Data-Driven Optimization of Railway Track Inspection and Maintenance Using Markov Decision Process

By
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January 8, 2016

A thesis submitted to the
Faculty of the Graduate School of
The State University of New York at Buffalo
in partial fulfillment of the requirements for the degree of
Master of Science

Department of Industrial and Systems Engineering

ABSTRACT

The goal of this thesis is to develop a data-driven condition-based maintenance policy for the track inspection. This thesis will help in maintaining high service level of the railway tracks which is a difficult task to accomplish. We use a two-year track geometry inspection dataset which contains a variety of geometry measurements for every foot. We separate the data based on the time interval of inspection run, calculate the aggregate TQI for each section, develop a Markov Chain for modeling track deterioration, build a Markov Decision Process (MDP) for track maintenance decision making and optimize it using value iteration algorithm. By comparing with existing maintenance policy with Markov Chain Monte Carlo (MCMC) simulation, the new maintenance policy developed in this thesis results in saving around 10% maintenance costs.

Keywords: Railway Track Inspection and Maintenance; Track Geometry Defects; Condition-based Maintenance; Markov Decision Process

ACKNOWLEDGEMENT

I would like to express my sincere appreciation and gratitude to Dr. Qing He for his guidance during my term of candidature. Without his understanding, wisdom, patience, enthusiasm and encouragement this study would not have been possible. I am thankful to him for pushing me farther than I thought I could go.

I would like to express my sincere gratitude to Department of Industrial and Systems Engineering at University at Buffalo, The State University of New York for letting me fulfill my dream of pursuing my graduate coursework here.

I would like to thank my parents for all their blessings. I would like to thank my family – my brother, Abhimanyu and my sister-in-law, Debanjali and all my friends for all the motivations and stress busters. They all kept me going and without their support it wouldn't have been possible.

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Chapter 1: Introduction

1.1 Background

Mechanical systems are bound to faults and failures with time and usage. Railway tracks are no different in this issue. In the United States, railways are one of the major modes in freight transportation. It is also used, in a fair amount, by people to commute between two places. This increases the pressure on railways to be at its best service level anytime. In 2009, out of 1890 train accidents, 658 were due to track defects (Peng 2011). Major failures of railway tracks can cause a heavy loss to company, lawsuits, delay in getting back operations and in extreme case fatalities. This increases the pressure to maintain better service level.

Railway track defects can be classified into two different types of defect namely track geometry defect and track structural defect. Track geometry defects arise due to irregularities in the various track geometry measurements. The track structural defect occurs when the structure and support system of the railway tracks constituting of sleepers, joints, fasteners, ballast and other underlying structure fails. The main aim of the research is to develop a track preventive maintenance strategy, which also take corrective maintenance into account, to maintain the best service level of railway track with minimal costs. For this purpose, we use the track geometry inspection data.

For our research we have used the following five track geometry measurements:

- Gage: It is the measurement of the distance between the heads of the inner surface of rails.
- Cant: The amount of vertical deviation between two flat rails from their designed value (He, et al. 2015).

- Twist: It is defined as the percentage change in cant per unit length.
- Cross-level: It is defined as the difference in height of the two rails.
- Warp: It is the difference in cross-level measurement between any two points less than 62-ft apart.

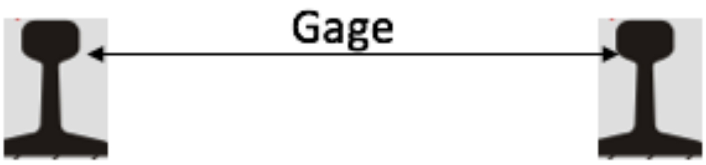

Figure 1. Track Gage Measurement

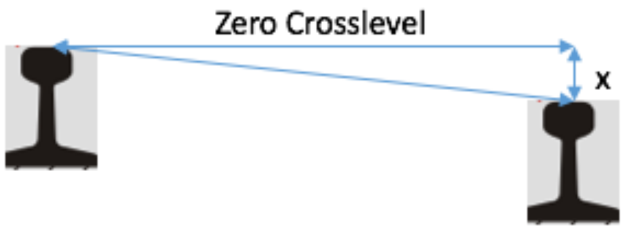

Figure 2. Track Cross-level Measurement

Preventive maintenance helps in preventing any major failures from happening. The primary objective of preventive maintenance is to preserve system functions in a cost-effective manner (Tsang 1995). Preventive maintenance can be further classified as condition-based preventive maintenance or interval-based (time interval or tonnage interval) preventive maintenance (Yang 2003). In interval-based preventive maintenance, maintenance activities take place after a certain period of time and system is restored to its initial state. In condition-based preventive maintenance, maintenance actions are taken depending on the current state of the system after each inspection. Our focus in this research is related to condition-based preventive maintenance at discrete time intervals. After the inspection, there can be no action taken on the system or a minimal maintenance repair is done to restore the system back into previous working state or a major maintenance work is done to restore the system to as good as new condition (Chen and Trivedi 2005).

Track Quality Index (TQI) is a numeric representation of the ability of railroad track to perform its design function, or, more precisely support the train movements required of it (Fazio and Corbin 1986). In short, it tells us if the track is in a good state or a bad state. If the track is in a bad state, we perform appropriate maintenance activities to improve its condition and take it to the good state. Depending on the TQI value, we plan our actions. This makes it easier to develop a state using a range of TQI value. Assuming the future state of the track only depends upon the current state, we can say the system behaves as a Markovian system. Also, there are more than one action that can be taken from a state, the problem can be easily formulated as a Markov Decision Process. This thesis aims to help the railway industry to keep high service levels all the time. This will help in reducing the cost expenditures by railroads as well as preventing failures which may lead to derailments and accidents. Techniques developed in this thesis can also be used by other industries to maintain their system too.

In addition, over the period of time, the condition of railway track can degrade from a good state to unusable state either gradually or abruptly. This can occur due to cumulative tonnage, defective wheels, the impulsive force on tracks, etc. This type of defects is termed as geo-defects in this paper (He, et al. 2015). When geo-defects are detected, corrective maintenance action takes place. Corrective maintenance is an approach in which a failed system is repaired and restored back to operating condition.

1.2 Challenges

One of the major challenges for track maintenance is to (1) accurately predict the track geometry deterioration (e.g. TQI) for preventive maintenance, (2) accurately predict the occurrence probability of geo-defects for corrective maintenance, (3) provide optimal maintenance policy, which implies the correct actions for the certain level of track state. In track inspection, the condition of the track can change a lot over a period of time due to high traffic volume, high tonnage, inclement weather and errors in inspections run. This makes the preventive maintenance more challenging task. The other challenge of this thesis is to keep the maintenance cost as low as possible.

1.3 Contributions

The contribution of this thesis lie in the following aspects:

(1) Model and predict track geometry deterioration (e.g. TQI) with a Markov Chain for preventive maintenance.

(2) Model and predict occurrence probability of geo-defect with logistics regressions based on historical inspection data for corrective maintenance.

(3) As a first attempt, this thesis uses Markov Decision Process to derive optimal inspection maintenance policy for railway tracks.

(4) In MDP model, we consider the random arrivals of geo-defects and its repairing cost. Geo-defects repairing is a corrective maintenance action whereas the maintenance actions taken for the degrading state is a preventive

maintenance action. Both have been addressed in this thesis, which add to the realism in the problem.

1.4 Thesis Objectives

The objective of this thesis is to model railway track deterioration, predict geo-defect arrivals and derive optimal data-driven maintenance policy. The results of this thesis will help in taking a better decision as to what actions should be followed when in a particular state for a particular discrete time event.

Following are the steps undertaken:

(1) Analyze the data to get the Track Quality Index (TQI).

(2) Organize the data into three different data frames based upon the time interval of inspection runs.

(3) Aggregate the value of TQI of each foot of data to get the TQI of a 0.1-mile segment.

(4) Allocation of states of Markov chain corresponding to the TQI value and calculate the action followed based upon the information of the next state. This constructs a Markov Decision Process.

(5) Given the transition probabilities, we use Markov Chain Monte Carlo simulation to make 40000 step transition of Markov Chain. This gives us an estimate for the number of actions taken in a particular state and thus, we derive the existing maintenance policy.

(6) Given existing maintenance policy, simulate this Markov Chain model using Markov Chain Monte Carlo simulation to get the estimated cost of existing policy for maintaining 1 mile of railway for a period of 10 years.

(7) Optimize the Markov Decision Process using value iteration algorithm.

(8) Run a Markov Chain Monte Carlo simulation to estimate the cost of the optimized policy.

(9) Sensitivity analysis to check for the uncertainties in the simulation.

1.5 Thesis Organization

The thesis has been developed to form a condition-based maintenance policy using MDP for maintaining railway tracks. Chapter 2 of this thesis deals with literature review. Chapter 3 deals with data description and its analysis. Chapter 4 deals with a methodology to develop the Markov Decision Process. Chapter 5 deals with a methodology to develop the existing policy using the data, derive and analyze the policy using MCMC. Chapter 6 deals with the development of optimal using value iteration algorithm. Chapter 7 deals with a conclusion and future research.

Chapter 2: Literature Review

This section conducts a review of the previous work done in this field. This chapter is divided into three parts. The first part deals with the Track Quality Index (TQI). The second part is related to Track Preventive Maintenance. The third part is related to Markov Decision Process (MDP).

2.1 Track Quality Index

The Track Quality Index (TQI) has been one of the most researched indices to represent track state. Traditionally, TQI is derived from track geometry measurements, which reflect how well the track structure is performing. Therefore, TQI indicates the current status of track geometry deterioration. An overall track maintenance planning model can be developed easily if the geometry TQI data is supplemented with other data that pertains to the structural data (Fazio and Corbin 1986). TQI also helps in maintaining a track deteriorating record (El-Sibaie and Zhang 2004).

The track geometry is measured for each foot by the track geometry car, an automated track inspection vehicle on a rail transport system used to test several geometric parameters without obstructing normal railroad operations. These measurements are later aggregated at a segment level to calculate the TQI. (Schlake, Barkan and Edwards 2011).

The method of calculating TQI also varies with the location of the railway system. A milepost of railway track is divided into smaller section and various geometry parameters are measured. These geometry statistics are then summed up to get the TQI value of the section (Berawi, et al. 2010). In China, the TQI is calculated as the sum of the standard deviation of seven track geometry measurements (Bai, et al. 2015). In the United States, the TQI is calculated as the ratio of traced space curve length to the track segment length (El-Sibaie and Zhang 2004). As the TQI is calculated as an aggregated model, it is a possibility that the TQI misses out on individual severe measurements such as geo-defects (He, et al. 2015).

TQI quantifies the degradation of railway tracks. When the tracks are completely degraded, a corrective maintenance activity is applied. When the tracks are in the degrading state, a preventive maintenance activity can be applied.

In our research too, we calculate the TQI as an aggregate model. Later we incorporate the stochastic arrivals of geo-defects, as an individual external factor, to assess the condition of track in a better manner.

2.2 Track Preventive Maintenance

When the railway tracks fail, the cost incurred by a company might be divided into lawsuits, downtime cost, loss of material cost etc. Multivariate statistical models have been developed improving the ability to predict the probability of broken rails and other kinds of failure (Dick, et al. 2003). When the cost incurred by a device failure is larger than the cost of preventive maintenance, it is worthwhile carrying out preventive maintenance (Chen and Trivedi 2005). Studies have been conducted to find the relationships between renewal and maintenance activities (Grimes and Barkan 2006)

Track preventive maintenance refers to the procedure where the tracks undergo a maintenance schedule in order to prevent the tracks from failing during use. Track preventive maintenance can be a time-based preventive maintenance where the tracks are monitored and maintenance activity takes place time to time. Track preventive maintenance can also be a condition-based preventive maintenance where the maintenance activities depend upon the current condition of the track. Condition-based planning and management are a significantly more efficient method of managing the rail asset than the traditional rules-based approach, because it takes into account the local differences in behavior and performance, as they affect the degradation of the rails (Zarembski 2010).

