Technical Report - MALPRIS project

Manifest and Latent Processes Risks based Approach for Determination of Intervention Strategies for a Road Link

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Executive Summary

In the management of civil infrastructure, of which road links are a part, it is important to determine preservation strategies that minimize the total of all costs (TC) to all stakeholders within an investigated time period. Such analyses are often carried out either as a minimization problem using the discount flow method or the annual average cost method (Kobayashi and Kuhn, 2007). One important, but subtle, feature of these analyses is that they are dependent on the model used to predict the deterioration of the infrastructure.

Deterioration models used for this purpose can be classified as those that: 1) estimate the average deterioration of all similarly classified objects or elements, and 2) estimate the deterioration of each object or element. For the former, statistical methods are often used in order to model the regularities behind deterioration processes based on a significant amount of information. For the latter, physical methods are often used to directly model the deterioration processes. In many cases, the statistical methods are also referred as "probabilistic" or "stochastic" models, and the physical models are referred as "deterministic" methods.

The selection of the deterioration models has a direct impact on the determination of the solution for the optimal control problem in infrastructure management, i.e. the determination of the optimal preservation strategy for a group of infrastructure objects.

This report focuses extensively on the application of deterioration and intervention models that can be used for determination of optimal intervention strategy for a road link composed of multiple infrastructure objects (e.g. road sections, bridges, culverst).

In the introduction chapter (Chapter 1), we describes the necesity of the research and the description of cost models used in Switzerland. Also, a description of the case study in the Canton of Walliss, Switzerland is given. In the case study, we selected a road link composed of 11 objects (road sections and bridges) that are under deterioration and requires to perform interventions so as to recover their service.

Chapter 2 details the mathematical formulation of the 7 proposed models that are considered in this study. There are 7 types of models and all of them are probabilistic in nature: the block replacement model (BR); the periodic group repair model (PGR); two periodic intervention with minimar repair models (PIMR); the age replacement model (AR); the multi-stage exponential Markov model with hazard risk(MAMOHA); the semi-Markov model (SM). Each of the model is then coded using R, in excel spreatsheets and in AMPL programing language. The script of the program for each model is given in the Appendix of the report.

In Chapter 3, we desribes the estimation methodology and the description of input parameters used for the proposed models. Also, under each model's subsection, estimation results are given and compared. Chapter 5 presents the estimation results on the same case studies and give a brief comparison of the models. The last chapter gives a discussion and conclusion of the report. It is concluded that the BR, AR, and the Markov models are more applicable to the case study. It is also concluded that executions of interventions on multiple objects instead of on single object could significantly reduce the negative impacts incurred by the stakeholders, and thus the intervention strategies with grouping of objects are likely to be optimal strategies.

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Symbols

Symbol	name/description
λ or θ	deterioration rate
$\lambda(t)$ or $\theta(t)$	deterioration function
ρ	discount factor
x	characteristic variable
β	unknown parameter
$f(t)$	density function of variable t
$F(t)$	distribution function of variable t
$\tilde{F}(t)$	survival function of variable t
RMD	remaining duration
IS	intervention strategy
OIS	optimal intervention strategy
ET	average elapsed time

Chapter 1

Introduction

1.1 General introduction

Cost efficiency is is one of the most important parts in public road management (IS). Therefore it is crucial to find an optimal intervention strategy (OIS), which not only considers the owner costs, but tries to minimize the total costs (TC) of all stakeholders. They can be divided into three groups:

- infrastructure owner or operator
- infrastructure users
- other affected stakeholders

Not going into detail about the actual cost minimization models, it is important to mention, that the deterioration model has great influence upon the outcome of such cost minimization models.

In this report seven different intervention strategy models will be investigated and the estimation results are compared so as to recommend the best type of model for practical use.

