th>Expected Service Life from Intervention Year (Years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&gt;5</td>
</tr>
<tr>
<td>2</td>
<td>4-5</td>
</tr>
<tr>
<td>3</td>
<td>2-3</td>
</tr>
<tr>
<td>4</td>
<td>0-1</td>
</tr>
</tbody>
</table>

The following figures describe the associated distress level for state 1 to state 4.
As it can be seen, state 1 shows that only a small number of stones are missing from the surface layer. The overall pavement performance in state 1 is still in good condition. Thus, it does not affect the safety and comfort level of road users. When the condition starts to deteriorate and reaches lower states (state 2, 3, and 4), RWS needs to prepare to do maintenance. The poor condition of pavement will create problems for riding comfort and safety.

In this research, state 4 is defined as the worst state which requires immediate intervention in the following year. In state 4, the area of stone loss in the porous asphalt surface layer is much bigger. In this situation, the pavement is in poor comfort condition due to issues related to roughness and noise. Additional loading from the vehicle can lead to extreme damage and unsafe condition. As a result, cars can get damaged and windows might be broken by the loss of stone from raveling. In state 4, the maximum speed on the pavement also needs to be reduced.

Due to its damaging effect, state 4 needs to be avoided. It is important for RWS to know the time when the pavement network reach state 4 so that they can immediately plan a maintenance intervention. Finally, RWS need to do immediate maintenance when pavement section reach state 4.

**Filtered Database**

The filtering process results in two set of database to build the prediction models, which are pavement network with and without maintenance. The filtered database consist of codes to indicate the inspection year data to indicate the timing of inspection year, data of location of pavement section (surface layer, road, and carriageway), and expected life from the inspection year. Figure 3.15 shows a small example of database for pavement without maintenance. More examples of the database can be found in Appendix C.

<table>
<thead>
<tr>
<th>Inspection Year</th>
<th>Surface Layer</th>
<th>Road</th>
<th>Carriageway</th>
<th>Expected Life ( t )</th>
<th>Expected Life ( t+1 )</th>
<th>State ( t )</th>
<th>State ( t+1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>1</td>
<td>1HRL</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>1</td>
<td>1HRL</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>1</td>
<td>1HRL</td>
<td>3</td>
<td>2</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>2</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>2</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>2</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>2</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>2</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>3</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>3</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>3</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>3</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>3</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>3</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>3</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>3</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0405</td>
<td>ZOAB</td>
<td>3</td>
<td>1HRL</td>
<td>11</td>
<td>10</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

**Figure 3.15 Filtered Database**
As an illustration, the first data point in Figure 3.15 shows the inspection data from year 2004 and 2005. In 2004, the expected life (or intervention year) of the particular pavement section is 3 years. In 2005, the pavement section was evaluated should be maintained in the next 2 years. Next, the expected life is converted into state with the criteria in Table 3.2. Finally, the Markov chains prediction models will be built by using the data from the two last columns, which are the states in year $t$ and $t+1$.

### 3.3.2 Model Classification

This research seeks to observe the influence of several variables toward the performance of the pavement. These variables are maintenance activities, surface layers, carriageways, and traffic level. Therefore, the outcome of the models will be classified according to these variables. The complete classification can be observed in the following table.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age of Asphalt</td>
<td>With Maintenance</td>
</tr>
<tr>
<td></td>
<td>Without Maintenance</td>
</tr>
<tr>
<td>Surface Layer</td>
<td>ZOAB</td>
</tr>
<tr>
<td></td>
<td>ZOABTW</td>
</tr>
<tr>
<td></td>
<td>ZOAB+</td>
</tr>
<tr>
<td>Carriageway</td>
<td>Single Carriageway: Lane: 0HRM</td>
</tr>
<tr>
<td></td>
<td>Multiple Carriageway: Lane: 1HRL+1HRR</td>
</tr>
<tr>
<td>Traffic</td>
<td>High Traffic: Road Number: A2, A15, A16, A67</td>
</tr>
<tr>
<td></td>
<td>Low Traffic: Road Number: A7, A31, A32</td>
</tr>
</tbody>
</table>

One of the variables that will be investigated is the influence of maintenance activities. Firstly, the database to build the prediction models is classified into two categories: “with maintenance” and “without maintenance”. Pavement sections “with maintenance” category takes into account the maintenance and renewal activities that happened in that observation years. Maintenance activities can be found by observing the age of asphalt over the years.

The RWS database consists of two types of data, which are expected service life and age of asphalt. In the database, maintenance activities are defined as the replacement of porous asphalt surface layer with a new layer. Therefore, in the database, maintenance activities are indicated by the reduction of the asphalt age in the database.

As an illustration, asphalt in one pavement section is 7 years old at year 2004. In the next year (year $t+1$), the age is expected to become 8 years old. However, if maintenance occurs, the age of asphalt is “reduced” due to a newer construction year. In such case, the age of asphalt in the year 2005 is lower than 7 years. For example, in the case of a new surface layer, the age of asphalt can become 1 year old.
“Without maintenance” category does not take into account the data points where maintenance and renewal process have occurred. In general, the database without maintenance have fewer data points compared to the database of pavement network with maintenance.

Table 3.4 Classification for Maintenance

<table>
<thead>
<tr>
<th>Category</th>
<th>Criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>With Maintenance</td>
<td>$a_{t} = (a_{t} + 1)_{t+1}$</td>
</tr>
<tr>
<td>Without Maintenance</td>
<td>$a_{t} &gt; (a_{t} + 1)_{t+1}$</td>
</tr>
</tbody>
</table>

Next, the prediction models are classified based on the variables of carriageway number and traffic level. However, not all of the classification have sufficient data to build the prediction model. Generally, there are two reasons why it is impossible to build the model. Firstly, there is insufficient data to fill in the transition probability matrix. If there is not enough transition among the states for two consecutive years, the model could not be developed. The lack of state transition is indicated by the diagonal component in the TPM that contain zero. In this case, the future prediction cannot be observed. Secondly, the data for the particular classification simply do not exist. The complete classification of the model and the unavailable matrix cells (denoted by “N/A”) is presented in the next figure.

![Complete Modelling Classification](image)
3.4 Calculation and Results

3.4.1 Example of Calculation

This section explains the calculation example of a prediction model for ZOAB in multiple carriageway networks. This calculation example shows the pavement condition without maintenance, where data points containing maintenance activities have been omitted. Firstly, the expected service life data are taken from the data set for year $t$ and year $t+1$. For this example, the data set that is used to build the model is RWS inspection database from year 2004 to 2013. The expected service life data is converted into the states, which describe the pavement condition from the best (state 1) to the worst (state 4). The following table shows a small example of data set to build Markov chains.

<table>
<thead>
<tr>
<th>State in year t</th>
<th>State in year t+1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
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<td>2</td>
<td>3</td>
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<td>2</td>
<td>3</td>
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<td>3</td>
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<td>3</td>
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<tr>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

In this example, the total number of the population is 53757 for year $t$. Table 3.6 below shows the distribution of state in the initial year (year $t$). It can be seen that state 1 has the highest population which accounts for 72% from the total population.

<table>
<thead>
<tr>
<th>State</th>
<th>n</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>38624</td>
<td>72%</td>
</tr>
<tr>
<td>2</td>
<td>9615</td>
<td>18%</td>
</tr>
<tr>
<td>3</td>
<td>4912</td>
<td>9%</td>
</tr>
<tr>
<td>4</td>
<td>606</td>
<td>1%</td>
</tr>
<tr>
<td>total</td>
<td>53757</td>
<td>100%</td>
</tr>
</tbody>
</table>
Next, the number of the state moving from state $i$ in year $t$ to state $j$ in year $t+1$ are calculated. As an illustration in Table 3.7, the number of pavement sections that initially are in state 2 in year $t$ and move to state 3 in year $t+1$ is 3640.

Table 3.7 Example of State Transition

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Total ($N_i$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>33413</td>
<td>4602</td>
<td>556</td>
<td>53</td>
<td>38624</td>
</tr>
<tr>
<td>2</td>
<td>72</td>
<td>5811</td>
<td>3640</td>
<td>92</td>
<td>9615</td>
</tr>
<tr>
<td>3</td>
<td>46</td>
<td>351</td>
<td>3053</td>
<td>1462</td>
<td>4912</td>
</tr>
<tr>
<td>4</td>
<td>14</td>
<td>3</td>
<td>63</td>
<td>526</td>
<td>606</td>
</tr>
</tbody>
</table>

To develop a transition probability matrix (TPM), the transition probability for each individual state $p_{ij}$ need to be calculated by dividing the total number of pavement sections in the network that moved from state $i$ to state $j$ by the total number of pavement sections in state $i$ at the starting year. As an example, the total number of pavement sections that start at state 2 and move to state 3 in the next year is $p_{23}$, which equals to 3640. The total number in state $i$ is indicated by total number of population for each rows in Table 3.7, which are $N_1 = 38624$, $N_2 = 9615$, $N_3 = 4912$, $N_4 = 606$. The number of transition $i$. As an example, $p_{23}$ is calculated by dividing 3640 ($N_{23}$) by 9615 ($N_2$), which equals to 0.38. It results in the following TPM:

$$p_{ij} = \frac{N_{ij}}{N_i}$$

$$\begin{bmatrix}
0.87 & 0.12 & 0.01 & 0.00 \\
0.01 & 0.60 & 0.38 & 0.01 \\
0.01 & 0.07 & 0.62 & 0.30 \\
0.02 & 0.00 & 0.10 & 0.87
\end{bmatrix}$$

From the TPM, it can be seen that there are small parts that contain $p_{ij}$ when $i < j$ such as $p_{21}, p_{31},$ and $p_{43}$. In reality, pavement sections cannot automatically move to a better state without any maintenance activities. Thus, it shows an error in the database record that contributes to the data pollution. Another requirement to build the prediction model is that the descending diagonal line in the matrix must contain a positive value. $p_{11}, p_{22}, p_{33},$ and $p_{43}$ should not contain zero. Otherwise, the Markov chains predictions cannot be built.