Track preventive maintenance involves a lot of complex costs such as inspection cost, different kinds of maintenance cost, track downtime costs, labor costs, material costs etc. A lot of research has been done in the field of scheduling preventive maintenance effectively to improve the cost incurred to a company. Preventive maintenance cost a lot when done too early or too late. (Peng, Kang, et al. 2011) used models to significantly reduce in travel and penalty costs. Time-space network models have been created to address the rising issue of maintenance cost (Peng and Ouyang 2012). Optimization models were built to minimize both maintenance and renewal costs as well as delays related to operational services (Andrade 2014). Mathematical programs have been suggested to schedule routine maintenance activities and unique maintenance activities (Budai, Huisman and Dekker 2006). Decision Rules Model are used to provide planning/scheduling solutions by following a set of rules used in maintenance schedule (Santos, Teixeira and Antunes 2015).

Implementation of condition-based preventive maintenance reduces the need for maintenance during the eleventh hour. Methods have been developed to create a system for reliable fault diagnosis and trend of equipment failures using neural networks (Yam, et al. 2011). Machine vision techniques have been used to recognize and detect defects in track components (Molina, et al. 2011).

Sometimes it is possible for a system to continue to operate in a degraded way even after failure. The optimal time to repair to maximize the reward can be calculated by mathematical equations (Castro and Sanjuán 2008).

The system's deterioration can be modeled as a Markov process or a Poisson process. This modeling can help in taking better maintenance actions. In our research, the deterioration is modeled as a Markov Decision Process.

2.3 Markov Decision Process

Markov Decision Process is a sequential decision model where the set of available actions, rewards, and transition probabilities depends on the current state and not the states occupied in past or actions chosen in the past (Puterman 2005). Markov Decision Process (MDP) has been successfully implemented in the optimization of maintenance schedule and procedure for deteriorating systems. Research have been done to optimize the maintenance policy of circuit breakers using MDP (Ge, Tomasevicz and Asgarpoor 2007). MDP also has been used to develop a season-dependent, dynamic optimal policy to respond to the time-varying weather conditions for wind turbines (Byon and Ding 2010).

A semi-Markov Decision Process (SMDP) are extensions of MDP formalism that generalizes the notion of time - in particular, by allowing the time interval between the states transition to vary stochastically (Hoffman and de Freitas 2011). The sojourn time for each state is a general continuous random variable. A continuous-time Markov Chain with an exponentially distributed sojourn time is an SMDP. For the case of discrete-time, the sojourn times are discrete (geometric) random variables independent of the next state (Baykal-Gursoy 2007). Condition based maintenance policy has been developed for railway track inspection using Semi-Markov Decision Process but without the actual inspection data (Chen and Trivedi 2005).

MDP has been used to a generalized condition based maintenance model. MDP has provided an optimal effective maintenance decision based on the condition revealed at that point of time (Amari, McLaughlin and Pham 2006). When we have a partial information about the deteriorating system, MDP can be still implemented to gain knowledge about condition based maintenance (Hontelez, Burger and Wijnmalen 1996).

An optimized MDP suggests following the action from a particular state to maximize the reward. These actions can be modeled as the maintenance action to be taken. When cost is associated with the MDP, we correlate it to a negative reward the problem changes to a minimization problem. The states are the various conditions that the system follows from being in a new state to a failure state.

In our thesis, the three maintenance action, namely, no maintenance, minor maintenance, and major maintenance is modeled as three actions. A range of TQI gives the boundary limit to be in a particular state of Markov chain. We formulate our problem as Markov Decision Process.

Chapter 3: Data Description

3.1 Data Collection

Data plays one of the pivotal for this study. Railway personnel and other firms collect a huge amount of data related to various sections to study and maintain the optimal functioning. Various studies can lead to building a smarter transportation system.

The data for this study was collected from Class I railroad during March 2009 to December 2011. The data provided involved three different line segments. The line segment data we considered has 137 miles of data. Other two line segments data are of 121 miles and 109 miles respectively. We selected 50 miles of data for our analysis. The data consists of various railway geometry measurements such as gage, cross-level, surface, twist, warp, dip, cant, along with the geo-location details such as milepost, inspection speed, track curvature and track class giving each section an unique identity.

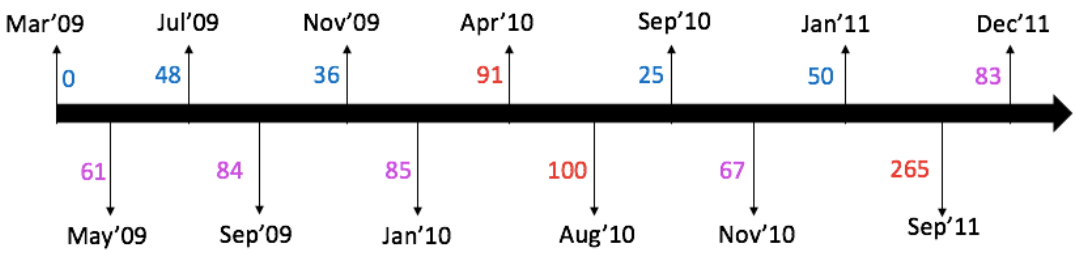

Figure 3: Inspection Run Timeline

For a particular milepost, we have data for thirteen inspections. In Figure 3, we show the timeline of inspection runs as found from the data in between March 2009 to December 2011. The numbers represent the days from the previous inspection. As we have no data for inspection before, we consider the number of days from the previous inspection to be zero.

3.2 Data Analysis

3.2.1 Calculation of TQI

The track geometry data for each foot is aggregated into ten segments per mile, each made up of 528 ft. (or 0.1 mile). We then proceed to the calculation of TQI. The TQI is calculated for each track geometry measurement individually using the following formula in R (El-Sibaie and Zhang 2004, 81-87)

$$TQI = \left(\frac{L_s}{L_o} - 1\right) \times 10^6 \qquad (1)$$

where,

TQI = Track Quality Index

L_s = traced length of space curve, feet; and

L_o = fixed length of track segment, feet.

The value of L_o is fixed at 528 ft. For the value of L_s we use the following formula (El-Sibaie and Zhang 2004)

$$L_s = \sum_{i=1}^{n} \sqrt{(\Delta y_i^2 + \Delta x_i^2)} = \sum_{i=1}^{n} \sqrt{(\Delta y_i^2 + 1)} \qquad (2)$$

where,

Δy_i = difference in two adjacent measurements, in feet

Δx_i = sampling interval along the track (= 1 ft.)

i = sequential number

Thus, L_s is calculated for the adjacent measurements using the above formula.
In the presence of track geometry data for left track and right track separately, such as in the case of surface and cant, we consider the measurement with higher absolute value.

The data provided to us comprises measurements of each foot of data. 1 mile of data must have 5280 ft. of data. We set a threshold of the presence of 5000 ft. of data to consider it for our analysis. If the milepost has 5000 ft. of data, the missing data is estimated by taking the mean value of the given data for that particular milepost and geometric defect. We calculate the TQI for gage, twist, surface, cant and cross-level defects and combine them to form a data frame. As the track irregularities can occur due to a combination of multiple track geometry measurements, we consider multiple track geometry measurements for the TQI. A data frame is created with geometry measurements for each segment as row names and inspection dates as column names.

From the data frame, the 95% quartile TQI value of each geometry measurement for a segment is calculated over the period of inspection. This value is then used to normalize the TQI values of each geometry measurements for a segment for various inspection dates. The mean values of each geometry measurements for a segment is then calculated to determine the TQI value of each segment over time.

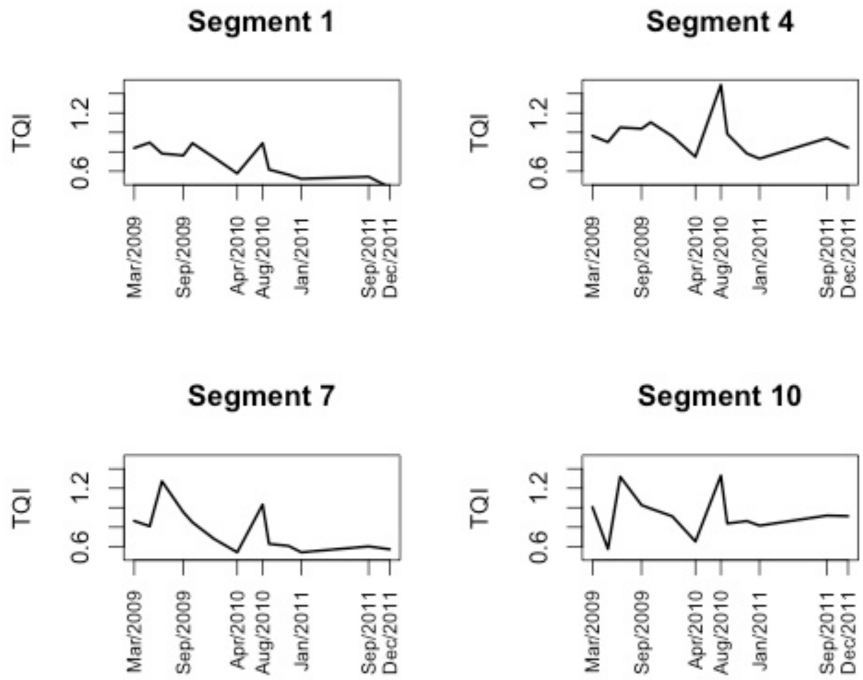

Figure 4. TQI plot for various segments over time

From Figure 4, we can identify the changes in TQI value over time. After each inspection run, the geometry measurements are recorded. Our assumption is that given no maintenance, the track will keep deteriorating. This is shown by the increasing trend of TQI. However, the decreasing trend of the TQI value indicates the occurrences of maintenance between inspection interval. When the inspections are done after maintenance activities, there is a drastic dip in the TQI value. If the inspection is not performed in a long time, the track degrades and the TQI value rises.

3.2.2. Geo-Defects

Geo-Defects are the defects renders the track in unusable condition. The geo-defects accounts for sudden changes in the track geometry measurement. In our research, we consider only red tags or red defects, which violate the FRA pre-defined rules (He, et al. 2015).

These geo-defects cause the track to fail suddenly and makes it dangerous to use the tracks until the repair is done. They may also arise even after an inspection.

A data frame is created consisting of only red-defects data. Three new columns are added to the data frame. The first column contains the date. The second column contains the milepost. The third column consists of segments in the specific milepost. The original data frame has a column containing the specific location. When we calculate the floor value, we get the milepost of the location. Then for the decimal part, we multiply it with 5280 to convert it to feet and then divide it with 528 to calculate the segments.

Now that we have the exact location of milepost and segments, we map it to the TQI data and store the number of geo-defects detected. We use the two data frames to generate a two column data frame. The first column shows the measurement of TQI values. The second column shows the number of geo-defects. We modify the second column to show the presence or absence of geo-defects using the values 0 and 1 only.

Now we apply logistic regression using the *glm()* function in R. Logistic Regression measures odds or probability of the dependency of the categorical dependent variable on one or more independent variables using a logistic function. In our case, the only independent variable is TQI and the dependent variable is the presence of geo-defects. The purpose of applying logistic regression is to determine the probability with which geo-defects arrive at particular TQI.

Table 1: Logistic Regression Plot

	Estimate	Std. Error	z value	Pr(>|z|)	Significance code
(Intercept)	-3.3457	0.3154	-10.607	<2e-16	***
TQI	0.7490	0.3905	1.918	0.0551	.