1.2 Performance Indicators and intervention types

1.2.1 Performance Indicators

1.2.1.1 road objects

To be able to compare different road objects, a performance indicator should be defined. In Switzerland, this is done by the national Standard SN 640925b. This performance indicator consists of 6 parts (I_0 to I_5) where each indicator (called *performance index*) represents an attribute of the road condition. Indexes I_0 and I_1 are used alternatively and describe the surface damage and are recorded manually. All other indexes relate to physical values which can be measured (preferably automated)

Table 1.1: Performance indicators according to SN 640925b

Index	Name	Measured value	Unit	Recording method
I_0	Surface damage without rut depth	Type and area of damage	NA	Visual
I_1	Surface damage with rut depth	Type and area of damage, rut depth	NA	Visual and manual/automated
I_2	Longitudinal evenness	Standard deviation of angular value	‰	Automated
I_3	Transversal evenness	Rut depth	mm	Manual/automated
I_4	Grip	Coefficient of friction	-	Automated
I_5	Bearing capacity	Deflection	$\frac{mm}{100}$	Manual/automated

The indexes can take the following values:

Table 1.2: performance index ranges for roads

Index value	Definition German	English translation
0 to 1	gut	good
1 to 2	mittel	medium
2 to 3	ausreichend	sufficient
3 to 4	kritisch	critical
4 to 5	schlecht	bad

1.2.1.2 Bridge-type objects

For bridge-type objects, a likewise model exists. However, there are some differences: The index values are only allowed to take the following integer numbers: 1,2,3,4,5 and 9 Also, there are only two indexes (load bearing structure and technical equipment). More information can be found in: (ASTRA, 2005) In the following table, a short overview is given:

TABLE 1.3: Integer performance indexes for bridges

Index value	Definition German	English translation
1	gut	good
2	akzeptabel	acceptable
3	beschädigt	damaged
4	schlecht	bad
5	alarmierend	alarming
9	unkontrollierbar	no inspection possible

1.2.2 Intervention types

The SIA Norm 469 defines three intervention types:

***Instandhaltung* - maintenance:** all interventions to remediate small deficiencies. Used for maintaining the serviceability.

***Instandsetzung* - restoration:** all interventions to restore serviceability and/or safety. Usually larger interventions, which remove visual damages as well as the underlying cause for them.

***Erneuerung* - renewal:** bringing the object or parts thereof in newly-built condition. This is the largest type of interventions.

1.3 Cost model

This section briefly explains the cost model used in Switzerland. Cost items are classified into stakeholder groups such as owner, user, and social cost. Following texts and equations describe the approach to estimate the cost.

If considered only for one type of intervention strategy, the total cost is G_τ:

$$G_\tau = G_1 + G_2 + G_3, \tag{1.1}$$

where, G_1, G_2, and G_3 are owner cost, user cost, and social cost respectively. The owner cost is defined in following equation:

$$\begin{aligned} G_1 = N.(1+\rho)^\tau &+ \sum E_y.(1+\rho)^{-(t-\tau)} \\ &+ \sum B_y.(1+\rho)^{-(t-\tau)} - R_n.(1+\rho)^{-(n-\tau)}, \end{aligned} \tag{1.2}$$

where, N is new construction cost; ρ is discount factor; τ is intervention time; E_y is intervention cost (y is year); B_y is operation cost; n is management period; R_n is residual value; t is time, at which intervention is done. If considering only intervention, equation (1.2) can be simplified as:

$$G_1 = \sum E_y.(1+\rho)^{-(t-\tau)}. \tag{1.3}$$

The user cost G_2 is defined as:

$$\begin{aligned} G_2 = \Big(\sum Z_B &+ \sum T_B + \sum U_B\Big)_t .(1-\rho)^{-(t-\tau)} \\ &+ \Big(\sum Z_Z + \sum T_Z + \sum U_Z\Big)_t .(1-\rho)^{-(t-\tau)}, \end{aligned} \tag{1.4}$$

where, Z_B is time delay cost due to intervention site; T_B is vehicle operation cost (VOC) due to intervention site; U_B is accident cost; Z_Z is condition state dependent time delay cost; T_Z is condition state dependent VOC; U_Z is condition state dependent cost. If without considering user cost before and after intervention, a reduced form of equation (1.4) is often used:

$$G_2 = \Big(\sum Z_B + \sum T_B + \sum U_B\Big)_t .(1-\rho)^{-(t-\tau)}, \tag{1.5}$$

