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Publication Date
2013

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Adaptive Optimization Methods
in System-Level Bridge Management

By

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A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Civil and Environment Engineering

In the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Samer M. Madanat, Chair
Professor Carlos F. Daganzo
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Fall 2013

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Abstract

Adaptive Optimization Methods in System-Level Bridge Management

By

Haotian Liu

Doctor of Philosophy in Civil and Environment Engineering

University of California, Berkeley

Professor Samer, M. Madanat, Chair

In 2012, over 25% of the bridges in the United States were rated as *structurally deficient* or *functionally obsolete*. Moreover, 35% of bridges are serving beyond their theoretical design lifespan and the number has been projected to increase over the next decade. The imperative needs of improving the overall condition of the bridge system has been impeded by the shortage of funding available for bridge repairs and maintenance. In 2006 the gap between Federal Highway Administration's (FHWA) estimates to eliminate the bridge maintenance backlog and the actual appropriations to bridges for repairs and maintenance from the Highway Bridge Program was $43.4 Billion. In 2009, the gap increased to $65.7 Billion. Such conflict has made effective bridge management more critical than ever.

In bridge management, agencies collect bridge condition data and develop deterioration models that predict the bridges' future conditions and associated costs, based on which maintenance, rehabilitation and reconstruction (MR&R) decisions are made. It is therefore critical to have accurate deterioration models. However, limited availability of data and incomplete understanding of the deterioration process result in inaccurate models, which lead to sub-optimal MR&R decisions and significant cost increases.

To address the inaccuracy stemming from limited bridge condition data, researchers have proposed Adaptive Control (AC) methods that update the deterioration models successively as new data become available. The underlying belief is that agencies can obtain more accurate deterioration models through updating and subsequently improve their MR&R decisions and achieve cost savings. State-of-the-art bridge management systems, such as Pontis, use a class of AC procedures known as Certainty Equivalent Control (CEC). The procedure used in Pontis updates the transition probabilities (i.e., the parameters of the component deterioration models) after each condition survey, and uses the updated probabilities in subsequent planning of MR&R decisions. Unfortunately, CEC does not necessarily lead to more accurate models, or guarantee savings in system costs; in other words, updating of the type in Pontis is not necessarily beneficial.

In the present dissertation, an AC method, Open-Loop Feedback Control (OLFC), is proposed for system-level bridge management. The performance of OLFC and the Pontis CEC is tested in a numerical study and empirical results show that OLFC has superior performance with

respect to two criteria. In terms of *improvement in model accuracy*, the Pontis CEC yields systematic bias in model parameter estimates and therefore does not improve model accuracy. In all testing scenarios, the resulting deterioration models lead to faster deterioration than the true models. OLFC, on the other hand, results in consistent convergence to the true models in all testing scenarios and improves model accuracy. When evaluated by *system costs*, the Pontis CEC consistently results in higher system costs than the no-updating scenario. The increases are on the order of $180 Million at the level of the State of California. To the contrary, updating with OLFC consistently achieves system costs savings compared to the no-updating scenario, and results in system costs that do not differ significantly from the system costs when true models are used for MR&R decision-making.

In addition, a computationally tractable optimization routine is developed for MR&R decision-making. The routine ensures strict conformity to system budget constraints and achieves satisfactory computational efficiency even given high levels of heterogeneity in bridge systems.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

First and foremost I am indebted to my advisor and mentor Prof. Samer Madanat. Throughout my PhD studies, he has provided me with unconditional support and treated me not only as a student but a colleague. He unreservedly shared his knowledge and gave invaluable ideas that formed the backbone of my thesis. I sincerely appreciate his compassion, generosity, and kindness.

I also dedicate my heartfelt gratitude to the rest of my thesis committee, Prof. Carlos Daganzo and Prof. Zuo-jun Shen. Prof. Daganzo has supported me unconditionally by being on all of my examination committees and by giving insightful critiques of my research. I thank him for giving the thesis a thorough read that greatly improved its quality. I thank Prof. Zuo-jun Shen for coming onto my committee on short notice, and for his invaluable inputs that improved the thesis' methodology and extended the horizon of future work.

Thank you to ITS faculty who have enriched my experience at UC Berkeley. I could not have been more blessed to have had the opportunities to work with every one of you. I thank Prof. Mark Hansen for chairing my preliminary examination, for being on my qualifying examination committees and for providing insights into my research. I am indebted to Dr. Jasenka Rakas for her generosity in times of need. I am grateful for having gained knowledge from Prof. Adib Kanafani, Prof. Michael Cassidy and Prof. Alexander Skabardonis in and out of classrooms. I thank Prof. Joan Walker for supervising me on my written qualifying examination.

Outside of ITS, I must thank Prof. Rhonda Righter from the IEOR department, for nurturing me with knowledge and for recommending me unreservedly. I must thank Prof. Haiyan Huang from the Statistics department, for patiently answering all my questions and for helping me through the course of my M.A. in the Statistics department. I have to thank La Shana from the Statistics department, without whom my M.A. in Statistics would have been impossible.

Thank you to the staff of ITS, especially Aza, Bernie, Chris, Helen, Kendra, Rita, and Yu, who provide immeasurable assistance to the students in their care. Aza and Yu always took great care of my funding charts, which greatly saved my mind for my PhD studies. I am grateful to have worked closely with Helen and Bernie, the joy of meeting whom everyday was essential to keep me going. Kendra, Rita and Chris helped me so much in and out of the library. To the staff of CEE, especially Shelley who always embraced me with patience answered all of my questions, and Jenna who always cheerfully greeted me and helped me get what I needed.

I could not have finished the thesis without the support from my beloved friends from ITS. I must thank Vij for the countless conversations, both academic and worldly. I must thank everyone currently and previously in McLaughlin 116. The long hours in the office were always enjoyable thanks to you. I am also indebted to every ITS student that contributes every day to a

better program which knits us all together. I also must thank all my brothers and sisters from CFC Berkeley Church, especially those from my HOS fellowship. Through you God's grace has always been sufficiently shined upon me.

I cannot thank my family enough. Thank you to my father for respecting me as an adult, even at times he did not fully understand or agree with my decisions. You have sacrificed so much for me to pursue my dream. Thank you to my mother for loving me unconditionally, for putting my needs above hers, and for unreservedly supporting all of my decisions. Thank you to my brother for being there fulfilling my responsibilities as a child and for being a wonderful companion to my parents.

Last and most important, I have to thank Jesus Christ and my Heavenly Father. Thank you for your salvation even when I was still a sinner. Thank you for loving me when I was not at all lovable. Your cross carried me through my four and half years and will always carry me till the day I see your glory.

CHAPTER 1

INTRODUCTION

1.1 Motivation

Transport infrastructure refers to the fundamental physical and organizational structures required for the operation of a transportation system. It sustains and enhances a society's economy by providing essential and supplementary commodities and services. Transport infrastructure includes but is not limited to: road and highway networks, bridges, mass transit systems, railways, canals and airports. The quality of a nation's transport infrastructure is an important index for the nation's development (Munnell and Cook, 1990; Banister and Berechman, 2001; Jiang, 2001). It is therefore very important to effectively plan, construct and maintain the infrastructure system to maximize societal benefits.

For highway networks, bridges are critical components. In case of emergencies, such as earthquakes and other natural disasters, terrorist attacks, and wars, their robustness becomes extremely critical. Therefore, poor planning and maintaining of the highway network and bridges can be catastrophic; Bridge 35W in State of Minnesota, USA collapsed into the Mississippi River in 2007 during the evening commuting period, resulting in thirteen fatalities and 145 injuries. What followed immediately were prolonged traffic congestion, impeded river navigation, and significant economic loss. The state's Department of Employment and Economic Development estimated the collapse reduced the state's economic output by $113,000 per day and cost bridge users $400,000 a day in travel time and higher operating costs.

In fact, the tragedy was not inevitable; Minnesota officials were warned, according to USA Today, as early as 1990 that the bridge was "structurally deficient," indicating that the bridge was no longer reliable or safe. In 2005, the bridge was again rated as "structurally deficient" and in possible need of replacement. The subsequent 2006 inspection identified problems of cracking and fatigue. The state, however, did not pay the bridge enough engineering attention which would have improved its structure integrity, until the disaster happened. At the

time of its collapse, the bridge was 40 years old, while the average design lifespan for bridges of the same type is 50 years.

The above incident is one example of infrastructure failures. Due to their damaging, or even devastating, consequences to the society, agencies invest efforts into the prevention of those catastrophic incidents. In addition to failure prevention, infrastructure maintenance also includes but is not limited to routine maintenance and incidental damage repair, which are equally important to support the functionality of the transport network and reduce societal costs; for example, regular patching and overlays of pavements reduce wear and tear of automobiles, and prolongs the lifespan of pavements which in return reduces traffic delay.

The planning of failure prevention, routine maintenance, incidental damage repair, etc., is enclosed in the concept of infrastructure management, which refers to the process of allocating resources to individual facilities for maintenance, rehabilitation and reconstruction (MR&R), so as to ensure safety, functionality and serviceability of the system. Despite the social and economic significance of well-managed infrastructure systems, agencies are often faced with limited resources that prohibit them from keeping the systems in their best condition. In the last two decades, the bridges in the United States have continually faced a shortfall of funding for necessary repair and maintenance, which resulted in a deteriorated system. During the period of 2006 to 2009, more than 26% of the bridges nationwide are classified as *structurally deficient* and *functionally obsolete.*. In recent years (2006 – present), the gaps between the Highway Bridge Program appropriations to bridges and federal estimates of funding to eliminate bridge backlog have been increasing, with the 2006 level being $43.4 billion and the 2009 level being $65.7 billion. It has become more critical than ever for agencies to utilize the limited resources efficiently. (Refer to http://t4america.org/resources/bridges/overview/.)
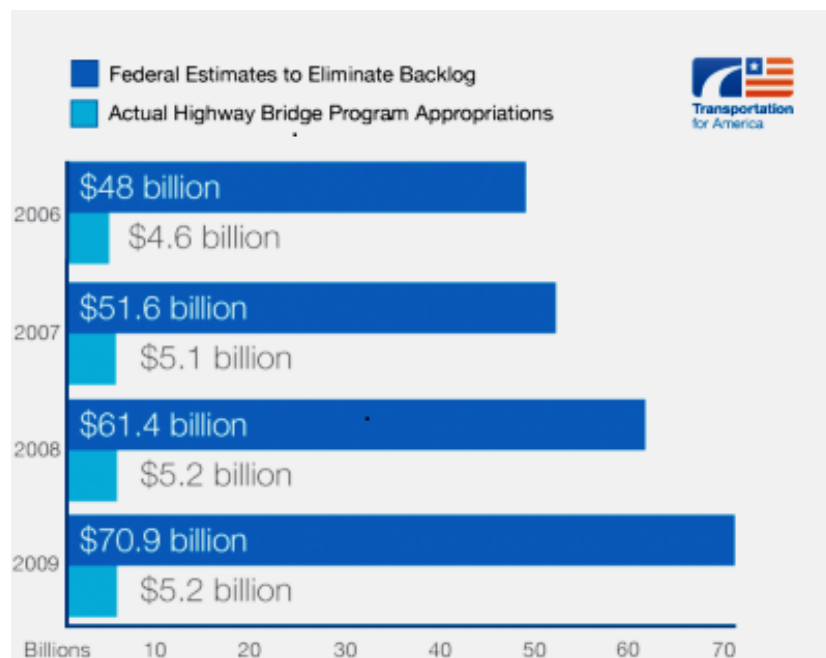
Figure 1.1: Even though the appropriations have been increased by $650 million from 2006 to 2009, the needs for eliminating the backlog have increased by $22.8 billion. Moreover, in recent years agencies have been focusing on the construction of new bridges, which is competing with the appropriations to deteriorated bridges. Moreover, recently passed legislation from Congress eliminated the Highway Bridge Program (HBP), which means bridges now have to compete with other surface transportation modes for funding.

Figure 1.1: Bridge repair funding levels vs. need estimates
(http://t4america.org/resources/bridges/overview/)

1.2. Problem Overview

Effective bridge management requires agencies to collect bridge condition data and develop deterioration models that predict the bridges' future conditions and associated costs, based on which MR&R decisions are made. It is therefore critical to have accurate deterioration models. However, limited availability of data and incomplete understanding of the deterioration process result in inaccurate models, which lead to sub-optimal MR&R decisions and significant cost increases (Madanat 1993).

To address the inaccuracy stemming from limited bridge condition data, researchers have proposed Adaptive Control (AC) methods that update the deterioration models successively as new data become available. The underlying belief is that agencies can obtain more accurate deterioration models through updating and subsequently improve their MR&R decisions and achieve cost savings. State-of-the-art bridge management systems, such as Pontis (Golabi and Shepard 1997), use a class of AC procedures known as Certainty Equivalent Control (CEC). The procedure used in Pontis updates the transition probabilities (i.e., the parameters of the component deterioration models) after each condition survey, and uses the updated probabilities in subsequent planning of MR&R decisions. Unfortunately, CEC does not necessarily lead to more accurate models, or guarantee savings in system costs (Bertsekas, 2005); in other words, updating is not necessarily beneficial. Another AC method described in Bertsekas (2005) is Open-Loop Feedback Control (OLFC), which has been shown to guarantee improvement in model accuracy when new data are used for updating, but has not yet seen its application in bridge management.

1.3 Research Objectives

In the existing literature there has been no systematic study that investigates the performance of the Pontis CEC and OLFC in system-level bridge management. The present dissertation aims to develop a comprehensive methodological framework that tests the performance of the two AC methods in accordance with the following criteria:

- Model accuracy improvement. A desirable AC method should help agencies gradually improve their knowledge of deterioration models; and

- System cost savings. A desirable AC method should achieve system cost savings as opposed to the no updating scenario.

Moreover, the framework must allow for a realistic representation of bridge deterioration, which is reflected in the choice of deterioration models. Finally, the framework should be capable of optimal MR&R decision-making. Therefore a computationally tractable optimization routine must be developed so as to ensure strict conformity to system budget constraints.

1.4 Outline of the Dissertation and Summary of Main Findings

The present dissertation is structured as follows:

- Chapter 2 describes bridge maintenance responsibility and provides a general description of the current condition of the bridges in the United States. It further identifies the issues associated with bridge management with respect to funding availability, management strategies and policy support;

- Chapter 3 reviews the existing literature for the current practice of bridge management with respect to deterioration models, optimization routine and AC methods. Different deterioration models, including Markovian models, hazard-based models, etc., have been analyzed in order to identify the model class most suitable for bridge deterioration. In addition, various optimization routines have been examined with respect to applicable scenarios, computational cost, etc. Lastly and most importantly, chapter 3 reviews the application of AC methods in infrastructure management;

- Chapter 4 develops the methodological framework for system-level bridge management, which consists of two parts: 1) The estimation of hazard-based deterioration models using data from the national bridge inventory (NBI) database; and 2) An optimization routine that is capable of making MR&R decisions for a bridge system of relatively large scale while ensuring system budget constraints are satisfied;

- Chapter 5 presents the numerical study that tests the performance of the two AC methods by simulation. The formulations of two AC methods are given. System costs are obtained by updating with the two AC methods and are compared to two cost baselines: 1) the Perfect Information (PI) baseline: system costs obtained by decision-making with true deterioration models; and 2) the Open-Loop (OL) baseline: system costs obtained by decision-making with imperfect deterioration models and no updating. Furthermore, the models obtained at the end of the updating period by the two AC methods are compared to the true deterioration models to examine which AC method achieves improvement in model accuracy;

- Chapter 6 extends the study to Markovian systems. The performance of the two AC methods is examined under the following circumstances: 1) Deterioration is truly a Markovian process; and 2) Deterioration is not history-independent but agencies adopt Markovian representations. System costs obtained with both AC methods are compared; and

- Chapter 7 provides a summary and directions for further research.

The main findings of the numerical studies are:

- ***OLFC outperforms the Pontis CEC in terms of system costs.*** The Pontis CEC consistently yielded higher system costs than no updating. OLFC, on the other hand, consistently achieved system costs savings compared to no updating and yielded system

costs that are not significantly different from decision-making with true deterioration models;

- ***OLFC outperforms the Pontis CEC in terms of model accuracy improvement.*** The Pontis CEC consistently resulted in models that represent faster deterioration than the true models when updating ends. The analysis demonstrates that such bias is not random but rather stems from the updating mechanism of the Pontis CEC. In contrast, OLFC consistently led robust convergence to the true deterioration models; and

- ***OLFC demonstrates greater potential than the Pontis CEC when deterioration is misrepresented by a Markovian process.*** When deterioration is not Markovian but agencies adopt Markovian representations, the Pontis CEC results in system costs that are not statistically different from decision-making with fixed Markovian representations. Under relatively low agency cost, OLFC achieves great system costs savings as opposed to decision-making with fixed Markovian representations. When agency cost is high, OLFC yields increases in system costs but the magnitude is small;

1.5 Statement of Contributions

The present dissertation investigates the performance of two AC methods, the Pontis CEC and OLFC, in the context of system-level bridge management. The contributions are summarized as:

- Development of a computationally feasible optimization routine for system-level bridge management. The routine ensures strict conformity to system budget constraints and does not compromise computational efficiency even when the system is of large scale;

- Implementation of hazard-based deterioration models in system-level bridge management. This relaxes the Markovian assumption imposed on infrastructure deterioration by much of the existing literature and allows for a more realistic representation. In addition the present dissertation has demonstrated that it is costly to adopt Markovian representations when deterioration is truly non-Markovian;

- Demonstration, through a numerical study, that the AC method deployed in the Pontis system, Certainty Equivalent Control (CEC), does not guarantee improvement in deterioration model accuracy or savings in system costs; and

- Demonstration, through a numerical study, that Open-Loop Feedback Control (OLFC) guarantees improvement in deterioration model accuracy and savings in system costs.

The research is anticipated to aid transportation agencies in the efforts of maximizing the utility of limited funding for bridge repairs and maintenance and minimizing the total societal costs.

CHAPTER 2
BACKGROUND

Despite their significant social and economic impacts, infrastructure systems are not always well maintained due to a combination of: 1) incomplete knowledge of infrastructure systems, in terms of deterioration mechanism and modeling, etc.; 2) lagging technologies for inspection and/or maintenance; 3) insufficient funds for maintenance; and 4) inadequate political support, in terms of funding prioritization.

Bridges, the vital component of the complex transport system, are the most vulnerable element because of their distinct function of joining highways as the crucial nodes; in addition they are exposed to aggressive environments (Frangopol and Liu, 2007) and undergo fast deterioration. At the same time they are among the most under-maintained elements in terms of funding appropriations. The number of bridges repaired in the period of 2008~2012 was three times fewer than the number for 1992~1996. As of 2012, approximately 25% of the bridges in the United States are classified as *structurally deficient* or *functionally obsolete* due to insufficient maintenance and rehabilitation. Transportation for America's 2013 Bridge Report described the worrying situation in the following way: "… Laid end to end, all the country's (the United States) deficient bridges would span from Washington, DC to Denver, Colorado – more than 1,500 miles."

This chapter aims to demonstrate that with the nation's bridges under-maintained, the need for effective bridge management in the United States is imperative. Section 2.1 provides an overview of the definition of bridge maintenance activities and the responsible entities. Section 2.2 reviews the current condition of bridges in the United States with respect to bridge functionality and in-service duration. The statistics show that the percentages of deteriorated and aged bridges are alarming, while the funding available for maintenance has continued failing to keep up in the last decade, as shown in section 2.3. The chapter concludes with the importance of fostering more effective bridge management.

2.1   Bridge Maintenance Responsibilities

Bridge Maintenance Definition

In the state of California, bridges are classified as a type of "Roadway Facilities" (Caltrans, 2006). The legal definition of maintenance for roadway facilities as provided by the California Streets and Highways Code, General Provisions, Section 27, includes the following:

a. The preservation and keeping of rights of way, and each type of roadway, structure, safety convenience or device, planting, illumination equipment and other facility, in the safe and usable condition to which it has been improved or constructed, but *does not include reconstruction or other improvement*;

b. Operation of special safety conveniences and devices, and illuminating equipment; and

c. The special or emergency maintenance or repair necessitated by accidents or by storms, or other weather conditions, slides, settlements or other unusual or unexpected damage to a roadway, structure or facility.

According to Maintenance Manual Volume I (Caltrans, 2006), bridge maintenance activities include: "… repairing damage or deterioration in various bridge components, removing debris and drift from piers, bearing seats, abutments, etc., cleaning out drains, repairing expansion joints, cleaning and painting structural steel, sealing concrete surfaces, the maintenance of electrical and mechanical equipment on moveable span bridges, and the operation of the moveable spans …." The readers are advised to refer to Chapter H of the manual for examples of defects that require maintenance and more detailed descriptions of the procedures to be taken.

Entities with Maintenance Responsibilities

Bridges are mostly maintained in accordance with ownership. For example, according to the nation bridge invenotry (NBI) database (2012), out of the 12,180 bridges California State Highway Agency (CSHA) owns, 12,157 bridges are maintained by CSHA. Table 2.1 selectively lists the statistics for other agencies in California. (Note that some bridges are owned by multiple agencies, in which case the owner is recorded in the hierarchy of State, Federal, county, city, railroad, and other private entities.)

Table 2.1: Ownership vs. maintenance responsibility by agency in the State of California

Agency	*County Highway Agency*	*City or Municipal Highway Agency*	*National Park Service*	*U.S. Forest Service*
Ownership	7,238	4,568	51	295
Maintenance Responsibility	7,208	4,553	51	291

2.2 Bridges in the United States

An Overall Deficient System

As of 2012, 66,749 bridges – more than 11 percent of the highway bridges in the United States – are classified as *structurally deficient* (SD), according to the Federal Highway Administration (FHWA). (The statistics are published on the FHWA website. To avoid failure, SD bridges call for immediate attention and require maintenance, rehabilitation or replacement.) In the meantime, 84,748 bridges are classified as *functionally obsolete* (FO), which means these bridges require substantial resources to be corrected.

The percentages of SD bridges and FO bridges in the United States have been decreasing over the period of 1992 to 2012, with the statistics plotted in Figure 2.1; nonetheless in 2012 more than 25% of bridges are classified SD or FO: the bridge system still requires significant improvement and funding support. The total numbers of SD, FO and all bridges by year are plotted in Figure 2.2.
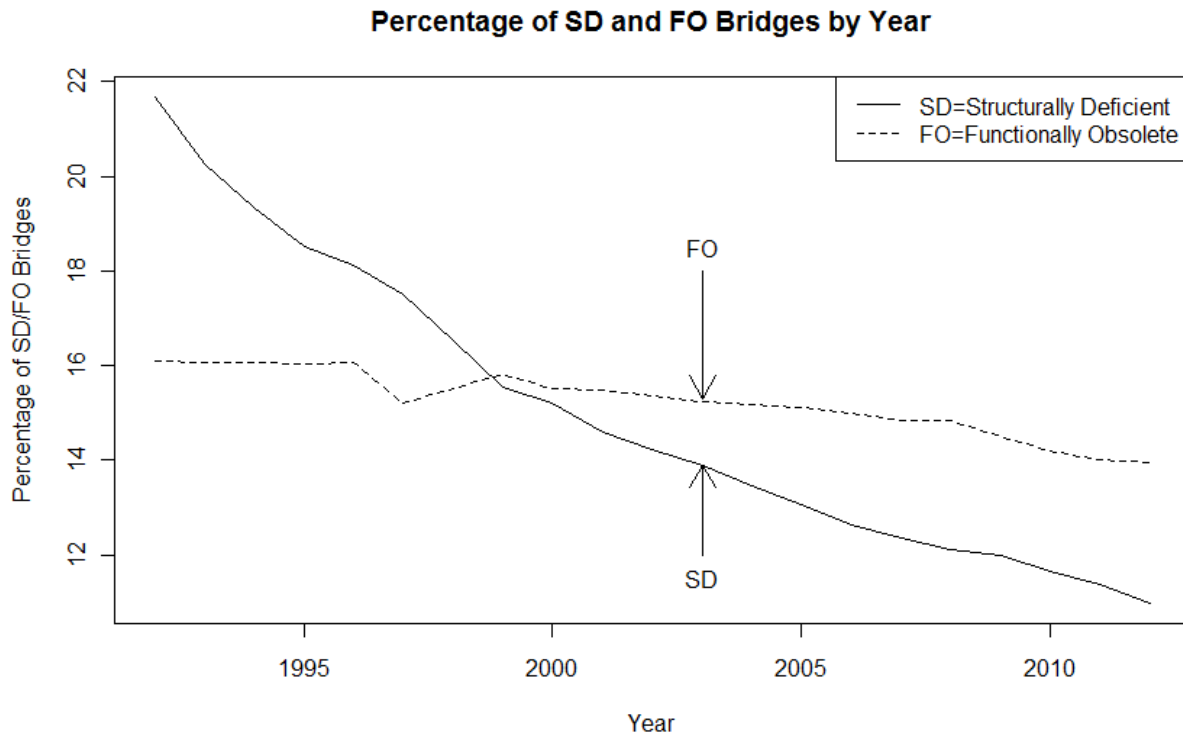
Figure 2.1: Percentage of SD and FO bridges in the United States from 1992 to 2012