The measurement shown in Table 1 is calculated in R. The results shown in the table shows the coefficient, the standard error, the associated z-statistic, the p-value and the significance of p-value. The coefficient denotes how the log odds of the response variable change with a unit change in the value of predictor variable. In our case, the response variable is geo-defects and predictor variable is TQI. The significance code shows how much significance does the predictor variable carry for the outcome of the response variable. The significance code is related to p-value generated for particular predictor variable. Following is the significance code for particular p-values:

- When p- value $\in [0,0.001]$, the significance code is '***'. This suggests that the predictor is extremely significant.
- When p-value $\in [0.001,0.01]$, the significance code is '**'. This suggests that the predictor is significant for the outcome of the response variable.
- When p-value $\in [0.01,0.05]$, the significance code is '*'. This suggests that the predictor is significant for the outcome of the response variable.

- When p-value ∈ [0.05,0.1], the significance code is '.' . This suggests that the predictor variable still has an effect for on response variable.
- When p-value >0.1, the significance code is ' '. This suggests that the predictor variable has no effect on the response variable.

As the p-value of TQI is close to 0.05 and significance code '.', TQI is a significant variable to cause the arrival of geo-defects. The logistic regression model generated from the above table is as follows:

$$P(Geo - Defects) = \frac{exp\ (-3.3457+0.7490*TQI)}{1+ exp\ (-3.3457+0.7490*TQI)} \qquad (1)$$

The value of β_0 = -3.3457 is the model constant. The value of β_1= 0.7490 shows that there is an increase in odds of arrival of geo-defects with an increase in TQI value. We use this model later in Section 4.3 to determine the probability of geo-defects arriving for particular track TQI. In the following plot, we see how the probability of arrival of geo-defects increases with increase in TQI value.

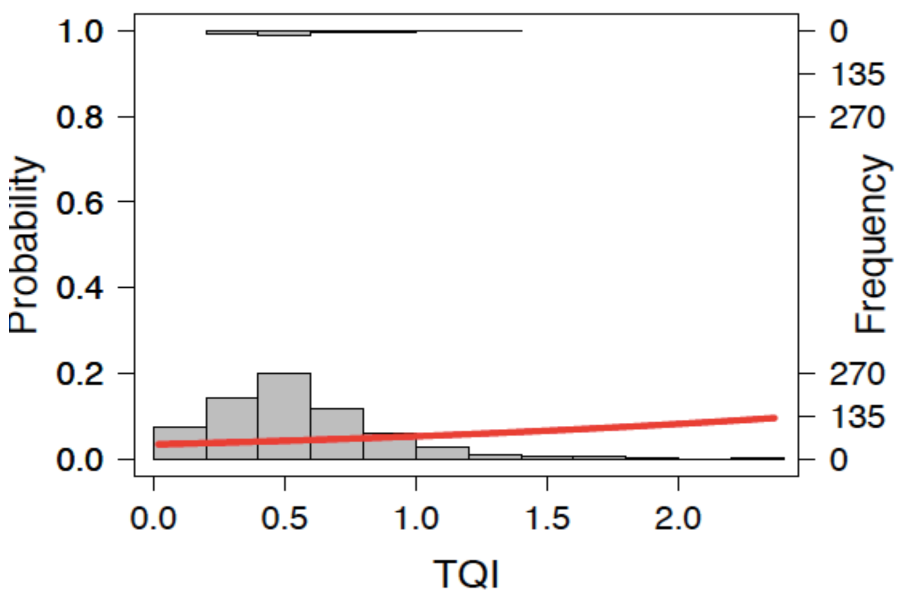

Figure 5. Logistic Regression Plot

Figure 5 illustrates how the probability rises with the rise in TQI value. The histogram at the lower half of the plot shows the frequency of absence at a different distribution of TQI. The histogram at the upper half of the plot shows the presence of geo-defects at a different distribution of TQI.

Chapter 4: Methodology

4.1 Assumptions in the Thesis

Here is the list of assumptions made in this thesis:

- The minor maintenance action takes the Markov chain from it's current state to the previous state in the order (e.g. from state 3 to state 2).
- The major maintenance action improves the track condition by two states or more (e.g. from state 4 to state 2).
- All the cost associated with the Markov Decision Process model has labor cost included.
- In this study, we do not consider the derailment cost and other costs such as material costs, etc.

4.2 Development of Markov Decision Process Model

We start with creating a discrete time Markov chain. A Markov chain is way representing a process where events move from one state to another. This change of state depends only on the current state and, therefore, is memory-less. When we describe the process over discrete periods of time, it is known as discrete-time Markov chain or DTMC.

The data given to us does not have a constant interval between inspections. Therefore, we create a discrete time model by dividing the data based on the dates of inspection into three levels.

$$T = \begin{cases} 0 - 58\ days\ \ (58th\ day\ is\ 33rd\ percentile) \\ 59 - 85\ days\ (85th\ day\ is\ 66th\ percentile) \\ 86\ days\ and\ above \end{cases}$$

Now we start marking the states. The states are divided based on the quartile values of TQI. Following is the way of dividing the states:

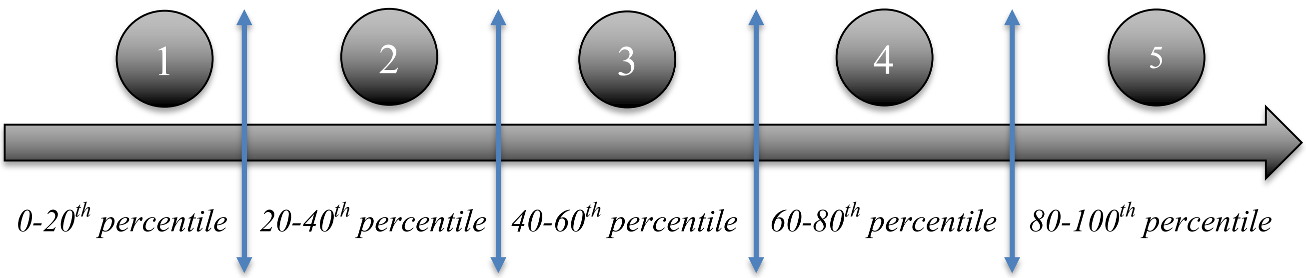

Figure 6. Determination of Markov chain states based on TQI values

The concept in Figure 6 is implemented to the TQI data frame to determine the state of the current section of the milepost. This is the building phase of Markov chain model.

Once we have determined the states, we start calculating actions taken for moving from one state to another. When over the period of time, the state gets worse or TQI value increases then, there is no action taken or A=0. When there is a slight improvement in TQI or the final state is just one before the original state, then there is minor maintenance work done or A=1. When the transition causes a major drop in TQI values or final state is two or more states less than the initial state, then it is a major maintenance or A=2.

$$A\ given\ S\ and\ S' = \begin{cases} 0 & if\ S' - S \geq 1 \\ 1 & if\ S' - S = 1 \\ 2 & if\ S - S' \geq 1 \end{cases}$$

Now that we have determined the state and defined the actions. We can easily develop the transitional probability matrix using the following equation:

$$P(S' \mid S, A, T) = \frac{N_{SS'}}{\sum_{j=1}^{TS} N_{Sj}} \qquad (3)$$

where S = current state,

S' = New state

A = Action taken

T = Discrete time period

TS = Total number of states

In equation (3), $N_{SS'}$ represents the number of times there has been a transition from state S to state S' given action A and time period T. In equation (3), the term $\sum_{j=1}^{TS} N_{Sj}$ represents the total number of time a transition has taken place from given state S to all other states given action A and time period T. The transition probability matrixes are developed using equation (3).

From the transition probability matrixes shown in Figure 7, 8 and 9, we can easily infer how the states degrade when no action is taken as shown for action = 0. As there are no maintenance actions, the state moves from the current state to worse states only. When we apply minimum maintenance action, the states move from their current state to the previous operating state as shown in the matrix under for Action =

1. When we apply major maintenance action, the states improve by at least 2 states or more. When major maintenance is applied to the track in state 2, the consequence is same as minimum maintenance action.

When T= 0 - 58 days

For Action = 0

States	**1**	**2**	**3**	**4**	**5**
1	0	**0.2**	**0.2**	**0.15**	**0.45**
2	0	0	**0.62**	**0.22**	**0.16**
3	0	0	0	**0.26**	**0.74**
4	0	0	0	0	**1**
5	0	0	0	0	**1**

For Action = 1

States	**1**	**2**	**3**	**4**	**5**
1	**1**	0	0	0	0
2	**1**	0	0	0	0
3	0	**1**	0	0	0
4	0	0	**1**	0	0
5	0	0	0	**1**	0

For Action = 2

States	**1**	**2**	**3**	**4**	**5**
1	**1**	0	0	0	0
2	**1**	0	0	0	0
3	**1**	0	0	0	0
4	**0.14**	**0.86**	0	0	0
5	**0.13**	**0.30**	**0.57**	0	0

Figure 7. Transition Probability Matrix for T= 0 - 58 days and A= 0,1,2 Respectively

When T= 59 - 85 days

For Action = 0

States	**1**	**2**	**3**	**4**	**5**
1	0	**0.48**	**0.22**	**0.08**	**0.22**
2	0	0	**0.46**	**0.29**	**0.25**
3	0	0	0	**0.56**	**0.44**
4	0	0	0	0	**1**
5	0	0	0	0	**1**

For Action = 1

States	**1**	**2**	**3**	**4**	**5**
1	**1**	0	0	0	0
2	**1**	0	0	0	0
3	0	**1**	0	0	0
4	0	0	**1**	0	0
5	0	0	0	**1**	0

For Action = 2

States	**1**	**2**	**3**	**4**	**5**
1	**1**	0	0	0	0
2	**1**	0	0	0	0
3	**1**	0	0	0	0
4	**0.47**	**0.53**	0	0	0
5	**0.16**	**0.42**	**0.42**	0	0

Figure 8. Transition Probability Matrix for T=59-85 days and A= 0,1,2 Respectively

When T > 85 days

For Action = 0

States	**1**	**2**	**3**	**4**	**5**
1	0	0	**0.12**	0	**0.88**
2	0	**1**	0	0	0
3	0	0	0	0	**1**
4	0	0	0	**1**	0
5	0	0	0	0	**1**

For Action = 1

States	**1**	**2**	**3**	**4**	**5**
1	**1**	0	0	0	0
2	**1**	0	0	0	0
3	0	**1**	0	0	0
4	0	0	**1**	0	0
5	0	0	0	**1**	0

For Action = 2

States	**1**	**2**	**3**	**4**	**5**
1	**1**	0	0	0	0
2	**1**	0	0	0	0
3	**1**	0	0	0	0
4	**0.5***	**0.5***	0	0	0
5	**0.37**	0	**0.63**	0	0

Figure 9. Transition Probability Matrix for T above 85 days and A= 0,1,2 Respectively

*Note: In the transition probability matrix in Figure 9 for Action =2, we don't have the data for the transition from state 4 to other states. Therefore, we assume the transition probabilities are the same for Action 0 and Action 1.

In Figure 7, we can see that due to frequent inspection, the state of the track doesn't degrade much until and unless there are arrivals of geo-defects as in the case of state 2 in Action 0. The major maintenance activity as seen in the data, for this particular time interval T=0-58 days, is also the minimum. When major maintenance activity takes place, the highest chances of moving from current state are to the closest possible improved state. For example, if the current state is 5, then there is a probability of 0.57 that the future state will be state 3.

Figure 8, shows the transition probability for state changes when T = 59- 85 days. The inspection is done on regular basis and this prevents the track condition to get extremely worse. For example, if the state is 3, then there is a probability of 0.56 of moving to state 4.

Figure 9 shows the transition probability for the state changes when T > 85 days. The inspection is after a long period of time. Thus, we can see that the degradation of state to the worst state is extremely possible. For example, the probability of moving from state 1 to state 5 is 0.88 and the probability of moving from state 3 to state 5 is 1. Thus, the count of major maintenance work is highest in this time period. The arrival of geo-defects is also highest in this period.