Next, to generate the prediction for pavement performance for the upcoming year ($a_t$), the following formula is used. $P^T$ is the transpose of transition probability matrix where $a_0$ is the initial condition. For every prediction years, the same initial transition probability matrix is used. The result of the matrices depends on the power of $t$, which indicates the prediction year. So, every prediction year will eventually use specific matrix that correlates to the prediction year $t$. 


\[ a_t = (p^T)^t a_0 \]

Keep in mind that the Markov chains are independent of time, which means that the initial condition can start at any year. In this example, the initial \( a_0 \) is calculated to be the actual probability of the year 2013 for ZOAB in multiple carriageways networks. Each rows in the initial condition \( a_0 \) represents different states from state 1 to state 4.

\[
a_0 = \begin{bmatrix} 0.58 \\ 0.26 \\ 0.13 \\ 0.03 \end{bmatrix}
\]

Then, the distribution of the states in year \( t \) (\( a_t \)) will be calculated for every years for the next 10 years. Hence, there are 10 different \( a_t \) showing predicted performance for the upcoming 10 years, from 2014 to 2023. In figure 3.17, year 1 shows the result of predicted performance in year 2014 while year 10 shows the predicted performance in year 2023.
<table>
<thead>
<tr>
<th>Year</th>
<th>TPM Transpose</th>
<th>Initial Vector</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.87 0.01 0.01 0.02</td>
<td>0.58 0.01 0.01 0.02</td>
<td>0.508142</td>
</tr>
<tr>
<td>2</td>
<td>0.749429 0.01477 0.021333 0.041049</td>
<td>0.58 0.01477 0.021333 0.041049</td>
<td>0.444683</td>
</tr>
<tr>
<td>3</td>
<td>0.650442 0.023007 0.033551 0.055234</td>
<td>0.58 0.023007 0.033551 0.055234</td>
<td>0.391111</td>
</tr>
<tr>
<td>4</td>
<td>0.565987 0.032006 0.045028 0.066571</td>
<td>0.58 0.032006 0.045028 0.066571</td>
<td>0.346024</td>
</tr>
<tr>
<td>5</td>
<td>0.494179 0.041265 0.055388 0.075698</td>
<td>0.58 0.041265 0.055388 0.075698</td>
<td>0.308166</td>
</tr>
<tr>
<td>6</td>
<td>0.433324 0.050333 0.064533 0.083084</td>
<td>0.58 0.050333 0.064533 0.083084</td>
<td>0.276433</td>
</tr>
<tr>
<td>7</td>
<td>0.381902 0.058899 0.072494 0.089085</td>
<td>0.58 0.058899 0.072494 0.089085</td>
<td>0.249871</td>
</tr>
<tr>
<td>8</td>
<td>0.33856 0.066748 0.079357 0.093975</td>
<td>0.58 0.066748 0.079357 0.093975</td>
<td>0.227663</td>
</tr>
<tr>
<td>9</td>
<td>0.302107 0.073817 0.085234 0.097971</td>
<td>0.58 0.073817 0.085234 0.097971</td>
<td>0.209114</td>
</tr>
<tr>
<td>10</td>
<td>0.271504 0.08008 0.09024 0.101243</td>
<td>0.58 0.08008 0.09024 0.101243</td>
<td>0.193632</td>
</tr>
</tbody>
</table>

Figure 3. 17 Example of Probability over the Years
To observe the trend of the performance over the next 10 years, the results of \( a_t \) can be plotted into a graph. From Table 3.8, it can be observed that the probability of pavement section to be in state (from 1 to 4) keeps changing over the years. A graph that shows the performance prediction model for the next 10 years can be seen in Figure 3.18.

<table>
<thead>
<tr>
<th>state</th>
<th>years</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
<td>0.58</td>
<td>0.5081</td>
<td>0.4447</td>
<td>0.3911</td>
<td>0.3460</td>
<td>0.3082</td>
<td>0.2764</td>
<td>0.2499</td>
<td>0.2277</td>
<td>0.2091</td>
<td>0.1936</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>0.26</td>
<td>0.2335</td>
<td>0.2156</td>
<td>0.1997</td>
<td>0.1851</td>
<td>0.1719</td>
<td>0.1599</td>
<td>0.1492</td>
<td>0.1399</td>
<td>0.1317</td>
<td>0.1246</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td>0.13</td>
<td>0.1906</td>
<td>0.2212</td>
<td>0.2379</td>
<td>0.2469</td>
<td>0.2516</td>
<td>0.2538</td>
<td>0.2545</td>
<td>0.2543</td>
<td>0.2536</td>
<td>0.2526</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>0.03</td>
<td>0.0677</td>
<td>0.1184</td>
<td>0.1713</td>
<td>0.2219</td>
<td>0.2684</td>
<td>0.3099</td>
<td>0.3464</td>
<td>0.3782</td>
<td>0.4056</td>
<td>0.4291</td>
</tr>
</tbody>
</table>

Figure 3.18 Example of Probability Graph

The above figure shows the prediction of pavement performance without maintenance activities. The horizontal axis shows the prediction year and the vertical axis show the probability of pavement sections being in the certain state. It starts with the initial condition \( a_0 \), which represents the actual probability of state 1 to 4 in year 2013. Different colours of the lines show state 1 to state 4, which indicating the condition of the pavement section. State 1 is the best condition while state 4 is the worst condition.

From the graph, it can be observed the probability of pavement sections being in the best condition (state 1) will gradually decline in the next few years. The probability of state 3 and state 4 (the worse states) will keep increasing over the years. Since the data set to build this prediction model does not
contain maintenance, it is expected that the condition of state 4 keeps increasing. After the year 2018, the probability of state 4 is larger than state 1. It means that there is a high probability of finding pavement sections to be in the worst condition.

The probability of state 4 keeps increasing until the end of prediction years, where pavement network has a probability of almost 42% of them to be in a bad condition. For the road agencies, this will be the time when immediate intervention or maintenance action is required. As explained previously, condition of state 4 indicates various implications for the road users. The high number of pavement sections in state 4 will disrupt the overall use of the pavement network.

In general, Markov chains will produce a constant level of performance predictions after a certain amount of time. In the performance prediction models, the constant level of performance is indicated by the steady-state lines in the last few years of the prediction years. However, due to high deterioration rates from pavement network without maintenance, the steady-state lines in Figure 3.18 is unlikely to be observed in the first 10 years of prediction. The complete performance prediction graphs for all the categories in Table 3.3 can be found in Appendix E.
Chapter 4: Results and Analysis

This chapter elaborates on the results of the pavement performance prediction models for the pavement surface layers. Firstly, prediction models for all of the categories are explained. Next, the effectiveness of maintenance on the performance of pavement surface layers is discussed. The discussion then go on to the validation procedure that measures the accuracy of the pavement prediction models. Finally, a discussion on the feasibility of Markov chains in predicting pavement performance is presented.

4.1 Service Life Prediction

The purpose of this research is to predict the performance of pavement network in time. In order to reach this objective, this research will provide average performance models for asphalt’s service life prediction. The service life prediction models describe the performance of ZOAB, ZOABTW, and ZOAB+ for the next 10 years from 2013. With these prediction models, road agencies can obtain an estimation of the average condition of their road networks in the future. They will be able to determine the remaining time that their networks are still in good condition. Thus, they can predict the required time for maintenance and quantity or area from their pavement networks that need to be repaired.

In this research, the prediction models are divided into two different scenarios: prediction models with maintenance and without maintenance. In the prediction models without maintenance, data points that contain maintenance activities are omitted from the database. Meanwhile, the prediction model with maintenance takes into account all of the maintenance activities during the last 10 years. The result of the prediction model with maintenance is discussed in the sub-section 4.1.1, while the result of the prediction model without maintenance is discussed in the sub-section 4.1.2. Next, the difference between the two scenarios is assessed in sub-section 4.1.3 and measure the maintenance effectiveness is discussed.

4.1.1 Service Life Prediction for Network with Maintenance

Figure 4.1 presents the expected average performance of the pavement surface layers for different carriageways and traffic categories. The models use the Markov chains method to predict the probability of pavement sections remain in a good condition for the next 10 years. As starting point, the actual situation in 2013 is used for each data set. The development over time is based on the probabilities developed on the basis of the whole data set, including regular maintenance.

The horizontal axis represents prediction years and the vertical axis represents the probability of the pavement network to be in state 1. In this case, state 1 is defined as pavement being in good condition. The maximum value of 1 in vertical axis indicates that the probability that all pavement sections are in good condition is 100%. On the contrary, the value of 0 indicates that there is no probability to find pavement sections in a good condition, which means that the pavement sections have moved to worse conditions (state 2, 3, or 4).
The prediction models with maintenance utilize the data with respect to maintenance and renewal effects. The Markov chains use a transition probability matrix (TPM) that is built based on the inspection data from year 2004 to 2013. The initial condition is taken from the actual probability for each category in 2013 and then the model generates predictions for the development over time. Different colours of the graphs represent different surface layers of ZOAB, ZOABTW, and ZOAB+.