Total number of bridges in the United States by year

Total numbers of SD and FO bridges in the United States by year
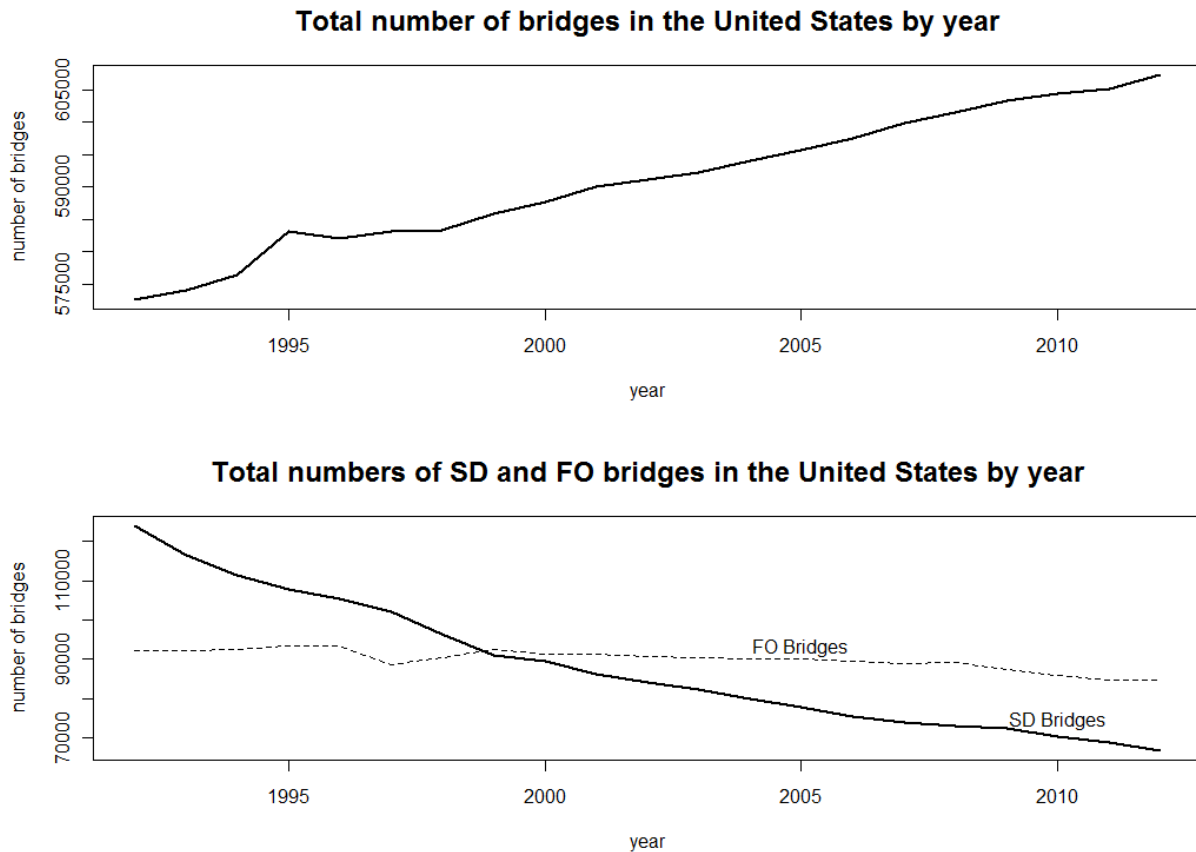
Figure 2.2: Total number of bridges by year and total numbers of FO or SD bridges by year in the United States

An Overall Aging System

As of 2011, 205,020 (statistics obtained from the FHWA website) out of the nation's 605,102 bridges – or more than 30% – have exceeded the expected 50-year lifespan (referred to as aged bridges in the following text), while the number was 200,774 out of 604,485 in 2010. Furthermore, the number is projected to be 383,060 in year 2030 and 542,170 in year 2050 (refer to http://t4america.org/resources/bridges/overview/). In addition, as of 2011, out of the 66,749 SD bridges, 46,789 are aged bridges; the count for FO bridges is 39,328 (out of 84,748). In fact, the percentage of aged bridges in each category – SD, FO or all bridges – has been increasing over the period of 2005 through 2011, as illustrated in Figure 2.3. The United States is faced with an aging bridge system.
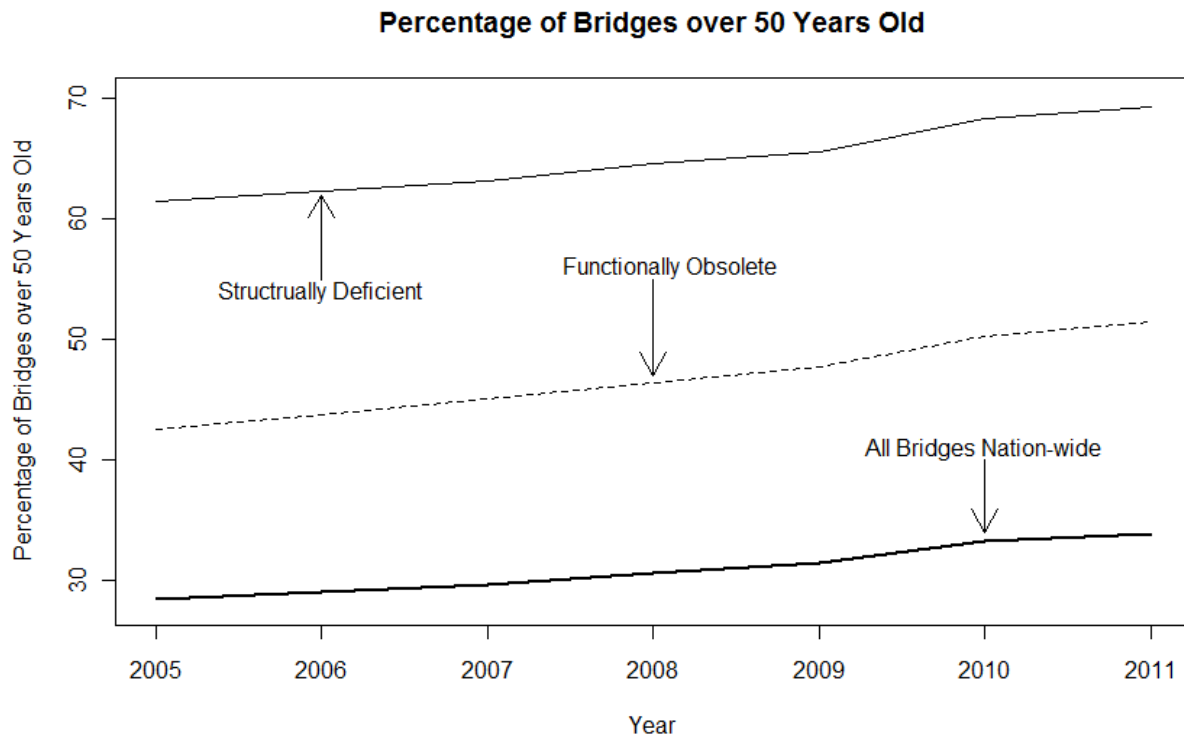
Figure 2.3: Percentage of bridges over 50 years old of SD, FO and all bridges in the United States from 2005 to 2011

2.3   Growing Needs vs. Funding Insufficiency and Ineffective Management

Growing Costs to Manage Bridges

From 2006 to 2009, the FHWA's estimates of cost to repair or replace only the deficient bridges eligible under the Federal Highway Bridge Program increased from $48 billion to $70.9 billion; in 2013, this estimate increased to almost $76 billion. These backlog costs will continue to rise (to potentially three times the current cost) if bridge maintenance is deferred over the next 25 years (ASCE 2013 Report Card for America's Infrastructure).

Funding Insufficiency

Despite the growing needs for funding, Federal, state, and local bridge investments have not been keeping pace with the imperative needs of maintaining the bridge system. The investment backlog for all bridges in the United States is estimated to be $121 billion, according to FHWA. To eliminate the bridge backlog by 2028, the FHWA estimates that the nation would need to invest $20.5 billion annually; however, at this time only $12.8 billion is being spent annually on the nation's bridges.

Caltrans' 2011 5-year maintenance plan reported that 2,575, approximately 20% of the state bridge inventory, were backlogged in major maintenance contract needs. The plan further

conducted an analysis of alternative levels of maintenance investment, which is summarized in Table 2.2:

Table 2.2: Analysis of alternative levels of maintenance investment (Caltrans' 5-year maintenance plan, 2011)

Level of Funding	*Annual Cost*		*Annual Accomplishments (in Number of Bridges)*	*Average Annual Change in Backlog*		*Future SHOPP[2] Cost Avoidance*	
	Level[1]	Vs. Baseline		Change	Vs. Baseline	Level[1]	Vs. Baseline[1]
Baseline	155.1	–	689	↓92	–	1,564	–
Reduce Backlog	159	↑2.51%	723	↓126	↑36.96%	1,641	save 73.1
Eliminate Backlog	201	↑29.59%	849	↓252	↑173.91%	1,928	Save 318.1

*1. Values in million dollars;
 2. SHOPP stands for State Highway Operation and Protection Program.

The results in Table 2.2 indicate that marginal increases in the baseline funding can bring about benefits that are much larger in scale. By adding $3.9 million, a 2.51% increase, to the baseline funding, Caltrans can accomplish maintenance contract work on 36.96% more bridges and save $73.1 million. Such significant marginal benefits indicate that the current funding level is considerably lagging behind the needs.

Ineffective Management

As indicated in Figure 2.2, in recent years, most transportation agencies have focused on new bridge construction and have consequently delayed repairs and maintenance (refer to http://t4america.org/resources/bridges/overview/). The website reports that: "… In 2008, all states combined spent more than $18 billion, or 30 percent of the federal transportation funds they received, to build new roads or add capacity to existing roads. In the same year, states spent $8.1 billion of federal funds on repair and rehabilitation of bridges, or about 13 percent of total funds…. Over a 25-year period, deferring maintenance of bridges and highways can cost three times as much as preventative repairs…."

At the same time, some agencies have not been deploying optimization-based prioritization methods for bridge maintenance decision-making. Even though states are federally mandated to have a Bridge Management System (BMS) for decision-making, *NCHRP Synthesis 243* found that: "… many DOTs are using management systems primarily to record or monitor infrastructure conditions …" Six agencies were reported to prioritize capital expenditures before maintenance. In addition, Some DOTs interviewed by the *NCHRP report 397* personnel were reported to base funding allocation to bridges versus other transportation programs solely on high-level committee decisions. At least two agencies reported decision-making "… based on a highway corridor approach in which bridge needs are accounted for only within the broader context of roadway (particularly pavement) needs, with the roadways receiving greater priority…." The situations reflect a lack of policy support for bridge maintenance.

Future Competition from Other Policy Considerations

ASCE also expressed its concern about the lack of policy support for bridge maintenance work in its 2013 report card: "… recently passed surface transportation legislation from Congress, Moving Ahead for Progress in the 21st Century (MAP-21), eliminated the Highway Bridge Program, instead rolling it into the National Highway Performance Program (NHPP). However, the off-system bridges are not included in the NHPP, but have been placed in the Surface Transportation Program. With the nation's bridges divided between two programs without guaranteed set-asides for repair, bridges may need to compete with other transportation programs for funding, which could have a negative impact on conditions."

2.4   Call for Effective Bridge Management

It is evident that faced with the conflict between funding insufficiency and the growing needs, state agencies must be able to utilize available resources in an (improved) optimal manner to keep the nation's bridges in satisfactory condition. Moreover, (improved) optimal management strategies also allow agencies to predict lower funding needs without compromising maintenance needs by gaining economic efficiency.

CHAPTER 3

LITERATURE REVIEW

As described in previous chapters, it is critical for a country to maintain its infrastructure systems at a satisfactory level to increase/sustain its economic competitiveness and enhance its resilience to catastrophic circumstances (earthquakes, wars, terrorist attacks, etc.). To the contrast, the bridges in the United States are under-maintained and deteriorated, with over 30% of them serving beyond their designed life span. In the meantime, funding appropriations for bridge repair and maintenance have continued failing to keep up with the growing needs. With the conflict between limited funding and impetrative needs for more proactive maintenance, effective bridge management is more important than ever before.

Chapter 3 will be dedicated to a review of the existing literature for effective maintenance of infrastructure systems, in the context of bridge systems. In bridge system management, agencies collect and analyze condition data and make maintenance, rehabilitation and reconstruction (MR&R) decisions for their facilities over a planning horizon. Up to the early 1970s, bridge MR&R decisions were made on as-needed basis, employing the best existing practice (Thompson et al. 1998), and the reactive planning appeared to have sufficiently addressed bridge safety issues. However, several bridge failures in the late 60s, especially the tragic collapse of the Silver Bridge over the Ohio River in 1967, raised national concerns about bridge safety and directed engineering attention towards safety-emphasizing management of deteriorated bridges. In 1970, congress mandated the United States Department of Transportation to develop and implement the national bridge inspection standards (NBIS) and procedures (P.L. 91-605), which resulted in the establishment of national bridge inventory (NBI) database. The database then became the primary source that the Federal Highway Administration (FHWA) utilized for bridge management fund allocation and provided continual support for MR&R decision-making.

In the late 1980s, funds available for bridge maintenance were gradually outpaced by the needs. The concept of optimum planning with limited resources subsequently attracted attention, and was recognized in the congressional Intermodal Surface Transpiration Efficiency Act (ISTEA) in 1991. The act mandated each state to have a bridge management system that assists optimum planning of MR&R decisions. In 2000, FHWA required life-cycle cost (LCC) being considered as an objective for optimum planning of infrastructure maintenance (FHWA, 2000). In the meanwhile, researchers have proposed many other competing objectives that should be considered simultaneously (Frangopol et al. 1999, Frangopol et al. 2000, Robelin and Madanat 2008; NCHRP report 590). Nowadays, the area continues being advanced by research efforts.

This chapter will be structured to reflect the typical procedure of bridge management:

- Section 3.1 will discuss bridge inspection, in terms of inspection frequency, general procedure and issues associated with bridge inspection data;

- Upon inspection data collected, agencies analyze the data and make optimal MR&R decisions with the assist of optimization routines; hence in section 3.2 the readers will find a review of deterioration models and in section 3.3 of optimal decision-making methods;

- Once MR&R actions have been applied to bridges, new condition data will be collected and correspondingly used to update the deterioration models. In section 3.4 a review of adaptive control methods is provided; and

- Section 3.5 will utilize the Pontis system, commercialized by American Association of State Highway and Transpiration Officials (AASHTO) and licensed to more than 40 states in the U.S. as of 2008, as an example to illustrate how MR&R decisions are systematically made in practice.

Most importantly, Section 3.5 will identify the issues associated with the Pontis system and phrase the research motivation. While the present dissertation's scope will be confined to the optimal resource allocation aspect of bridge system management, it is worth pointing out that it is equally important to deploy advanced maintenance technologies.

3.1 Bridge Inspection

Bridge inspection responsibilities are associated with bridge ownership. States are responsible for insuring that all public highway bridges within the State are inspected in accordance with the NBIS, including those owned by local Agencies or other public authorities; states are not responsible for bridges owned by Federal agencies, tribes or private entities (FHWA, 2013). For example, the State of Indiana is responsible for the inspection of all bridges state- and county-owned (Indiana Department of Transportation, 2013).

The compliance of NBIS is enforced at the state level or the Federal level. If a state advises the local owners of NBIS compliance issues, such as the need to close or place load restrictions on bridges, but the local owners fail to follow the advice from the State, it is entitled to withhold Federal-aid project approvals from within the non-compliant locality. Many times, approvals of State-funded projects are also withheld from non-responsive locals Furthermore, if a locally owned bridge is not inspected or appropriately posted or closed to insure safety, FHWA will hold the State DOTs responsible, and subject to potential withholding of Federal-aid authorizations (FHWA, 2013).

3.1.1   Inspection Frequency

The NBIS require all bridges and culverts greater than 20 ft. in length on U.S. public roads inspected biennially. Bridges that have serious deficiencies, or carry heavy truck traffic and have questionable structural details, or recently have gone through unusual traumas (floods, fire, etc.) are inspected more frequently as required (as often as every month). A small percentage of bridges that are in excellent condition and meet certain other criteria may be inspected at intervals longer than 2 years with prior FHWA approval (generally new bridges may fall in this category). Table 3.1 lists the number of bridges with respect to their designated inspection frequency in the State of California: most of bridges (78.91%) are inspected at least biennially.

Table 3.1: The number of bridges vs. designated inspection frequency in California

Frequency (months)	2	6	12	24	48
No. of Bridges	1	4	307	19266	5233
Percentage	4e-3%	0.01%	1.24%	77.65%	21.09%

3.1.2   Inspection Procedures and Issues

There are many types of inspections that apply to bridges, and they are either mandated by FHWA or subject to state-specific policies. The FHWA mandated inspection types are (Indiana Department of Transportation, Bridge Inspection Manual, 2013):

- Initial Inspection. The baseline inspection that applies to new and previously not inventoried bridges, and bridges that recently undergo major rehabilitation or change of configuration or geometry. As part of the initial inspection, inspectors evaluate a bridge

and decide what other foreseeable inspections will be required throughout its life, including Fracture Critical, Special, or Underwater Inspections;

- Routine Inspections. Regularly scheduled inspections consisting of observations and/or measurements needed to determine the physical and functional condition of a bridge, and to identify any changes from previously recorded conditions. The Routine Inspection also ensures that the bridge continues to satisfy present service requirements. They are required to be carried out at least every 24 months;

- Fracture Critical Inspections. Regularly scheduled inspections to examine the fracture critical members or member components of a bridge. (Fracture critical members are steel tension members or steel tension components of members, whose failure would probably cause all, or a portion of, the bridge to collapse.) Fracture critical members require more thorough and detailed inspections than the members of non-fracture critical bridges. They are required to be carried out at least every 24 months;

- Underwater Inspections. Routinely scheduled inspections that apply to bridges with substructure units in water to ensure safety. They are required to be carried out at least every 60 months; and

- Damage Inspection. An unscheduled inspection to assess structural damage resulting from environmental factors or human actions.

Among the above listed items, routine inspections provide the most comprehensive information on the components common to most bridges: deck, superstructure and substructure. Among them decks are critical structural components that are in direct contact with traffic to provide a smooth riding surface and distribute bridge live loads. They also undergo the fastest deterioration and therefore must be monitored diligently.

The primary method for routine inspections is visual inspection, during which an inspector detects a wide variety of surface flaws such as cracks, discontinuities, corrosion, and contamination. Visual inspections are economic but they have limited capability of revealing the true condition of bridge components, e.g. a reinforced concrete deck with fully developed corrosion might appear to have only minor cracks or delamination, therefore would be given a higher rating by visual inspection than it should have received. Moreover, visual inspections are subject to individual inspectors' judgments; quality control is therefore difficult. Non-destructive testing (NDT) methods and partially-destructive testing (PDT) methods are developed to complement visual inspections, but they can only detect material integrity of a component and are more expensive; hence the use of NDT and PDT methods are still limited.

Therefore, the issues associated with bridge inspection data are:

- Slow accruement. Most bridges are inspected biennially; therefore bridge condition data accrue slowly, which conflicts with the needs of sufficient data for deterioration model development;

- Unsatisfactory quality. Visual inspection, the primary method for obtaining bridge data, does not necessarily reveal the true condition of the bridges; moreover, individual inspectors might introduce their own subjectivities. NDT and PDT methods are more

capable of revealing the true condition of a bridge component, but due to economic reasons they are not as widely adopted; and

- After the collapse of the I35-W Bridge in Minneapolis in 2007, federal officials attempted to order emergency inspections of all steel truss bridges, and found that many records within the NBI were inaccurate or out of date. The unexpected errors might have come from tallying or recording of the data, etc.

As previously stated, deterioration models are developed from or updated by inspection data. Due to the abovementioned issues, the developed models will be inaccurate. Researchers have attempted to reduce systematic inaccuracy associated with inspector subjectivities and measurement errors by adopting hidden Markov models (Lenanth and Bryan, 2012). The insufficiency of data can be dealt with by updating deterioration models when new condition data become available. This will be discussed in Section 3.3 and 3.5.

3.2 Deterioration Models

Since the 1970s, bridge deterioration models have been developed to describe the mathematical relationships between the condition of a bridge component and the causal factors that affect the component's condition, such as traffic loading, environmental factors, etc. There exist many different types of bridge deterioration models in the literature, but the most recognized ones are deterministic models and stochastic models. This section is accordingly divided into 3 subsections for the review of *deterministic models*, *stochastic models* and *other models*.

3.2.1   Deterministic Deterioration Models

Deterministic models relate the factors affecting bridge component deterioration, such as age, traffic loading, to the component's condition using a simple mathematical or statistical formulation, such as the mean, standard deviation and regression. The predicted conditions are calculated deterministically by ignoring the randomness in the bridge deterioration process and the existence of unobserved explanatory variables (Jiang and Sinha 1989; Madanat and Ibrahim 1995), i.e. each prediction might yield only one value.

There are various methods for developing deterministic deterioration models. For example, the straight-line extrapolation method (SLE) (Morcous, 2000) assumes a linear relationship between traffic loading and maintenance history. It requires two inputs to calculate the linear relationship: an initial condition (given by either expert judgment or industry standards) and a condition measurement (given by inspection). SLE is appreciated for its simplicity and yields relatively accurate short-term predictions of conditions. Nonetheless if a bridge has undergone some maintenance activities, SLE will not work. In the case where multiple explanatory variables are involved, the mathematical relationship can be determined by regression.

Deterministic models are simple and hence efficient for the analysis of networks with a large population. But they generally suffer from the following drawbacks (Morcous et al., 2002):

• They neglect the uncertainty due to the inherent randomness of infrastructure deterioration and the existence of unobserved explanatory variables;

• They predict the average condition of a family of facilities regardless of the current condition and the condition history of individual facilities;

• They estimate facility deterioration for the ''no maintenance'' strategy only because of the difficulty of estimating the impacts of various maintenance;

• They disregard the interaction between the deterioration mechanisms of different facility components such as between the bridge deck and the deck; and

• They are difficult to update when new data is obtained.

3.2.2 Stochastic Deterioration Models

Stochastic deterioration models treat the bridge deterioration process as one or more random variables that capture the uncertainty and randomness of this process. Two types of probabilistic models have been used for infrastructure facility deterioration prediction: state- and time-based models (Mauch and Madanat, 2001).

3.2.2.1 State-based Models

In NBI and many state bridge data systems, bridge component conditions are recorded as discrete integers; for example, in NBI deck conditions are coded as an integer ranging from 0-9, with *0* representing an unacceptable failure condition and *9* representing the best possible condition (e.g. a new bridge). (For bridges that the deck rating is not applicable, *N* is recorded.) Examples of the NBI and Commonly Recognized Elements (CoRe) recording formats are listed in Table 3.2 and Table 3.3.

Table 3.2: NBI recording format for bridge decks

National Bridge Inventory ratings for bridge decks	
Rating	Description of the condition
9	EXCELLENT CONDITION
8	VERY GOOD CONDITION: no problems noted.
7	GOOD CONDITION: some minor problems.
6	SATISFACTORY CONDITION: structural elements show some minor deterioration.
5	FAIR CONDITION: all primary structural elements are sound but may have minor section loss, cracking, spalling, or scour.
4	POOR CONDITION: advanced section loss, deterioration, spalling, scour.
3	SERIOUS CONDITION: loss of section, deterioration, spalling, or scour have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present.
2	CRITICAL CONDITION: advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support. Unless closely monitored, it may be necessary to close the bridge until corrective action is taken.
1	"IMMINENT" FAILURE CONDITION: major deterioration or section loss present in critical structural components or obvious vertical or horizontal movement affecting structural stability. Bridge is closed to traffic but corrective action may put back in light service.
0	FAILED CONDITION: out of service—beyond corrective action.
N	Not applicable

Table 3.3: Commonly Recognized Elements (CoRe) recording format for bridge elements

	Commonly Recognized Elements (CoRe) ratings for bridge elements	
1	PROTECTED: The element's protective materials or systems (e.g. paint or cathodic protection) are sound and functioning as intended to prevent deterioration of the element.	
2	EXPOSED: The element's protective materials or systems have partially or completely failed (e.g. peeling paint or spalled concrete), leaving the element vulnerable to deterioration.	
3	ATTACKED: The element is experiencing active attack by physical or chemical processes (e.g. corrosion, wood rot, traffic wear and tear), but is not yet damaged.	
4	DAMAGED: The element has lost important amounts of material (e.g. steel section loss), such that its serviceability is suspect.	
5	FAILED: The element no longer serves its intended function (e.g. the bridge must be load posted).	

State-based models predict the probability that a facility will undergo a change in condition state at a given time, conditional on an array of explanatory variables such as traffic loading, environmental factors, design attributes, and maintenance history (Mauch and Madanat, 2001). The most commonly used state-based deterioration models are Markovian models. The formulation of Markovian deterioration models is given by:

$$P_{ij}(a) = P(S_{\tau+1} = j \mid S_\tau = i, A_\tau = a), \forall i, j, \tau, a \tag{3.1}$$

where $P_{ij}(a)$ is the transition probability of the facility condition changing from state i to state j under maintenance activity a; S_τ and $S_{\tau+1}$ are the states of a facility at the start and end of period τ, and are drawn from a finite state set; A_τ is the MR&R action drawn from a finite action set, applied to the facility at the start of τ. The current planning stage τ is restricted to take values smaller than the planning horizon *T*. The transition probabilities form a square transition matrix of dimension |*S*| x |*S*|.

The Markovian assumption implies that the transition between any pair of states depends only on the initial condition at the current planning stage given the action to be applied, i.e. the transition probabilities do not depend on the history of deterioration. The Markovian models are widely adopted in Bridge Management Systems (BMSs), such as Pontis and BRIDGIT.

However, the Markovian (memory-less) property may not hold in reality, or may hold only for some types of deterioration processes (Mishalani and Madanat, 2002, Frangopol and Das, 1999). The limitations of Markovian models are summarized as:

- History Independence. The predicted conditions depend only on the current conditions, rather than the entire/selected history of deterioration (Madanat et al., 1997);

- Restrictive assumptions. Markovian models assume discrete transition time intervals, constant bridge population, and stationary transition probabilities, which are sometimes impractical (Collins et al., 1975);

- It is difficult for Markovian models to consider the interactive effects between the deterioration mechanisms of different bridge components (Sianipar and Adams 1997; Cesare et al., 1992);

- It is difficult for Markovian models to explicitly account for bridge population heterogeneity. The traditional approach is to divide the population into relatively homogenous groups that share certain attributes (material, structure type, etc); and

- The transition probabilities are first obtained often through expert judgment (Pontis User Manual 4.4; Tokdemir et al., 2000) which can be subjective. Therefore they might require frequent updating when new data are obtained as bridges are inspected, maintained, or rehabilitated (Tokdemir et al., 2000).