For the current Markov chain model, we have three different actions associated with it. When we have multiple actions and rewards associated with each action, then the Markov chain model acts as a Markov Decision Process. In Markov Decision Process, the final states are random as well as depends on the decision maker.

Below is the diagram for Markov Decision Process in our case for T = 59-85 days.

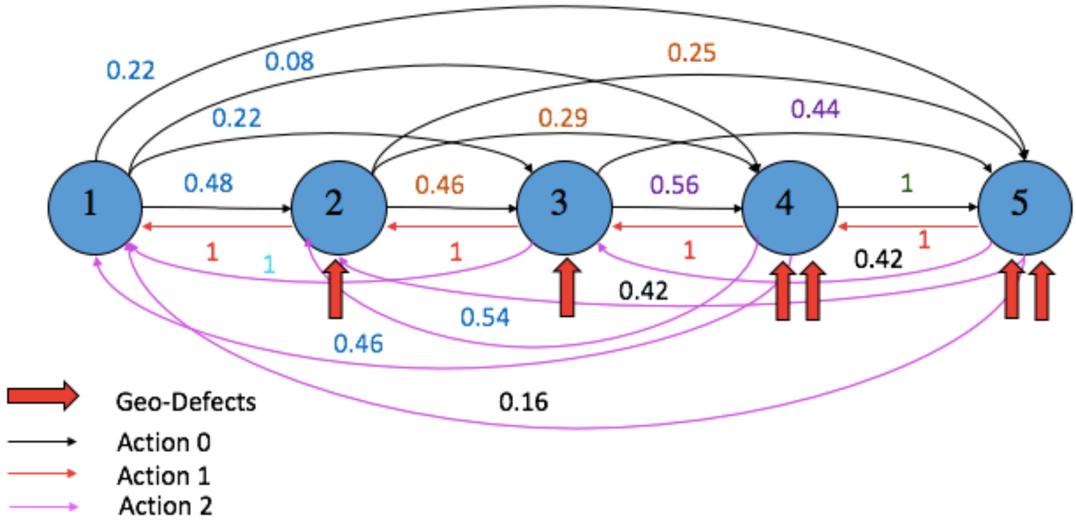

Figure 10. Markov Decision Process for **T** = 85 days

Figure 10 clearly demonstrates the different actions possible from each state, the probability of moving to another state following a particular action and arrival of geo-defects. When action 0 or no maintenance activity is followed, then the states move to the worse states. If we take state 2 as an example, we can see that it can move to state 3 with a probability of 0.46, state 4 with a probability of 0.29 and state 5 with a probability of 0.25. As the inspection and the maintenance activities are done quite frequently, the states don't degrade much unless there are geo-defects arriving.

In Figure 10, Action 1 stands for minimum maintenance where the states go to the previous operating state. For example, if the current state is 3 and a minimum maintenance is done, then the condition of the track moves to state 2. Therefore, this procedure takes place with a probability of 1 for all the given states.

In Figure 10, Action 2 stands for major maintenance where the condition of the track improves by at least 2 states. Therefore, major maintenance can be done state 3 onwards. When a major maintenance is done in state 2, it acts as a minor maintenance and goes to state 1. When a major maintenance activity is done, the state moves from current state to the next possible acceptable state most of the times. For example, the track condition moves from state 5 to state 3 with a probability of 0.42, to state 2 with a probability of 0.42 and to state 1 with a probability of 0.16. If major maintenance is applied at state 4, there is a 0.54 probability of moving to state 2 and a 0.46 probability of moving to state 1.

4.3 Arrival of Geo-defects

In this section, we use the model created in equation (1) to calculate the probability of geo-defects. Let us consider the TQI value to be 2.5. If we use the logistic regression model, where we replace TQI with value as 2.5, we get a probability of arrival as 0.19.

For our calculation, we have the range of TQI values for a particular state. Therefore, we calculate the mean of the probability of arrival of geo-defects in that range and round it to three significant digits.

Table 2: Probability of Arrival of Geo-Defects for the Particular States

State	**Probability of geo-defects**
1	0
2	0.061
3	0.069
4	0.097
5	0.219

4.4 Reward Associated with Markov Decision Process

A reward is awarded when particular action A is followed in Markov Decision Process to move from state S to state S'. Thus, reward is defined as a R = f(S, A, S'). The major objective of any Markov Decision Process is to maximize the total reward R over a period of time.

In our case, we have a cost C associated with each action. This cost is equivalent to the negative of a reward i.e. R = - C. Thus our problem reduces to maximizing the negative costs associated with the process.

The cost associated with a railway track maintenance process in the following manners:

$$Annual\ Cost = \begin{cases} Inspection\ Cost \\ Minor\ Maintenance\ Cost \\ Major\ Maintenance\ Cost \\ Geo - Defects\ Cost \\ Other\ Costs\ such\ as\ materials\ cost\ etc. \end{cases}$$

In our cost distribution, we have assumed that the total cost includes all the labor costs. Note that derailment cost is not taken into account in the scope of this thesis. But it can be easily incorporated in our model provided by derailment risk modeling (He et al. 2015).

The actual amount of each cost is set as below:

- Inspection Cost - $100/mile

- Minor Maintenance Cost - \$500/mile
- Major Maintenance Cost - \$1000/mile
- Geo-Defects Repair Cost - \$1000/defect

4.5 Markov Chain Monte Carlo Simulation

Monte Carlo methods refer to a procedure where samples are drawn from random distributions repeatedly to get a numerical result which is close to the actual result. When this method is applied to Markov Chains it is known as Markov Chain Monte Carlo (MCMC) simulation (Gilks 2005).

In MCMC, we generate random numbers using a uniform distribution ~U (0,1). We use the random number to determine the action to be taken given the policy. Once we have an action to be taken, we generate another random number using a uniform distribution ~U(0,1). This random number is matched to the cumulative sum of transition probabilities, for the current state and action, to get the future state. While the transition takes place from current state to new state, we generate the geo-defects in the current current state using a uniform random number and current state. We match this random number to the available probability of arrival of geo-defects for a particular state as represented in Table 2. Once the next step is reached, we repeat the same procedure and move forward in the chain. During this procedure, we keep a count of each action taken to move from current state to another state as well as the number of red defects generated.

The quality of samples generated from MCMC is a function of the number of steps. The simulation length is made for 10 years. If we consider the inspection time interval to be 58-85 days, then we can assume that there are 4 inspections per year or 40 inspections for the length of the simulation. Thus, we have 40 steps of transition. To get a stable result, we conduct such 10 year MCMC simulation 1000 times.

Chapter 5: Analysis of Existing Maintenance Policy

5.1 Existing Policy

The policy is defined as the action taken in an MDP when present in a certain stage. Mathematically it is represented as $\pi(A|S)$. The existing policy is the one that is being used in railroad maintenance practice, which can be further derived from the TQI data. First, we count the number of various actions taken from current state to reach a future state for various time periods. To obtain the policy, we calculate the percentage of a particular action taken in a particular state to the sum of all actions taken in the particular state. The percentage of actions taken for a particular state in a particular time interval are shown in Table 3 , 4 and 5 below.

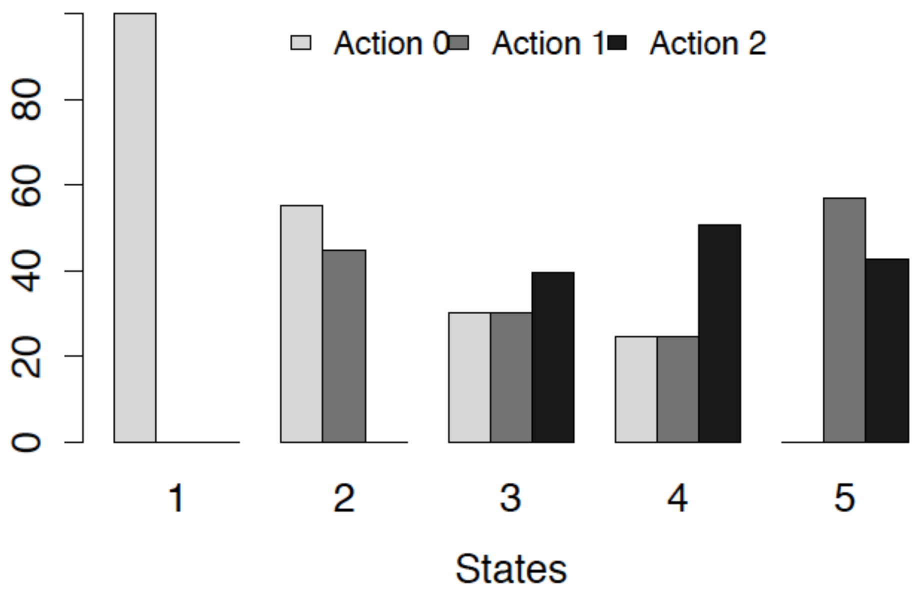

Figure 10. Existing Policy for T = 0 - 58 days as Derived from Data

Table 3. Existing Policy for T= 0-58 days as Derived from Data (in %)

States	Action 0	Action 1	Action 2
1	100	0	0
2	55.18	44.82	0
3	30.15	30.15	39.70
4	24.63	20.63	58.74
5	0	57.14	42.86

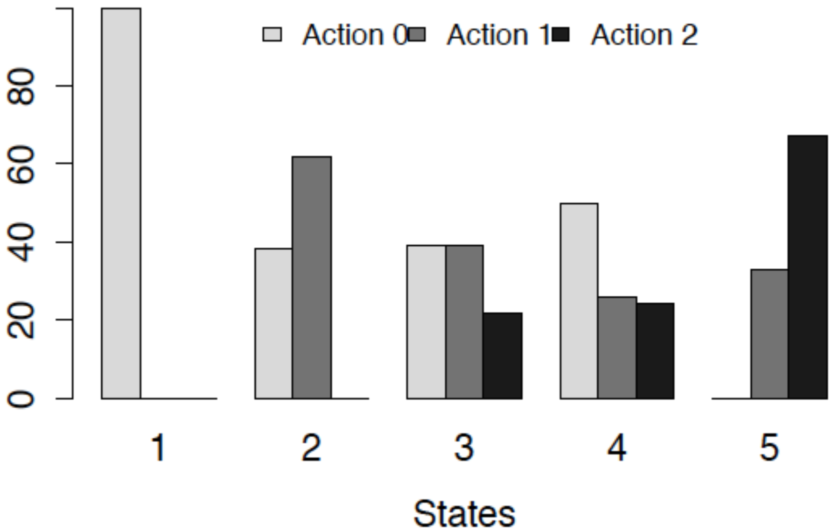

Figure 11. Existing Policy for T = 59 - 85 days as Derived from Data

Table 4. Existing Policy for T= 59-85 days as Derived from Data (in %)

States	Action 0	Action 1	Action 2
1	100	0	0
2	38.10	61.90	0
3	39.06	39.06	21.88
4	50	25.80	24.20
5	0	32.82	67.18

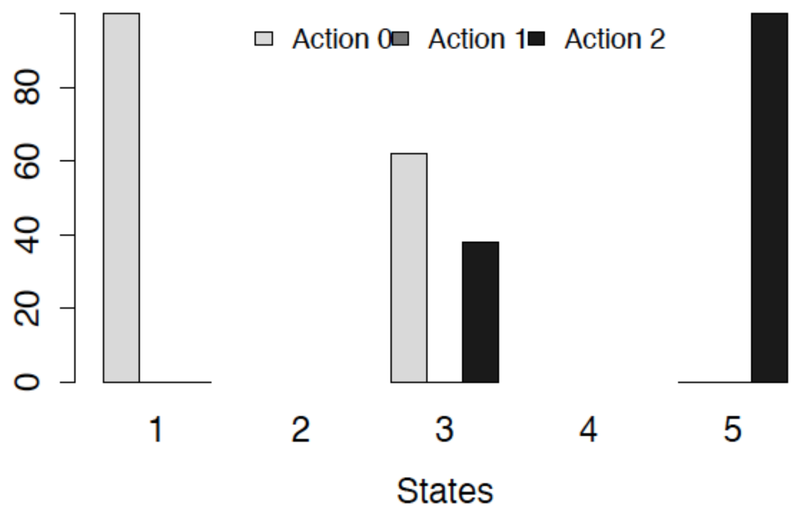

Figure 12. Existing Policy for T > 85 days as Derived from Data

Table 5. Existing Policy for T > 85 days as Derived from Data (in %)

States	Action 0	Action 1	Action 2
1	100	0	0
2	NA	NA	NA
3	61.90	0	38.10
4	NA	NA	NA
5	0	0	100

From Figure 10,11 and 12 and Table 3,4 and 5, we see that there is an inconsistency in the maintenance policy. If we consider the time period T=0-58 days and refer to Figure 10 and Table 3, we can see in state 4 no action is done 24.63%. Also, in state 5, minimum maintenance is done 57.14% whereas in state 5, ideally major maintenance should be done most of the time.