The cost incurred to society and environment G_3 is calculated as follows:

$$G_3 = K_{accident} + K_{noise} + K_{pollution} + K_{CO_2}, \tag{1.6}$$

where,

$$K_{accident} = A_{property}.K_{property} + A_{injury}.K_{injury} + A_{death}.K_{death}, \tag{1.7}$$

$A_{...}$ and $K_{...}$ in equation (1.7) are numbers and unit costs associated with property, injury, and death respectively. The numbers A_e, with e representing indexes: property, injury, and death are defined as follows:

$$A_e = 365.DTV.s.\theta_e(I_4).\psi, \tag{1.8}$$

where, DTV is daily traffic volume; s is track/section length; $\theta_e(I_4)$ is condition state dependent factor for e; ψ is correction factor for accident rate.

Noise cost K_{noise} is defined as:

$$K_{noise} = p.K_{dBA}.L_{eq}, \tag{1.9}$$

where, p is number of affected people; K_{dBA} is unit cost per dBA per person; L_{eq} is average noise/sound level.

Pollution cost is basically cost due to increasing of particle emission, which is estimated by using following equation.

$$\begin{aligned} K_{pollution} = {} & s.365.DTV.\mu.T_{\nu}^{LKW}/29.1.K_{LKW} \\ & + s.365.DTV.(1-\mu).\lambda.T_{\nu}^{PWD}/7.7K_{PW} \\ & + s.365.DTV.(1-\mu).(1-\lambda).T_{\nu}^{PWB}/8.6K_{PW} \\ & + K_M, \end{aligned} \tag{1.10}$$

where, μ is proportion of heavy traffic; T_{ν}^{LKW} is fuel consumption of truck; K_{LKW} is pollution cost due to truck; λ is proportion of diesel vehicle; T_{ν}^{PWD} is fuel consumption of diesel vehicle; K_{PW} is pollution cost due to diesel vehicle; T_{ν}^{PWB} is fuel consumption of gasoline vehicle; K_M is pollution cost due to gasoline vehicle.

Cost due to exhaustion of CO_2 is calculated with following equation.

$$\begin{aligned} K_{CO_2} = s.365.DTV.K_{CO_2}.[\mu.T_{\nu}^{LKW}/100.\gamma_D + (1-\mu).\lambda.T_{\nu}^{PWD}/100.\gamma_D \\ +(1-\mu).(1-\lambda).T_{\nu}^{PWB}/100.\gamma_B], \end{aligned} \tag{1.11}$$

where, K_{CO_2} is cost per ton of CO_2; γ_D is emission of CO_2 per litre of diesel; γ_B is emission of CO_2 per litre of gasoline.

Chapter 2

The Models

In this chapter, we describe in detail the formulation of seven mathematical models that are considered suitable for determining OISs for a road link. Some of the models are used to determine OIS for a single object but can also be extended to be suitable for use with road link level, which composed of multiple objects. The model which are described in this section are considered as preventive maintenance models and have been applied in practices (Gertsbakh, 1997; Adey and Hajdin, 2005; Lethanh, 2009; Adey et al., 2010). It is noted that the terminology "object" used in this section and for the rest of the document is referred to infrastructure object or civil infrastructure (e.g. road section, bridge, cultverts).

To hamornize notations used across models, we define a framework for management of a road link (Fig. 2.1). In Fig. 2.1, $l = (1, \cdots, L)$ is index of road link and L is total number of link of a network. In each link l, there are N_l total of objects $n_l = (1, \cdots, N_l)$. For a object n_l, several intervention type k_{n_l} can be selected.