In this case, four categories were chosen to see various influencing factors on pavement performance. The four categories are single carriageway, multiple carriageways, high traffic, and low traffic. The two sets of graphs are discussed in the next sections.

**Single Carriageway and Multiple Carriageways**

The difference in the number of carriageways seems to have an influence on the pavement performance. For ZOAB, there is a sharp increase of probability in single carriageway (top left hand picture) that shows the improvement effect from maintenance activities. In this research, an increase in performance is defined as the increase of the probability to find pavement in good conditions. The maintenance affects the performance of pavement in the first 5 years, leading to stable conditions after that.

This situation indicates that if the current maintenance regime is continued and no radical changes in traffic and weather, circa 70% of the wearing courses will be in good condition. During those first five years, the performance of ZOAB on single carriageway shows an increase of 28%. Meanwhile, in multiple carriageways networks, the performance jump only accounts for 3.6% improvement. The comparison between single carriageway and multiple carriageways can also be observed in ZOAB+. 
For ZOAB+, single carriageway network also shows a better performance compared to multiple carriageways networks.

There are several possible explanations behind the findings. First, maintenance intensity plays a role for the difference performance. Multiple carriageways receive a much higher number of maintenance compared to single carriageway. It shows that the single carriageway networks have a higher probability to be in good condition multiple carriageways networks.

The findings may also be caused by the difference in available data points and traffic levels. Single carriageway network only has 13% of the data points compared with the data from multiple carriageways, thus the results are less representative. In reality, Markov chains might overestimate the improvement effect from maintenance activities.

The third explanation is related to the traffic level. Roads in the Netherlands are classified into 4 different classes. Class D is the most important roads with high traffic level, strategically located, and being passed by vehicles with heavy loads. Class A is the smaller road with less traffic. Most of the single carriageway were parts of the Class A. Therefore, single carriageway performs better than multiple carriageways due to the lower level of traffic.

**High Traffic and Low Traffic**

The influence of traffic can be observed by comparing the graphs of high traffic and low traffic (left bottom and right bottom graphs in Figure 4.1). These two categories are based on locations with different traffic levels. In this case, there is no comparison possible between high and low traffic levels for ZOABTW and ZOAB+ due to the limited data availability to build the model. ZOAB is the only surface layer for which there is sufficient data to build the model. Although the initial probability of ZOAB in good condition is higher in pavement network with high traffic, there is no striking difference in the behaviour of the pavement over the next few years. Both of them stays at approximately the same level as the initial condition, with a fluctuation range of 10%. Hence, in this case, no significant differences between high and low traffic that can be obtained. A possible explanation for this finding is that the number of pavement sections is much higher for low traffic networks. In addition, there are also more maintenance found in low traffic compared to high traffic.

**Surface Layers**

When comparing the three surface layers, an interesting finding can be found. The performance of ZOAB+ and ZOABTW will still slightly deteriorate, but the decreasing rate for ZOAB+ is not as significant as the one in ZOABTW. A number of possible explanations for these results are discussed.

As written in Chapter 3, ZOAB+ is the surface layer that was built with the highest expected service life. Accordingly, ZOAB+ is also the most expensive to be built. Meanwhile, ZOABTW is porous asphalt which consists of two layers while ZOAB is the standard porous asphalt concrete. Theoretically, ZOAB will perform better than ZOABTW. The prediction models from Markov chains reveal the same trend. ZOAB+ performs the best and followed by ZOAB and ZOABTW.
Another possible reason for this result is the difference in total data population between the three types of surface layer (Figure 4.2). The number of data points for single carriageway is disproportionately smaller than the data for multiple carriageways. Low traffic networks also have a smaller number of data points than high traffic networks. The categories that contain a higher number of data points will have better accuracy in representing the actual condition.

![Figure 4.2 Data Population for Service Life Prediction with Maintenance](image)

**Conclusion**

The performance prediction models show that with the current maintenance regimes, ZOAB and ZOAB+ have higher chance to remain in good condition on single carriageway networks compared with on multiple carriageways networks. Three possible reasons for this finding are the smaller data population for single carriageway, lower traffic level in actual condition, and higher number of maintenance for multiple carriageways. The first reason would mean a less accurate prediction and is no reason to adjust maintenance planning. The second is an actual network effect that can be taken into account in planning. The third reason implies a better improvement for multiple carriageways due to better maintenance regime. Among of the three surface layers, ZOAB+ has the best quality and followed by ZOAB and ZOABTW. From the graphs, no significant findings can be drawn from the behaviour of pavement networks with different traffic levels.

4.1.2 Service Life Prediction for Network without Maintenance

This section elaborates on the performance prediction for pavement network without maintenance. In contrast with Figure 4.1, this performance model excludes the maintenance activities in the database. These models only incorporate pavement sections that have not received maintenance or renewal treatments. In this case, maintenance is defined as the renewal of pavement surface layers. The total number of renewal activities in the database is approximately 10%. The results between the two prediction models (with and without maintenance) is going to be analysed to understand the effect of maintenance activities.
However, even though the maintained sections are excluded from the data, the fact remains that sections reaching a poor state are maintained. As such, the real continued degradation of the network that would occur if no maintenance was done, is not in the data set and cannot be predicted with the model. The analysis in this section is the best estimate of the effect of lack of maintenance, but it is an underestimation of the real effect.

The horizontal axis in Figure 4.3 represents the prediction years and the vertical axis represents the probability of pavement sections to be in a good condition. Different colours of the lines show different surface layers. The initial condition is taken from the actual probability for each category in 2013.

![Figure 4.3 Service Life Prediction for Network without Maintenance](image)

The condition of pavement network without maintenance will deteriorate much faster than the condition of the pavement network with maintenance activities. In this case, pavement deterioration is defined as the decreasing probability to find pavement sections in good condition. In addition, pavement prediction will behave differently under the influence of different categories.

Another interesting observation can also be found for the rates to reach the steady-state lines. In general, it can be seen that the network performance with maintenance in Figure 4.1 will lead to steady state lines. However, in Figure 4.3, the prediction has not yet reach a steady state-line for the next 10 years. It happens due to the different deterioration rates. Lower deterioration rates will accelerate the Markov chains predictions to reach a steady-state condition. Eventually, after certain number of years of predictions, Markov chains will shows a constant condition.
Single Carriageway and Multiple Carriageway

The difference in carriageway plays an influence on how pavement deteriorates. For ZOAB, the probability of the deterioration is roughly 10% in single carriageways and up to 40% in the multiple carriageways. ZOAB+ also shows bigger deterioration rates in multiple carriageways than in single carriageway. These findings are similar to pavement network with maintenance. The prediction model for pavement network without maintenance also shows that the single carriageway networks perform better than the networks in multiple carriageways.

Another explanation for this finding is the difference in total population between the single and multiple carriageways. The available data points to build the prediction model for single carriageway is only 12% for ZOAB compared by the multiple carriageways networks. Hence, single carriageway might have less accuracy in representing the actual condition.

![Figure 4. 4 Data Population for Service Life Prediction With Maintenance](image)

High Traffic and Low Traffic

In this scenario, the influence of traffic level can be observed in ZOAB surface layer. For ZOAB, the probability of good performance in high traffic will decrease up to 40% in the next 10 years, while pavement network in low traffic will only decrease up to 35%. The possible explanation for this finding is related to the traffic level. Higher level of load from traffic will influence the deterioration (Khurshid, Irfan, & Labi, 2011; Thom, 2014). Thus, road agencies can expect that low traffic networks will require less maintenance than high traffic networks. Due to the limitation of the data, the comparison between high and low traffic for ZOABTW and ZOAB+ cannot be observed.

Surface Layers

Comparing the three surface layers, it can be seen that ZOABTW has the highest deterioration rates and followed by ZOAB and ZOAB+. This finding is in agreement with the expected service life of the three surface layers. ZOAB+ is designed to have the highest expected service life while ZOABTW is designed to have the short expected service life.
The sharp deterioration rates in ZOABTW might be contributed from the fact that Markov Chains contains a bias in overestimating data points. In ZOABTW, the amount of the actual probability of worse condition is very small. However, Markov Chains TPM captures it as factors with big influence. This issue will be explained further in section Model 4.6.

Figure 4.1 and Figure 4.3 explain the effect of maintenance activities toward the prediction of pavement performance. In general, pavement without maintenance has bigger deterioration rates than pavement with maintenance. As an example, most of the prediction models without maintenance in Figure 4.3 have steeper slopes compared to the prediction models with maintenance in Figure 4.1. This case especially can be observed in This finding supports the theory that maintenance plays a significant role in preserving the pavement condition (Khurshid et al., 2011; Labi et al., 2003; Zhang et al., 2013).

Conclusion

Pavement networks without maintenance show the same overall trends as pavement networks with maintenance. Single carriageway networks will perform better than multiple carriageways networks and low traffic networks will have higher chance to remain in good life. Possible explanations behind these findings are the influence of traffic level and the smaller population to build the model. Among the three surface layers, ZOAB+ has the best quality and followed by ZOAB and ZOABTW. These findings confirm the theory on the influence of surface layers and traffic level on pavement performance. However, for all the categories, pavement network without maintenance show a higher deterioration rate. This is also as expected, it shows that renewal activities will prolong the expected service life of pavement networks. An important remark for this sections is that since there are no actual failed sections in the data set, only the maintained sections have been taken out of the analyses. So, it gives an optimistic indication of the network performance over time when no maintenance is done.