Similarly, in T=59-85 days, in state 4 no action is taken 50% of times. This will lead to degradation of track condition, failures, and accidents. We observe in state 3, 61.88% of times major maintenance action is performed whereas in state 4, 24.20% of times major maintenance is done. This data verifies how inconsistent is the current maintenance policy. More major maintenance is expected to be conducted in the more degraded state.

In T> 85 days, the inconsistency persists as 61.90% of times no action is done in state 3. In this time period, inspections are done after a long period of time and thus count maintenance activities should be more.

Next we perform a Markov Chain Monte Carlo (MCMC) simulation to estimate the percentage of actions taken over a period of 10 years.

5.2 Existing Policy Derived from MCMC

We conduct MCMC to check if the existing policy can be duplicated by MCMC. After 1,000 simulation run, we get a numeric result for particular actions taken at each step during the course of transition.

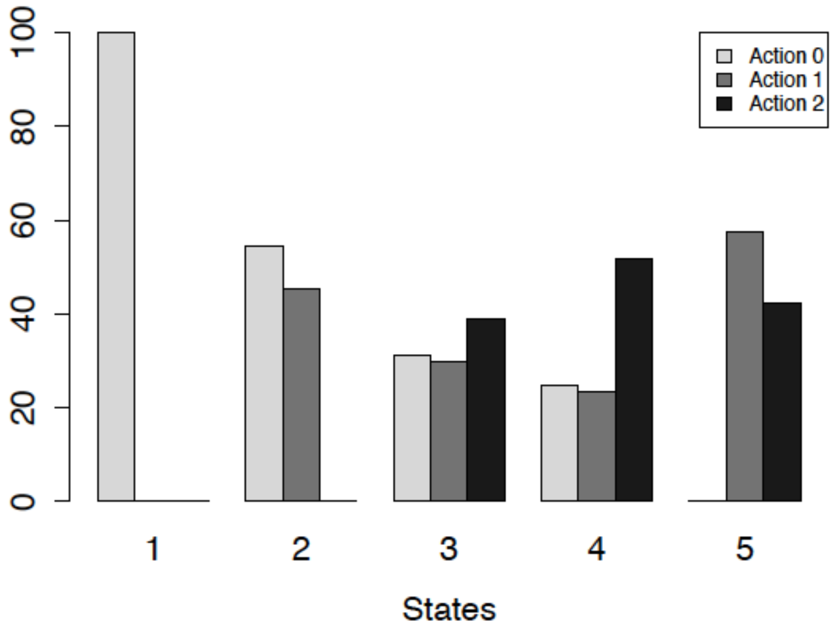

Figure 13. Existing Policy Derived from MCMC in T = 0 - 58 days

Table 6. Existing Policy Derived from MCMC for T=0-58 days

States	Action 0	Action 1	Action 2
1	100	0	0
2	55.17	33.83	0
3	30.15	30.15	39.70
4	24.62	24.62	50.76
5	0	57.14	42.86

Table 7. Percentage (%) Difference in the Policy Values Derived from Simulation and Observation respectively for T = 0-58 days

States	Action 0	Action 1	Action 2
1	0	0	0
2	0.01	0.01	0
3	0	0	0
4	0	0	0
5	0	0.01	0.01

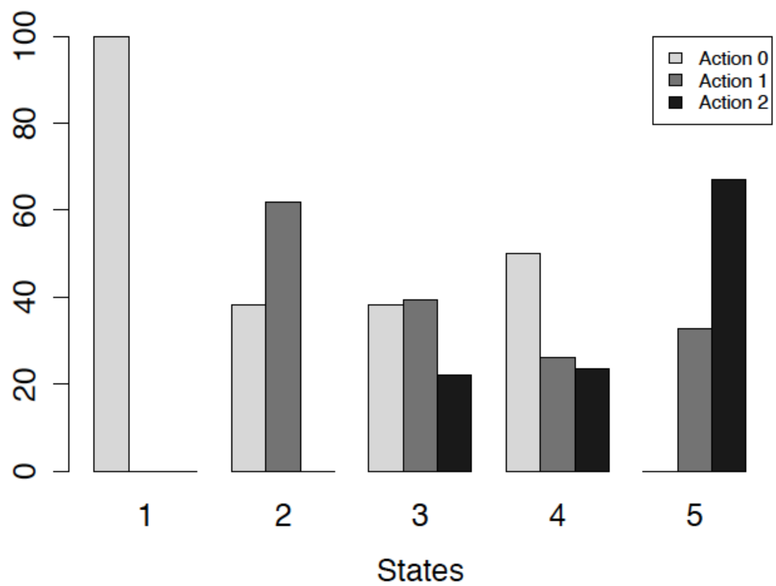

Figure 14. Existing Policy Derived from MCMC for T=59-85 days

Table 8. Existing Policy Derived from MCMC for T=59-85 days (in %)

States	Action 0	Action 1	Action 2
1	100	0	0
2	38.10	61.90	0
3	39.06	39.06	21.88
4	50	25.80	24.20
5	0	32.81	67.19

Table 9. Percentage (%) Difference in the Policy Values Derived from Simulation and Observation respectively for T=59-85 days

States	Action 0	Action 1	Action 2
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0.01	0.01

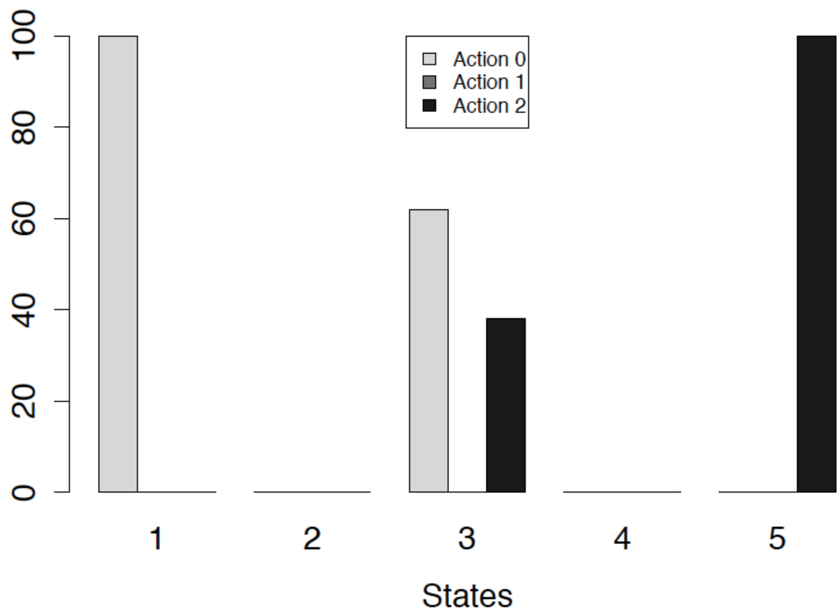

Figure 15. Existing Policy Derived from MCMC for T > 85 days

Table 10. Existing Policy Derived from MCMC for T > 85 days (in %)

States	Action 0	Action 1	Action 2
1	100	0	0
2	0	0	0
3	61.90	0	38.10
4	0	0	0
5	0	0	100

Table 11. Percentage (%) Difference in the Policy Values Derived from Simulation and Observation respectively for T > 85 days

States	Action 0	Action 1	Action 2
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0

From Table 7, 9 and 11 we can see that there is no difference between MCMC simulation and observations in the percentage of actions taken at particular state over a period of time. These tables validate our simulation model to the data-driven model. This simulation helps us explore the inconsistency in the actions taken and the inappropriate actions taken by determining the cost incurred in a long term. This will cause a heavy loss due to improper maintenance policy which is made up of 10,000 miles and above for Class I railroad.

5.3 Cost Associated in Existing Policy

For every action taken, there is a certain amount of cost associated to it. With the help of MCMC method, we calculate the cost of each action taken at a particular step of the simulation. The cost is cumulated over a period of 10 years to get the estimated cost for maintaining 1 mile of railway track. The mean value is represented by the bold blue line in histograms below.

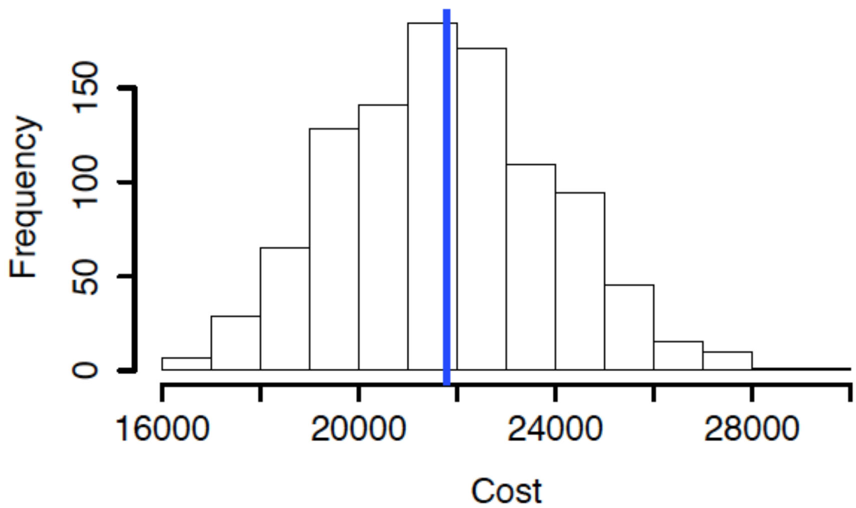

Figure 16. Distribution of total cost calculated for maintaining 1 mile of track for 10 years using MCMC for T = 0 - 58 days with an average of $21,784/mile

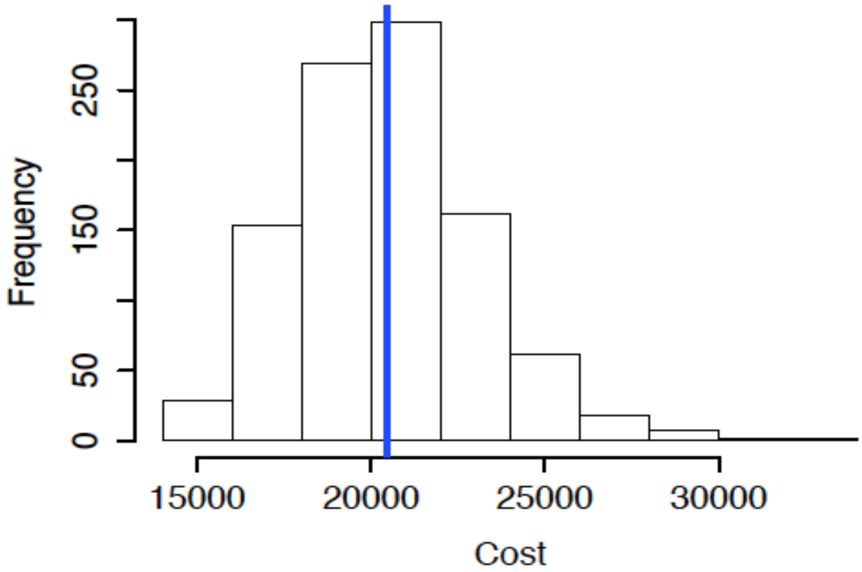

Figure 17. Distribution of total cost calculated for maintaining 1 mile of track for 10 years using MCMC for T = 59 - 85 days with an average of $20,456.60/mile