2.1 Block replacement (BR) model

An object n is in operation period and being scheduled for planned intervention (PI) with a predetermined time T_n. It is assumed that whenever the life time of an object becomes T_n, the object is renewed. The renewal intervention expects to cost an amount of money C_n^{pi} (pi means planned intervention). Within any of the predetermined renewal time T_n, the object can be either in operational state (hereafter referred as state 1) and not operational state (hereafter referred as state 0). At state 0, i.e. collapse of bridge, or inadequate sercive level of road section, the object will eventually cost the owner to repair or renewal (hereafter refered as intervention) it to state 1. The cost to fix the

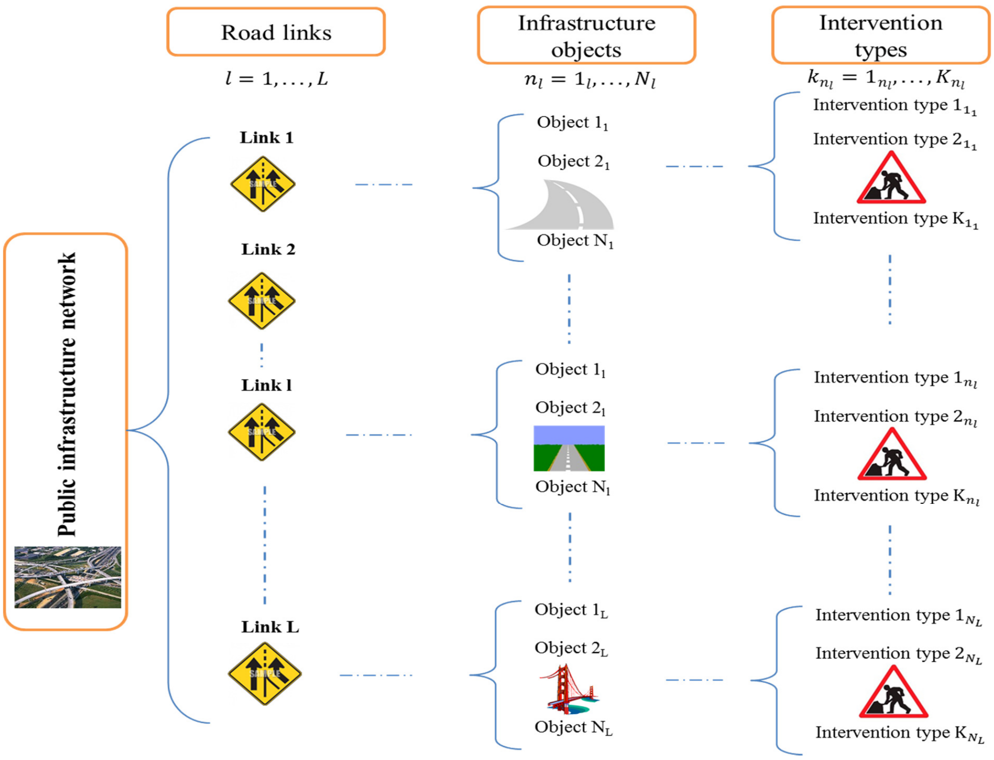


FIGURE 2.1: Road links intervention framework

object and make it as new or likely new is considered as unplanned intervention cost and being denoted as C_n^{ci} (ci means unplanned intervention). Since it if often the case that intervention time on each object n is significantly small in comparision with the service life of the object, the intervention time is thus considered as negligible in the model. Fig. 2.2 illustrates the scheme of block replacement model.