Researchers have refined the simple Markovian transition probabilities to address some of the limitations listed above. For example, Robelin and Madanat (2007) presented a history-dependent Markovian deterioration model with augmented states that relaxes the Markovian assumption. The deterioration and maintenance history of a facility is accounted for by considering two additional variable, the last maintenance action (including "no action taken") the facility undergoes and the time it is applied. Some studies also proposed to parameterize Markovian transition probabilities with age of bridge, traffic loading, etc., and therefore explicitly account for population heterogeneity. Econometric methods such as *Poisson* regression and *probit* regression have been used to estimate the parameters of these models and to compute the transition probabilities (Mauch and Madanat, 2001; Madanat and Wan Ibrahim 1995; Madanat et al. 1995, 1997).

3.2.2.2 Time-based Models

Time-based deterioration models were initially proposed to relax the Markovian assumption of history-independence in infrastructure deterioration. The essential idea is that the transition probability of a facility should be affected by not only its current condition, but also its deterioration history. One class of time-based deterioration models currently widely recognized is hazard-based duration models. The readers are referred to Lancaster (1994), Hensher and Mannering (1994) and Bhat (2000) for in-depth descriptions of them. Hazard-based duration models model deterioration in a survival analysis framework, with failure defined as transitioning out of a condition state and survival otherwise. If a facility has stayed in the current condition state for τ years, the probability it undergoes a change in condition state in the time period $[\tau, \tau + \Delta]$ is given by:

$$R(\tau, \Delta) = P(\tau < T < \tau + \Delta \mid T > \tau) = \frac{F(\tau + \Delta) - F(\tau)}{S(\tau)} \qquad \textbf{(3.2)}$$

where T is the duration random variable, $R(\tau, \Delta)$ is the transition probability in duration $[\tau, \tau + \Delta]$; $F(\tau)$ is the failure cumulative distribution function of T, and equals to $P(T < \tau)$; $S(\tau)$ is the survival cumulative distribution function of T, and equals to $1 - F(\tau)$. The hazard rate or deterioration rate function, subsequently, is defined as:

$$\lambda(\tau) = \lim_{\Delta \to 0} \frac{R(\tau, \Delta)}{\Delta} = \frac{f(\tau)}{S(\tau)},$$
(3.3)

where $f(\tau)$ is the failure probability density function.

Hazard-based duration models also allow researchers to explicitly account for causal factors that affect deterioration (Mishalani and Madanat, 2002; DeLisle et al., 2004). For example, Mishalani and Madanat (2002) presented the Weibull specification of hazard-based duration models:

$$\lambda(\tau) = p\lambda^p \tau^{p-1},$$
(3.4)

where p is the shape parameter, and λ is the scale parameter. They further parameterized λ to be $\lambda = e^{\beta X}$, where X is an array of explanatory variables, such as Average Annual Daily Traffic, age, highway class, protective surface type, etc.; and β is the corresponding coefficient vector. It is also quite flexible to accommodate Markovian models with this specification by setting $p=1$.

Hazard-based duration models can also yield Markovian transition matrices that can be readily deployed in a Markovian Decision Process framework. The reader will find a detailed discussion in Chapter 4.

3.2.3   Other Models

Mechanistic Models Mechanistic Models describe the specific deterioration mechanism of bridge components. They are generally developed and tested in laboratories. Examples of mechanistic models include:

- The corrosion process of steel bridges (Komp 1987; Sobanjo, 1991).

$C = At^B$, where C = average corrosion penetration, t = time in years, A, B = parameters determined through regression analyses;

- Carbonation depth equations in concrete bridge components (Parrott, 1987)

$d = At^n$, where d = carbonation depth, t = time in years, A = diffusion coefficient and n = exponent (approximately ½).

Mechanistic models are usually detail-oriented and therefore are useful for safety-critical structures. They are effective at the project level when the level of analytical complexity is relatively low; at the network level, bridge components might have several failure models and therefore mechanistic models become ineffective (Lounis and Madanat, 2002; Kayser and

Nowak, 1989). As a result, these models are not widely adopted by bridge management practitioners or Departments of Transportation.

Artificial Intelligence Models Artificial intelligence models (AI) aim to automate intelligent behaviors with modern computer techniques and have seen their applications in a wide range of areas, including comprise expert systems (CES), artificial neural networks (ANN) and case-based reasoning (CBR) and machine learning (ML).

Sobanjo 1997 investigated the feasibility of applying *ANN* in bridge deterioration modeling. A multi-layer *ANN* was utilized to relate the age of the bridge superstructure (in years) to its condition rating (an integer from 1 to 9). A more detailed investigation of AI has been made by Tokdemir et al. (2000) to predict the bridge sufficiency index ranging from 0 to 100 by using age, traffic, geometry, and structural attributes as explanatory variables. Because *ANN* aims to find an optimal polynomial fit, it still suffers from the drawbacks of deterministic deterioration models (Morcous et al., 2002), along with the following difficulties:

- There is no clear rules in the determination of an efficient *ANN* architecture (Boussabaine, 1996; Hua, 1996); and

- *ANN* requires conversion of input variables to numerical values for maximum performance; however the conversion might cause loss of information that was carried in the original representation (Arditi and Tokdemir, 1999).

3.3 Optimization Decision-Making Methods

This section provides a review of optimal decision-making methods with respect to specific objectives of system bridge management.

3.3.1   System Bridge Management Objectives

Bridge maintenance decision-making is encompassed in the broader concept of preserving public investments, which is now widely treated as an asset management problem. Based on this premise, life-cycle cost was among the first well-accepted criteria in bridge management. In 2000, FHWA required infrastructure maintenance decisions being made based on life-cycle cost analysis (LCCA) (FHWA, 2000). In the context of *bridge management*, life-cycle costs are evaluated by integrating agency and user costs, discounted over a designated planning horizon. The agency costs consist of the actual cost of implementing maintenance actions, and can be obtained through state agencies, while the user costs, incurred by the public, are a translation of the condition of the bridges to monetary units. The determination of agency and user costs is specific to a maintenance problem's scope. For example, maintenance decisions made by considering multiple bridge elements (including bridge deck, substructure and superstructure) should evaluate agency and user costs differently than maintenance decisions made by considering one bridge element (e.g. deck only).

Recent research efforts have argued that multiple objectives, rather than minimal life-cycle costs alone, should be simultaneously considered when managing bridge systems. Reliability indices of bridge structures were among the first additional objectives that were investigated, due to the fact that bridges are safety-critical facilities. As early as 1994, the first edition of the AASHTO LRFD Bridge Design Specifications (AASHTO 1994) had advised bridge engineers to consider reliability indices in bridge design and management. Frangopol et al. (2001), Frangopol and Kong (2000), Robelin and Madanat (2008) and many other studies gave detailed descriptions of bridge management planning based on reliability indices. Research efforts continued to recognize more merit measures that should be included in bridge management, including condition, safety and durability (Miyamoto et al. 2000; Furuta et al. 2004). NCHRP project 12-67, which was published as NCHRP report 590 in 2007, proposed a comprehensive multi-objective methodology for more balanced bridge management decision-making. Nowadays the consensus has been reached that bridge management should be multi-objective. In the following section, optimal decision-making methods specific to each objective will be reviewed.

3.3.2   Optimal Decision Making Methods

3.3.2.1 Life-cycle Cost Analysis Based Methods

Life-cycle cost analysis (LCCA) is an important economic analysis used in the selection of alternatives while considering both pending and future costs, where the life of a project can be

determined by the active period of the object for which decisions are made. In bridge management, it is typically defined by a planning horizon (e.g. 20 years) set by agencies. The life-cycle costs are correspondingly calculated by integrating agency costs and user costs, discounted to the current year.

As previously mentioned, a large fraction of the existing literature models infrastructure deterioration as a Markovian process, i.e. the future conditions of a facility depend only on the current condition of the facility and the action to be taken. The management problem can therefore be framed as a Markovian Decision Process (MDP) problem, which can be solved by a Dynamic Programming (DP) approach: *Bottom-Up*. The DP solution starts at the end of the planning horizon T, and rolls backward in planning year to find the minimum system cost-to-go for the current year. (A cost-to-go for the current planning year t is defined as the agency and user costs over the time period $[t, T]$ discounted to t.) The following formulation demonstrates the recursion from year $\tau+1$ back to τ:

$$\begin{cases} a^*(i,\tau) = \arg\min_{a \in A} \{AC(a,i) + \alpha \sum_{j \in S} [V^*(j,\tau+1) + U(j)]P_{(a,\tau)}(i,j)\} \\ V^*(i,\tau) = \min_{a \in A} \{AC(a,i) + \alpha \sum_{j \in S} [V^*(j,\tau+1) + U(j)]P_{(a,\tau)}(i,j)\} \end{cases}$$

(3.5)

where:

$V^*(i,\tau)$ is the minimum cost-to-go (from τ to T) if a facility is in condition state i in year τ, and $a^*(i,\tau)$ is the corresponding action that achieves this optimum. Likewise, $V^*(j,\tau+1)$ is the minimum cost-to-go (from $\tau+1$ to T) if the facility is in condition state j in year $\tau+1$;

$P_{(a,\tau)}(i,j)$ is the probability of the facility transitioning from state i to state j from year τ to year $\tau+1$ given MR&R action a is applied;

$AC(a,i)$ is the agency cost of applying action a to the facility given it is in condition state i;

$U(j)$ is the user costs given the facility is in condition state j; and

α is the discount factor, and is equals to $1/(1+\gamma)$, where γ is the discount rate.

At the current planning year t, an agency simply selects the action that minimizes $V(s(t),t)$, where $s(t)$ is the condition state the facility is in at t. The facility-level DP minimizes costs as if agencies always have sufficient resources to apply the MR&R actions required to achieve the minimal expected cost-to-go. In other words, it does not consider any budget constraints. Consequently, if one were to form the optimal solution for a system-level problem by simply aggregating all facility-level optimal solutions, there is no guarantee that the system budget constraints would be met.

Yeo at al. (2010) presented a Two-stage Bottom-up approach that considers a budget constraint for the current planning year t. In the first stage, N independent problems for N individual facilities in the system are solved from the end of the planning horizon T up to year t+1. Then in year t, for each facility they order all MR&R actions that can be applied to the

facility (referred to as actions available to the facility in later text) with respect to their costs-to-go. A feasible solution for the system is $\{a_1, a_2, ..., a_N\}$, if 1) a_n is available to facility n in year t; and 2) $\sum_{n=1}^{N} a_n \leq B_t$, with B_t being the budget constraint for year t. In the second stage, they minimize the system cost-to-go over all feasible solutions. However, this approach does not consider budget constraints beyond planning year t by inherently assuming that resources beyond year t are always sufficient. As a result it could incur high system costs if future budget constraints are binding (Medury and Madanat 2013).

To further illustrate the challenge of incorporating budget constraints, we assume that the number of possible actions available for any facility at any given planning year is $|A|$. We use an ***action path*** of the facility over the designated planning horizon to refer to a sequence of MR&R actions $\{a_t, a_{t+1}, ..., a_{T-1}\}$, if $a_\tau \; \forall \tau \in \{t, ..., T-1\}$ is available to the said facility. Therefore, the total number of possible actions paths for the facility is $|A|^{(T-t)}$, and is increasing exponentially with the length of the planning horizon. At the system level, the number of possible combinations of action paths for all the facilities is $|A|^{N(T-t)}$. To find the optimal system-level solution, one will need to minimize the total system costs over $|A|^{N(T-t)}$ possible action path combinations subject to the budget constraints. In a case of $|A| = 4$, $T - t = 20$, and $N = 200$, the number is $10^{2,408}$, resulting in high computational complexity. This is referred to as the "curse of dimensionality".

The Top-down (Golabi et al. 1982) approach was proposed to address this problem in the context of pavement management. It was motivated by the realization that pavement segments are relatively homogeneous and therefore can be grouped with respect to selected characteristics (traffic, material, etc.) to reduce the dimension of the problem. The formulation is given by:

1) Objective function

$$\min_{d.v.^*} \sum_{k} \left\{ \underbrace{\sum_{\tau=t}^{T-1} \sum_{a} \alpha^{\tau-t} C_{k,a}^\tau \cdot \left(\sum_{s} w_{k,a,s}^\tau\right)}_{\text{discounted action costs}} + \underbrace{\sum_{\tau=t+1}^{T} \sum_{a} \alpha^{\tau-t} \left(\sum_{s} w_{k,a,s}^\tau\right) \cdot U_{k,s}^\tau}_{\text{discounted user costs}} \right\} \tag{3.6}$$

*Note: d.v. means decision variables.

where:

$w_{k,a,s}^\tau$ represents the proportion of facilities that are: 1) in group k, with K being the number of groups; 2) in state s at the beginning of year τ; and 3) assigned with action a at the beginning of year τ;

$U_{k,s}^\tau$ is the user cost associated with group k for state s in year τ;

$C_{k,a}^\tau$ is the agency cost of implementing action a on group k in year τ; and

2) Kolmogorov equations:

$$\sum_{s}\sum_{a} w_{k,a,s}^{\tau} \cdot P_{k,a}^{\tau}(s,j) = \sum_{a'} w_{k,a',j}^{\tau+1}, \tau \in [t, T-1],$$ (3.7)

where:

$w_{k,a',j}^{\tau+1}$ represents the proportion of facilities that are: 1) in group k; 2) in state j at the beginning of year $\tau+1$; and 3) assigned action a' at the beginning of year $\tau+1$;

$P_{k,a}^{\tau}$ is transition matrix for group k with the application of MR&R action a, and $P_{k,a}^{\tau}(s,j)$ is the (s,j)th entry of it; and

3) Budget Constraints

$$\sum_{k}\sum_{a}(\sum_{s} w_{k,a,s}^{\tau}) \cdot C_{k,a}^{\tau} \leq B_{\tau}, \tau \in [t, T-1],$$ (3.8)

where B_{τ} is the budget constraint in year τ;

The complexity of the above system problem in terms of total number of decision variables is $|A| \cdot |S| \cdot (T-t) \cdot K$. If $|A|=4$, $|S|=10$, $(T-t) =20$, and $K=200$, the system problem has 160,000 decision variables and therefore is more solvable. The Top-down approach ensures conformity to budget constraints and yields the true system optimum. However, it only gives MR&R decisions at a group level for the current planning year, and thus does not assign facility-specific MR&R action. Medury and Madanat (2013) developed the Simultaneous Network Optimization (SNO) that improved on this approach by changing the current year's action assignment from group-level to facility-level. Instead of using $w_{k,a,s}^{t}$ as the decision variables for the current planning year t, SNO uses a binary variable $X_{k_q,a,s}^{t}$, with 1 representing assigning action a to facility k_q and 0 otherwise. Therefore the formulation of SNO only differs from the Top-down approach in the current planning year:

$$\min_{d.v.} \sum_{k} \left\{ \begin{array}{l} \underbrace{\sum_{a}(\sum_{s}\sum X_{k_q,a,s}^{t}) \cdot C_{k,a}^{t}}_{\text{current year cost}} + \underbrace{\sum_{\tau \in [t+1,T-1]}\sum_{a} \alpha^{\tau-t} C_{k,a}^{\tau} \cdot (\sum_{s} w_{k,a,s}^{\tau})}_{\text{discounted future action costs}} \\ + \underbrace{\sum_{\tau \in [t+1,T]}\sum_{s} \alpha^{\tau-t}(\sum_{a} w_{k,a,s}^{\tau}) \cdot U_{k,s}^{\tau}}_{\text{discounted user costs}} \end{array} \right\}$$ (3.9)

$$\text{s.t.} \begin{cases} \sum_{s}\sum_{a}\sum_{i} X_{k_q,a,s}^{t} \cdot P_{k,a}^{t}(s,j) = \sum_{a'} w_{k,a',j}^{t+1} \\ \sum_{k}\sum_{a}(\sum_{s}\sum_{i} X_{k_q,a,s}^{t}) \cdot C_{k,a}^{t} \leq B_t \end{cases}.$$ (3.10)

The variable count remains unchanged. In a heterogeneous system where facilities cannot be grouped, SNO is still computationally intractable because of the large number of decision variables. A computationally feasible approach will be presented in Chapter 4.

So far the management problem has been approached in the DP framework and the difficulties stemming from large numbers of decision variables have been discussed. Researchers have realized such limitation and proposed evolutionary algorithms (EA) to search for near-optimal solutions. The EA are stochastic search methods whose mechanisms are inspired by biological evolution and/or the social behavior of species, such as reproduction/inheritance, mutation, recombination, crossover and selection.

One class of the EA that has been used in many studies in infrastructure management is the genetic algorithms (GA) (Liu et al. 1997; Chan et al. 1994; Furuta et al. 2004; Chootinan et al. 2006). It is a search heuristic that mimics the process of natural selection: *survival of the fittest*.

Chan et al. 1994 illustrated how to apply GA in pavement management. The decision making process started with inputting problem parameters (distress type, road segments, planning periods, etc.) and defining the objective function (minimizing life-cycle costs, maximizing network repair efficiency, etc.). Then a set of parent solutions, e.g. a string of maintenance decisions, were generated and evaluated in parallel according to the objective function. The next step was to generate child solutions of the parent solutions to improve the *fitness* and was achieved with two operators:

- **Crossover**. In genetics, an allele is defined as one of a number of alternative forms of the same gene or same genetic locus. In infrastructure management, the parallel would be a fragment of an ordered system solution, e.g. all maintenance actions for a specific facility over the planning horizon. The crossover operator samples alleles from different parent solutions and combine them to form an offspring; and

- **Mutation**. In crossover, no new alleles were generated. The mutation operator, on the other hand, generates an offspring by changing its parent's allele(s). For example, an offspring solution can be generated by changing a facility's current maintenance action from *Do-Nothing* to *Repair* and leaving the rest of the parent solution unchanged.

The GA then evaluates offspring's' fitness and decides if the stopping criterion has been reached. It is worth noting that in the generation process, constraints on budgets, man power, materials, etc. could be correspondingly imposed.

The GA is efficient with combinatorial problems such as infrastructure decision-making; however it has several limitations. For example, the stopping criterion varies across problems and may not be clear. Moreover, the GA might only converge to local optima or even arbitrary points rather than the global optimum. Nonetheless, GA is still desirable for its computational effectiveness and capability of incorporating multiple objectives.

3.3.2.2 Reliability-based Optimization

Bridges are safety-critical structures, but the application of reliability techniques in bridge management had long lagged behind the application in other types of civil infrastructures. It is not until the mid-1990s that reliability-based bridge management started to prosper in the literature. Examples of reliability-based bridge management include Mori (1992), Mori and Ellingwood (1994), Thoft-Christensen (1995), Frangopol et al. (2001), Kong and Frangopol (2003), Robelin and Madanat (2008).

Mori and Ellingwood (1994) investigated the trade-off between inspection and repair with time-dependent reliability analysis. Reliability was incorporated into the management of structures in two ways: 1) a component in the objective function that represents the cost of structure failure. The value of this component increases with the structure's failure probability; and 2) restrict the failure probability to not exceed an established target. The trade-off therefore was established between inspection costs and maintenance costs and structural reliability. The methodology described in this paper translated reliability into monetary costs and indirectly optimized it.

Frangopol et al. (2001) adopted reliability-based condition states for bridges and quantified the effectiveness of maintenance actions in terms of improvement in reliability level. They showed that the expected number of bridges that required rehabilitation was drastically reduced when preventative maintenance actions were applied. Kong and Frangopol (2003) further presented a reliability-based optimization framework at the system level.

Robelin and Madanat (2008) developed a reliability-based method for system-level bridge management. The first step of the method solves facility-level management problems independently and obtains a facility-specific function $f_i(p)$ which is the present value of the optimal maintenance and replacement cost of facility i over the planning horizon if the probability of failure of that facility is kept below p. The second level solves the system-level problem by minimizing the maximum of the facility failure probabilities when keeping the total maintenance and replacement costs $\sum_{i=1}^{n} f_i(p_i)$ below the designated budget B. They found that under continuous $f_i(p)$ the optimum was achieved when all facilities' failure probabilities were equal; furthermore, the discrete case results validly approximated the continuous case.

3.3.2.3 Multi-objective Optimization

Recent research efforts realized that bridge management should consider multiple performance criteria, such as (life-cycle) costs, bridge condition, safety, traffic flow disruption and vulnerability. NCHRP report 590 (2007) provided a theoretical framework for multi-objective optimization in network- and facility-level bridge management.

The performance criteria considered were:

- **Preservation of bridge condition**: National Bridge Inventory (NBI) condition ratings, health index, and sufficiency rating;

- **Traffic safety enhancement**: Geometric and inventory/operating rating;

- **Protection from extreme events**: Vulnerability ratings for scour, fatigue/fracture, earthquake, collision, overload, and other human-made hazards;

- **Agency cost minimization**: Initial cost, life-cycle agency cost;

- **User cost minimization**: Life-cycle user cost

The solutions are based on utility theory, which uses techniques such as *weighting*, *scaling* and *amalgamation* to construct the utility function. The network-level problem was then formulated as a multi-choice, multi-dimensional knapsack problem (MCMDKP) and the incremental utility-cost ratio, Lagrangian and pivot and complement approaches were found satisfactory. The readers are referred to NCHRP report 590 for a more detailed description.

3.4 Adaptive Control Methods

There are two types of uncertainties associated with bridge component deterioration models: aleatoric uncertainty, referring to the stochastic nature of deterioration; and epistemic uncertainty, characterizing the lack of complete knowledge of the true deterioration models. Researchers have accounted for epistemic uncertainty concerning deterioration models by updating these models with data collected through condition surveys over time (Golabi and Shepard 1997; Durango and Madanat 2002; Durango-Cohen and Madanat 2008). Adaptive control methods were proposed therein to incorporate new data as they become available with the aim of improving model accuracy.

The adaptive control scheme used in current bridge management systems is the Certainty Equivalent Control (CEC). It is a sub-optimal control scheme where optimal decisions are made by fixing the uncertain quantities at their "typical" values. Pontis updates deterioration models by running regression on new and prior data to improve the prior models (Pontis 4.4: User's Manual). Therefore the posterior models after each update produce point estimates of the transition probabilities. The posterior models give predictions of bridge components future conditions, and Pontis makes MR&R decisions for that planning cycle accordingly. Unfortunately, CEC may perform strictly worse than an Open-Loop control method, in which no updating takes place (Bertsekas 2005).

Bertsekas (2005) describes two other adaptive control methods: Open-Loop Feedback Control (OLFC) and Closed-Loop Feedback Control (CLC). Instead of obtaining point estimates as CEC does, OLFC considers a set of possible models. The information is used to predict a distribution of future conditions. OLFC then makes MR&R decisions based solely on all the information available up-to-date, i.e. as if no further measurements will be made, while CLC improves on this basis by explicitly considering future measurements. Therefore CLC is the strict optimal adaptive control scheme.

Durango and Madanat (2002) presented both OLFC and CLC within Markovian Decision Process (MDP). Facility deterioration was modeled as a weighted mixture of multiple Markov chains, each characterized by its own transition probability matrix, where the weights represent the belief of each model being the correct model. When new data become available, the mixture probability mass function is updated iteratively by a Bayesian formula. The authors found that adaptive control methods consistently performed better than Open-Loop control in terms of lifecycle costs. Moreover, with regards to convergence to the true mixture probability mass function and cost-to-go, CLC performed better than OLFC. This superiority was enhanced as the initial assignment of mixture probability mass functions deviated from the true one.

However, even though CLC is a superior approach to OLFC, it is not applicable to system-level bridge management. Because CLC accounts for future measurements, it gives rises to prohibitive computational costs. OLFC, on the other hand, is computationally feasible and can provide satisfactory results.

3.5 The Pontis Bridge Management Procedure and Research Motivation

3.5.1 The Pontis Bridge Management Procedure

The Pontis system was initially developed for the FHWA in 1989 and is licensed to more than 40 states in the U.S. as of 2008. It is a full-featured BMS that provides support in: *bridge inspection data management*, *needs assessment and strategy development*, and *project and program development*. Pontis 4.4 has 7 modules, of which the *preservation module* develops network-wide least-cost investment strategies for maintaining structures in serviceable condition over time. The major components of the module are (Pontis 4.4 User Manual):

- An expert judgment elicitation program to initially develop a probabilistic model that predicts the deterioration of different structure elements when different types of preservation actions (including no action) are taken;

- An updating program to improve the deterioration model each year by observing the changes in bridge condition as recorded on new inspections, together with the actions that have been taken;

- An expert judgment elicitation program to initially develop cost estimates for possible preservation actions that may be taken for each structure element;

- An updating program to improve cost models by taking into account the actual costs of actions taken;

- An optimization model that combines the considerations of deterioration, action effectiveness, and action cost to determine the most cost-effective long-term policies. This model calculates the optimal actions to be taken on each type of structure element in each type of environment in each possible condition state. The optimization model can be updated to reflect changes to deterioration or cost information. The model updating procedure can be run on an annual or biannual basis; and

- A capability to perform sensitivity analysis in order to determine the effect of changes in cost assumptions on the optimization results.

The deterioration models in Pontis are Markovian models with CoRe ratings as presented in section 3.2.2.1. These models are also (Frangopol et al. 2001):

- Single Step Functions. An element may not transition more than one condition state within any given year;
- Time-invariant. The transition matrices do not vary with time.

These assumptions are restrictive and have found their counterexamples in bridge inspection data. The objective of the optimization model is to minimize life-cycle costs; structure reliability is not explicitly considered. Furthermore, improvement plans (widening lanes and/or shoulders, increasing clearances, etc.) are made separately from preservation plans.

The updating procedure in Pontis is "… one of the innovative aspects of Pontis…" (Golabi and Shepard 1997). It enables agencies to simultaneously make MR&R decisions and improve deterioration model accuracy. The inherent adaptive control strategy in Pontis is the CEC procedure as presented in section 3.4. The CEC is computationally inexpensive, but it does not guarantee improvement in deterioration model accuracy and could lead to sub-optimal MR&R decisions.

3.5.2 Research Motivation

As mentioned in section 3.4, OLFC guarantees improvement in model accuracy when additional data are used to update the models. Therefore, in the present dissertation, the application of OLFC in BMS will be investigated against the CEC.