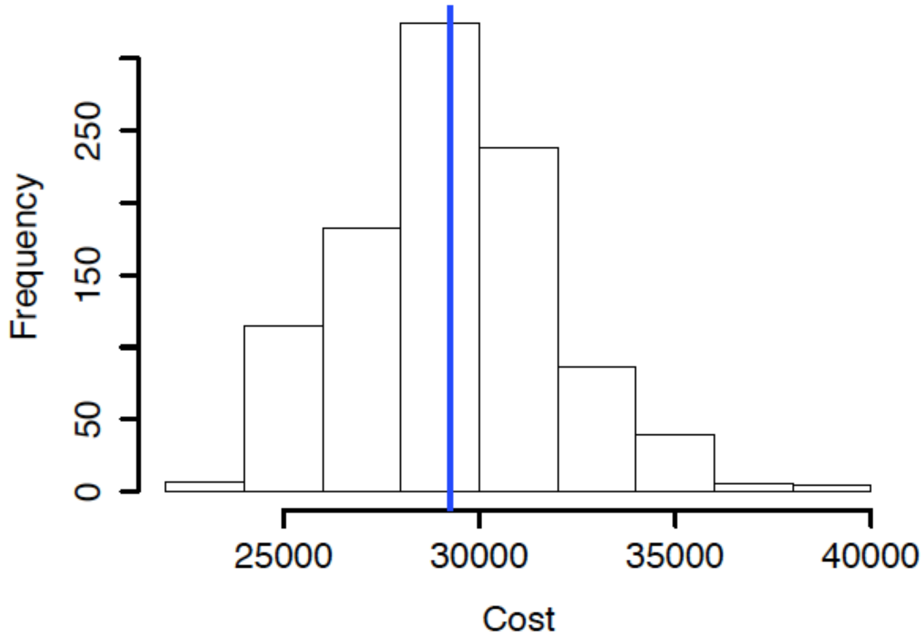

Figure 18. Distribution of total cost calculated for maintaining 1 mile of track for 10 years using MCMC for T > 85 days with an average of $29,259.30/mile

The histograms are generated from MCMC method. The mean cost for maintaining 1 mile of railway track for 10 years is calculated in each of the histogram and is represented by the blue line in the middle of the histogram.

Table 12. Mean Cost of Maintaining 1 Mile of Track for a Period of 10 Years Using Existing Policy Calculated From MCMC

Time Period	Mean Cost Estimated Using $\pi(A\|S)$ (in USD)
T = 0 - 58 days	21,784.00
T = 59 - 85 days	20,456.60
T > 85 days	29,259.30

Chapter 6: Optimization for Condition-Based Maintenance with Markov Decision Process

6.1 Overview

We have formulated a Markov Decision Process (MDP) in the previous sections. In this section, we aim to optimize the MDP. Our main aim is to find an optimal policy π^* which describes the optimal action to be taken in each state. The optimal policy π^* also aims at maximizing the reward associated with an MDP.

To solve an MDP problem, the most widely used techniques are value iteration algorithm, policy iteration algorithm, and linear programming method. In our research, we use the value iteration algorithm, which converges exponentially fast. Over the period of time, value iteration method has been developed to solve different types of problems. For example, it can be used to determine the average cost for a dynamic programming problem (Bertsekas 1998).

6.2 Introduction to Value Iteration Algorithm

Value iteration algorithm (Bellman 1957) is a method to compute the optimal value of an MDP. Value iteration works well if the state space is cyclic.

The idea behind value iteration is to maximize the rewards collected over the period of time. But while moving from one state to another in an MDP, we are concerned with only the immediate reward. We don't know if this path will lead us to a state with high reward. Thus, essentially the value iteration looks for the true value of state and follow the path where it can earn maximum rewards.

$$Q_{i+1}(S, A) = \sum_{S'} P(S' \mid S, A, T)\,(R(S, A, S') + \gamma(Vi\,(S'))) \quad (4)$$

$$V_{i+1}\,(S) = max_{\,a \in A}\,(Q_{\,i+1}(S, A)) \quad (5)$$

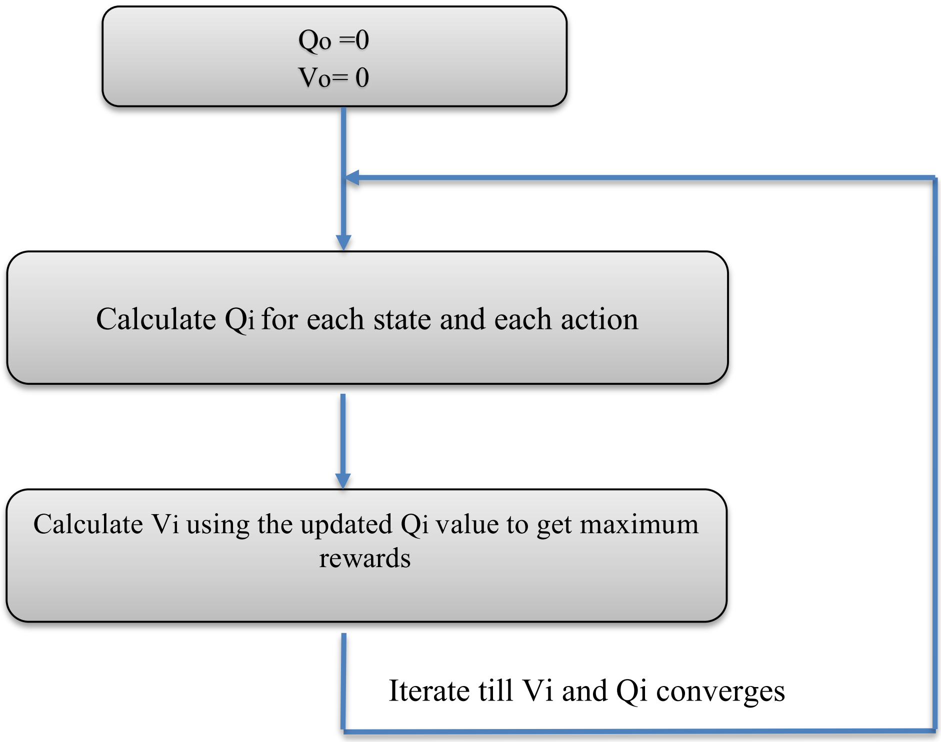

Figure 19. Flowchart of Value Iteration Algorithm

Initially, we define two functions Q_i and V_i. Q_i represents the Q-function with i stages remaining. V_i represents the value function i stages to go. Value iteration algorithm works recursively and has no end. We find an optimal solution when the values of Q* and V* converges. While applying this algorithm, we start at the end and move backward updating the value of Q* and V*. γ in the equation (2) stands for a discount in rewards over a period of time. In our case we assume $\gamma = 1$.

Figure 19 shows the flowchart of the value iteration algorithm. We start with an initial value $V_0 = 0$. We calculate Q_1 for the current value of V_0 and proceed to calculate the value of V_1. We go on iterating the value of V_i at each step for all the states till the values converge and we get an optimal policy.

The computation time for the value iteration algorithm in R is about 4.5 seconds for 40 iterations in a laptop with i5 CPU and 4 GB Memory.

6.3 Optimal Policy

The optimal policy is found using the value iteration algorithm. This policy helps in gaining the maximum rewards. In our case, following this policy the cost is minimized. Mathematically the optimal policy is represented as $\pi^*(A|S)$. Following is the graph of $\pi^*(A|S)$.