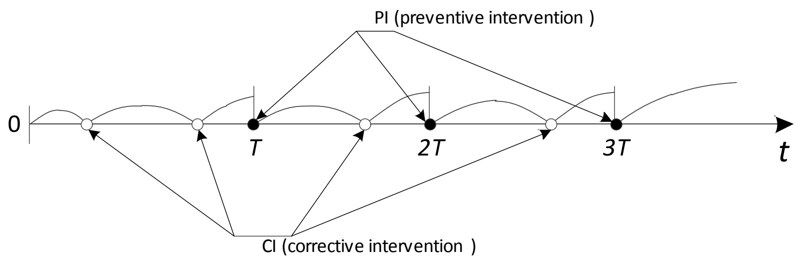


FIGURE 2.2: Block replacement intervention scheme-cost criterion

The failure probability of object n within a renewal period T_n is assumed to follow a distribution function $F_n(t)$. The mean cost over one renewal period T can be formulated as the summation of planned intervention cost C_n^{pi} and unplanned intervention cost C_n^{pi}.

$$E_n[R] = (C_n^{pi} + m_n(T_n) \cdot C_n^{ci}) \cdot exp(-\rho t) \tag{2.1}$$

Where, $m_n(T_n)$ is the mean number of unplanned intervention, which can be defined by using historical data or a suitable distribution function. As a result, the mean cost per unit time is defined as

$$\eta_n^A(T_n) = \frac{(C_n^{pi} + m_n(T_n) \cdot C_n^{ci}) \cdot exp(-\rho t)}{T_n} \tag{2.2}$$

Eqs. 2.1 and 2.2 involves only the cost of interventions and therefore this type of model is also referred as “Periodic (Block) Replacement-cost type criterion” (Gertsbakh, 1997).

Another type of BR model is called “Block replacement: availability criterion”, which is different from the BR-cost criterion type in that the time of both preventive and unplanned interventions are not negligible. Assuming that the time of unplanned intervention and planned intervention are t_n^{ci} and t_n^{pi}, respectively (Fig. 2.3). The operational time of the object is T. Thus, the mean duration of one renewal period is $T_n + m_n(T_n) \cdot t_n^{ci} + t_n^{pi}$. In this respect, the objective is trying to maximize the total operational time T as it is considered as reward. The average reward per unit of calendar time will eventually gives the “stationary availability”.

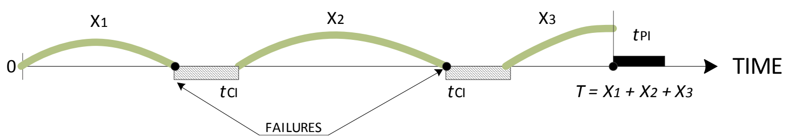


FIGURE 2.3: Block replacement intervention scheme-availability criterion

$$\eta_n^B(T_n) = \frac{T_n}{T_n + m_n(T_n) \cdot t_n^{ci} + t_n^{pi}} \tag{2.3}$$

2.2 Periodic group repair (PGR) model

The PGR model has its assumption that a road link composed of n objects is inspected in a predetermined interval of T, which is refered as inspection period. In the end of each period, each object is inspected by engineers. The intervention rules are then defined as if the condition of the object is beyond a critical level (or threshold), the object needs to be repaired/renewed so as its condition state becomes new or likely new again. The illustration of the periodic operation of n objects in a road link is given in Fig. 2.4.

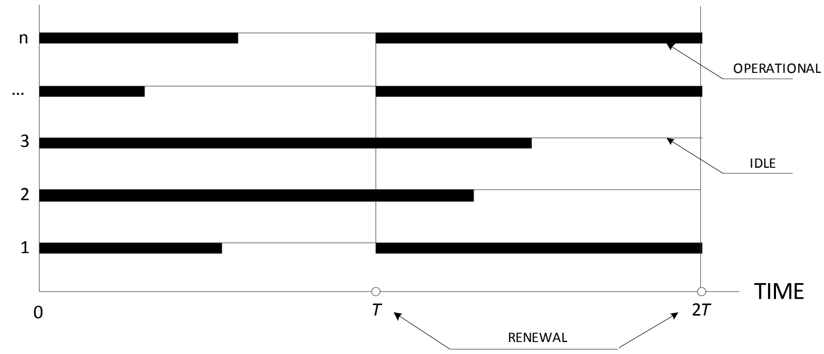


FIGURE 2.4: Periodic operation of n objects

On average, the cost of carrying out inspection is defined as

$$C_I = \sum_{i=1}^{N} c_i + c_s \tag{2.4}$$

where c_i is inspection cost and c_s is set up cost for the inspection.