4.1.4 Maintenance Effectiveness

Maintenance effectiveness is usually done by measuring the effectiveness of preventive maintenance (Khurshid, 2011; Labi, 2006). However, the database records for this research do not capture the preventive maintenance activities. Instead, it only consists of renewal activities for the surface layers. Therefore, this section will measure the effect of renewal activities in prolonging the expected service life of asphalt wearing courses.

In general, it can be seen that maintenance activities will prolong the good condition of surface layers. It is indicated by the fact that pavement network without maintenance has a higher deterioration rate, as can be observed in Figure 4.3. However, the effectiveness of renewal activities cannot be directly measured due to the limitation of the current prediction. As a consequence, the results of the Markov chains prediction still contains bias since the prediction model still captures the effect of good pavement from maintenance activities. Hence, the effectiveness of renewal activities is measured by its ability in prolonging the expected service life.

An attempt is made to measure the effectiveness of maintenance in prolonging the pavement service life with the following formula. The value of the intervention years from the database is translated as the expected service life of the pavement. The difference between the service life from maintenance activities will be combined and will be divided by the number of maintenance activities in the database.
records. Finally, road agencies can obtain the average increase in expected service life due to maintenance activities.

\[
\text{average increase in expected service life} = \frac{\sum_{t=0}^{n} \text{expected service life}_{t+1} - \text{expected service life}_{t}}{n}
\]

The figure below shows the population for the extension of service life. The first 3 years were omitted from the calculation since those numbers indicate errors in the database records. In practice, the service life of pavement surface layers can vary from 5 to 19 years. From the calculation, it is found out that the number that occurs most frequently in the extension of service life for ZOAB and ZOABTW is 7 years while the mode for ZOAB+ is 10 year.

![Graph showing the extension of service life for different types of pavement layers.](image)

Figure 4. 5 Extension of Service Life from Maintenance
The average service life extension for ZOAB, ZOABTW, and ZOAB+ are shown in the following table.

Table 4. 1 Average Increase in Expected Service Life

<table>
<thead>
<tr>
<th>Surface Layers</th>
<th>Increasing Expected Life (Years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZOAB</td>
<td>8.6</td>
</tr>
<tr>
<td>ZOABTW</td>
<td>7.8</td>
</tr>
<tr>
<td>ZOAB+</td>
<td>7.4</td>
</tr>
</tbody>
</table>

This result indicates that the expected service life from the renewal activities is lower than the average service life of surface layers in Chapter 3. In this case, RWS needs to evaluate the expected life for their surface layers. However, this result might contain a bias due to the limited data of recorded renewal activities. This case can be specifically true for ZOAB+, where it has only been built since the year 2008. Since they are relatively new surface layers, there is still a limited number of renewal activities that have been performed and results in the low value of the increasing expected life. Thus, in reality, the effect of renewal of ZOAB+ surface layer is likely to be different.

Conclusion

In this research, maintenance effectiveness is measured by observing the effect of renewal activities in prolonging expected service life. Maintenance effectiveness is difficult to be quantified since Markov chains do not completely eliminate the effect of renewal activities. The average increase of expected service life for all of the 3 surface layers are calculated to be approximately 7 to 8 years.

4.2 Validation of Service Life Prediction

This section elaborates on the validation procedure for service life prediction. The validation procedure will measure the accuracy between the actual and the Markov chain prediction. The validation procedure is given in Figure 4.6. Performance prediction in 2014 will be compared with the actual condition in 2014.

In order to obtain performance prediction with Markov chains, there are several things that need to be done. Firstly, the TPM is built based on the historical data from year 2004 to 2013. By using the TPM, Markov chains will produce the performance prediction for the next year (2014). The initial condition in the Markov chains is the actual probability in 2013. Finally, the result of the prediction in 2014 will be compared with the actual probability in 2014.
Figure 4.6 Validation Procedure for Prediction Models

Figure 4.5 explains the results of the prediction. The light blue bar shows the actual probability in year 2013. The Markov chains prediction is presented in the middle bar (the dark blue bar). The grey bar represents the actual probability in year 2014. The observation is done on the four condition states. State 1 shows the good condition while the state 4 shows the worst condition.

Figure 4.7 Validation for All Surface Layers

To obtain the accuracy of the prediction, the height difference between the middle bar and the right hand side bar will be observed. From the Figure 4.5, it can be seen that the three surface layers have a different degree of accuracy.
For ZOAB, in state 1 and 2, it can be seen that the prediction bars are slightly lower probability than the actual conditions. On the contrary, in state 3 and state 4, the prediction bars are higher performance than the actual conditions. It shows that the Markov chains prediction underestimates the good condition and overestimates the bad condition. It could further be seen that the difference between the actual and the prediction in every state is less than 4%.

On the contrary, ZOABTW has a lower accuracy than ZOAB with a bigger difference between actual and prediction bars, which could reach up to 8%. The lower accuracy might be contributed to the fact that ZOABTW has the smallest population to build the model. In ZOABTW, state 1 is predicted to be lower while the rest of the states are predicted to be higher than the actual conditions. In this case, the Markov chains prediction model underestimates the good condition and overestimates the bad conditions. On the other hand, for ZOAB+, the accuracy is quite high. The difference between the actual and prediction condition is less than 1.5%. In conclusion, the average difference for the 3 prediction models is relatively small, with the value around 2.4%. The good accuracy shows that RWS can use the prediction models to forecast the future condition of their pavement networks.

![Graphs showing validation for different categories](image)

**Figure 4.8 Validation for Different Categories**

In order to understand more of the details, the validation is done for the contributing categories. The corresponding categories are single carriageway, multiple carriageways, high traffic, and low traffic. The result of the validation procedures for different categories are illustrated in Figure 4.6. The first row indicates the different categories for ZOAB. The second row shows results for ZOABTW while the third row shows results for ZOAB+.

For ZOAB in single carriageway, the predicted number of sections in condition of state 1 (the good condition) is almost half of the actual condition. In the same category, state 2, 3, 4 are predicted to be higher than the actual condition. The possible reason for this result is the big difference between the actual condition in year 2013 and 2014. Since Markov chains prediction model is based on the actual condition of the previous year, hence, it could not capture the extreme result in the year 2014.
Looking at ZOAB in multiple carriageways and high traffic, a consistent trend can be found. Lower prediction values are found for state 1 & 2 and higher prediction values for state 3 & 4. This conclusion is consistent with the prediction of the surface layers. Markov chains will undervalue the good condition. Thus, although this prediction has a good accuracy, RWS needs to keep in mind that the prediction models show a slightly pessimistic result. These prediction models are suitable in maintaining the good condition since the distress will be maintained before the required time. However, as a consequence, this conservative approach requires RWS to create a higher maintenance budget than the actual needs.

In addition, it is quite surprising to find that for ZOAB in low traffic network, the probabilities of state 2 and 3 are significantly higher than the rest of the results. It indicates a higher probability of the pavement to be in a bad condition. For the road agencies, this condition implies the need to perform maintenance in the following year. In contrast, all ZOABTW results show that more than 70 percent of pavement networks are still in good condition. ZOAB+ has even more superior advantages than the rest of the surface layers. It shows more than 80% of probability that the pavement networks are in good condition thus requires less maintenance. The prediction of ZOAB+ is in line with the real condition where ZOAB+ possess a longer expected service life compared with the other two surface layers.

**Conclusion**

The pavement performance models show different results for the various asphalt surface layers and categories. In general, the models show a slightly pessimistic predictions. There is a consistent trend that can be found: state 1 and 2 are predicted to be lower and state 3 and 4 are predicted to be higher than actual. Markov chains will undervalue the condition of good pavement and will overestimate the condition of worse pavement networks. In addition, the average difference between the prediction and the actual model is 2.3%. ZOAB has lower probability of pavement in good condition (60%) and ZOAB+ has high probability of good condition (more than 80%).
4.3 Predicted and Actual Performance

In this research, Markov chains will produce a prediction model which describes the average network-level performance. To gain an understanding on the difference between the actual condition and the prediction model, it is necessary to see the comparison between the two of them.

Figure 4.9 Predicted and Actual Probability for Network with Maintenance

The solid lines in Figure 4.9 represent the expected prediction from Markov chains while the dots describe the actual probability as it occurred on the pavement network. The different coloured lines represent the different states, from state 1 to 4, indicating the different condition of the pavement. The horizontal axis shows the number of years for future prediction. The figure above depicts the pavement network performance with maintenance for ZOAB network. The starting condition for the actual and prediction models is the actual state of ZOAB network in 2004.

From the above graph, it can be observed that the actual percentage of pavement network contains greater fluctuation than the predicted ones. In general, the predicted performance has steady lines throughout the 10 years. The constant trend in the lines reveals that Markov chains produce the average expected performance based on the historical observation data.
The dots, which represent the actual condition, are obtained by calculating the percentage of the states for every year. Every year contains a different percentage for every state which indicates the dynamic nature of the pavement condition on the network level. For the actual condition, fluctuation may occur since in reality the pavement performance will increase and decrease to a certain level. The ascending line in the good condition can be explained by two things. Firstly, maintenance activities will result in pavement condition that return from the worst to the best condition.

Secondly, throughout the years, new pavement sections were built. It increases the probability to be in good condition since the new pavement conditions start off in good condition. Thus, it explains the increasing trend for state 1 in the first 6 years. The dynamic data set to build Markov chain can be found in the Appendix F.

The pavement performance will reach its best condition in 2009 with 77% of pavement network in state 1 (good condition). After year 2009, the performance will gradually decline and fall into 56% of good condition in 2013. The descending lines show a natural phenomenon where the performance will deteriorate due to aging and the influence of traffic load.