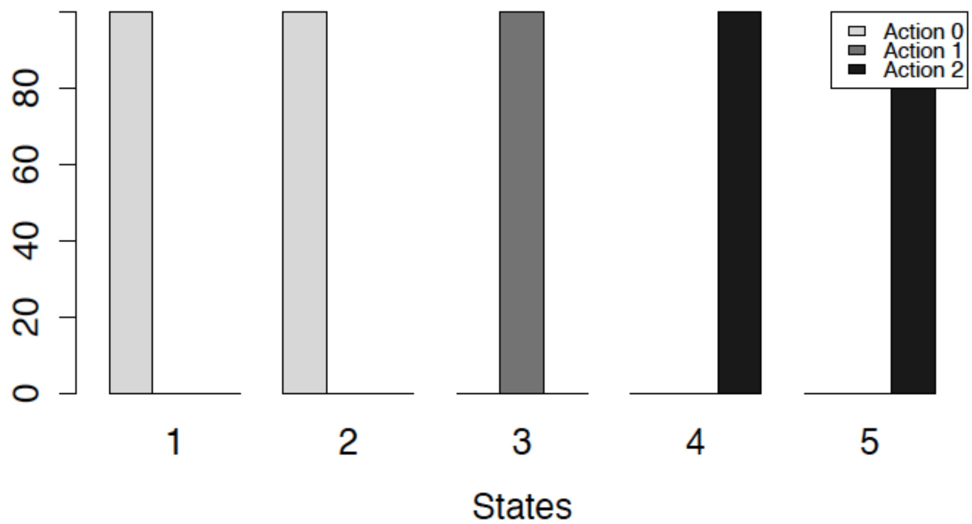

Figure 20. Actions in Optimal Policy for particular states at T=0-58 days

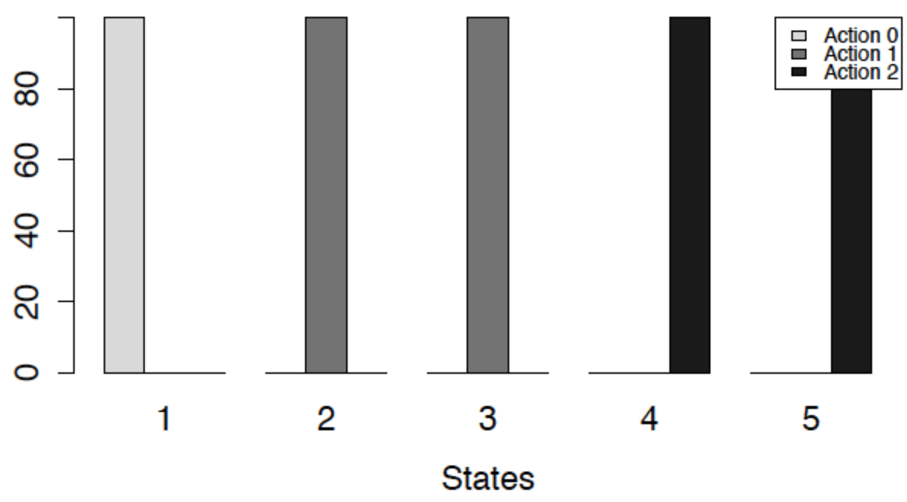

Figure 21. Actions in Optimal Policy for particular states at T= 59-85 days

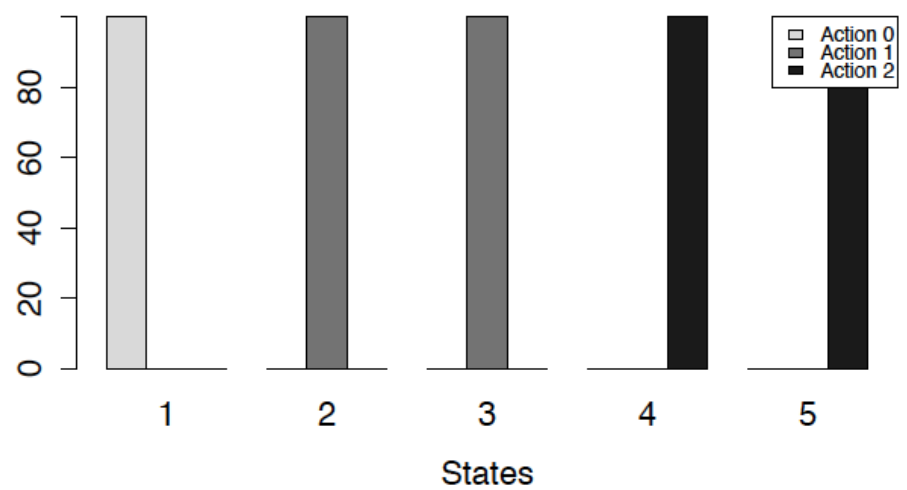

Figure 22. Actions in Optimal Policy for Particular States at above T > 85 days

The optimal policies suggest one particular action for a particular state in a particular time period. This helps in maintaining a uniformity in the maintenance policy. For example, had we followed the existing policy as shown in Figure 13 and Table 6 for state 4, then we had 24.62% times no action, 24.62% times minimum maintenance and 50.76% major maintenance. Following the optimal policy in Figure 20, we can see that when we are in state 4, then there is only major maintenance action suggested. If we continue with no action in state 4, the track might degrade to state 5 or there can be a major failure which might lead to the high frequency of geo-defects and even train accidents. Also, the inconsistency increases the cost. If we choose no action in state 4, then the inspection cost is not utilized and we have to again pay inspection cost later to determine it's new condition and then take a call for maintenance or repair policy.

The optimal policy also suggests the actions to be taken for states 2 and states 4 in time period T > 85 days which is otherwise unavailable from the data.

6.4 Cost of Optimal Policy

We put the optimal policy $\pi^*(A|S)$ in MCMC simulation to obtain the cost associated with maintenance of 1 mile of railway track for 10 years. This value is represented in histograms below by a bold red line.

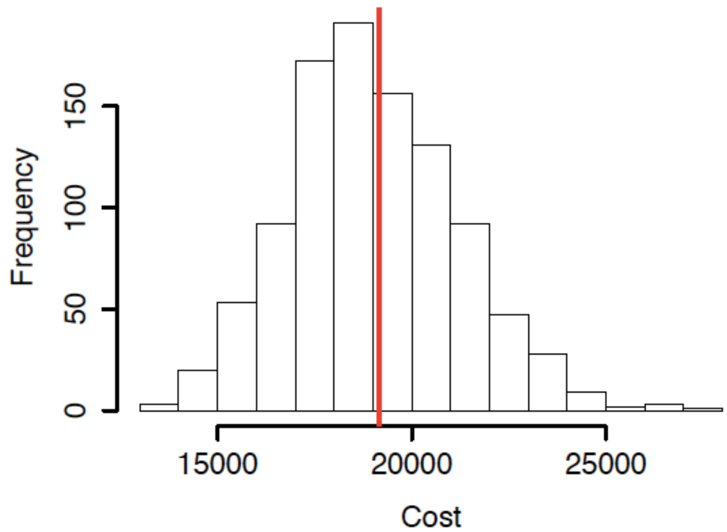

Figure 23. Distributed cost calculated for maintaining 1 mile of track for 10 years using optimal policy and MCMC for T= 0-58 days with an average of \$19,168.10/mile

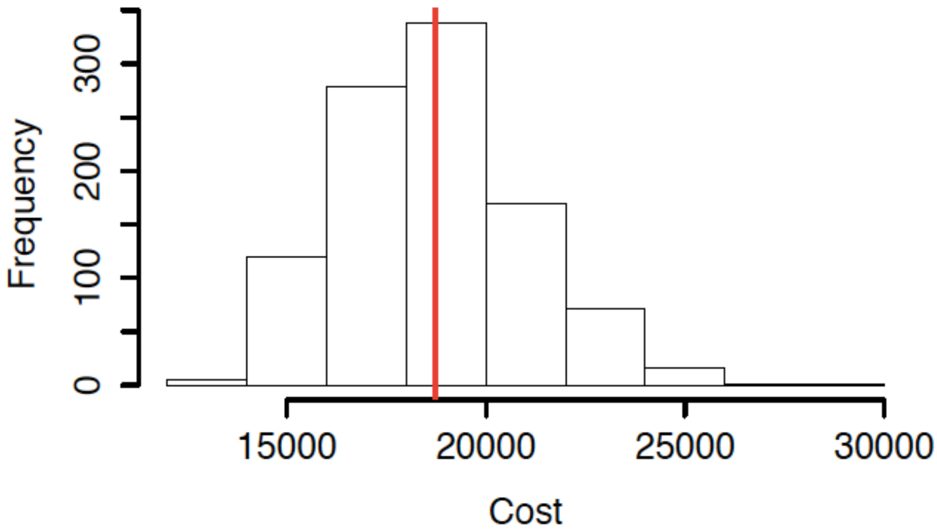

Figure 24. Distributed cost calculated for maintaining 1 mile of track for 10 years using optimal policy and MCMC for T= 59-85 days with an average of $18,727/mile

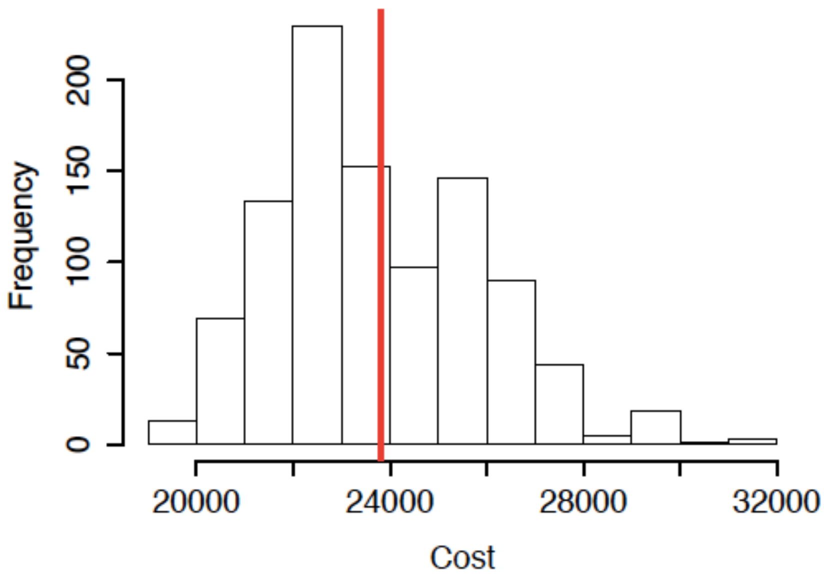

Figure 25. Distributed cost calculated for maintaining 1 mile of track for 10 years using optimal policy and MCMC for T> 85 days with an average of $23,816.90/mile

As one can see, Figure 23, 24 and 25 show that the mean value of each histogram has shifted to left side compared to the mean value of the histograms for existing policy, depicted in Figure 16, 17 and 18. This shows that the optimal has a positive effect in cost savings.

6.5 Savings and Results

Our aim is to minimize the cost of maintaining 1 mile of railway track over the period of 10 years. In Table 13, we compare the cost using existing policy and optimal policy for all time intervals.

Table 13: Savings of Optimal Policy compared Existing Policy

	Mean Cost Estimated Using π(A|S) (in USD)	Mean Cost Estimated Using π^*(A|S) (in USD)	Savings
T = 0-58 days (33rd percentile)	21,784	19,168.10	12%
T = 59-85 days (66th percentile)	20,456.60	18,727	8.45%
T > 85 days	29,164	23,816.9	18.33%

The overall cost to the company is minimized when the interval of inspection run is T= 59-85 days. This interval between 2 and 3 months should be ideally preferred because this provides a balance between inspection costs and maintenance cost. The arrival of geo-defects can be monitored easily in this period. Below we plot the bar chart for the average cost using existing policy and optimal policy for a range of days. This plot gives us a better visualization of the situation.

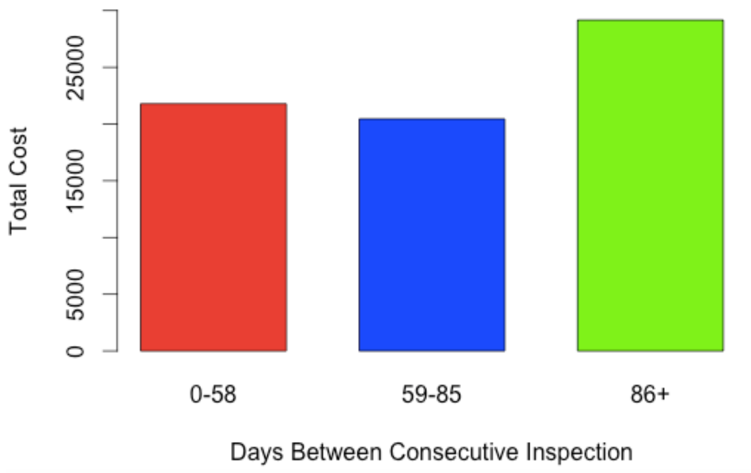

Figure 26. Total Cost versus Days Between Consecutive Inspection Using Existing Policy

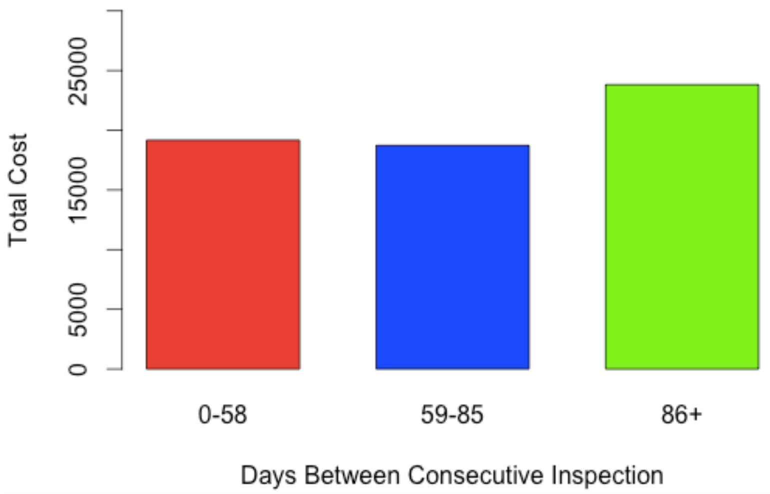

Figure 27. Total Cost versus Days Between Consecutive Inspection Using Optimal Policy

6.6 Sensitivity Analysis

Sensitivity analysis is conducted to check the dependency on various inputs. In our research, we analyze the sensitivity of various kinds of cost and see what effect it generates on overall cost. For this purpose, we follow a one-factor-at-a-time or OFAT procedure. The values of various cost are changed as shown in Table 8 one at a time.

6.6.1. Inspection Cost

In this section, we change the of inspection cost from $100 per 1 mile of track. We change the value of inspection cost from $50 to $250 per 1 mile of track. We increase the cost by $10 in every iteration. We check the impact of this change of cost on the optimal value.