The research idea is to create hypothetical MR&R decision-making scenarios and update the deterioration models with two methods respectively. To determine which one has superior performance, system costs and model convergence will be compared. The theoretical framework with case studies is presented in Chapter 4.

CHAPTER 4

METHODOLOGY

The present chapter aims to lay out the methodological framework for system-level bridge management by:

- Describing quantitatively the characteristics of the bridges in the State of California, and developing hazard-based deterioration models in section 4.1. (A hypothetical bridge system will be generated from the population for a numerical study that will be presented in chapter 5.) The deterioration models are further assumed to correctly represent the physical deterioration process (as if given by nature); and

- Developing a computationally tractable optimization method for system bridge management. The routine is capable of handling bridge systems of relatively large scale without compromising computational efficiency.

The methodology presented in this chapter is applicable to all infrastructure systems and can accommodate different constraints.

4.1 Data and Deterioration Models

The data used for the present dissertation is the National Bridge Inventory (NBI), specifically state-owned bridges in California within the period of 1992 – 2012. Among them, concrete bridges without protective surfaces for decks are selected. Moreover, bridges that received a rating of *N* for deck within any year are removed. 7,284 bridges are found to have complete records for the 21-year period. In Figure 4.1, the Average Annual Daily Traffic (AADT) and bridge age (Age) of these bridges for the year 2012 are plotted:
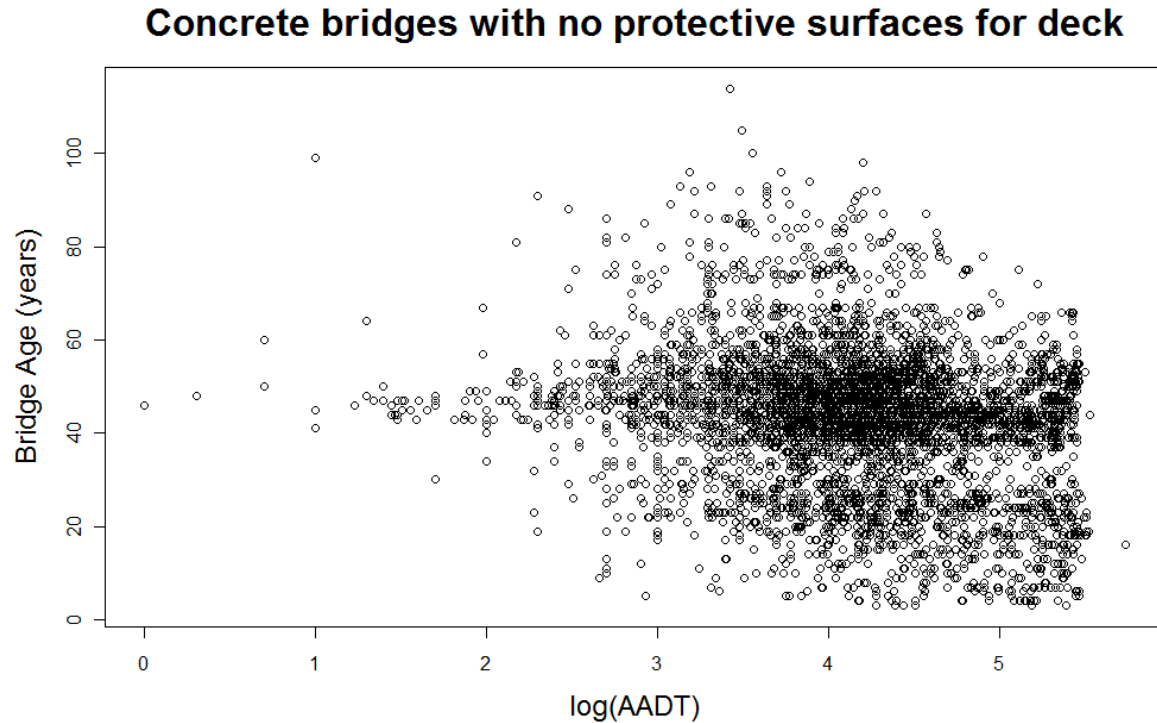
Figure 4.1: Log(AADT) vs. Age for California state-owned concrete bridges without protective surfaces (year 2012)

Figure 4.1 shows that heterogeneity in terms of *AADT* and *Age* is present in the selected bridge population. The rich combination of the two explanatory variables is beneficial for the accurate estimation of deterioration models.

As stated in chapter 3, hazard-based models can account for the deterioration and maintenance history of facilities and can represent Markovian models as well by adjusting the hazard rate to be independent of the time a facility has already spent in a condition state. The present dissertation adopts the Weibull specification of the Stochastic Duration Models (Mishalani and Madanat, 2002) for its flexibility in incorporating explanatory variables.

There is a variety of explanatory variables that should be accounted for in deterioration models: material, highway grade, AADT (Bolukbasi, Mohammadi and Arditi 2004); Age (Huang and Chen 2012); and so on. The population selection process has already implicitly considered material, owner and type of deck protective surface. The explanatory variables explicitly

included in the model are: *Age*, representing the cumulative effect of environmental factors; and *AADT*, representing the effect of traffic loading. The hazard rate formulation for Weibull is:

$$\lambda(t) = p\lambda^p t^{p-1} \tag{4.1}$$

where $\lambda = e^{\beta X}$, where X is a column vector of exogenous variables (AADT, Age and a Constant); β is a row vector of parameters to be estimated; and p is a shape control parameter to be estimated. The hazard rate function can therefore be expressed as:

$$\lambda(t) = pe^{-p\beta X} t^{p-1} \tag{4.2}$$

The estimated parameters for the decks of the selected bridge population are:

Table 4.1: Deterioration models estimated on the decks of the selected bridge population

State	p-Parameter	Betas		
		Beta-AADT	Beta-Age	Beta-Constant
9	2.5	-5.00E-07	-0.0001	0.8
8	2.25	-6.00E-07	-0.00015	0.75
7	2	-9.00E-07	-0.0005	0.7
6	1.8	-1.50E-06	-0.001	0.9
5	1.6	-2.00E-06	-0.002	0.8
4	3	-2.50E-07	-5.00E-05	0.6

A duration model for each NBI bridge deck state was estimated, except for states 3 and lower, for which observations were insufficient. The transition probabilities can be calibrated as described in Mishalani and Madanat (2002). The procedure is presented herein using a simplified case with states $\{2, 1, 0\}$. Bridge decks in state 2 can transition down by one state to state 1 and by two states to state 0. Likewise, decks in state 1 can transition down by one state to state 0 (Mishalani and Madanat 2002). For decks in condition state 2, the probability where no transition in condition state occurs in $[t, t + \Delta]$ is given by:

$$P_{2,2} = 1 - R_2(t, \Delta) = \frac{\exp[-\lambda_2^{P_2}(t + \Delta)^{P_2}]}{\exp[-\lambda_2^{P_2}(t)^{P_2}]}, \tag{4.3}$$

where λ_2, P_2 are scale and shape parameters for condition state 2. The probability that the facility condition transitions by one state in $[t, t + \Delta]$ is:

$$P_{2,1} = \int_t^{t+\Delta} \Pr(T_{1,0} > t + \Delta - T_{2,1}) \cdot \Pr(T_{2,1} \mid T_{2,1} > t) dT_{2,1} = \int_t^{t+\Delta} S_1(t + \Delta - T_{2,1}) \cdot \frac{f_2(T_{2,1})}{S_2(t)} dT_{2,1}, \tag{4.4}$$

where $T_{2,1}$ is the duration variable for state 2; $T_{1,0}$ is the duration variable for state 1; $S_i, i = 1,2$ are the survival probability function for state 1 and 2 respectively; f_2 is the survival probability density function for $T_{2,1}$. The explicit mathematical expression for this probability under the Weibull specification is:

$$P_{2,1} = \int_t^{t+\Delta} \frac{p_2 \lambda_2^{P_2} \tau^{P_2-1} \exp[-\lambda_1^{P_1}(t+\Delta-\tau)^{P_1} - \lambda_2^{P_2}(\tau)^{P_2}]}{\exp[-\lambda_2^{P_2}(t)^{P_2}]} \cdot d\tau \qquad (4.5)$$

where λ_1, P_1 are scale and shape parameters for condition state 1. Lastly, the probability that a facility condition transitions by two states is:

$$P_{2,0} = 1 - P_{2,1} - P_{2,2} \qquad (4.6)$$

Note that the transition probabilities are varying with the time that a facility has already spent in the state. Therefore, the "States" in the new transition matrices are not the condition states but rather augmented states, containing information on the condition state and time-in-state. From now on the augmented states are correspondingly denoted by s_{tis}, where s is the condition state and tis is the time-in-state. Thus, SDM have been converted to augmented Markovian models. The technique of state-augmentation has been used in infrastructure management systems to account for measurement uncertainty (Madanat 1993), model uncertainty (Guillaumot et al 2003) and history dependence (Robelin and Madanat 2007).

4.2 Optimization Decision-Making for Bridge Systems

As described in chapter 3, in the NBI database, the condition state for bridge decks takes integer values in [0, 9], so the total number of condition states is 10. Furthermore, within the selected bridge population, for any given condition state s, max(tis) ranges from 10 to 30 years. Therefore, the magnitude of the augmented state space is on the order of 100 (as opposed to 10 with Markovian models). If one were to formulate the optimization problem in with the SNO approach (Medury and Madanat 2013) with 200 bridges, the total number of variables would be:

$$\underbrace{200 \times \underbrace{4}_{|A| \text{ for } t}}_{N} + \underbrace{200 \times \underbrace{100}_{|S|} \times \underbrace{4}_{T-t} \times \underbrace{4}_{|A|}}_{N} = 320{,}800, \tag{4.7}$$

or 0.32 million. Moreover, in SNO, the number of Kolmogorov equations is equal to the number of augmented states, which is 0.08 million in the example. Hence the system constraints will correspond to a matrix of size $0.32 \times 10^6 \cdot 0.08 \times 10^6 = 2.56 \times 10^{10}$. For 2,000 bridges, the system constraints would be of size 2.56×10^{12}. Note that the constraint matrix is sparse, and can be handled effectively with sparse matrix computation. It is the number of decisions variables that causes high computational costs. Therefore, SNO is computationally expensive when the level of system heterogeneity is high.

However a closer examination of the transition process reveals that many variables in expression (4.7) are redundant. Suppose at planning year t a facility is in augmented state s_{tis}^t. An augmented state s_{tis}^τ is defined to be "accessible by s_{tis}^t in year $\tau > t$", if there exists a set of MR&R actions $\{a_t, a_{t+1}, ..., a_{\tau-1}\}$ such that $\Pr(s_{tis}^\tau \mid s_{tis}^t, \{a_t, a_2, ..., a_\tau\}) > 0$. Take year $t+1$ for example: given an MR&R action in t, the number of accessible states in $t+1$ is at most 3. (The deck either can stay in the current condition state, with tis increasing by 1; or change in condition state to two states at most and tis becomes 1.) Therefore, the total number of accessible states in year $t+1$ is at most 12, and the maximum (12) is only achieved when all accessible states are different from each other. Compared to 100, the number of states in year $t+1$ is overestimated by a factor of 10.

Table 4.2 lists the numbers of accessible states of a randomly selected bridge with $|S|=72$. The specific numbers might vary across different bridges, but the order of magnitude is the same. The number of accessible states is much smaller than $|S|$ in the first five years. In fact, the total number of accessible states in the first five years is 60, as opposed to $4 + 72 \cdot 4 = 292$ if formulated with all states.

Table 4.2: Numbers of accessible states (# A.S.) breakdown by year

Year	# A.S.	Year	# A.S.	Year	# A.S.	Year	# A.S.
1	1	6	30	11	55	16	67
2	5	7	36	12	58	17	69
3	12	8	41	13	61	18	70
4	18	9	46	14	63	19	71
5	24	10	51	15	65	20	71

For a single facility the potential reduction of the number of decision variables is up to 80%. Therefore, instead of 320,800 decision variables, 65,000 variables are sufficient for the problem, which can be handled by a single computer with commercial software such as CPLEX. When deterioration models are not Markovian or SDM, similar reduction of decision variables can still be achieved as long as the transition matrices derived from the deterioration models are sparse enough so that one state in one year can only access a small number of states in the next year. Such sparsity can be achieved by reasonably forming the augmented states.

CHAPTER 5

NUMERICAL STUDY

As described in chapter 3, CEC, the updating method in the Pontis system, does not necessarily guarantee improvement in model accuracy or cost savings; OLFC, on the other hand, guarantees both. However, the performance of either in the context of system-level bridge management is not yet clear due to complications stemming from truncation by optimization, budget constraints, etc., as the readers will discover in current and future chapters. In this chapter, a numerical study will be presented to compare the performance of OLFC and the Pontis CEC in system-level bridge management with respect to system costs savings and model accuracy improvement. A hypothetical planning agency is considered to manage a system of bridges with limited prior knowledge of the deterioration models.

- Section 5.1 establishes the cost and model benchmarks for comparisons;

- Section 5.2 describes the numerical study for the Pontis CEC and OLFC. For the Pontis CEC, two scenarios are presented: 1) the Pontis CEC initiated with deterioration models that correctly represent the physical deterioration process; and 2) the Pontis CEC initiated with imperfect deterioration models. (OLFC always initiates with imperfect deterioration models.) Computational results are presented with respect to different imperfect deterioration models; and

- Section 5.3 concentrates on the interpretation of the results.

5.1 Cost and Model Benchmarks

To ensure a fair comparison between OLFC and the Pontis CEC procedure, the following two cost baselines are used: Perfect Information and Open-Loop.

- Perfect Information (PI) baseline: evaluate system costs by assuming that there is no epistemic uncertainty in deterioration models; in other words, the agency has complete knowledge of the deterioration models. Therefore, the average cost over a planning horizon, taken over a large sample, would be a good representation of the true cost minimum. This baseline is not observable in the real world; and

- Open-Loop (OL) baseline: evaluate system costs by assuming that the agency has imperfect information of deterioration models, and is either unaware of it or unable to update; thus it makes MR&R decisions according to the imperfect models without any updating.

Intuitively, the Perfect Information (PI) and Open-Loop (OL) baselines should form the lower and upper bounds on the costs of an adaptive control approach, if the said approach can achieve cost savings.

For model convergence comparison, two adaptive control methods are evaluated differently:

- For the Pontis CEC, at any planning year, new point estimates of the parameters of the deterioration models will be generated and compared to their true values. If the estimated parameters after a period of updating stabilize around the true values (i.e. do no statistically differ from the true values), convergence is achieved; and

- For OLFC, a set of candidate models are proposed. Then at every planning year, the model weights, representing how much the agency believes them to be the true model respectively, are updated. Convergence is said to have been achieved when the weight of one candidate model meets or exceeds a set threshold (e.g. 99%). When the number of candidate models is large (e.g. 50), convergence can also be achieved with a small number of models (e.g. 2).

5.2 Numerical Study

A simple random sample of 200 bridges is drawn from the selected bridge population described in section 4.1 to form the bridge system for the numerical study. The study utilizes a simulation technique that alternates between two steps as described in Figure 5.1:

1) MR&R decision-making: select bridge-specific MR&R actions subject to system budget constraints by using the most up-to-date deterioration models; and

2) Deterioration model updating: generate bridge deck condition data (as if agencies have performed a condition survey) and update the deterioration models.

In step 2, the new condition data are generated according to the selected MR&R actions (in step 1) and the true models. If Do-Nothing is chosen, the models in Table 4.1 are used.
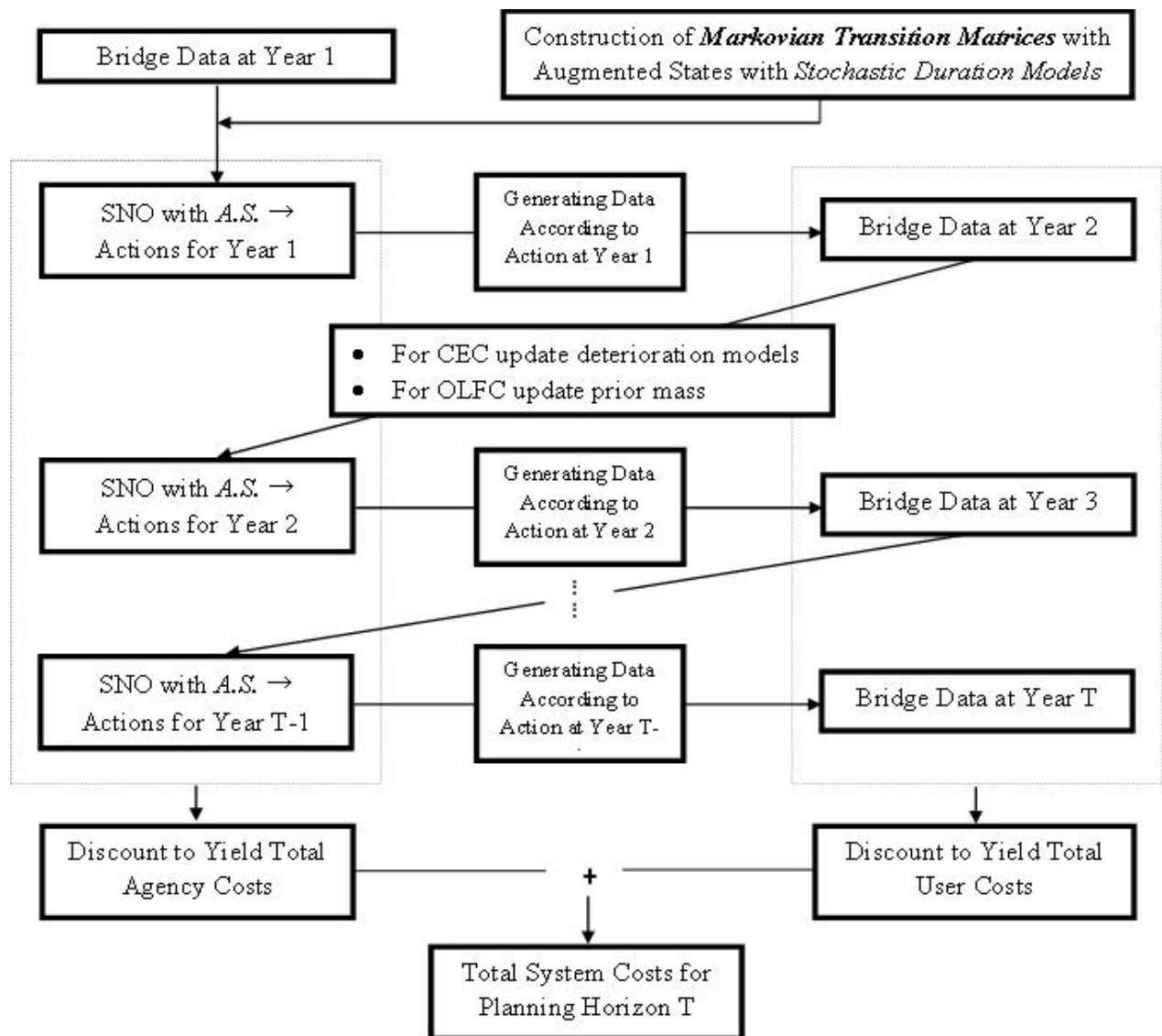
Figure 5.1: Bridge management with adaptive control methods

5.2.1 Predictability of Budgets and Determination of Length of Planning Horizons

Due to fluctuation in the economy, infrastructure maintenance plans are usually made only a few years into the future. For example, the San Francisco Bay Area Metropolitan Transportation Commission (MTC) uses a 6-year period of funding planning in conformity with the initial TEA-21 authorization; the reauthorization cycle for TEA-21 is also 6 years. Therefore, the MTC needs to plan its transportation programs within this cycle to ensure funding availability; State Transportation Improvement Program (STIP), a subprogram in MTC, is programmed every two years and each plan covers 5 years into the future. Similarly Streets and Highways Code section 164.6 requires the California Department of Transportation (Caltrans) to prepare a 5-year maintenance plan that addresses the maintenance needs of the State Highway System which includes bridges in the State of California. Hence, it is unrealistic to assume a longer planning horizon. The present dissertation adopts 5-year planning horizons, meaning that at each planning year agencies have knowledge of the budget constraints for at most the next five years.

5.2.2 PI and OL baselines

The PI and OL baselines are constructed with a cost structure adopted from Kong and Frangopol (2003). States 3, 2, 1 and 0 are specified as forbidden states in the optimization due to very high user costs. The system management problem is framed as follows: an agency needs to make MR&R decisions every year for 20 years (e.g. 1991 – 2010, referred to as a 20-year Policy-Making period from now on); at each year, the MR&R decisions are made with a 5-year planning horizon, meaning that the agency, at the current planning year, only has knowledge of the availability of funding for the next five years. Therefore the user and agency costs for 20 years combined produce the system cost statistics over the 20-year Policy-Making period. The discount rate is assumed to be 6%, which is consistent with the literature (Kong and Frangopol, 2003; Tilly, 1997) and National Cooperative Highway Research Program (NCHRP) discount rates (NCHRP 483, 2002). For illustration purposes, a constant annual budget level is assumed for 20 years. The results for the Perfect Information baseline with different annual budget levels are plotted in Figure 5.2 and all statistics are verified by 100-repetition simulations.

Note that only the used portion of the budgets is included as agency costs in the system costs, implying that the unused proportion can be made available for other objectives. When the annual budget exceeds $14 Million, the system costs stop decreasing, which means that the budgets are no longer binding. In the following studies an annual budget level of $10 Million is adopted to ensure that the budget constraint is binding.

System Costs as a function of Budget Level

Annual Budget Level = $10 Million

System Costs (in $Million)

Annual Budget (in $Million)
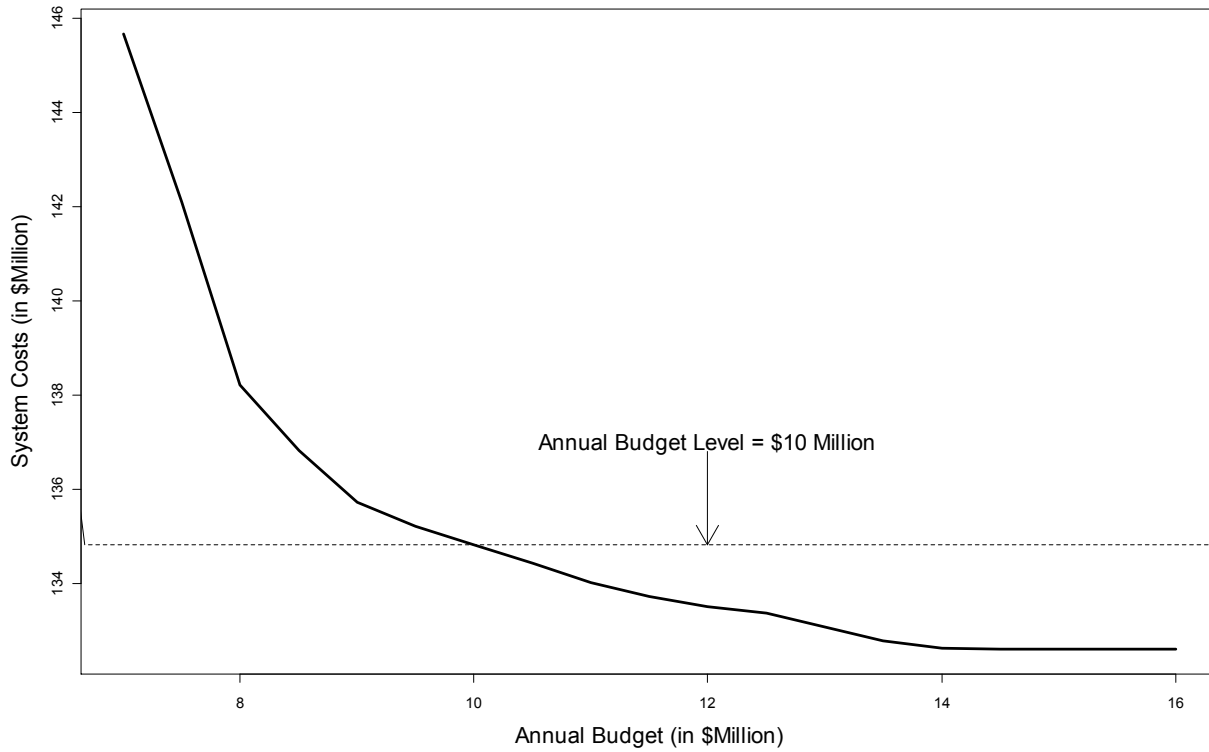
Figure 5.2: The relationship between annual budget level and system costs for a 20-year Policy-Making period

When generating the imperfect deterioration models for the OL baseline, a set of candidate models are proposed, each given a weight (The weights are referred to as a mass function from here on). For simplicity, the *beta*s of the candidate models are kept the same as those of the true models (Table 4.1), but the *p* parameter is varied as shown in Table 5.1:

Table 5.1: Values of the *p* parameter of the candidate models adopted for OL baseline scenario

State	OL				
	Candidate 1	*Candidate 2*	*Candidate 3*	*Candidate 4*	*Candidate 5*
9	1	2	2.25	3.5	4
8	1	1.85	2	3.25	3.75
7	1	1.75	1.8	3	3.6
6	1	1.6	1.6	2.75	3.2
5	1.4	1.6	1.6	1.6	1.6
4	3	3	3	3	3
Prior Mass	m_1	m_2	m_3	m_4	m_5

Note that $\sum_1^5 m_i = 1$. The candidate set includes models that represent slower (Candidates 1 through 3), as well as faster (Candidate 4 and 5), deterioration rates than the true models. The transition probability matrices generated by the candidate models will be weighted by the prior mass shown in the last row of Table 5.1, and summed to generate the matrices for the OL baseline scenario. By varying the mass function, different imperfect models can be generated for the OL baseline. In section 5.2.4 – 5.2.6, different mass functions will be explored.