When the probability of pavement sections in state 1, road agencies need to increase their maintenance effort in order to preserve their network to be in good condition.

Conclusion

Several efforts have been done to identify the correlation between the actual and predicted performance. In this case, only the ZOAB sections are used since this surface layer has an adequate number of data points. For the predicted performance with maintenance, Markov chains reveal the average future performance that is indicated by the steady lines. Interesting findings come from the probability in the actual condition. The actual condition of pavement networks with maintenance shows fluctuation due to maintenance effect, additional data points, and the deterioration process.

4.4 Project and Network-Level Comparison

Markov chains prediction provides an average performance which is built by a combination of pavement sections. One pavement network can consist up to thousands of individual pavement sections. Hence, it is interesting to see the performance of individual pavement sections throughout the years. In this case, a project-level performance is defined as the performance of an individual pavement section. An attempt to make a comparison between the project and network-level performance is elaborated in this section.

To illustrate the performance of a project level, three pavement sections from ZOAB surface layer are chosen as an example. These pavement sections are chosen from different road numbers in various location on ZOAB network. The following graph will examine the transition of pavement sections from the good condition to the worse conditions over the years. The conditions are represented by state 1 as good condition to state 4 as the worst condition. Different colours of the lines represent the performance on different pavement sections on ZOAB network. In reality, one road number can consists up to hundreds of pavement section. The horizontal axis shows the age of asphalt in years and the vertical axis represents the state. The renewal process is excluded in this model so that one life cycle of
deterioration process can be observed. The starting year for the three pavement sections are different from one to another, but this graph shows the performance throughout their life cycle.

Figure 4. 10 Project Level Performance for ZOAB

In the first 5 to 7 years, all of the pavement sections still remain in good condition (state 1). In the next several years, they will move to a worse condition. After one or two years remaining in the lower state, all of them will jump into the worst condition or the state 4.

Figure 4. 11 Network Level Performance for ZOAB
If being compared with the predicted performance of ZOAB network, the behaviour of project level performance is consistent with the behaviour of network-level performance. Figure 4.11 represents the behaviour of pavement network for ZOAB surface layer. The initial condition is pavement being in 100% good condition. In the network level, state 1 is the “dominant” state for the first 8 years. During the first 5 years, bad conditions (state 2, 3, 4) are starting to increase. In year 5, it can be observed that state 3 is starting to exceed state 2. It shows that the overall pavement network is shifting toward the worse conditions. In year 8, state 4 become the dominant state.

What is interesting to be observed is the “rate” of the transition from good to bad sections. Some pavement sections show a gradual deterioration from state 1, 2, 3, to 4 for every year. Another pavement section shows a sharp deterioration. Those pavement sections directly move from state 1 and to state 4 in only one year. Possible explanations for this result are the occurrence of accident and change of inspection method.

For several busy road sections in ZOAB network such as A13 and A44, the traffic level is too high and thus visual inspection becomes more difficult to be carried out. For these road sections, the inspection is done by digital imaging through a video. Later on, experts will determine the service life of the road from the video record. However, the inspection with the aid of digital imaging has a lower quality than the visual inspection. As a result, the accuracy of the service life prediction becomes lower.

Road accidents will also incidentally contribute to the sudden performance drop in the surface layer. Road accidents can suddenly damage the surface layer hence the good performance will directly drop to the worst state.

4.5 Network-Level Performance Based on Markov Chains and Combined Project-Level

This section compares the network-level performance based on Markov chains and from combined or average project-level performance. Figure 4.12 shows network level performance based on the Markov chains prediction and the actual average condition. While the Markov-based network level is developed by using Markov chains prediction, the actual average condition of network-level performance is developed by calculating the average probability of every state for every observation year.

In the next figure, different colours of the lines represent different states with state 1 as the best condition to state 4 as the worst condition. The horizontal axis represents the number of prediction years and the vertical axis represents the probability value. The starting point of both conditions is that the pavement sections are in 100% good condition. The graphs show one life cycle of pavement without maintenance intervention.

Currently, the existing database has several inconsistencies. Maintenance activities can appear in the middle of the observation years and thus affecting the performance. Hence, it will limit the number of pavement sections which have a complete life cycle. From the database, it is also found that the intervention years given by the visual inspection are not consistent. Pavement sections can be valued to be “better” in the next year without any maintenance. This condition contradicts the fact that over the years, the condition of pavement section becomes worse.
Inconsistencies are also found in the starting age of pavement section. The database contains a very limited number of data representing pavement sections with a complete cycle of deterioration. Although some of the data record the pavement condition from age 0, many data start at an older age. Due to this reason, additional data points, which reflect the history, have been added to the data set for modelling purpose. As an illustration, there is a pavement section with the age 4 in good condition (state 1). Data points on the previous years (age 1, 2, 3) will be added with the condition of state 1.

Figure 4. 12 Comparison between Network and Combined Project-Level Performance
In comparing two graphs in Figure 4.12, there are similar trends but also several differences that can be observed. In the first 5 years, Markov chains show lower probability of good condition compared to the actual condition. In the first 5 years, Markov chains overestimate the probability of pavement in bad condition. It can be seen that the probability in state 2 has already reached 20% in the first 3 years. In the actual condition, the first five years are still dominated by the good condition. The probability of bad condition will only appear after year 3.

Figure 4.13 describes the average states throughout the years. Different colours of the lines represent the best state, worst state, and the average state. The orange line shows the average combined state for every year. In the first 5 years, the average state is still in state 1. Only after the 6th year, the average state will gradually decline to the worse state.

In the later years (year 6 to year 10), network-level prediction shows that state 4 gradually becomes the dominant state. The growth of state 4 is quite sharp and could reach up to 35% in year 10. However, on network-level based on combined project-level performance, the increase of the state 4 is not that fast. In comparison, state 2 will reach up to 35% from year 6 to 10. Both of the good states in the two conditions show a similar declining trend in the last few years of observation.

However, cautions need to be applied in interpreting the results. The number of pavement sections to build the combination of project-level model only represents 70% of the total population. If the number of samples is changed, the result might also change significantly. To reduce this risk, the results were checked with experts and they indicated that the project-level deterioration from state one fits with their expectations.

**Conclusion**

The comparison between the predicted network-level from Markov chain with the actual performance from combined project level can reveals several things. Firstly, the prediction of dominant state in project level in the early phase is consistent with the performance on network-level. In addition, the
prediction of dominant state in the later phase are also consistent with the network level. However, for the Markov chains, it did not clearly show the transition in the middle phase. On network level, the probability of good condition is still overestimated by the dominant state. In reality, the actual state has changed. Another finding also shows the occurrence of a sudden deterioration on the project level due to the change of inspection method and road accidents.

An attempt was made to compare the predicted performance from Markov chains and the actual pavement performance in ZOAB network. In the first 5 years, this comparison shows that the good condition is underestimated by Markov chain prediction while in the later phase, it is overestimated. However, with a limited sample size in project-level, caution must be applied, since the findings might not consistent with other pavement sections.

4.6 Markov Chains Feasibility

This section evaluates the feasibility of using Markov chains in building pavement prediction models. Four criteria are chosen to measure the feasibility of Markov chains, which are accuracy, reproducibility, flexibility, and user-friendliness.

Accuracy

In this research, accuracy is broadly defined as the degree of conformity of a measure to a true value. Accuracy is used as a parameter to measure the validation of the model. The objective of the validation is to observe the proximity between Markov chains prediction and the actual condition. The validation shows that the prediction model has a satisfying accuracy with an average difference of 2.3% between the prediction and actual condition.

This research also examines the influence of traffic level and carriageway toward the deterioration rates of pavement. The accuracy of these models will be checked by a conceptual validation. A conceptual validation is a process when the results will be verified by the experts to see whether the models are able to represent the actual condition.

The results of the network performance based on traffic and carriageways are in accordance with the conceptual validation. It is found that pavement networks with higher traffic level show faster deterioration rates compared with pavements with less traffic. In addition, single carriageway networks have better performance due to less traffic load and the smaller number of vehicles passing.

Different types of surface layers also influence the deterioration rate of the pavement network. From all the three surface layers, ZOAB+ has the best performance and followed by ZOAB and ZOABTW. In the real condition, ZOAB+ has the longest expected service life.

While short-term (one year) prediction shows a good accuracy, the accuracy of the long-term prediction is still difficult to be measured. An attempt to compare the ten years prediction with the actual condition is made in Section 4.3. Overall, the comparison shows the same deterioration trend between the actual condition and the prediction. However, with a limited sample size and different output in the states, this finding might not produce consistent results and thus should be treated with caution.
Currently, inconsistencies and errors in the data record are still captured in the database. These errors result in difficulties and bias in modelling the behaviour of pavement networks. Thus, RWS needs to improve the accuracy of the database records.

**Reproducibility**

Reproducibility is defined as the degree of ease in replicating the research in other networks. The reproducibility of the prediction model with Markov chains is easy as long as the structure of the data input is similar. The important requirement of reproducibility is that the pavement networks need to have a consistent set of the database with the same structure. The structure of the database needs to have the same properties such as the properties that indicate the age of asphalt, intervention year, and the classification of the location.

Furthermore, the pavement networks should also contain a sufficient number of transitions in their changing conditions. If the number of transition among the states is limited, the prediction models cannot be built. This case can be observed in the limited prediction model for ZOABTW. The number of data population is also directly proportional to its reliability. A larger data population will produce a better prediction model. However, one important point should be noted on the limitation of the Markov chains method.