The duration of intervention to renew the object if it is found in failure or critical state is denoted as t_n $(n = 1, \cdots, N)$

It is intuiative to state that the longer the operation time of the object, the more benefits the society (or stakeholders) can attain. Therefore, it is assumed that each object directly or indirectly provides to the society a benefit (or reward) of r_1 per unit of its operational time and a loss r_2 for each unit of its idle time (inspection time plus the repair and renewal time).

The objective of this model is to maximize the mean benefit per unit of calendar time given that the distribution of the operational time t_n for object n is $\tau_n \sim F(t_n)$. The total mean benefit $r(T)$ in a calendar time T is defined by following equation.

$$r(T) = \sum_{n=1}^{N} \left[\int_{0}^{T} \left\{ r_1^n + r_2^n (T - t_n) \right\} f(t_n) e^{-\rho \cdot t_n} dt_n + r_1^n T \left\{ 1 - F(T_n) \right\} \cdot e^{-\rho \cdot T} \right] \tag{2.5}$$

Where, $f(t_n)$ is the density function that the object n reaches critical state during an instant time period $[t_n, t_n + dt_n]$. ρ is discount factor. Thus, the mean benefit per unit of calendar time is defined as

$$\eta^C(T) = \frac{r(T) - C_I \cdot \exp(-\rho \cdot T)}{T} \tag{2.6}$$

Thus, the objective of the model is trying to find out the optimal time T^* [1].

$$T^* = \arg\max_{T} \left\{ \eta^C(T) \right\} \tag{2.7}$$

In order to solve Eq. (2.7), numerical solution must be developed and it is very much depending on the form of assumed distribution function $F(t_n)$. However, it can be noticed from the equation that if T is very small, there will be more inspections being carried out and therefore more inspection costs. On the other hand, if T is very large, then most of the time the objects are in idle state. There is a best time T^* that maximizes the benefits of operating the road link.

2.3 Periodic intervention with minimal repair (PIMR) model

In previous models, it is always assumed that when condition of an object reaches its critical state or failure state, renewal action is performed and completely bring the object back to original state. This assumption has a weakness that in reality, it is not always possible to renew the object. In stead of renewal, partial repair is preference. The partial repair does not guarantee to bring the condition of the object back to original state but it aims to reduce the rate of deterioration. Thus, after performing such an intervention, the deterioration rate of the object will likely has different rate than that of the original state.

There are two types of PIMR models, which are different because of the assumption in the deterioration rates.

2.3.1 PIMR-1: minimal repair with complete periodic renewal

In order to overcome the disadvantage of the previous described preventive models, the PIMR model in this section is formulated based on a more realistic assumption that the unplanned intervention eliminates the failures or critical state of the object but does not change the failure rates $\lambda_n(t)$ of the object n.

[1] in this report, the terminology optimal time, best time, optimal renewal time, optimal intervention time and optimal intervention return period are used interchangeably

Under minimal repair, the mean number of failures on a period $[0, T]$ is equal to

$$H_n(T) = \int_0^T \lambda_n(t)dt \tag{2.8}$$

and

$$\eta^D(T) = \frac{\sum_{n=1}^{N} [H_n(T) \cdot C_n^{ci} + C_n^{pi}] \cdot e^{-\rho \cdot T}}{T} \tag{2.9}$$

where, C_n^{pi} and C_n^{ci} are cost of planned intervention and unplanned intervention, respectively.

The hazard rate $\lambda_n(t)$ can be assumed to follow a distribution function.