5.2.3   Updating Protocols for the Pontis CEC and OLFC

The updating equation for the Pontis CEC is given by:

$$\mu^{t+1} = \underset{\mu}{\mathrm{argmax}}(\log likehood \mid Data_{(-\infty,t]}) \qquad\qquad (5.1)$$

where μ^{t+1} is the value of the p-parameter that maximizes the log-likelihood of data accrued up to time t using Maximum Likelihood Estimation.

The performance of the estimation method (Maximum Likelihood Estimation) was tested beforehand with two scenarios for each condition state: without censoring and with censoring at *tis*=n years. In survival analysis, censoring refers to the event that an object has not failed by the time that an experiment is over. In the context of bridge deterioration, the experiment is natural deterioration, with failure defined as transitioning out of a condition state, and the application of any corrective action as a termination of the experiment. Therefore, if a facility has already spent n years in its current condition state without any corrective action (experiment has not been terminated at n years) and then gets assigned a corrective action at *tis*=n years, the facility will have not "failed" by *tis*=n years, i.e. it has been censored at *tis*=n years.

Note that longer *tis'* are associated with higher transition probabilities and therefore cause higher costs. As a result, shorter *tis* are associated with Do-Nothing actions and yield complete "failure" observations, whereas longer *tis* are associated with corrective actions and yield censored observations. Discarding censored data is problematic, because it will favor "early failures" in the data and result in biased estimates. Therefore it is important to test the performance when censoring is present.

During testing n was set equal to 2, which implies fast deterioration; a small n also increases the difficulty of obtaining accurate estimates. Nonetheless the average estimation error/mean is quite small as shown in Table 5.2, which is consistent with Kalbfleisch and Prentice (2002). (With each repetition, the estimates of the p-parameters ($\hat{p}$) and the variances of the p-parameters ($\hat{Var}(\hat{p})$) are obtained; then across 100 repetitions, the sample means and variances are calculated.)

Table 5.2: Estimation power of the Weibull estimation functions

State	Statistics	True Values	No Censoring Estimates		Censoring at tis = 2 years	
			$\hat{p}$	$\hat{Var}(\hat{p})$	$\hat{p}$	$\hat{Var}(\hat{p})$
9	Mean	2.5	2.5075	0.1311	2.4914	0.2034
	Variance	---	0.0196	0.0001	0.0496	0.0004
8	Mean	2.25	2.2748	0.1196	2.2552	0.1796
	Variance	---	0.0164	0.0001	0.0324	0.0003
7	Mean	2.00	2.0005	0.1049	2.0095	0.1554
	Variance	---	0.0116	0.0000	0.0240	0.0001
6	Mean	1.8	1.8076	0.0946	1.8275	0.1492
	Variance	---	0.0100	0.0000	0.0194	0.0001

The Bayesian updating of deterioration models with OLFC is given by:

$$P(Model_m^{t+1} \mid Data^{t+1}) = \frac{L(Data^{t+1} \mid Model_m^t)P(Model_m^t)}{\sum_k L(Data^{t+1} \mid Model_k^t)P(Model_k^t)} \tag{5.2}$$

where $L(Data^{t+1} \mid Model_m^t), m = 1,...,5$ is the likelihood evaluated with new data under Model m at the end of period t; and $P(Model_m^t)$ is the prior distribution at the end of period t.

In sections 5.2.4 through 5.2.6, OLFC and the Pontis CEC will be compared when different prior mass functions are used for the OL baseline.

5.2.4 Imperfect Models that Represent Slower Deterioration Than the True Models

In this section, the initial prior mass function used is:

$$\{m_1 = 0.8; \ m_i = 0.05, i = 2,3,4,5\} \tag{5.3}$$

The resulting imperfect models for the OL baseline are:

Table 5.3: Values of the _p_ parameters of the imperfect models for the OL baseline (Slow Prior[*])

State	9	8	7	6	5	4
_p_ Parameter	1.2	1.16	1.125	1.05	1.5	3

[*]Note: Slow Prior refers to the scenario where the OL baseline's models represent slower deterioration than the true models.

5.2.4.1 The Pontis CEC (Slow Prior)

Two scenarios for the Pontis CEC are presented herein:

- The Pontis CEC initiated with the PI models. The agency had perfect information of the deterioration models but was unaware of it. Therefore it updates the deterioration models, starting with the true models (as in Table 4.1); and

- The Pontis CEC initiated with the OL models. The models that the agency starts with are the set of models used for the OL baseline scenario (and later for the OLFC scenario).

By applying SNO with the accessible states simplification described in section 4.2, the system cost statistics are computed over a 20-year Policy-Making period and shown in Table 5.4. Each scenario is verified by a 100-repetition simulation.

Table 5.4: System costs for PI, OL, the Pontis CEC initiated with PI and with OL (Slow Prior)

Cost Statistics ($Million)	*The Pontis CEC Initiated with PI model*	*PI*	*OL*	*The Pontis CEC Initiated with OL model*
Mean	147.56	134.82	141.34	143.78
[Min, Max]	[142.56, 151.24]	[131.13, 136.68]	[139.02, 144.17]	[140.09, 147.05]
Stand Error	1.55	1.02	0.98	1.45
Two-sided T-test P-Value	<2.2.e-16		<2.2.e-16		<2.2.e-16

It can be seen that the Pontis CEC initiated with the OL models performed worse than Open-Loop by $2 Million and that the Pontis CEC starting with the PI model strayed away from Perfect Information: updating was not beneficial. The bi-scenario comparison t-statistics p-values are listed in the bottom row, all of which are low. This means that the system costs differences are not due to the stochastic nature of deterioration, but rather arise from the control strategy that was applied.

Note that the bridge system for the simulation consists of only 200 bridges, as opposed to over 12,000 bridges owned by the state of California. In other words, a $2 million increase in the previous numerical example may correspond to $120 million at the level of the state of California.

The average models (characterized by the *p* parameter) obtained from the Pontis procedure initiated with the OL models after 20 years of updating are presented in Figure 5.3 and 5.4. Results for state 9 and state 8 are presented while other states showed the same pattern. The means of the estimated *p*-parameter for state 9 strayed away from the true value (2.5), which is delineated by the horizontal dashed line, and they yielded models that have faster deterioration than the true models.

5.2.4.2 OLFC (Slow Prior)

The initial prior mass function for OLFC is the same for the OL baseline. The system costs statistics for a 20-year Policy-Making period are presented in Table 5.5. All results are obtained from 100 simulation repetitions.

Table 5.5: System costs comparison among PI, OLFC, OL and the Pontis procedure initiated with OL (Slow Prior)

Cost Statistics ($millions)	PI	OLFC	OL	The Pontis CEC Initiated with OL model
Mean	134.82	134.95	141.34	143.78
[Min, Max]	[131.13, 136.68]	[133.09, 138.16]	[139.02, 144.17]	[140.09, 147.05]
Stand Error	1.02	1.11	0.98	1.45
Two-sided T-test P-Value	0.3737	<2.2.e-16		<2.2.e-16

It can be observed that OLFC achieves significant savings over OL, and does not significantly differ from PI. The true models were not included in the OL set, but OLFC still reduced system costs.

The evolution of the model weights for state 9 and 8 in each year of the 20-year Policy-Making period is shown in Figure 5.5 and 5.6. The y-axes represent the model weights after each update (corresponding to the years in the Policy-Making period, represented by the x-axes) for each candidate model.
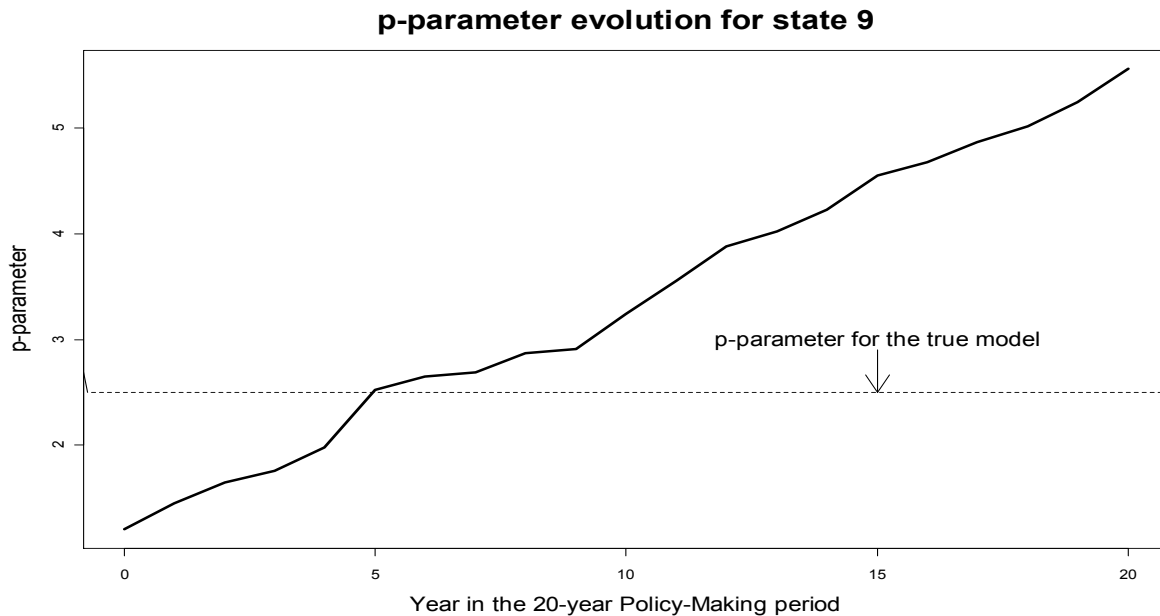
Figure 5.3: The evolution of p-parameter's means under the Pontis procedure initiated with OL for state 9 (Slow Prior)

p-parameter evolution for state 8
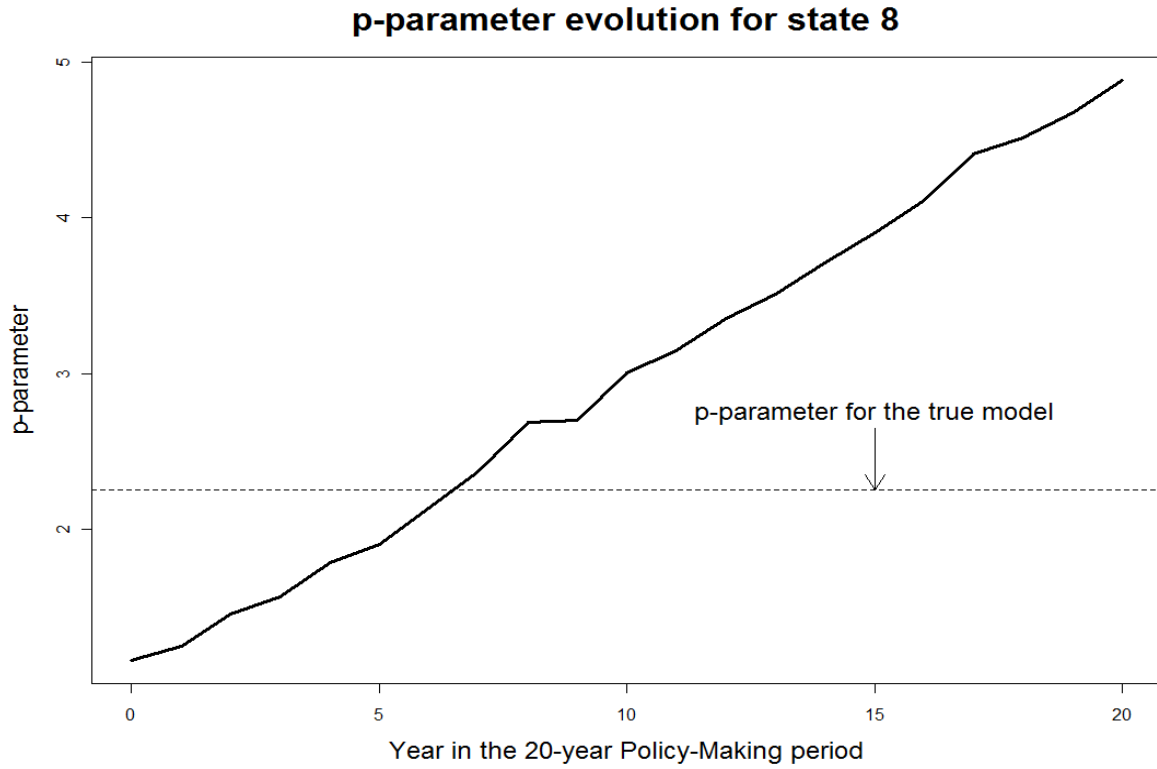
Figure 5.4: The evolution of p-parameter's means under the Pontis procedure initiated with OL for state 8 (Slow Prior)

Model convergence of OLFC for state 9
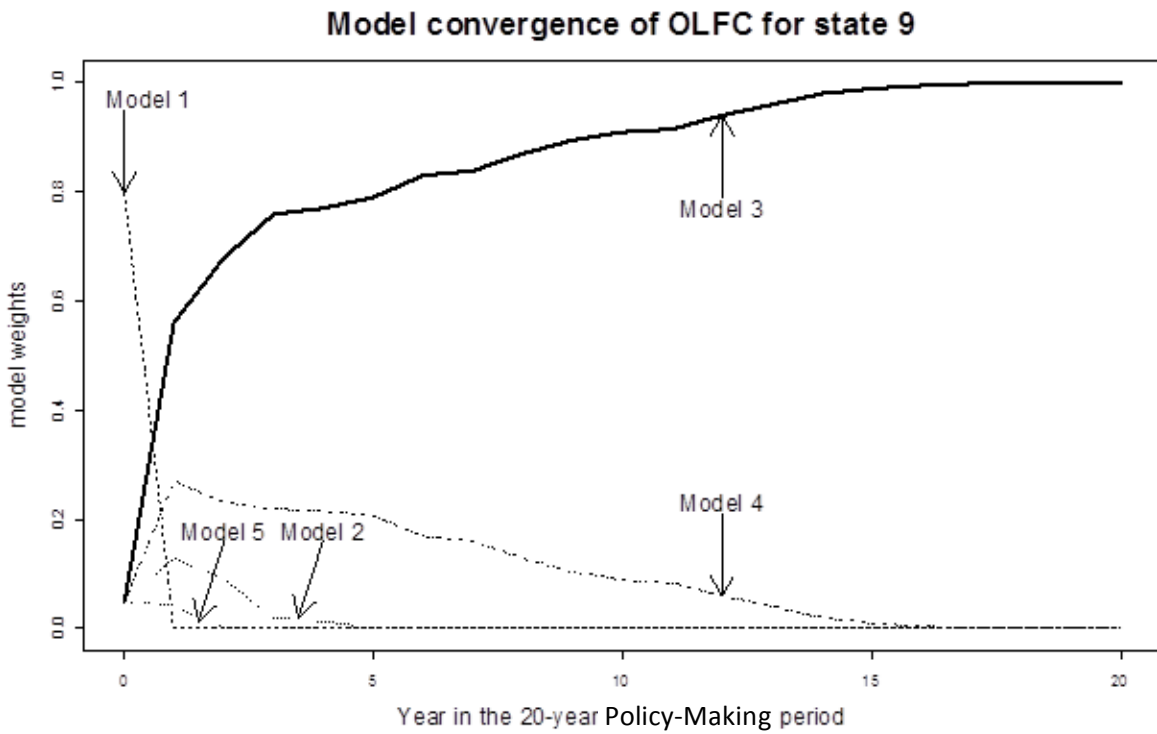
Figure 5.5: Model weights evolution over 20 years for state 9 under OLFC (Slow Prior)

Model convergence of OLFC for state 8
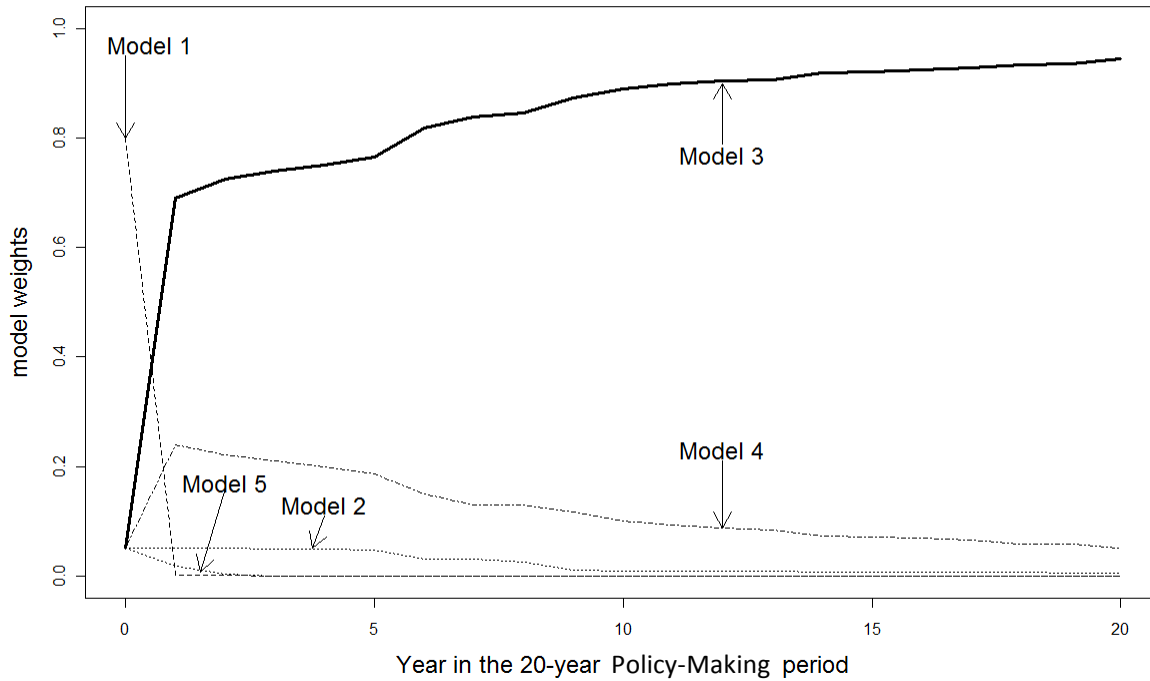
Figure 5.6: Model weights evolution over 20 years for state 8 under OLFC (Slow Prior)

For both state 9 and state 8, it can be observed that the weights for candidate 3, the candidate that is the closest to the true models, climbed up steadily. Candidate 2, which is fairly close to candidate 3, was gradually eliminated from consideration. Candidate 1 and 5 were ruled out after the first and third updates, respectively. Candidate 4 also dropped out eventually.

Recall that the Pontis procedure favored faster models, but OLFC does not suffer from this problem. The result is that OLFC is able to distinguish between models that are relatively close to each other. The weights statistics at the end of the 20-year planning period are presented in Table 5.6.

Table 5.6: Model weights after 20-year updating under OLFC (Slow Prior)

State		Candidate 1	Candidate 2	Candidate 3	Candidate 4	Candidate 5
9	Mean	0	0.0002	0.9998	0.0000	0
	Stand. Error	1e-14	0.0054	0.0354	0.0003	1e-9
8	Mean	0	0.0058	0.9442	0.0500	0
	Stand. Error	1e-14	0.0776	0.0876	0.0103	1e-10
7	Mean	0	0.3213	0.5482	0.1305	0
	Stand. Error	1e-14	0.0762	0.0942	0.0089	1e-10
6	Mean	0	1		0	0
	Stand. Error	1e-14	1e-10		1e-10	1e-10

5.2.5 Imperfect Models that Approximate the True Models' Deterioration Rates

In this section, the initial prior mass function used is:

$$\{m_3 = 0.8;\ m_i = 0.05, i = 1,2,4,5\} \tag{5.4}$$

The resulting imperfect models for the OL baseline are:

Table 5.7: Values of the *p* parameters of the imperfect models for the OL baseline (Medium Prior[*])

State	9	8	7	6	5	4
p Parameter	2.46	2.22	1.93	1.75	1.57	3

[*]Note: Medium Prior refers to the scenario where the OL baseline's models approximate the true models' deterioration rates.

The system cost statistics are presented in Table 5.8.

Table 5.8: System costs for PI, OL, OLFC and the Pontis procedure starting with OL (Medium Prior)

Cost Statistics ($Million)	PI	OLFC	OL	The Pontis Procedure initiated with OL model
Mean	134.82	134.97	134.93	146.99
[Min, Max]	[131.13, 136.68]	[130.27, 137.34]	[132.10, 136.66]	[142.31, 151.18]
Stand Error	1.02	1.46	0.82	1.48
Two-sided T-test P-Value	0.4296		0.8026	<2.2.e-16

The OL baseline has a system costs average that does not differ from the PI baseline statistically (p-value equal to 0.3774); this is because the weighted models approximate the deterioration rates of the true models. OLFC yielded higher system costs than OL but the difference is not statistically significant. The Pontis procedure, once again, resulted in system costs that are significantly higher than OL and OLFC.

The model convergence results are shown in Figure 5.7 through 5.10. For the Pontis CEC, the *p* parameters keep increasing for both state 9 and state 8 (Figure 5.7 and 5.8), showing the same trend as in section 5.2.4. For OLFC (Figure 5.8 and 5.10), convergence is consistently achieved, where model 3 was weighted over 99% after 10 years of updating. The weights statistics for OLFC at the end of the 20-year Policy-Making period are presented in Table 5.9.

Table 5.9: Model weights after 20-year updating under OLFC (Medium Prior)

State		Candidate 1	Candidate 2	Candidate 3	Candidate 4	Candidate 5
9	Mean	0	0.0000	1.0000	0.0000	0
	Stand. Error	1e-14	0.0007	0.0024	0.0012	1e-9
8	Mean	0	0.0000	1.0000	0.0000	0
	Stand. Error	1e-14	0.0083	0.0176	0.0099	1e-10
7	Mean	0	0.2783	0.5362	0.1855	0
	Stand. Error	1e-14	0.103	0.107	0.0374	1e-10
6	Mean	0	1		0	0
	Stand. Error	1e-14	1e-10		1e-10	1e-10

Figure 5.7: The evolution of p-parameter's means under the Pontis procedure initiated with OL for state 9 (Medium Prior)

p-parameter evolution for state 8

Figure 5.8: The evolution of p-parameter's means under the Pontis procedure initiated with OL for state 8 (Medium Prior)

Model convergence of OLFC for state 9
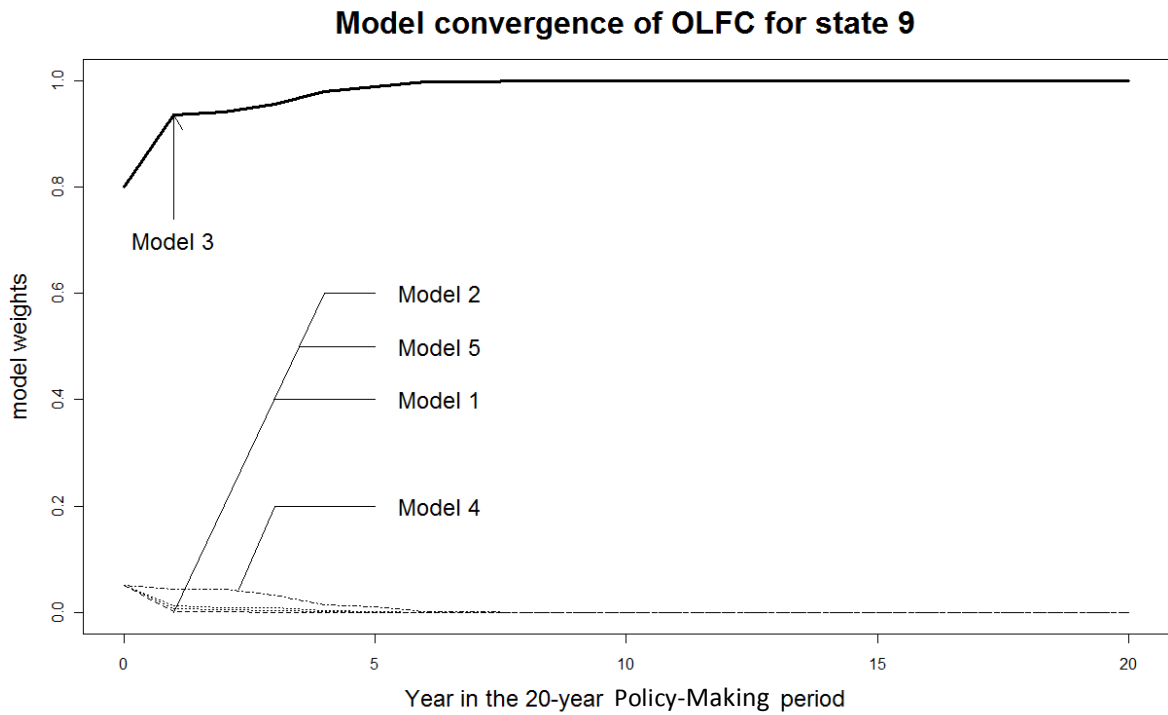
Figure 5.9: Model weights evolution over 20 years for state 9 under OLFC (Medium Prior)

Model convergence of OLFC for state 8
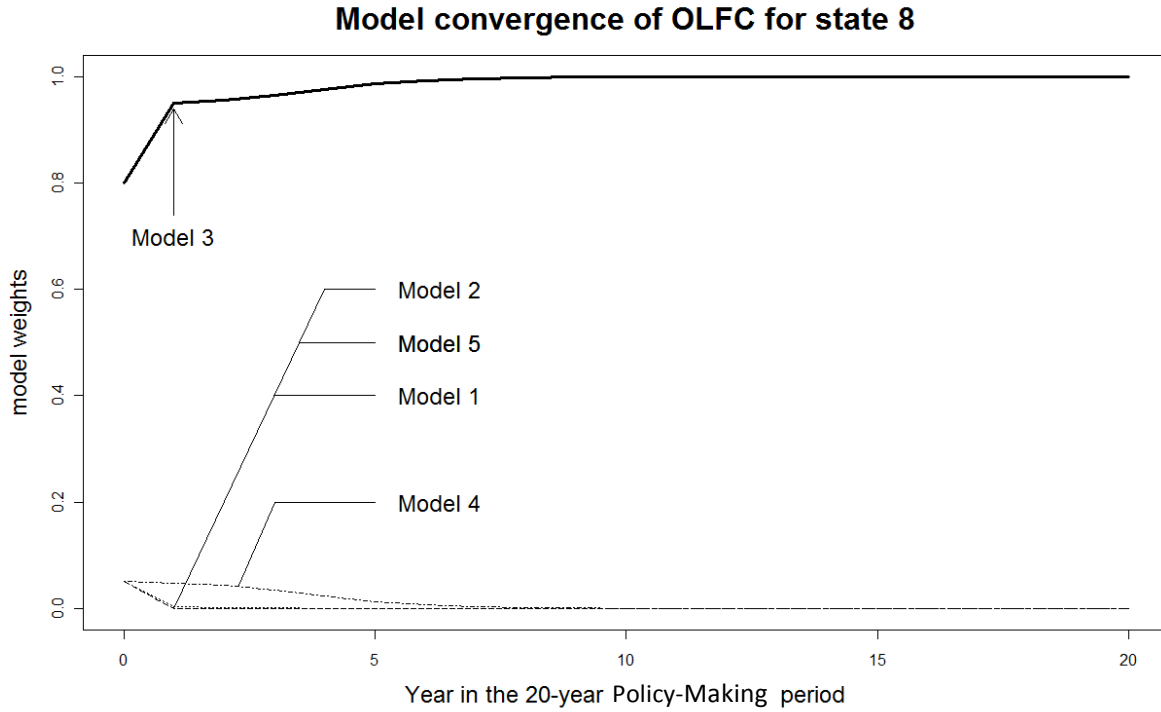
Figure 5.10: Model weights evolution over 20 years for state 8 under OLFC (Medium Prior)

5.2.6 Imperfect Models that Represent Faster Deterioration Than the True Models

In this section, the initial prior mass function used is:

$$\{m_5 = 0.8; \; m_i = 0.05, i = 1,2,3,4\} \hspace{3cm} \textbf{(5.5)}$$

The resulting imperfect models for the OL baseline are:

Table 5.10: Values of the *p* parameters of the imperfect models for the OL baseline (Fast Prior[*])

State	*9*	*8*	*7*	*6*	*5*	*4*
p **Parameter**	3.90	3.67	3.48	3.09	1.57	3

[*]Note: Fast Prior refers to the scenario where the OL baseline's models represent faster deterioration than the true models.