In obtaining the Transition Probability Matrix, what becomes important is the probability of \( p_{ij} \) which is a result of a division between \( N_{ij} \) (number of pavement sections that move from state \( i \) to state \( j \)) and \( N_i \) (number of pavement sections in state \( i \)). However, it does not specifically take into account the difference in total population among different states (\( N_i \)). In reality, one state can be overly populated compared to the other states.

\[
p_{ij} = \frac{N_{ij}}{N_i}
\]

<table>
<thead>
<tr>
<th>( X_t \backslash X_{t+1} )</th>
<th>1</th>
<th>2</th>
<th>..</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>[ p_{11} \quad p_{12} \quad p... \quad p_n ]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>[ p_{21} \quad p_{22} \quad p... \quad p_n ]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>..</td>
<td>[ p_{31} \quad p_{32} \quad p... \quad p_n ]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n</td>
<td>[ p_{41} \quad p_{42} \quad p... \quad p_n ]</td>
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</tr>
</tbody>
</table>

The effect of this unevenness can be observed in the case of ZOABTW. As it can be seen, the probability \( p_{ij} \) that states in the worse condition (state 3 and 4) are quite high in the TPM (\( p_{33}=0.65 \), \( p_{34}=0.31 \), and \( p_{44}=0.96 \)).
However, in real condition, the probability of the actual data is highly unevenly distributed among the rows $i$ (state). The actual data percentage of state 1,2,3,4 is 73.75%, 21.65%, 3.66%, and 0.94% in $t+1$. From here, it can be seen that state 1 is overly populated. However, the small number of the actual data in worse conditions (state 3 and 4) plays a bigger influence in determining the shape of the transition probability matrix. With such small data percentage (0.94%), Markov chains treat state 4 as an equal factor to other states. As a result, it produces a more pessimistic prediction.

In this case, the effect of the worse state is being overvalued with Markov Chain. Hence, to obtain a more realistic result, the distribution of the actual data among the states should be taken into account in determining the state classifications. The number of state classification can be increased so that each of the states contains data population that are evenly distributed among the states.

Ideally, in building TPM, certain number of years are required to describe the long-term historical performance and capture the “average” performance. However, the exact number of years are highly depend on the data variation. As an illustration, three years of historical data might be too limited to build a TPM to predict future performance. On the contrary, twenty years of historical data might contain too many variations due to the change in road network structure.

**Flexibility**

Flexibility is defined as the adjustability of the model to obtain necessary variations and insights on the pavement behaviour. In this research, prediction models from Markov chains offer several flexibilities for the road agencies. The first advantage of using Markov chains for prediction is the ability to deal with uncertainty from construction, the environment, and quality of materials (Austroads, 2012; Morcous, 2005). Hence, road agencies will still be able to obtain average expected performances despite the variations from the actual condition.

Next, Markov chains provide flexibility to observe pavement performance in various locations under different functions. This classification will be very beneficial for road agencies when they are required to obtain prediction models on certain networks. In this research, categories of function are divided based on the surface layer, traffic level, and carriageway. The prediction model shows that pavement network will have different deterioration rates for different categories.

In the future, there are many possibilities to be explored. Road agencies can observe the influence of several factors on the remaining life of the pavement. One of the interesting factors that can be observed is the influence of the age of asphalt toward the pavement performance.

Most importantly, road agencies will be able to generate observations on the project and network level performance. They can analyse whether certain pavement sections behave within the “normal range” compared to the rest of pavement sections in the same network. If deviations occur, they might need to conduct a further investigation or doing a laboratory test on a project-level on underperforming pavement sections.
In addition, the model also shows the effect of maintenance activities toward the long-term performance of a pavement network. Road agencies can gain benefit from the insights on the effectiveness of maintenance activities. It will guide them to decide whether the budget spent for maintenance activities produces the expected results.

Another issue that can be solved with Markov chains prediction models is related to the uncertainties of the maintenance budget. Government funding for infrastructure preservation has typically a high uncertainty due to the circumstances at the political level. Ideally, a pavement section will be rehabilitated by the end of its service life. However, due to the efficiency of budget and the practicality of maintenance works, pavement sections can be rehabilitated either too early or being deferred from its end of service life. In this condition, network-level prediction models can help road agencies in dealing with those uncertainties by consistently updating their latest condition of their assets. Such realistic information can be used by the road agencies for planning purposes.

**User-friendliness**

User-friendliness refers to the extent on how the model can be easily understood by the users (road agencies). One of the initial problems in maintenance optimization model is the complexity of the tools (Morcous & Lounis, 2005). The existing optimization models usually utilize complex mathematical tools and thus it becomes less user-friendly and difficult to be understood by road agencies.

The prediction model based on Markov chains answers the problems. The output of the Markov chains model is relatively understandable for the layman. The predictions were shown in the simple graphs which explain the future conditions of pavement networks throughout the years. Road agencies will understand which locations require the biggest maintenance effort in the future. With this relatively simple description, it will be easy for people to understand the condition of pavement networks in the future.

The interpretation of the model will be easy to be applied to maintenance planning input. By having an estimation on the future performance of pavement network, road agencies can use the prediction models as the decision support for maintenance planning.

In addition, a standard MS Office program is sufficient to build the model and no special software is required. When the models have been built, people can easily observe various prediction models under different categories.

Road agencies can create various prediction models under different influencing factors. In order to do that, they just need to adjust and filter the database to build a new TPM for Markov chains. However, the numbers of different predictions that can be built rely on the structure of the database. The higher number of functions captured in the database records, the more prediction models that can be built.

Hence, Markov chain is a feasible method to obtain pavement prediction models. The prediction models with Markov chains will be beneficial for the road agencies since it offers accuracy, reproducibility, and user-friendliness. The following table describes the summary of the four criteria with its concluding remarks.
Table 4.2 Summary of Markov Chains Feasibility

<table>
<thead>
<tr>
<th>No</th>
<th>Criteria</th>
<th>Remarks</th>
</tr>
</thead>
</table>
| 1  | Accuracy        | • Good accuracy for short-term prediction  
            | • Long-term prediction is still difficult to be validated                                    |
| 2  | Reproducibility | • Appropriate for network-level prediction  
            | • Requires certain structure of the database  
            | • Results are sensitive to the data population                                            |
| 3  | Flexibility     | • Suitable to overcome uncertainties from construction and environment  
            | • Able to obtain prediction for different categories  
            | • Good to compare project-level and network-level  
            | • Able to obtain insights on maintenance effectiveness  
            | • Suitable to deal with uncertainty from maintenance funding                               |
| 4  | User-friendliness | • Does not require special software  
            | • User-friendly for road agencies  
            | • Simplicity for interpretation                                                           |
Chapter 5: Conclusions and Recommendations

Chapter 5 explains the conclusion of this research. It starts with a brief summary of the problems and answers on the research questions. Next, advantages and limitations of the performance prediction models are discussed. The significant results of this research are highlighted. Finally, suggestions for the future research are proposed.

5.1 Conclusions

The pavement network is an essential component of a nation’s infrastructure that is vital to economic activities. The limited maintenance budget and the increasing trend for pavement preservation have encouraged road agencies to improve their maintenance optimization model, including in the Netherlands. Currently, maintenance optimization models are not favourable due to its mathematical computation complexity. Other problems in this field also include the integration of project and network-level prediction and the difficulties in measuring maintenance treatment effectiveness.

One of the most important components of maintenance optimization model is pavement prediction model. For the last few years, Markov chain is a method that has been widely applied to build pavement performance prediction models since it can be built based on the existing data. Raveling, which is the dominant failure mechanism in the Netherlands, is difficult to be modelled deterministically. Thus, the main research question in this research is “How to develop a network-level performance prediction model for raveling in open graded wearing courses with Markov chains?”

This research uses a case study from pavement maintenance program IVON from Rijkswaterstaat in the Netherlands. Markov chains method is used to predict pavement performance for three wearing courses, or surface layers, of porous asphalt: ZOAB, ZOABTW, and ZOAB+. The three surface layers differ in the composition of the bitumen and possess a different average expected service life. Ten years observation, from year 2004 to 2013, is chosen since it is sufficient to determine a long-term performance. To answer the main research question, the following sub-research questions are investigated. Sub-research question 2 predominantly answers for the main research question.

5.1.1 Answers to Sub-Research Questions

The sub-research questions related to the main research question are answered in this section.

1) What are the factors that influence the existing performance prediction model for raveling in IVON?

The factors that influence the existing performance prediction models in IVON are related with the current inspection system. The existing inspection method for raveling distress is done by two methods: visual or manual inspection and automated inspection with LCMS. Visual inspection is done by the experts, who determine the expected service life by directly evaluating the distress level of pavement sections. If the pavement section is evaluated to have a remaining service life of more than 5 years, the IVONLANG model will automatically calculate the intervention year based on factors such as types
wearing course, construction year, and traffic level. The results of the inspection are recorded in the IVON database.

The automated inspection is done with LCMS and it is recently utilized in RWS. Compared with the visual inspection, the LCMS has a potential to reduce inspection time, increase the objectivity of the results, and create a less hazardous condition for the inspectors. LCMS provides a prediction by comparing the image of the actual distress with the images of pavement distress from the database.

In IVON, the data of expected service life are recorded as intervention year. These intervention years are used as a decision support for RWS to determine the timing of maintenance. Both of the inspection results from LCMS and visual inspection can be applied as the input to build performance prediction models. However, this research uses the intervention year from the visual inspection.

2) Can an algorithm for pavement performance prediction for raveling be built, based on Markov chains?