2.3.2 PIMR-2: Minimal repair with partial renewal

The PIMR-2 model is different from the PIMR-1 model in the assumption of deterioration rate before and after intervention. Before the intervention, object n has a deterioration rate of $\lambda_n(t)$. After intervention, the deterioration rate of the object changes to $\lambda_n^*(t)$, which has a value ranging between $\lambda_n(0)$ and $\lambda_n(t)$ ($\lambda_n(0)$ is deterioration rate of the object in the first operational time).

In PIMR-2 model, it is assumed that in an interval $I_k = [T_{k-1}, T_k]$, the deterioration rate will be equal to the deterioration rate of previous interval I_{k-1} multiplied with a factor e_n^α (α takes a non-negative value and is considered as an unknown parameter). For instance, if the deterioration rate in period I_1 is $\lambda_n(t)$, then in period I_2, after performing partial renewal at time $t_n = T$, the deterioration rate will be $e^{\alpha_n} \cdot \lambda_n(t)$ (ranging between $e^{\alpha_n} \cdot \lambda_n(0)$ and $e^{\alpha_n} \cdot \lambda_n(T)$). In the third interval I_3, the deterioration rate will vary between $e^{2\alpha_n} \cdot \lambda_n(0)$ and $e^{2\alpha_n} \cdot \lambda_n(T)$) and so on. This implies that the mean number of failures of object n in interval I_1 is $H_{n,1} = H_n(T)$, in I_2 is $H_{n,2} = e^{\alpha_n} \cdot H_n(T)$. In period I_k, the mean number of failures will be equal to

$$H_{n,k} = e^{(k-1) \cdot \alpha_n} H_n(T) \tag{2.10}$$

It is assumed further that after K partial renewals on object n the object should be undergone a complete renewal (e.g. after resurfacing top asphalt concrete layer several time, it is necessary to renew also the base course). The renewal intervention (planned intervention) brings the deterioration rate to its initial level $\lambda_n(0)$.

The total cost TC_n over a period of $K \cdot T$ period is the summation of minimal repair cost c_n^{min}, the partial unplanned intervention cost C_n^{ci} and the planned intervention cost (or renewal cost in the end of the period) C_n^{pi}.

$$TC_n = \sum_{k=1}^{K} c_n^{\min} H_n(T) e^{\alpha(k-1)} e^{-\rho T} + (K-1) C_n^{ci} e^{-\rho(K-1)T} + C_n^{pi} e^{-\rho KT} \tag{2.11}$$

Following equation is used to compute the cost per unit time.

$$\eta_n(K_n) = \frac{TC_n}{K_n T} \tag{2.12}$$

If assuming that T is given, then the objective is to find the optimal value of K^* which offers the minimal cost per unit time $\eta_n(K_n)$.

2.4 Age replacement (AR) model

2.4.1 The AR-1 model-cost type criterion

It is assumed that the object starts its operation at time $t_n = 0$. The life time of the object, which can be defined by a threshold or critical condition state, follows a distribution function $F_n(t)$. It is assumed with a rule that a predetermined time T_n is defined as time to replace or renew the object when its life time reaches the age T_n. However, in any arbitrary time τ_n within the period $[0, T_n]$, the object can be failed or reached its critical condition state with a density function $f_n(\tau)$. Regarding the time of failure τ_n and predetermined time T_n, whichever, intervention must be performed. As the time variable τ_n follows a probabilistic distribution, the objective of the work is to choose when is the best time to carry out intervention, another words, to choose $Z_n = min(\tau, T)$. Suffice it to say that the first renewal occurs after a random time Z_n, and therefore the inter-renewal period has mean, which can be expressed in following equation.