The system cost statistics are presented in Table 5.11.

Table 5.11: System costs for PI, OL, OLFC and the Pontis procedure initiated with OL (Fast Prior)

Cost Statistics ($Million)	PI	OLFC	OL	The Pontis Procedure initiated with OL model
Mean	134.82	134.99	136.32	139.13
[Min, Max]	[131.13, 136.68]	[130.87, 136.01]	[133.29, 138.96]	[136.43, 145.29]
Stand Error	1.02	1.25	1.20	1.58
Two-sided T-test P-Value	0.3174	<2.2.e-16		<2.2.e-16

The Pontis CEC resulted in a system costs average that is again higher the OL baseline: updating was not beneficial. OLFC achieved system cost saving compared to the OL baseline and did not statistically differ from the PI baseline. The model convergence results for CEC are shown in Figure 5.11 through 5.13. Figure 5.11 and 5.12 illustrate the increasing trends of the estimates of the p parameter. In Figure 5.13, after 14 years, the p parameter for state 6 started to stabilize. It is not, however, because convergence has been achieved, rather that the fast deterioration represented by the models estimated by CEC has led agencies to always assign corrective actions to facilities if they are in state 6. Therefore, no data will be generated from the deterioration process; in other words updating stops when the p parameter surpasses a certain value.
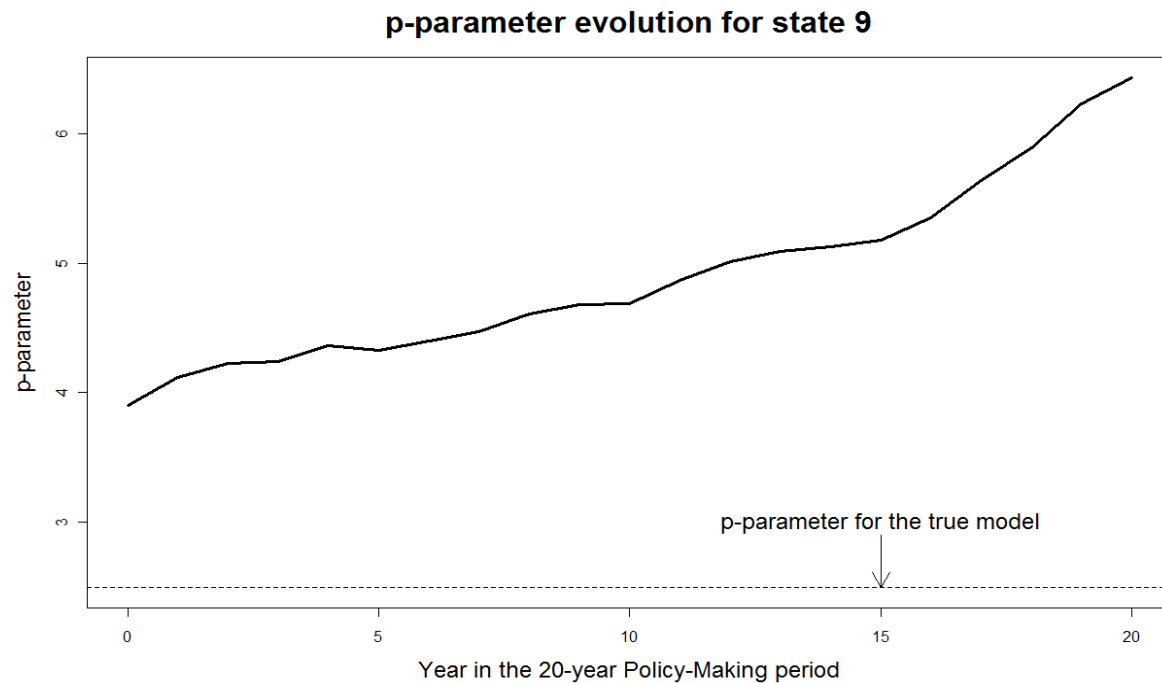
Figure 5.11: The evolution of p-parameter's means under the Pontis procedure initiated with OL for state 9 (Fast Prior)

p-parameter evolution for state 8
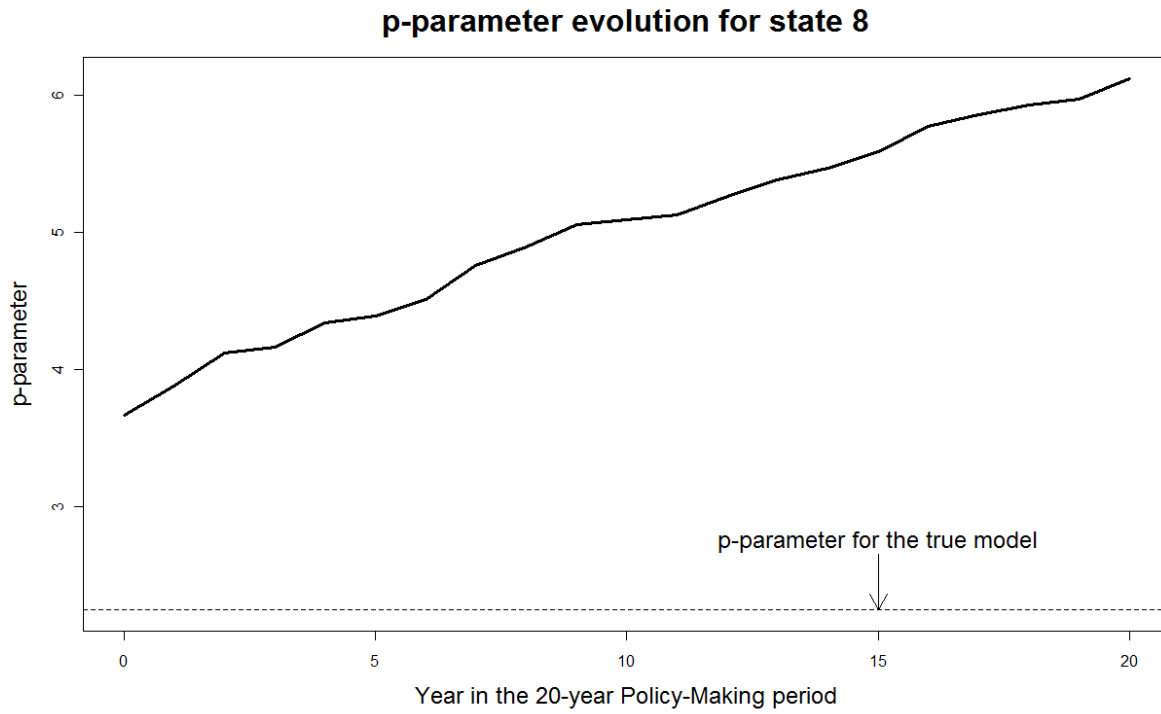
Figure 5.12: The evolution of p-parameter's means under the Pontis procedure initiated with OL for state 8 (Fast Prior)
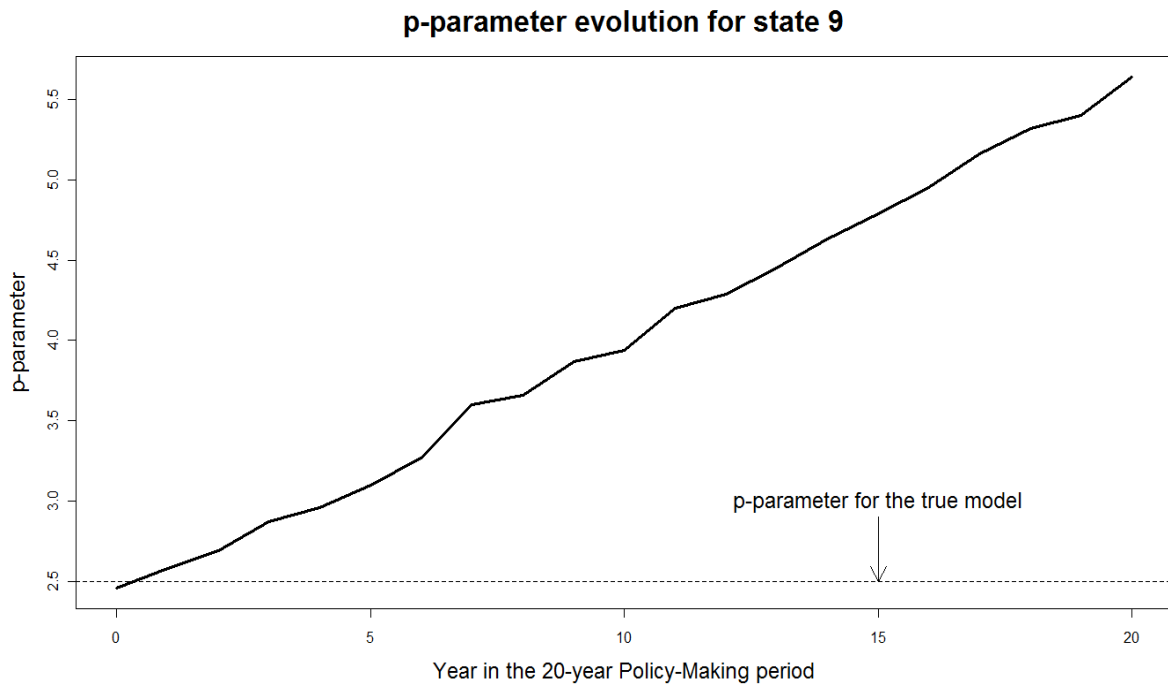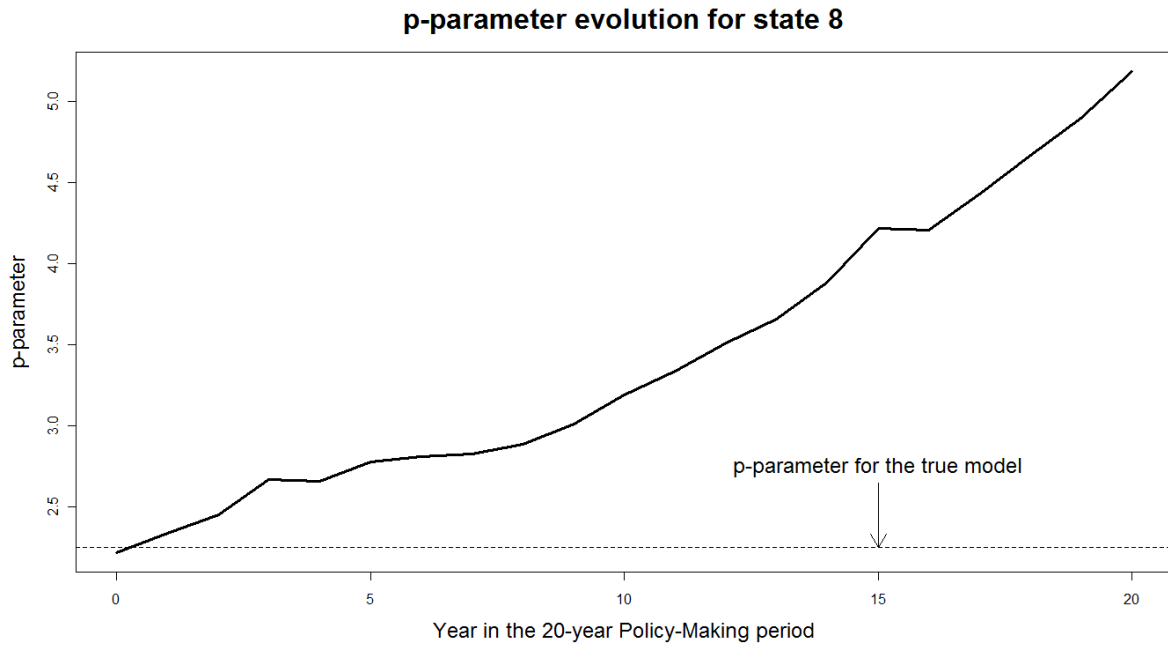
## p-parameter evolution for state 6
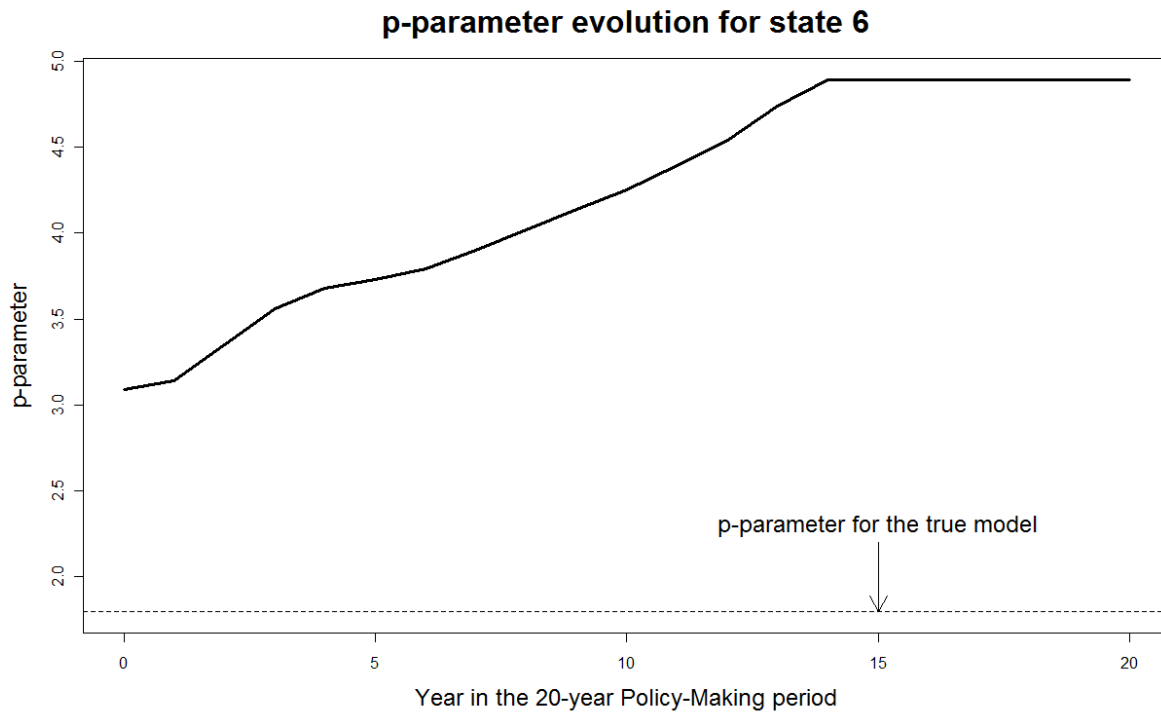
Figure 5.13: The evolution of p-parameter's means under the Pontis procedure initiated with OL for state 6 (Fast Prior)

56

Figure 5.14 through 5.16 illustrate the model convergence results for OLFC, with the weight statistics presented in Table 5.12. For state 6, compared to the Pontis CEC, OLFC still achieved consistent convergence, along with system costs that are not significantly different from the PI baseline.

Table 5.12: Model weights after 20-year updating under OLFC (Fast Prior)

State		Candidate 1	Candidate 2	Candidate 3	Candidate 4	Candidate 5
9	Mean	0	0.0000	1.0000	0.0000	0
	Stand. Error	1e-14	0.0017	0.0363	0.0082	1e-14
8	Mean	0	0.0000	1.0000	0.0000	0
	Stand. Error	1e-14	0.0074	0.0578	0.0094	1e-14
7	Mean	0	0.2239	0.6018	0.1743	0
	Stand. Error	1e-14	0.1142	0.0956	0.0068	1e-10
6	Mean	0	1		0	0
	Stand. Error	1e-14	1e-14		1e-14	1e-14
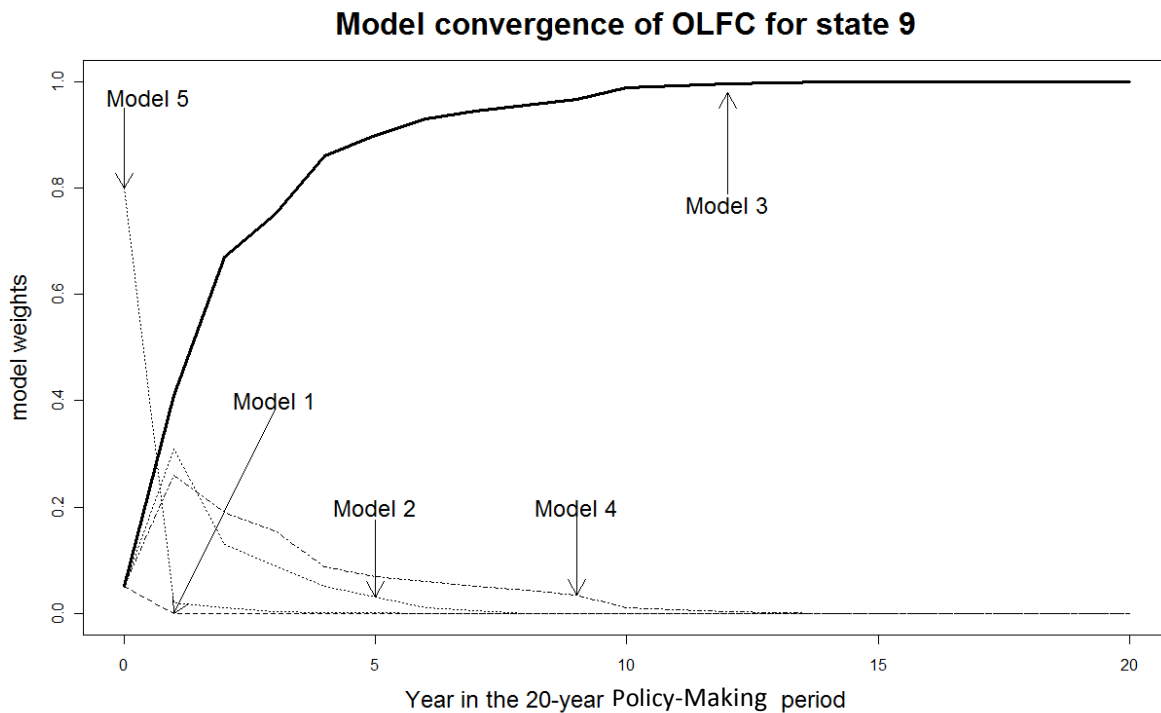
Figure 5.14: Model weights evolution over 20 years for state 9 under OLFC (Fast Prior)

Model convergence of OLFC for state 8
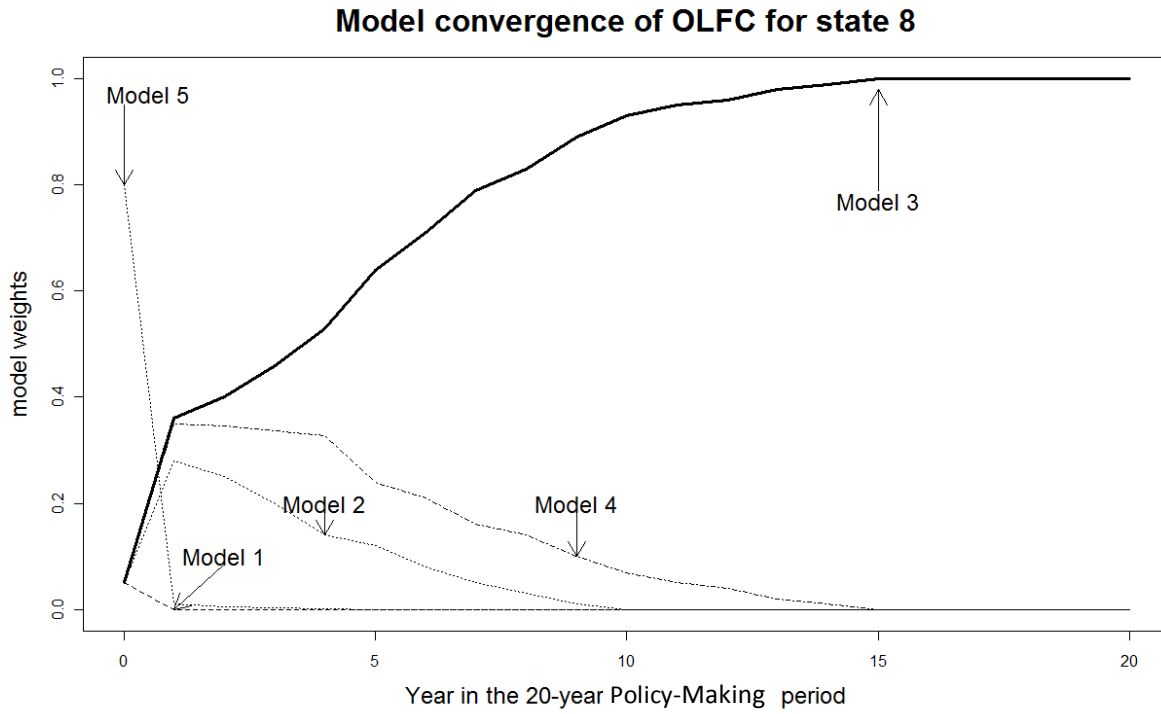
Figure 5.15: Model weights evolution over 20 years for state 8 under OLFC (Fast Prior)

Model convergence of OLFC for state 6
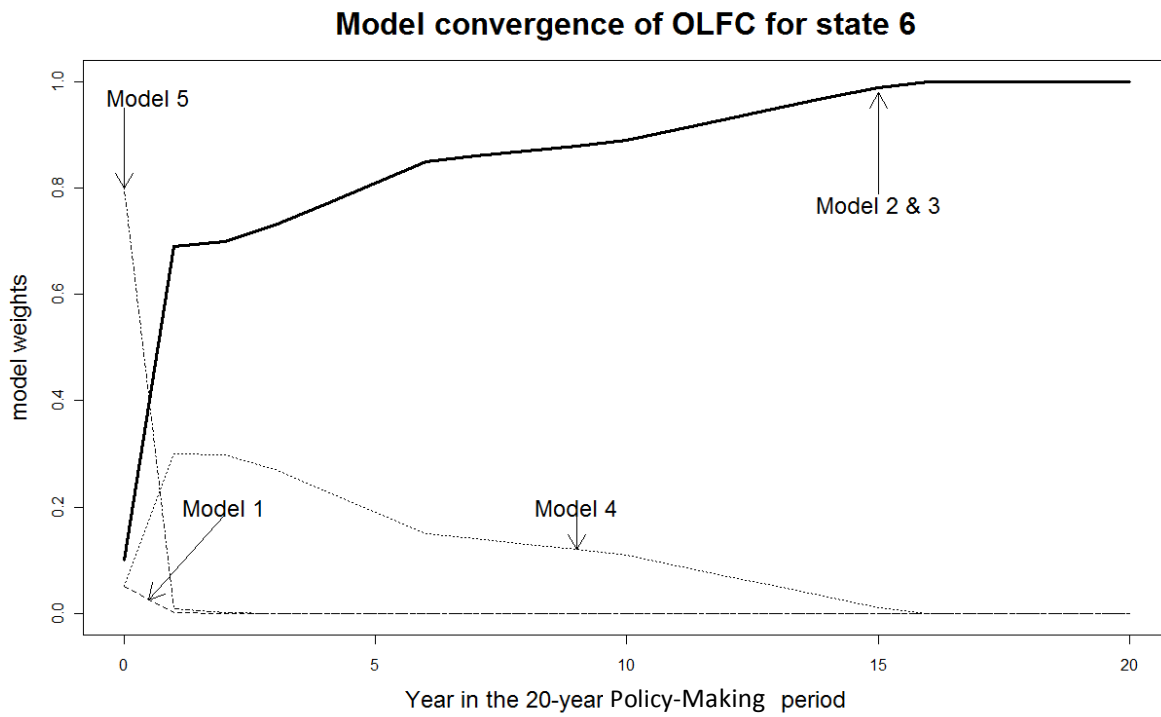
Figure 5.16: Model weights evolution over 20 years for state 6 under OLFC (Fast Prior)

5.3 Discussion

5.3.1   Discussion on Model Convergence

There is no guarantee that the Pontis CEC will lead to convergence, and even if it does, consistency of convergence is not guaranteed. In fact, subsequent data tend to reinforce the erroneous estimates from the last update. The reason is that the Pontis CEC is only optimal for linear deterioration models and quadratic cost functions (Bertsekas 2005), but infrastructure systems do not satisfy such requirements. As shown in section 5.2.4 through 5.2.6, the Pontis CEC has consistently biased estimation towards faster deterioration as updating goes and has resulted in the increasing trends of the p parameter. This is due to the following reasons:

- The data generated are not random samples from the deterioration process. In the optimization procedure, the mapping of actions to states is deterministic. In other words, the optimal action for a facility in a given state is only determined by the state itself. For example, if a facility has already spent three years in condition state 5, the optimal action to take will be determined by the optimization as $a(s_{tis} = 5_3)$, where s_{tis} is the augmented state with condition state equal to s and time-in-state equal to tis. Therefore, one will never observe s_{tis} pairing up with other actions other than $a(s_{tis} = 5_3)$. In the above example, suppose $a(s = 5, tis = 3)$ is reconstruction, the action-state pairs one would never observe are: (5_3, *Maintenance*), (5_3, *Temporary Repair*) and (5_3, *Do-Nothing*). Missing (5_3, *Do-Nothing*) means that part of the deterioration would not be observed; and

- The updating power heavily depends on the size N_{New} of the newly generated data. If N_{New} is small, the updating will be overridden by inherent randomness and consequently will be unable to reveal much information about the models. One might argue that by increasing the time between two updates one may be able to accumulate enough data for more effective updates. However, since maintenance and repair decisions need to be made on an annual cycle, this is not an option; and

- The observed increasing pattern of the *p*-parameter is not random: larger *tis'* are more often associated with a correcting MR&R action because they incur higher system costs than smaller ones and consequently would not appear in inspection data; therefore only the smaller *tis'* would be included in estimation and subsequently result in deterioration models that are faster than the true models.