Yes, an algorithm for pavement performance prediction for raveling can be built based on Markov chains. The algorithm the data of intervention year and construction year of 100 meter pavement sections. The data of intervention year in the database are converted into the state, which reflects the condition of pavement sections.

The transition probability \( p_{ij} \) describes the transition between the states from state \( i \) moving to state \( j \) in two consecutive years (year \( t \) and in year \( t + 1 \)). \( p_{ij} \) is obtained by dividing \( N_{ij} \) (the number of pavement sections moving from state \( i \) to \( j \)) by \( N_i \) (the total number of pavement sections in state \( i \)). The transition probability is utilized to build transition probability matrix \( P \). In this research, the historical data from year 2004 to 2013 are used to build the transition probability matrix.

Next, a performance prediction model can be built with the use of vector of state probabilities. In this research, it is defined as \( a_t \), which is the distribution of pavement condition (states) at prediction year \( t \). \( a_t \) is equal to the initial condition \( a_0 \) multiplied by the transition probability matrix raised to the power of prediction year \( (P)^t \).

The performance prediction models will predict the probability of pavement sections to be in good condition (state 1). The initial condition \( a_0 \) with Markov chains can start from any year. However, in this case, it uses the condition from the year 2013 to predict the performance of the next 10 years, from year 2014 to 2023.

An attempt is also made to observe the difference between the performance models which incorporate maintenance activities and the one who does not. The data of construction year in the database is used to identify the maintenance activities. Firstly, it is converted into the age of asphalt on the given pavement section. Normally, the age of asphalt will increase for every year. However, in the database, the age of asphalt is recorded to be 'reduced' if there is maintenance activity. From distinguishing this difference, the data set is classified into two conditions: pavement network with maintenance and without maintenance. Hence, there are two different scenarios for the pavement prediction models.

From the prediction models, a graph can be built to see how the performance changes over the years. After a few years of transition, it leads to steady-state lines showing a constant level of performance. The speed to reach the steady-state condition depends on the deterioration rates of the pavement.
3) **What is the expected performance of pavement on network level based on Markov Chains performance prediction models?**

This research classifies the prediction models into several categories based on the types of surface layer, number of the carriageways, and traffic levels. Three types of asphalt wearing courses are analysed in this research which are ZOAB, ZOABTW, and ZOAB+. The performance or service life prediction models show that ZOAB+ has the highest quality, followed by ZOAB and ZOABTW. In this case, the pavement quality is defined as the probability of pavement sections to be in good condition. This result confirms the fact that ZOAB+ has the highest expected service life among the three surface layers.

The number of carriageways gives influence on the pavement network performance. The models show that pavement networks in multiple carriageways deteriorate faster than networks in the single carriageway. One of the possible reasons for this finding is the difference in the number of the actual networks that is taken into account. Single carriageway networks consist of fewer number of pavement sections compared to the multiple carriageways networks. Next, single carriageway networks have less maintenance than multiple carriageways networks. Another reason is that single carriageway networks usually have lower traffic level than in multiple carriageways networks.

This research creates two categories consist of locations with different traffic levels. “Low traffic” category consists of network A7, A31, and A32, while “high traffic” category consists of A2, A15, A16, A67. In general, there is no significant difference that can be found in the performance between the two networks. A plausible explanation for this finding is the actual pavement sections is much higher for low traffic than for high traffic. Hence, the result might not represent the actual condition for “high traffic” networks. In general, the models show conservative or slightly pessimistic predictions.

An attempt is also made to compare the performance of the project and network level. The comparison shows several differences. In the first few years, predicted performance underestimates the probability of pavement sections in the good condition. However, in the later phase of the service life, it overestimates the probability of pavement sections in the good condition. The project-level performance also reveals that a sudden performance drop can be found due to several reasons such as the change of inspection quality and road accident.

4) **How to assess the effectiveness of maintenance treatments on network level?**

Theoretically, there are several ways to measure the effectiveness of maintenance activities. Short-term effectiveness is measured by performance jump and long-term effectiveness can be measured by the area bounded by the performance curve. In general, the performance prediction models show that pavement networks without maintenance deteriorate faster than the one with maintenance. However, cautions still need to be applied in interpreting this result since it is difficult to separate the effect of maintenance in the database.

Maintenance effectiveness, especially corrective maintenance, is difficult to be determined since the database do not contain records for corrective maintenance. However, there are some measures to evaluate the effect of surface layer renewal. The average increase of expected service life due to surface layer renewal are between 7 to 8 years for ZOAB, ZOABTW, and ZOAB+. These values are lower than the actual expected service life, which might happen due to a limited number of maintenance data.
5) **What is the feasibility of using Markov chains for building pavement performance prediction models?**

Markov chains have good flexibility in creating various performance models for different categories. Road authorities are also able to compare the performance of network and project level. This comparison will be beneficial to assess whether a pavement section is in the normal range of the network condition.

From the validation procedure, Markov chains prediction models show a good accuracy with the average difference of 2.4% between the actual condition and the prediction model. Markov chains are also easy to understand and do not require special software to build.

The reliability and the simplicity to replicate Markov chains will highly depend on the variables and the amount of the data set. The higher number of the data set available will increase the accuracy of the performance prediction models. However, the number of inspection years to build the prediction models should not be too long, since there will be a possibility of high variation in the data due to change in pavement management system.

5.1.2 **Summary of Main Research Question**

The IVON database consists of thousands pavement records where each data point represents 100 meter pavement section. Every pavement record consists of intervention year and construction year data. The intervention year data are converted into the expected service life of pavement sections based on raveling distress. Four states are chosen to denote the classification of pavement condition, from the best or initial condition (state 1) to the worst condition (state 4), as can be seen in Table 3.2. The construction year data are converted into the age of asphalt. These data are taken into account to indicate maintenance activities for two conditions of pavement prediction: with and without maintenance.

State classification data for pavement sections are used to build the transition probability matrix for Markov chains. With vector of state probabilities, Markov chains produce pavement performance predictions for year 2014 to year 2023. To observe the pavement performances for different scenario, the models are applied on different categories: types of surface layers, number of carriageways, and traffic levels. The complete algorithm for building the model can be found in Figure 3.10, and the example of calculation can be found in Chapter 3.4.

Pavement prediction models in this research can assist road agencies in doing the following: to predict the pavement performance on various networks, to compare the performance of project and network-level, and to deal with uncertainties from the environment. Most importantly, road agencies can determine the maintenance timing and compare various maintenance scenarios. With all the advantages, the models can serve as a decision support for road agencies in building a more reliable maintenance schedule for asphalt wearing course preservation. Eventually, a more reliable prediction model will contribute to a better maintenance optimization model.

However, a number of limitations need to be considered in this research. Firstly, the result of the model highly depends on the structure of the database. Secondly, the data points for the state classification are unevenly distributed. It results in some predictions might overestimate or underestimate the actual performance. The number of state classification needs to be increased so that each of the state contain
a proportional number of data. A state classification with the evenly distributed population will produce better prediction. Thirdly, due to the limited data in one deterioration cycle, it is difficult to completely separate the effect of maintenance performance. Hence, the result of the networks without maintenance still contains some biases.

Lastly, Markov chains performance prediction models cannot automatically provide insights on the actual condition of the networks. Interviews with people from the road agencies are still needed to validate the results and to gain a better insight into influencing factors in the real condition.

5.2 Recommendations for RWS

Based on the limitations encountered during the research, it is suggested that RWS do the following things:

Registered maintenance treatments

Currently, there is no direct code in the database to indicate the occurrence of maintenance treatments, especially for corrective maintenance. To build a maintenance effectiveness model, it will be necessary to have a direct measure that pointed out pavement sections which have received certain maintenance treatments.

Consistency of the database code

Inconsistencies in the database are found over the years. The name of the location changes from one year to another, and not all pavement sections are consistently found over the inspection years. Another issue also lies in the consistency of the initial condition of the pavement’s life cycle.

RWS needs to ensure the completeness of the historical data on each pavement sections. A complete inspection data can create opportunities to build a more reliable performance prediction models. Therefore, RWS can obtains a better understanding of their pavement networks performance.

5.3 Significance

The method to build pavement performance prediction models in this research might be applicable to pavement networks in other countries. Moreover, this research provides additional evidence with respect to pavement prediction modelling.

Multistate and state jump

Many researches have utilized Markov chains for developing pavement deterioration model. In the previous researches, pavement deterioration is mostly simulated to deteriorate to only one state in one duty cycle (Abaza et al., 2004; Black et al., 2005; Camahan et al., 1987; Hassan, Lin, & Thananjeyan, 2015; Ortiz-Garcia et al., 2006). However, in actual condition, there is a high possibility that the pavement condition can move to more than one state.

In the previous researches, pavement deterioration is usually governed by transition only to their next worse state. In reality, an event such as road accidents will enable the condition of pavement to go directly from the best state to the worst state. Hence, this research captures a more comprehensive behaviour of pavement transition that better represents the actual condition.
**Maintenance Effects**

The study of maintenance effectiveness is a growing body of literature in the last decade (A. Ahmed et al., 2012; Labi, Author, & Pike, 2006; Mamlouk & Zaniewski, 2001). However, there is still very limited literature that combine maintenance effort with deterioration rates in Markov chains. One of the examples can be found in studies by Abaza (2004).

This research creates two conditions, networks with respect to maintenance and networks without maintenance. The differences in performance between the two networks are observed. Hence, this research provides an additional example of the maintenance effectiveness from Markov chains deterioration model.

**Comparison between Project and Network Level**

Many studies have discussed the probabilistic and deterministic models to create pavement prediction model. This research seeks to observe the comparison between the performance on network-level and the average performance on the project-level. While this finding still contains many limitations due to the limited data, it does partially provide an example of pavement performance comparison on project and network-level.