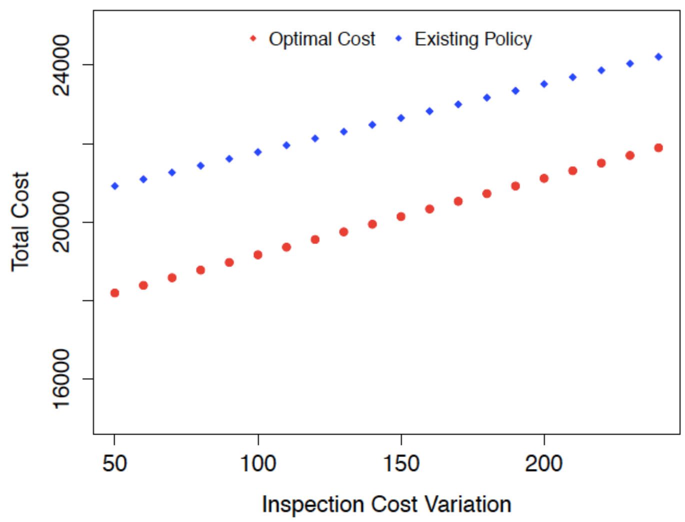

Figure 28. Sensitivity Analysis when Inspection Cost is Varied for T= 0 - 58 days

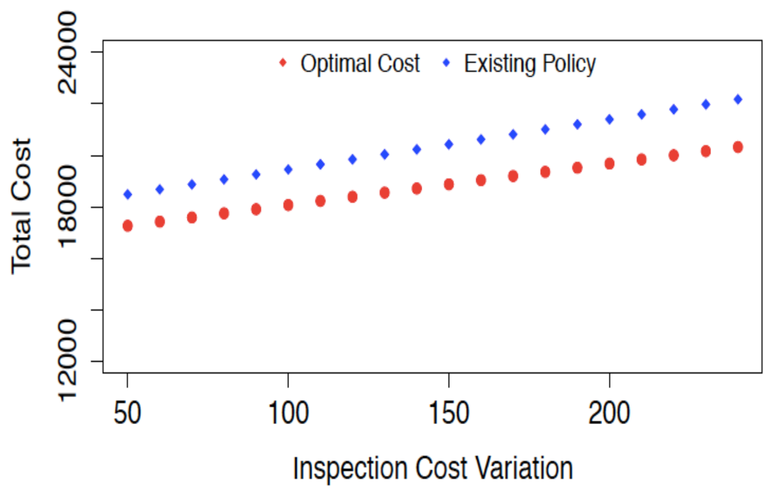

Figure 29. Sensitivity Analysis when Inspection Cost is Varied for T = 59-85 days

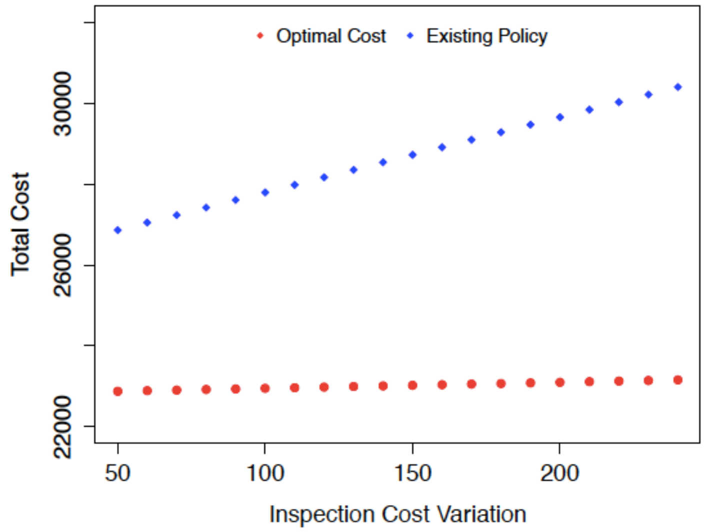

Figure 30. Sensitivity Analysis when Inspection Cost is Varied for T > 85 days

The total cost comprises of inspection cost, minor maintenance cost, major maintenance cost, and geo-defects repair. Figure 28 shows the sensitivity analysis for T=0-58 days. During the execution of no action policy, only the inspection cost is charged. In T=0-58, we have decreased the number of no actions and slightly increased the number of minor and major maintenance actions in our optimal policy. Therefore, the overall effect on the total cost is minimal when only inspection cost is increased. Also, as the track maintenance policy are rapidly followed the overall effect of increasing the inspection cost is reduced. In the case of T = 59-85 days and T > 85 days, we have an only minor maintenance plan in state 3 instead of all three actions getting executed at different rates as derived in existing policy. This has rapidly decreased the cost of maintenance in optimal policy. Thus, we see a great cost savings in Figure 29 and Figure 30. In T > 85 days, most of the track condition is in state 3.

6.6.2. Major Maintenance Cost

In this section, we change the of major maintenance cost from $1000 per 1 mile of track to a range of $750- $1250 per 1 mile of track. We check the impact of this change of cost on the optimal value.

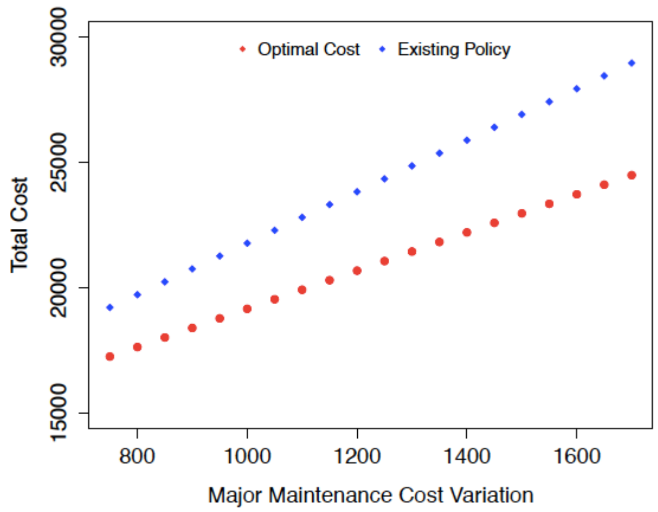

Figure 31. Sensitivity Analysis of Major Maintenance Cost for T= 0-58 days

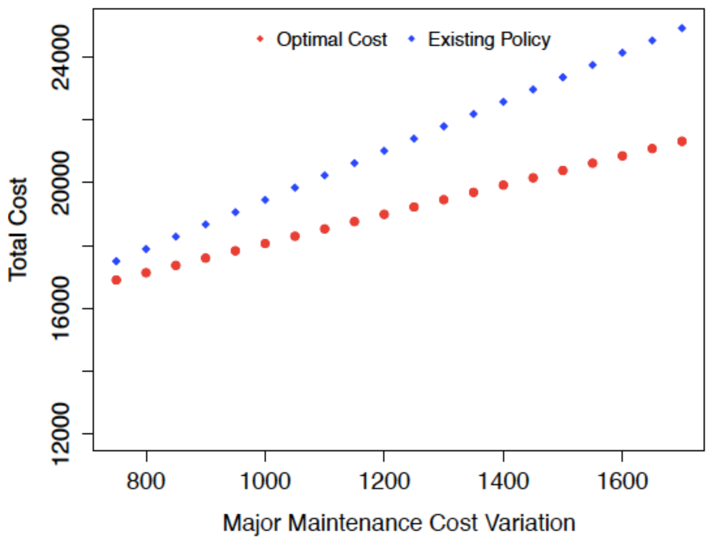

Figure 32. Sensitivity Analysis of Major Maintenance Cost for T= 59-85 days

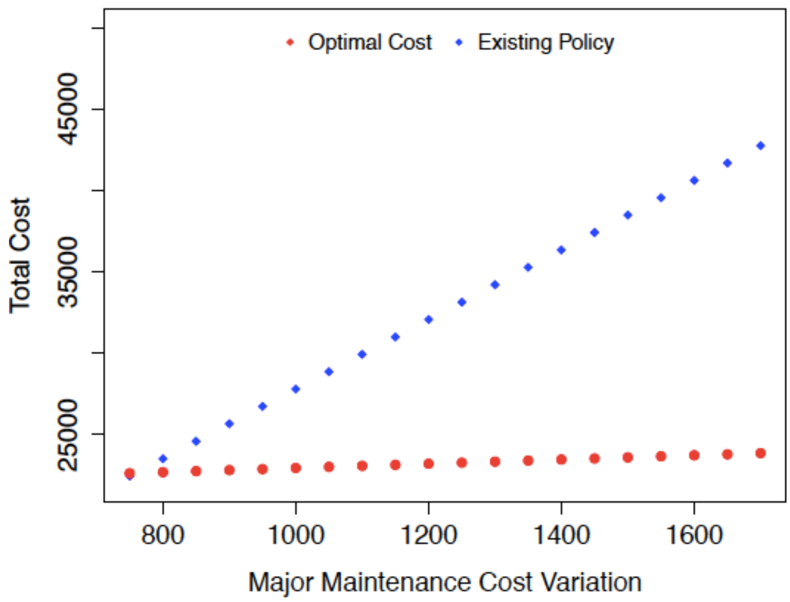

Figure 33. Sensitivity Analysis of Major Maintenance Cost for T>85 days

The total cost comprises of inspection cost, minor maintenance cost, major maintenance cost, and geo-defects repair. Figure 31 shows the sensitivity analysis for 0-58 days. In this case, the total number of major maintenance is less than in case of T = 59-95 days and T > 85 days. Therefore, with an increase in major maintenance cost, the savings rapidly increases. In Figure 33 we see the major maintenance cost having a huge effect on savings. This is because the number of major maintenance that were being done in existing policy was more than the number of major maintenance in optimal policy. In optimal policy for T > 85 days, we don't have a major maintenance action in state 3. This reduces the overall costs. Also, most of the condition of the track is in state 3 where a minor maintenance work is optimally done. Also, as the number of major maintenance is significantly higher in T > 85 than in other time periods, increasing the cost of major maintenance effects the savings, in a positive way, more than it does in T = 0 – 58 days and T = 59 – 85 days.

Chapter 7: Conclusion and Future Research

This research aims to develop a condition-based maintenance policy for the geometry of railway tracks. We utilized 33 months, 50 miles of track inspection data for our study. Given the geometry measurements of the track, we calculate the TQI value for each 0.1 mile segment. We use the inspection data to develop a discrete-time Markov Chain model. Using the TQI value, we map them to three maintenance actions (i.e. major maintenance, minor maintenance and no maintenance) that have been carried out at that particular states. Once we have built the MDP model, we apply Markov Chain Monte Carlo (MCMC) simulation to gain knowledge about the existing policy. We determine the cost of maintaining 1 mile of track for a period of 10 years.

To optimize the existing policy using MDP, we apply value iteration algorithm. It is a backward induction method. On iterating the steps of MDP multiple time, we get an optimal policy. This optimal policy acts as an input for MCMC simulation and we get the estimated optimal cost. The overall cost savings comes to 12% for T = 0-58 days, 8.45% for T = 59-85 days and 17.96% for T for above 85 days for 1 mile of data. For example, for T=59-85 days, the overall savings is $1729.60 per mile in 10 years. Typically a Class I railroad maintains about 10,000 miles of main line tracks in their network. If we consider 8.45% savings for maintaining 10,000 miles of main line track, the savings come to $1,7296,000 per 10 years.

7.1 Future Research

The future work could include the following aspects:

- Consider more detailed costs, such as derailment costs, downtime costs for the policy of preventive maintenance and inspection. Derailment costs can be modeled and estimated from historical train derailments caused by geo-defects (He et al. 2015). The downtime cost is a major part during the inspection and maintenance run. If the tracks are not maintained time to time or a geo-defect arrives, there might be a failure. This could cause a derailment and this cost can impact the overall cost scenario for the railway industry.

- Schedule the preventive maintenance activities in a railway network. The cost analysis done in this thesis can be used to develop a maintenance schedule program to decrease the overall cost, including logistics costs, crew labor costs, etc.
- The existing geo-defect prediction model only considers TQI value. We can further enhance this model with other variables, such as tonnage, track curvature, track class, and historical inspection and maintenance work, etc.
- The MDP developed in this thesis can be extended to be a Semi-MDP where the sojourn time in each state is a general continuous random variable.

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