   A graphical explanation is presented in Figure 5.17: the true deterioration probability density function is plotted as the dark curve that tails off with the dashed curve. To avoid higher system costs, optimization truncates the long tis', which correspond to the dashed tail. Therefore, what is observed is the left (dark) proportion of the deterioration distribution. Because Maximum Likelihood Estimation uses only observed data (therefore it fits only on the dark proportion of the true curve), the estimated deterioration model will have faster deterioration than the true model, and is depicted by the dense-point curve.

The Pontis procedure fitting with right truncated data
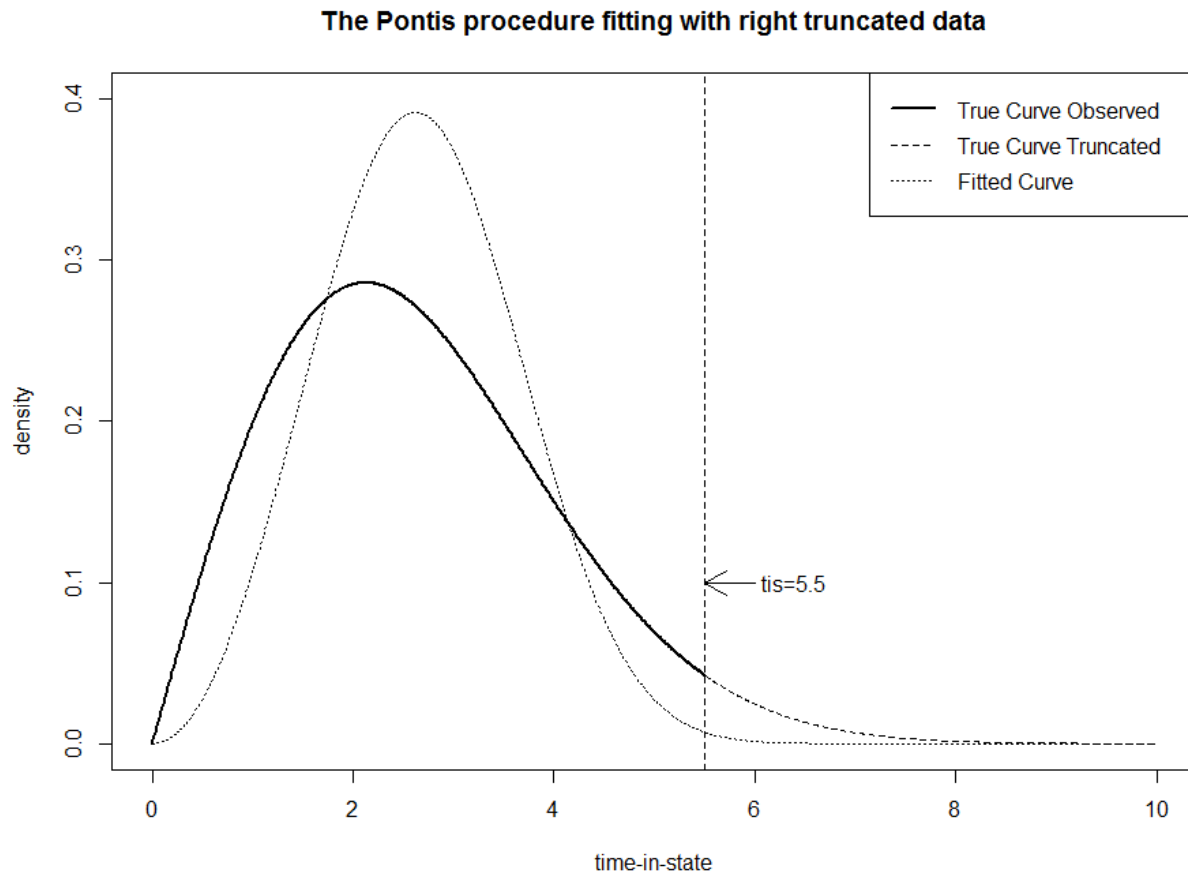
Figure 5.17: Graphical explanation of the Pontis procedure yielding faster models

OLFC does not re-estimate the parameters of the candidate models, but rather evaluate their likelihoods under new condition data; therefore it avoids bias introduced by estimation. This feature also enables the inclusion of candidate models that belong to different classes, as will be further discussed in Chapter 6.

5.3.2   Discussion on System Costs

Because the Pontis CEC leads agencies to believe that bridges deteriorate faster than they actually do, the agencies assign corrective actions more frequently than they should have. Due to the fact that larger bridges (large dimensions, heavy traffic, etc.) overweigh smaller ones in system costs, they tend to receive corrective actions more often and therefore consume a significant proportion of the system budget. The result is that smaller bridges are always on low priority in MR&R planning and are under-maintained. This problematic situation can lead to significant user costs and social equity issues.

CHAPTER 6

EXTENSION TO MAKOVIAN SYSTEMS

In the previous chapter, OLFC and the Pontis CEC have been compared by their performance in a bridge system that has time-dependent deterioration. In reality, infrastructure deterioration has been often modeled as a Markovian process; therefore it is essential to address the following questions:

- If deterioration is truly a Markovian process, would the two adaptive methods perform differently?

- If deterioration is not Markovian but an agency adopts a Markovian representation, would it increase system costs significantly?

- If deterioration is not Markovian but an agency adopts a Markovian representation and tries to update it with condition data, which adaptive method, the Pontis CEC or OLFC, would perform better in terms of system costs and model accuracy improvement?

Section 6.1 addresses the first and second bullet points, along with the first half of the third bullet point. The results indicate that Markovian representations of a time-dependent deterioration process yield significantly higher system costs. Section 6.2 focuses on the application of OLFC when updating the Markovian representations of a time-dependent deterioration process. The system costs are presented and compared to the system costs in section 6.1. Moreover section 6.2 presents how an agency can sequentially generate more candidate models as updating goes, so as to successively approach the true models when deterioration is truly Markovian.

6.1 The Pontis CEC

As stated in chapter 5, the Pontis CEC is optimal for linear systems. In fact if deterioration is truly a Markovian process, the Pontis CEC will yield unbiased estimates. Consider the following parameterization of the probability of transitioning from state i into state j:

$$P(i,j) = \exp(\beta X) / [\exp(\beta X) + 1] \tag{6.1}$$

where X is a vector of explanatory variables (including a constant 1), and β is the vector of coefficients. Formulation 6.1 defines a logistic model, where the dependent random variable takes binary values, with 1 representing transition and 0 not. The logistic transformation gives:

$$\ln\left[\frac{P(i,j)}{1 - P(i,j)}\right] = \beta X \tag{6.2}$$

The regression coefficients β can be estimated using maximum likelihood estimation (MLE).

However, the Markovian (memory-less of the deterioration and maintenance history) property may not hold in reality, or may hold only for some types of deterioration processes (Mishalani and Madanat, 2002, Frangopol and Das, 1999). Therefore, it is critical to answer the following question:

Is the Markovian representation of a time-dependent deterioration process acceptable in terms of system costs?

The following simulation is proposed to address the above question. A hypothetical agency is considered to manage a system of bridges whose conditions can be described by a $\{1, 2\}$ rating system, where 1 represents a good condition and 2 is unacceptable. The deterioration models of the facilities are Weibull and the hazard rate function is:

$$\lambda(\tau) = p\lambda^p \tau^{p-1} \tag{6.3}$$

where p is the shape parameter, and λ is the scale parameter and can be parameterized *as* $\lambda = e^{\beta X}$, where X is an array of explanatory variables and β is the corresponding coefficient vector.

A system of 200 bridges is generated with $p = 3, \lambda = 3$, with the transition probabilities listed in Table 6.1: the deterioration is considerably fast. Moreover all facilities start in condition state 1 with time-in-state (*tis*) equal to 2, i.e. second year in condition state 1. The user cost for condition state 1 is $0 and for condition state 2 is $450. Two maintenance alternatives are considered: Do-Nothing at $0 (same for both condition states) and reconstruction at $R (same for both condition states). Reconstruction always brings facilities back to be best possible state, i.e. condition state 1 with *tis* equal to 1. A discount rate of 6% is used when calculating system costs; furthermore no budget constraints have been imposed. MR&R decisions are made for a 20-year planning horizon.

The simulation then evaluates the following scenarios:

- Assume that perfect information on the deterioration models is available to agencies. Evaluate system costs by varying the reconstruction cost $R. The set of R that will be experimented is $[100, 150, 200, 250]$. The 20-year system costs averages are referred to as Perfect Information (PI) baselines;

- Agencies adopt a Markovian representation of the deterioration model due to a lack of knowledge. The deterioration model is in the form of a *2X2* matrix $\begin{bmatrix} P_{1,1} & P_{1,2} \\ 0 & 1 \end{bmatrix}$, where $P_{1,1}$ is the probability of continuing to stay in condition state 1 if a facility starts out in state 1 in that planning year. System costs are evaluated with a fixed $P_{1,1}$, i.e. no updating happens. This scenario is presented in section 6.1.1 with the PI baselines; and

- Agencies still adopt a Markovian representation of the deterioration model but realize that there exists epistemic uncertainty. Therefore they utilize the Pontis CEC procedure with the aim of improving model accuracy and achieving system cost savings.

Table 6.1: Transition probabilities from condition state 1 to condition state 2 with respect to different time-in-states

tis	1	2	3	4	5
$P_{1,1}$	0.7716	0.4917	0.2540	0.1044	0.0344
tis	6	7	8	9	10
$P_{1,1}$	0.0091	0.0019	3.2e-4	5.9e-5	0

6.1.1   PI Baselines and System Costs with Fixed $P_{1,1}$

The system costs statistics of the PI baselines are presented in Table 6.2:

Table 6.2: PI baselines with different reconstruction costs $R

R	100	150	200	250
Mean[1]	238.76	301.89	365.77	427.27
Min[1]	225.72	288.71	350.88	412.87
Max[1]	252.01	317.16	376.17	439.85
Standard Error[1]	4.96	5.21	4.35	5.40

[1]Values are in thousand dollars.

Now $P_{1,1}$ is proposed as a Markovian representation for evaluating system costs. The values of $P_{1,1}$ range from 0.3 to 0.95, with increments of 0.05. The system costs for a 20-year planning horizon are plotted in Figure 6.1 (y-axes are of the same scale). All results are verified by 100 repetitions.
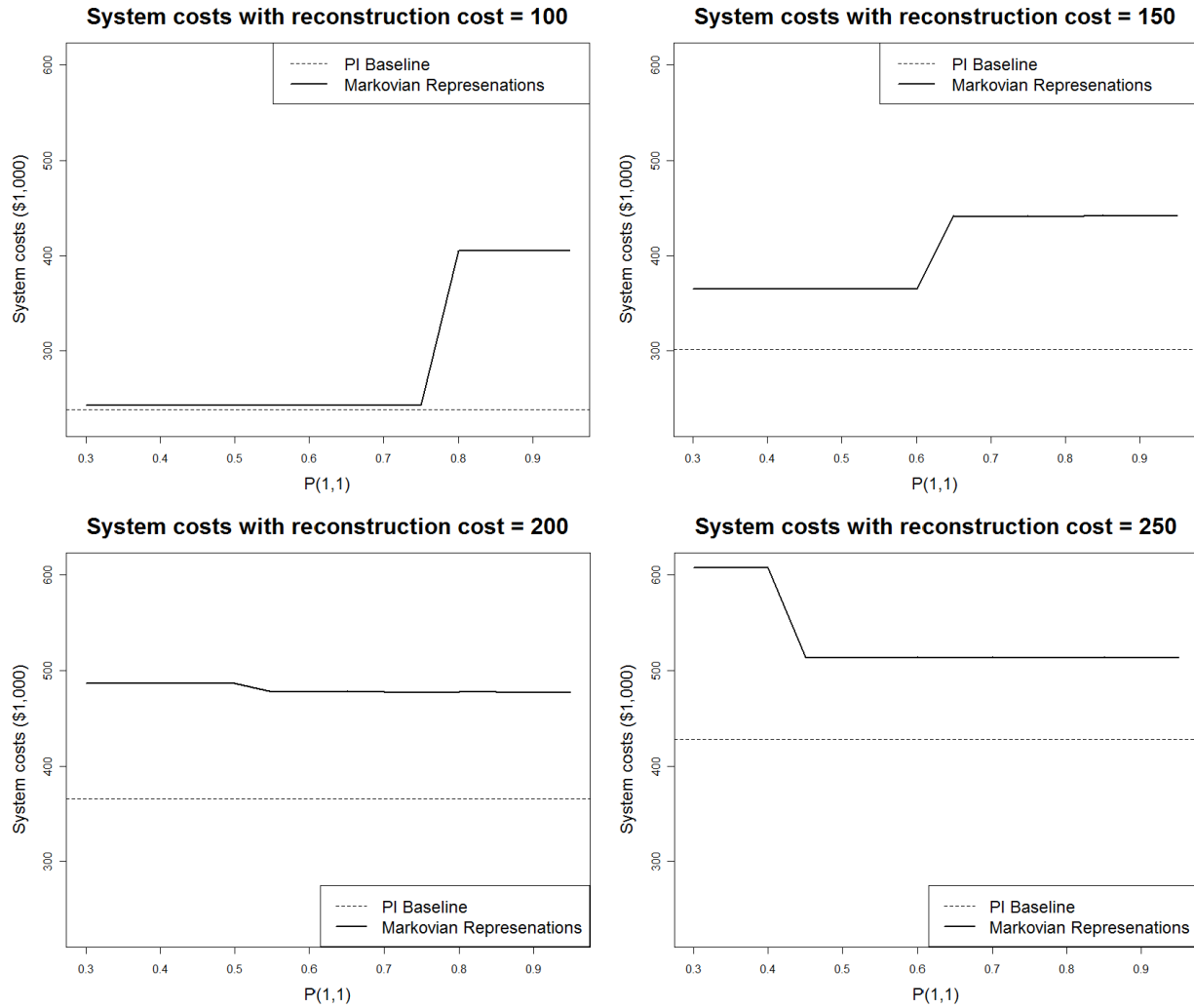
Figure 6.1: System costs under different fixed $P_{1,1}$ for a 20-year planning horizon

It follows that for all Markovian representations of the deterioration model, the system costs surpass the PI baselines. It is interesting that when agency cost (reconstruction cost $R) is much lower than user cost (R = 100 or 150 vs. 450) the faster representations (the left end of the graphs) are less costly compared to the slower ones, while when agency cost is comparable to user cost the slower representations become less costly than the faster ones. The complete statistics for the means of the system costs are presented in Table 6.3.

Table 6.3: System costs (in $1,000) means under Markovian representations of a time-dependent deterioration model

R	PI baseline	$P_{1,1}$						
		0.3	0.35	0.4	0.45	0.5	0.55	0.6
100	238.76	243.16	243.16	243.16	243.16	243.16	243.16	243.16
150	301.89	364.74	364.74	364.74	364.74	364.74	364.74	364.74
200	365.77	486.32	486.32	486.32	486.32	486.32	477.57	477.36
250	427.27	607.91	607.91	607.91	513.71	513.28	513.43	513.81

R	PI baseline	$P_{1,1}$						
		0.65	0.7	0.75	0.8	0.85	0.9	0.95
100	238.76	243.16	243.16	243.16	405.52	405.47	405.22	405.30
150	301.89	441.77	440.60	441.42	441.20	442.13	441.64	441.57
200	365.77	478.14	477.58	476.98	477.11	477.68	476.87	477.53
250	427.27	512.85	514.10	513.39	513.35	513.72	513.23	513.72

The above computational example shows that it can be costly to adopt Markovian representations when the true deterioration models are time-dependent. Therefore, an agency should carefully investigate whether the Markovian assumption holds.

6.1.2 Markovian Representation Learning with the Pontis CEC

In this section, a hypothetical agency is considered to utilize the Pontis CEC to update $P_{1,1}$, the Markovian representation of the system's time-dependent deterioration model. At the end of the planning year t, the agency collects bridge inspection data and observes that throughout the maintenance history the Do-Nothing action has been applied to facilities in condition state 1 in total $N_{DN,1}$ times. Out of those the facilities are observed to have transitioned into condition state 2 in total $N_{DN,1} - N_{DN,1,1}$ times. The new estimate of $P_{1,1}$ at the end of the planning year t therefore is:

$$P_{1,1}^t = N_{DN,1,1} \Big/ N_{DN,1} \tag{6.4}$$

The agency then makes MR&R decisions for the planning cycle of [t, $t+1$] using $P_{1,1}^t$. The system costs are plotted in Figure 6.2, with the complete statistics in Table 6.4.

Table 6.4: System costs (in $1,000) under Markovian representations (updated by the Pontis CEC) of a time-dependent deterioration model compared to fixed Markovian representations

R	PI Baseline	$P_{1,1}$	0.3	0.35	0.4	0.45	0.5	0.55	0.6
100	238.76	Fixed $P_{1,1}$	243.16	243.16	243.16	243.16	243.16	243.16	243.16
		the Pontis CEC[1]	243.16	243.16	243.16	243.16	243.16	243.16	243.16
		$P_{1,1}$	*0.65*	*0.7*	*0.75*	*0.8*	*0.85*	*0.9*	*0.95*
		Fixed $P_{1,1}$	243.16	243.16	243.16	405.52	405.47	405.22	405.30
		the Pontis CEC[1]	243.16	243.16	243.16	405.51	405.32	404.72	405.78

R	PI Baseline	$P_{1,1}$	0.3	0.35	0.4	0.45	0.5	0.55	0.6
150	301.89	Fixed $P_{1,1}$	364.74	364.74	364.74	364.74	364.74	364.74	364.74
		the Pontis CEC[1]	364.74	364.74	364.74	364.74	364.74	364.74	364.74
		$P_{1,1}$	*0.65*	*0.7*	*0.75*	*0.8*	*0.85*	*0.9*	*0.95*
		Fixed $P_{1,1}$	441.77	440.60	441.42	441.20	442.13	441.64	441.57
		the Pontis CEC[1]	441.22	441.21	441.24	441.22	441.64	441.22	441.80

R	PI Baseline	$P_{1,1}$	0.3	0.35	0.4	0.45	0.5	0.55	0.6
200	365.77	Fixed $P_{1,1}$	486.32	486.32	486.32	486.32	486.32	477.57	477.36
		the Pontis CEC[1]	486.32	486.32	486.32	486.32	486.32	477.46	477.00
		$P_{1,1}$	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**	**0.95**
		Fixed $P_{1,1}$	478.14	477.58	476.98	477.11	477.68	476.87	477.53
		the Pontis CEC[1]	477.32	477.38	477.77	477.87	477.37	476.84	476.68

R	PI Baseline	$P_{1,1}$	0.3	0.35	0.4	0.45	0.5	0.55	0.6
250	427.27	Fixed $P_{1,1}$	607.91	607.91	607.91	513.71	513.28	513.43	513.81
		the Pontis CEC[1]	607.91	607.91	607.91	513.45	513.85	513.40	513.53
		$P_{1,1}$	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**	**0.95**
		Fixed $P_{1,1}$	512.85	514.10	513.39	513.35	513.72	513.23	513.72
		the Pontis CEC[1]	513.51	512.31	513.28	513.86	513.92	513.06	513.03

[1]. The Pontis CEC refers to the scenarios where the Markovian representations are updated by the Pontis CEC.
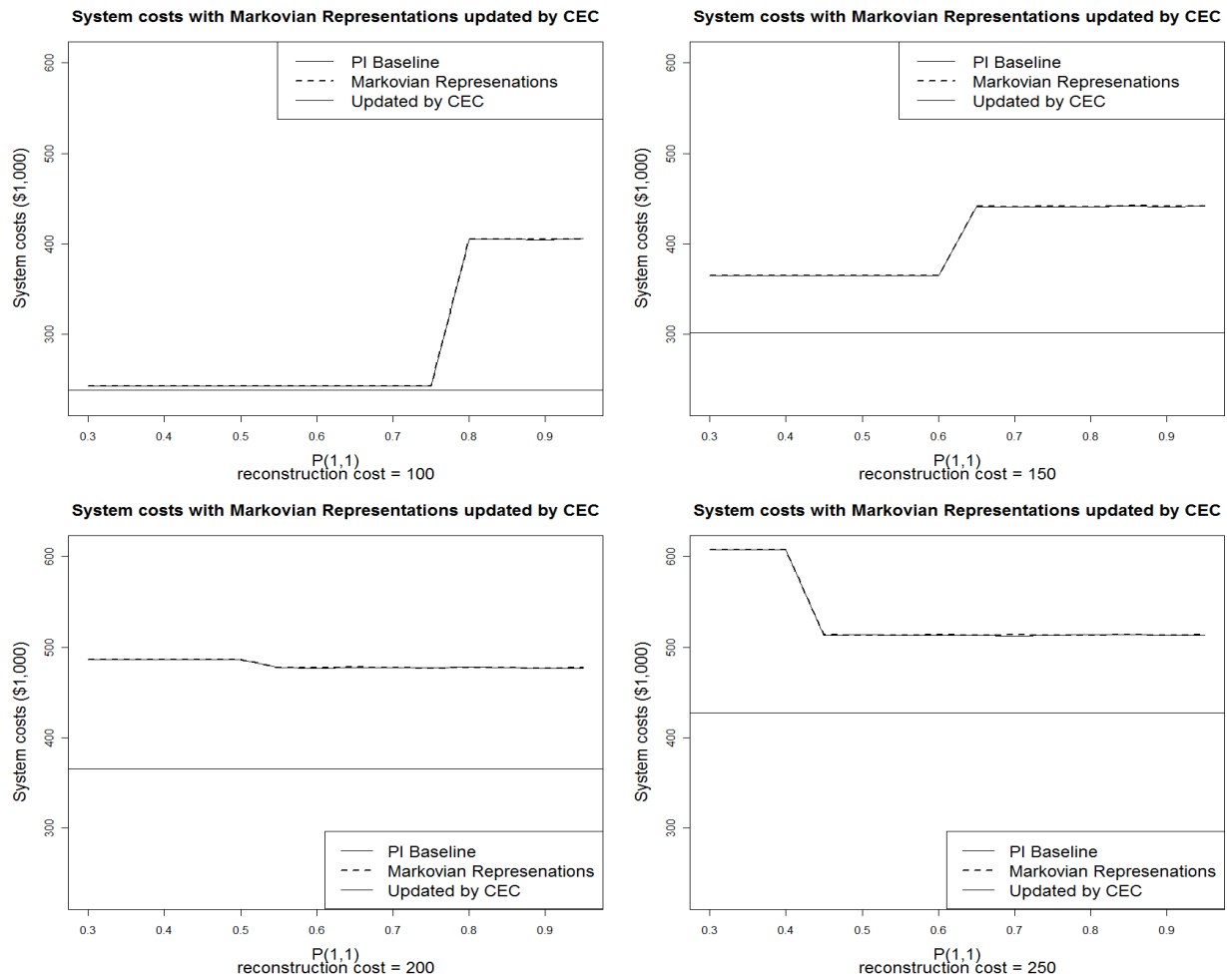
Figure 6.2: System costs with the Pontis CEC updating $P_{1,1}$ for a 20-year planning horizon with different reconstruction costs

It follows that the system costs when $P_{1,1}$ is being updated by the Pontis CEC do not significantly differ from the system costs where the $P_{1,1}$s are simply fixed.