**5.4 Future Research**

Due to the time limitation of the research, various things are still left unexplored. In the future, it is recommended that further researches are undertaken in the following area:

**Measure of Maintenance Effectiveness**

It will be interesting to measure the effectiveness of various maintenance types including preventive and corrective maintenance. Maintenance effectiveness is important to be investigated so that road authorities can directly understand the benefit of certain maintenance activities toward the overall performance of pavement network.

**Analysis of Mechanistic Factors**

Further research should be done on the influence of mechanistic factors. Influence of environment factors such as materials, the age of asphalt, soil condition, and water content will be important to be investigated.

**Maintenance Cost**

A comprehensive optimization model will include the cost benefit factors that is quantified in financial terms. Maintenance measures need to be quantified to obtain the total cost for different preservation scenario. Optimization model that includes cost factors will be beneficial for the road authorities to directly identify the maintenance alternatives with maximum benefit and the least amount of cost.
References


APPENDICES
# Appendix A: Types of Pavement Distress

<table>
<thead>
<tr>
<th>Asphalt Concrete Surfaces</th>
<th>Jointed Portland Cement Concrete Surfaces</th>
<th>Continuously Reinforced Concrete Surfaces</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A. Cracking</strong></td>
<td><strong>A. Cracking</strong></td>
<td><strong>A. Cracking</strong></td>
</tr>
<tr>
<td>1. Fatigue Cracking</td>
<td>1. Corner Breaks</td>
<td>1. Durability Cracking (&quot;D&quot; Cracking)</td>
</tr>
<tr>
<td>2. Block Cracking</td>
<td>2. Durability Cracking (&quot;D&quot; Cracking)</td>
<td>2. Longitudinal Cracking</td>
</tr>
<tr>
<td>3. Edge Cracking</td>
<td>3. Longitudinal Cracking</td>
<td>3. Transverse Cracking</td>
</tr>
<tr>
<td>4. Longitudinal Cracking</td>
<td>4. Transverse Cracking</td>
<td></td>
</tr>
<tr>
<td>5. Reflection Cracking at Joints</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Transverse Cracking</td>
<td><strong>B. Joint Deficiencies</strong></td>
<td></td>
</tr>
<tr>
<td><strong>B. Patching and Potholes</strong></td>
<td><strong>5. Joint Seal Damage</strong></td>
<td></td>
</tr>
<tr>
<td>7. Patch Deterioration</td>
<td>5a. Transverse Joint Seal Damage</td>
<td></td>
</tr>
<tr>
<td>8. Potholes</td>
<td>5b. Longitudinal Joint Seal Damage</td>
<td></td>
</tr>
<tr>
<td><strong>C. Surface Deformation</strong></td>
<td>6. Spalling of Longitudinal Joints</td>
<td></td>
</tr>
<tr>
<td>9. Rutting</td>
<td>7. Spalling of Transverse Joints</td>
<td></td>
</tr>
<tr>
<td>10. Shoving</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>D. Surface Defects</strong></td>
<td><strong>C. Surface Defects</strong></td>
<td><strong>C. Miscellaneous Distresses</strong></td>
</tr>
<tr>
<td>13. Raveling</td>
<td>8b. Scaling</td>
<td>9. Lane-to-Shoulder Dropoff</td>
</tr>
<tr>
<td><strong>E. Miscellaneous Distresses</strong></td>
<td>9a. Polished Aggregate</td>
<td>11. Lane-to-Shoulder Separation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>14. Water Bleeding and Pumping</td>
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<tr>
<td></td>
<td></td>
<td>15. Longitudinal Joint Seal Damage</td>
</tr>
</tbody>
</table>

Figure 1. Types of Pavement (Haas, 2015)
Appendix B: Filtering Guidelines

The filtering procedure in this section is done to convert the raw data from RWS inspection into a database with sufficient properties for Markov chains modelling purpose. In this thesis, the filtering process is done with MS Excel. The use of other programs might result in different filtering processes.

- Filter the same road, lane, carriageway
  - Compile lists of same road, lane, location, and carriageways as the reference variables for the three surface layers for every inspection year
  - Create pivot table for each year so that the structure of the data can be observed
  - For two consecutive years, remove the nonconformity (unique) road numbers for each surface layer
  - Remove the entry which has negative value for age and expected life

- Find the right hand lane
  - To find the carriageways, find the maximum lane number for every section
  - Compare the lane number for two consecutive years
  - If the number of lane in t+1 is bigger than the number of lane in t, use the number of lane in t+1
  - Use the location (indicated by km of the road) in t+1 as a reference value
  - Create new code that contains surface layer, road number, carriageway, and lane

Output: Database with the same amount of road, lane, and carriageway for every two consecutive years
- Find the same location
  - Create unique code for each pavement section
  - Find the reference value from the lane that indicated as the right hand lane
  - Generate series of data for each location with ‘start value’ and ‘amount of data’ with the increment of 0.1

<table>
<thead>
<tr>
<th></th>
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<th></th>
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<tr>
<td>Lane 1</td>
<td>18.1</td>
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<td>18.1</td>
<td>18.1</td>
<td>18.1</td>
<td>18.1</td>
<td>18.1</td>
<td>18.1</td>
<td>18.1</td>
<td>18.1</td>
</tr>
<tr>
<td>Lane 2</td>
<td>18.1</td>
<td>18.1</td>
<td>18.1</td>
<td>18.1</td>
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<td>18.1</td>
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<td>18.1</td>
<td>18.1</td>
</tr>
</tbody>
</table>

- Combine with the code of pavement type with the available location

Output: Database with the 32.841 unique code with age and expected life for all the 10 years inspection data.

- Retrieve the data of age and construction year
  - From the unique code, retrieve the data of age and construction year for every two consecutive years
  - Remove the location which does not have value to compare
  - Retrieve the data of ‘age’ and ‘intervention year’ from the source of the years

<table>
<thead>
<tr>
<th>Observation year</th>
<th>Code 2004</th>
<th>Age</th>
<th>Intervention year</th>
<th>Code 2005</th>
<th>Age</th>
<th>Intervention year</th>
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<td>0405</td>
<td>30AB_1</td>
<td>11</td>
<td>30AB_1</td>
<td>12</td>
<td>2</td>
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<tr>
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<td></td>
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<tr>
<td>0405</td>
<td>10AB_2</td>
<td>11</td>
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<td>0405</td>
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<tr>
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<td>10AB_9</td>
<td>12</td>
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</tbody>
</table>

Output: In total, there are 198.802 data points to build the model from the ten year inspection data (from 2004-2013).
Appendix C: Example of the Filtered Database

The following figure shows the example of filtered database. In this example, \( t \) is year 2004 and \( t+1 \) is year 2005. The expected life data are converted into state, which are used to build transition probability matrix in the Markov chains.

<table>
<thead>
<tr>
<th>Inspection Year</th>
<th>Surface Layer</th>
<th>Road</th>
<th>Carriageway</th>
<th>Age ( \tau )</th>
<th>Age ( \tau+1 )</th>
<th>Expected Life year ( t )</th>
<th>Expected Life year ( t+1 )</th>
<th>State year ( t )</th>
<th>State year ( t+1 )</th>
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</tr>
</tbody>
</table>

Figure 3. Filtered Database Example

Accessing the complete database can be done by contacting Department of Road and Railway Engineering TU Delft
Appendix D: Data Population

This section shows the difference in total number used for building the prediction model.

![Graph showing data population for single vs. multiple carriageway with maintenance](image1)

**Figure 4. Data Population for Carriageway with Maintenance**

![Graph showing data population for high vs. low traffic with maintenance](image2)

**Figure 5. Data Population for Traffic Level with Maintenance**
Figure 6. Data Population for Carriageway with Maintenance

Figure 7. Data Population for Traffic Level with Maintenance
Appendix E: Additional Graphs

This section shows the results of pavement performance prediction models for all of the categories. The ten-year prediction starts from 2013. Hence, year 0 represents the initial condition of year 2013, year 1 represents the prediction condition of year 2014, up to year 10 which represents the condition of year 2023. Different colors of the lines show the predicted condition of state 1 to state 4. The graphs show the probability of pavement network to be in certain states.

Figure 8. Surface Layer: ZOAB. With Maintenance. Carriageway: Single.

Figure 9. Surface Layer: ZOAB. With Maintenance. Carriageway: Multiple.
Figure 10. Surface Layer: ZOAB. With Maintenance. Traffic: High.

Figure 11. Surface Layer: ZOAB. With Maintenance. Traffic: Low.

Figure 12. Surface Layer: ZOAB. Without Maintenance. Carriageway: Single.
Figure 13. Surface Layer: ZOAB. Without Maintenance. Carriageway: Multiple.

Figure 14. Surface Layer: ZOAB. Without Maintenance. Traffic: High.

Figure 15. Surface Layer: ZOAB. Without Maintenance. Traffic: Low.
Figure 16. Surface Layer: ZOABTW. With Maintenance. Carriageway: Multiple.

Figure 17. Surface Layer: ZOABTW. Without Maintenance. Carriageway: Multiple.

Figure 19. Surface Layer: ZOAB+. With Maintenance. Carriageway: Multiple.

Figure 20. Surface Layer: ZOAB+. With Maintenance. Traffic: Low.

Figure 22. Surface Layer: ZOAB+. Without Maintenance. Carriageway: Multiple.

Figure 23. Surface Layer: ZOAB+. Without Maintenance. Traffic: Low.