For model convergence, $P_{1,1} = [0.3, 0.35, 0.4]$ was never updated by the Pontis CEC. The evolution of other $P_{1,1}$s is plotted in Figure 6.3.
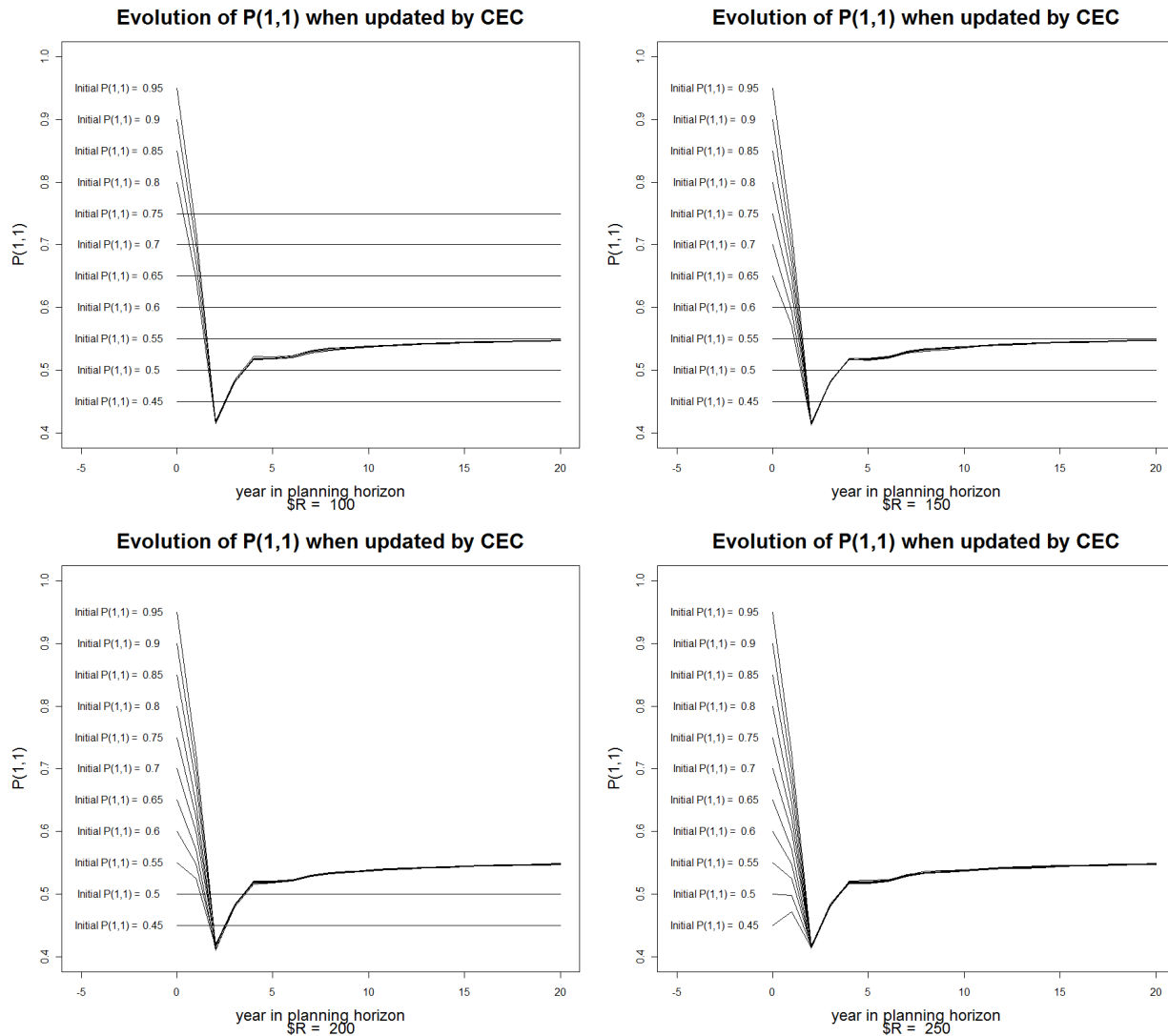
Figure 6.3: Evolution of $P_{1,1}$s with different starting points when the Pontis CEC is applied

When agency cost is relatively low (R = 100 or 150), some $P_{1,1}$s never got updated; for all $P_{1,1}$s that did get updated, they converged to almost the same value (~0.547) at the end of the 20-year planning horizon. Moreover, in year 2 all updated $P_{1,1}$s roughly equaled to 0.415. Recall that the system started all bridges in the same condition state; therefore the first year maintenance action will be identical within the system. That $P_{1,1}$ got updated in the first year implies all facilities received Do-Nothing that year. So the first year deterioration data exhibited a transition probability of 0.4917, per Table 6.1, with 200 bridges. As a result on average 49.17% of, or 98, bridges, went into condition state 1 with *tis* equal to 3; for the 51% that transitioned into

condition state 2, reconstruction was assigned and no deterioration data was generated. In the second year the 98 bridges exhibited a transition probability of 0.2540. According to expression 6.4, the updated $P_{1,1}$ would be $(0.4917 * 200 + 0.2540 * 98)/(200 + 98) \cong 0.4135$.

As updating progressed, more *tis'*=1 were generated (bridges were getting reconstructed and went back into condition state 1 with *tis* equal to 1). Updated $P_{1,1}$s were consequently drawn closer to 0.7716, per Table 6.1, and finally converged to 0.547. Note all numbers presented herein are specific to the above computational example. The readers can alter the parameters' values for other considerations. The complete statistics of $P_{1,1}$s after 20 years of updating are provided in Table 6.5.

Table 6.5: Values of $P_{1,1}$ after 20 years of updating by the Pontis CEC with different starting $P_{1,1}$, pooled for all \$R

Starting $P_{1,1}$	0.3	0.35	0.4	0.45	0.5	0.55	0.6
Mean	0.3	0.35	0.4	0.5477	0.5469	0.5474	0.5478
Stand Error	0	0	0	0.0013	0.0014	0.0006	0.0011

Starting $P_{1,1}$	0.65	0.7	0.75	0.8	0.85	0.9	0.95
Mean	0.5477	0.5481	0.5474	0.5473	0.5471	0.5480	0.5476
Stand Error	0.0003	0.0009	0.0012	0.0010	0.0008	0.0010	0.0009

6.2 OLFC with Markovian Models

When deterioration is Markovian, transition essentially is a Bernoulli process. Continuous influx of data will guarantee convergence to the true model under OLFC according to the law of large numbers. In previous sections, the Markovian representations of the time-dependent deterioration model of a bridge system were updated by the Pontis CEC and the results of a simulation indicated that learning with the Pontis CEC did not cause significant changes in system costs. In section 6.2.1, the simulation will be repeated with OLFC. Section 6.2.2 provides a discussion of the application of OLFC to infrastructure systems that have Markovian deterioration models. Section 6.2.3 discusses how to apply OLFC when candidate models belong to different classes.

6.2.1 Markovian Representation Learning with OLFC

For OLFC, a set of candidate $P_{1,1}$ s are proposed with an initial prior mass function $[w_1, w_2, \dots, w_M]$, where M is the number of candidate $P_{1,1}$s. At the end of the planning year t, the agency collects bridge inspection data and observes that in year t the Do-Nothing action has been applied to facilities in condition state 1 in total $N_{DN,1}$ times. Out of those the facilities are observed to have transitioned into condition state 2 in total $N_{DN,1} - N_{DN,1,1}$ times. The posterior mass function at the end of the planning year t therefore is:

$$w_m^t = \left. w_m^{t-1} \cdot Likelihood(Data^t | P_m^{t-1}) \middle/ \sum_1^M w_m^{t-1} \cdot Likelihood(Data^t | P_m^{t-1}) \right. \tag{6.5}$$

where P_m^{t-1} is the $P_{1,1}$ of the mth candidate at the end of planning year t-1 and:

$$Likelihood(Data^t | P_m^{t-1}) = P_m^{t-1 \ N_{DN,1} - N_{DN,1,1}} \cdot (1 - P_m^{t-1})^{\ N_{DN,1}} \tag{6.6}$$

The agency then makes MR&R decisions for the planning cycle of $[t, t+1]$ using:

$$P_{1,1}^t = \sum_1^M w_m^t \cdot P_m^t \tag{6.7}$$

The candidate $P_{1,1}$s range from 0.3 to 0.95 with increments of 0.05. To generate different starting points for OLFC, one candidate $P_{1,1}$ is initially weighted 80% (referred to as *the confidence center*), while the rest of the candidate $P_{1,1}$s evenly split a total weight of 20%. The system costs are plotted in Figure 6.4, with the complete statistics in Table 6.6.
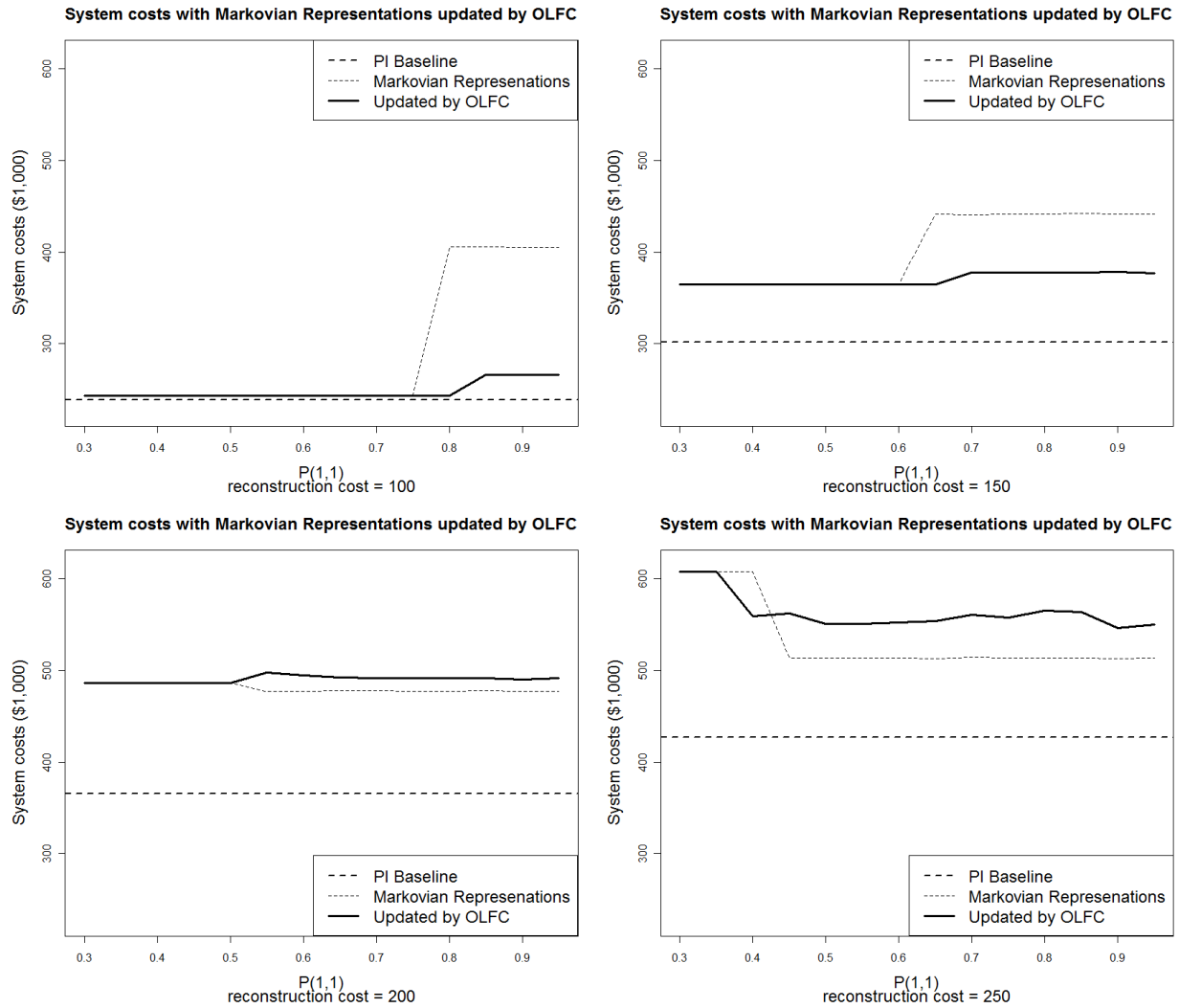
Figure 6.4: System costs (in $1,000) of Markovian representations (updated by OLFC) of a time-dependent deterioration model

When agency cost is relatively low (R = 100 or 150) and updating initiates with slow Markovian representations, OLFC achieves significant cost-savings compared to fixed $P_{1,1}$s and the Pontis CEC. The biggest system cost reduction was achieved when R = 100 with the confidence center equal to 0.95, and the value is equal to $139,010 (equal to $405,300 minus $266,290, or 34.30% of $405,300). When the confidence center was 0.35~0.6, OLFC and the Pontis CEC yielded system costs that do not significantly differ from each other.

On the other hand, when agency cost is relatively high (R = 200 or 250) and updating initiates with slow Markovian representations, OLFC becomes costly compared to fixed $P_{1,1}$s and the Pontis CEC. When R = 200 and the confidence center was chosen from 0.55~0.95, the increases in system costs range from $15,000 to $20,000; when R = 250 the increases scale up to about $40,000.

Table 6.6: System costs (in $1,000) under Markovian representations (updated by OLFC and the Pontis CEC) of a time-dependent deterioration model

R	PI Baseline	$P_{1,1}$	0.3	0.35	0.4	0.45	0.5	0.55	0.6
100	238.76	the Pontis CEC[1]	243.16	243.16	243.16	243.16	243.16	243.16	243.16
		OLFC[2]	243.16	243.16	243.16	243.16	243.16	243.16	243.16
		$P_{1,1}$	0.65	0.7	0.75	0.8	0.85	0.9	0.95
		the Pontis CEC[1]	243.16	243.16	243.16	405.51	405.32	404.72	405.78
		OLFC[2]	243.16	243.16	243.16	243.16	266.33	265.82	266.29

R	PI Baseline	$P_{1,1}$	0.3	0.35	0.4	0.45	0.5	0.55	0.6
150	301.89	the Pontis CEC[1]	364.74	364.74	364.74	364.74	364.74	364.74	364.74
		OLFC[2]	364.74	364.74	364.74	364.74	364.74	364.74	364.74
		$P_{1,1}$	0.65	0.7	0.75	0.8	0.85	0.9	0.95
		the Pontis CEC[1]	441.77	440.60	441.42	441.20	442.13	441.64	441.57
		OLFC[2]	364.74	377.74	377.55	377.83	377.44	378.16	376.96

R	PI Baseline	$P_{1,1}$	0.3	0.35	0.4	0.45	0.5	0.55	0.6
200	365.77	the Pontis CEC[1]	486.32	486.32	486.32	486.32	486.32	477.46	477.00
		OLFC[2]	486.32	486.32	486.32	486.32	486.32	497.50	494.36
		$P_{1,1}$	0.65	0.7	0.75	0.8	0.85	0.9	0.95
		the Pontis CEC[1]	492.32	491.78	491.67	491.31	491.63	490.33	491.38
		OLFC[2]	477.32	477.38	477.77	477.87	477.37	476.84	476.68

R	PI Baseline	$P_{1,1}$	0.3	0.35	0.4	0.45	0.5	0.55	0.6
250	427.27	the Pontis CEC[1]	607.91	607.91	607.91	513.45	513.85	513.40	513.53
		OLFC[2]	607.91	607.91	559.53	562.63	551.18	551.08	552.30
		$P_{1,1}$	0.65	0.7	0.75	0.8	0.85	0.9	0.95
		the Pontis CEC[1]	513.51	512.31	513.28	513.86	513.92	513.06	513.03
		OLFC[2]	554.06	560.97	557.36	565.15	563.72	546.08	550.49

*1. The Pontis CEC refers to the scenarios where the Markovian representations are updated by the Pontis CEC;
 2. OLFC refers to the scenarios where the Markovian representations are updated by OLFC.

For model convergence, when R = 100, OLFC only updated the scenarios where the confidence center was chosen from 0.85~0.95 and updating only happened in the first year. This is because agency cost is relatively low; therefore reconstruction is actively applied to avoid penalty in terms of user costs. When R increases to 150, reconstruction is applied less frequently; as a result more Do-Nothing actions are applied and deterioration data are generated, which enables OLFC to update the scenarios where the confidence center was chosen from 0.70~0.95. However, updating still only happens in the first year. This trend can be generalized to scenarios where R = 200 and 250. The convergence results are shown in Table 6.7.

Table 6.7: Model convergence results when Markovian representations are updated by OLFC

R	Confidence Center[1]	0.85		0.90		0.95	
100	$T_U{}^2$	1		1		1	
	Ending Value	0.4916		0.4967		0.4921	

R	Confidence Center[1]	0.70	0.75	0.80	0.85	0.90	0.95
150	$T_U{}^2$	1	1	1	1	1	1
	Ending Value	0.4936	0.4958	0.4926	0.4971	0.4887	0.5023

R	Confidence Center[1]	0.55	0.60	0.65	0.70	0.75
200	$T_U{}^2$	2	2	2	2	2
	Ending Value	0.4417	0.4591	0.4715	0.4739	0.4745

R	Confidence Center[1]	0.80	0.85	0.90	0.95
200	$T_U{}^2$	2	2	2	2
	Ending Value	0.4772	0.4756	0.4845	0.4787

R	Confidence Center[1]	0.40	0.45	0.55	0.55	0.60	0.65
250	$T_U{}^2$	7	7	7	7	7	7
	Ending Value	0.4642	0.4575	0.4726	0.4729	0.4712	0.4679

R	Confidence Center[1]	0.70	0.75	0.80	0.85	0.90	0.95
250	$T_U{}^2$	7	7	7	7	7	7
	Ending Value	0.4589	0.4645	0.4546	0.4572	0.4811	0.4750

[*] 1. The table only lists confidence centers that have been updated by OLFC;

2. T_U refers to the length of updating in years, e.g. 2 means that updating happens in year 1 and 2.

6.2.2 OLFC in Markovian Systems

When an agency is faced with a brand new infrastructure system and is confident that the deterioration process is Markovian, it can apply OLFC by starting with a set of transition probabilities that is a proper discretization of [0, 1], the natural boundaries for transition probabilities. For example, an agency can assume the following deterioration models are equally likely for a condition state:

Table 6.8: Possible starting models for the application of OLFC in a Markovian system

	Model 1	Model 2	Model 3	Model 4	Model 5
Do Not Transition	0.1	0.3	0.5	0.7	0.9
Transition	0.9	0.7	0.5	0.3	0.1
Model Weights	0.2	0.2	0.2	0.2	0.2

Once updating starts, OLFC will quickly distinguish the model(s) that is the closest to the true model. An agency can set its own rule of convergence. (For example, if the total weight of a selection of models is less than 1%, the agency concludes that the model(s) has been ruled out and convergence has been achieved upon the rest of the models.) Suppose after a period of updating convergence has been achieved with the weights $\begin{bmatrix} 0.05, \ 0.15, \ 0.6, \ 0.15, \ 0.05 \end{bmatrix}$.

The next step is to sample with finer intervals around the models from the previous step to create a new set of candidate models. In the above example, updating has ruled out Model 1 and Model 5; an agency can safely sample around Model 2 to 4 and create the following candidate model set:

Table 6.9: Resampled candidate models after first round of convergence

	Model A (Model 2)	*Model B*	*Model C (Model 3)*	*Model D*	*Model E (Model 4)*
Do Not Transition	0.3	0.4	0.5	0.6	0.7
Transition	0.7	0.6	0.5	0.4	0.3
Model Weights	0.083	0.25	0.334	0.25	0.083

Note that the agency can preserve the learning outcome of the previous step, which is the relative magnitudes of Model 2 through 4 ($0.083/0.334 = 0.15/0.6$). The reason that the sampling was conducted in between Model 2 to 4 is due to the directional property of OLFC: the ending distribution also implies the relative location of the true model among the candidate models. The heavier a model's ending weight is, the closer it is to the true model. The sum of the weights of the new models, however, is completely arbitrary. The alternation between the above two steps will eventually lead the agency to the true model.

6.2.3   Application of OLFC when candidate models belong to different classes

When agencies cannot decide on the class of the deterioration models (e.g. hazard-based models, Markovian models, or Poisson models), OLFC allows them to include all different classes in the candidate set. The only requirement is to have all transition matrices generated by different candidate models have the same dimensions so that they can be weighted and summed.

CHAPTER 7

CONCLUSIONS AND

FUTURE RESEARCH

7.1 Contributions and Main Findings

The present dissertation has investigated the performance of two adaptive control (AC) methods in the context of system-level bridge management. The research has made the following contributions to the field of bridge management:

- Development of a computationally feasible optimization routine for system-level bridge management. The routine ensures strict conformity to system budget constraints and does not compromise computational efficiency even when the system is of large scale;

- Implementation of hazard-based deterioration models in system-level bridge management. This relaxes the Markovian assumption imposed on infrastructure deterioration by much of the existing literature and allows for a more realistic representation. In addition the present dissertation has demonstrated that it is costly to adopt Markovian representations when deterioration is truly non-Markovian;

- Demonstration, through a numerical study, that the AC method deployed in the Pontis system, Certainty Equivalent Control (CEC), does not guarantee improvement in deterioration model accuracy or savings in system costs; and

- Demonstration, through a numerical study, that Open-Loop Feedback Control (OLFC) guarantees improvement in deterioration model accuracy and savings in system costs.

The main findings of the numerical studies are as follows:

System Cost Savings

In all scenarios the Pontis CEC caused significant increases in system costs compared to no updating (the OL baseline), regardless of the imperfect models that updating initiates with. The numerical study has shown that the increases are on the order of $3 million for a system of 200 bridges, and can potentially be scaled up to $180 million at the level of the State of California which is responsible for the maintenance of over 12,000 bridges.

On the other hand, OLFC achieved significant cost savings compared to the OL baseline when updating initiates with imperfect models that represent slower or faster deterioration than the true models. In fact OLFC yielded system costs that do not statistically differ from the PL baseline. When the imperfect models approximate the true models' deterioration, the PI baseline, the system costs with OLFC and the OL baseline do not statistically differ from each other.

Model Accuracy Improvement

The Pontis CEC consistently resulted in models that have faster deterioration than the true models, regardless of the imperfect models that updating starts with. In other words, the Pontis CEC never achieved convergence to the true models. This is not due to the randomness in deterioration, but because:

- The Pontis CEC is only optimal for linear deterioration models and quadratic cost functions (Bertsekas 2005), but infrastructure systems do not satisfy such requirements. The Stochastic Duration Model (SDM) adopted in the present dissertation is an example of nonlinear deterioration models; and

- In the process of optimal resource allocation, bridge deck condition does not stay in a state (especially the poor states) for too long so as to avoid high system costs. As a result, the deterioration probability density curve will be right truncated and the condition data will be biased towards short *tis*', as if the facilities always deteriorated at short *tis*'. Maximum likelihood estimation infers the entire deterioration probability density function with the partial information and consequently yields model parameters that represent fast deterioration.

OLFC, on the other hand, does not suffer from the abovementioned problems. It evaluates the likelihoods of each candidate model; the model weights are updated with respect to the relative magnitudes of the likelihoods. With sufficient data, OLFC is capable of distinguishing models that are very similar. In all scenarios, OLFC successfully identified the candidate models that best approximate the true models.

Extension to Markovian Systems

When deterioration is truly a Markovian process, both OLFC and the Pontis CEC will achieve consistent convergence to the true models and bring about system costs savings. The present

dissertation has also compared the performance of OLFC and the Pontis CEC when deterioration is non-Markovian but agencies adopt a Markovian representation. The main findings are summarized as follows:

- It is costly for an agency to use a Markovian representation for MR&R decision-making when deterioration is not memory-less. The computational example has shown that the increases in system costs could be up to 100%. Moreover, when agency cost is considerably lower than user cost, MR&R decision-making with the slower representations (e.g. transition probability ~0.1) causes significant increases in system costs. When agency cost is comparable to user cost, MR&R decision-making with the faster representations (e.g. transition probability ~0.7) is more costly;

- When an agency uses the Pontis CEC to update the Markovian representations of a non-Markovian system, the system costs do not differ statistically from the system costs when fixed Markovian representations are used for MR&R decision-making; and

- When an agency uses OLFC to update the Markovian representations of a non-Markovian system, the system costs differ statistically from the system costs when fixed Markovian representations are used for MR&R decision-making. When agency cost is considerably lower than user cost and updating starts with slower representations, OLFC achieves significant cost savings (up to −34%) compared to MR&R decision-making with fixed Markovian representations. When agency cost is comparable to user cost and updating starts with slower representations, OLFC causes increases in system costs (up to +10%).

Moreover, OLFC can accommodate candidate models from different model classes by properly forming the augmented state space. The Pontis CEC, on the other hand, cannot conduct learning with more than one model class.

7.2 Future Work

7.2.1 Relaxation of the Assumption of Knowledge of Other MR&R Actions

In the numerical study in chapter 5, the impacts of maintenance, rehabilitation and reconstruction actions have been assumed known to agencies. However, this might not be true in reality. Due to the variability in contractor competency, project quality management and other factors, the MR&R actions' impacts on facilities might vary and therefore become part of the learning process. (For example, reconstruction does not necessarily bring facilities back to the best possible condition as assumed.)

One important extension of the present dissertation is to incorporate learning of the impacts of MR&R actions when new condition data become available. This can be accomplished by constructing for each MR&R action a set of candidate models whose weights are successively updated by OLFC. System cost and model convergence should be investigated;

furthermore, candidate models of different classes should be included to study which model class is most suitable for quantifying the impacts of the MR&R actions.

7.2.2 Accommodation of Different Model Classes

In the present dissertation, the candidate model set for OLFC has only included one model class: either SDM or Markovian. However, agencies do not necessarily have knowledge of the deterioration model class.

Future research can include different model classes in OLFC's candidate model set by ensuring that the deterioration matrices generated by each candidate model have the same dimensions. The consistency in dimensions is required because the candidate matrices will be weighted and summed to form the matrix for decision-making. It would be interesting to investigate how OLFC will perform in such case in terms of system costs and model accuracy improvement.

7.2.3 Accommodation of Network Constraints

In the present dissertation, only monetary constraints have been included. Future research can extend to include other constraints when investigating the performance of AC methods, such as:

- Network constraints. Some bridges are in the same network; concurrent maintenance work on multiple bridges might to a great extent diminish the network's mobility and cause high user costs. On the other hand, concurrent maintenance work might bring about economies of scale on equipment (such as concrete mixing truck) and hence savings in agency costs. Such constraints can be reflected in the constraints or in the objective function; and

- Requirements for network condition improvement. Such improvement requirements can be incorporated by setting up maintenance priorities and/or the target proportions of bridges in good condition by the desired timeline.

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