$$E(Z_n) = \int_0^{T_n} [1 - F_n(t)]dt \tag{2.13}$$

The mean cost during one renewal period is thus equal to $F_n(T) \cdot C_n^{ci} + [1 - F_n(T)] \cdot C_n^{pi}$. Thus, the mean cost per unit time is obtained

$$\eta_n^{age}(T) = \frac{\{F_n(T) \cdot C_n^{ci} + [1 - F(T)] \cdot C_n^{pi}\} \exp(-\rho \cdot T)}{E[Z_n]} \tag{2.14}$$

In age replacement model, once might interests in estimating the mean time to failure $E(\tau_{n,f})$ of object n. In order to estimate that, it might be worldwide to consider the scheme of intervention historical path of the object or of objects with almost identical features. For instance, the object n starts its operation at time $t = 0$. On a random number N of occasions the age T is reached before failure occurs, and on the $(N+1)th$ cycle the failure takes place before T is reached. In such a case, the failure occurs at time $\tau_{n,f} = T \cdot N + \epsilon$, where the probability that $N = k$ is calculated as $P(N = k) = [1 - F(T)]^k F(T)$, $k \geq 1$, and $E[\epsilon]$ lies in $[0, T]$. Consequently, it is obvious to obtain $E[N] = [1 - F(T)]/F(T)$ and therefore the bounds on the mean time to failure satisfied following condition (Gertsbakh, 1997).

$$\frac{T[1 - F(T)]}{F(T)} < E[\tau_{n,f}] < \frac{T}{F(T)} \tag{2.15}$$

2.4.2 The AR-2 model-Availability type criterion

In the availability type criterion of the AR model, in stead of looking into the cost, time is considered for interventions (noted that in AR-1 model, intervention time is negligible). This type of consideration is similar to the model described in Eq. (2.3) in section 2.1. With the availability type criterio AR model, the discount factor ρ is therefore not considered.

In the AR-2 model, it is assumed that the planned intervention time and the unplanned intervention time are t_n^{pi} and t_n^{ci}, respectively. Each of the intervention time has its defined probability distribution. One renewal period of an object n will be either equal to $X_n = t_n + t_n^{ci}$, if the object reaches critical state in the interval $[t_n, t_n + dt]$, $t_n \leq T_n$, which occurs with probability $f_n(t)dt$, or to $X_n = T_n + t_n^{pi}$, if the life time of the object becomes T_n without failure, which happens with probability $1 - F_n(t)$. Thus, the mean value of X_n is defined as

$$E\left[X_n\right] = \int_0^{T_n} \left[1 - F_n(t)\right] dt + t_n^{ci} \cdot F_n(T) + t_n^{pi} \cdot \left[1 - F_n(T)\right] \tag{2.16}$$

If the operational time is considered as reward of operating the object, then it is important to look at the mean reward per unit time, which is regarded also as the stationary availability of operating the object.

$$\eta_n^F(T) = \frac{\int_0^{T_n} \left[1 - F_n(t)\right] dt}{E\left[X_n\right]} \tag{2.17}$$

The objective is then to maximize the value of $\eta_n^F(T)$ by finding the optimal value of T^*.

$$T^* = \arg\max_T \left\{\eta^F(T)\right\} \tag{2.18}$$

2.5 The Markov model with hazard risk (MAMOHA)

2.5.1 Deterioration part of the MAMOHA model

Markov model has been widely used in infrastructure management, especially for bridge management system (BMS) and pavement management system (PMS). In Markov model, it is important to define the matrix of Markov transition probability (m.t.p) p_{ij}, $i, j = 1, \cdots I$, (I is absorbing condition state). The transition probability from condition state i to state j is expressible by means of conditional probability. For visualization of the deterioration process, Fig. 2.5 is referred.

$$Prob[h(\tau_B) = j \quad | \quad h(\tau_A) = i] = p_{ij} \tag{2.19}$$

where τ_A and τ_B are considered as inspectime time. In cadinal form, the m.t.p can be written as

$$p_{ij} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1I} \\ 0 & p_{22} & \cdots & p_{2I} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \tag{2.20}$$

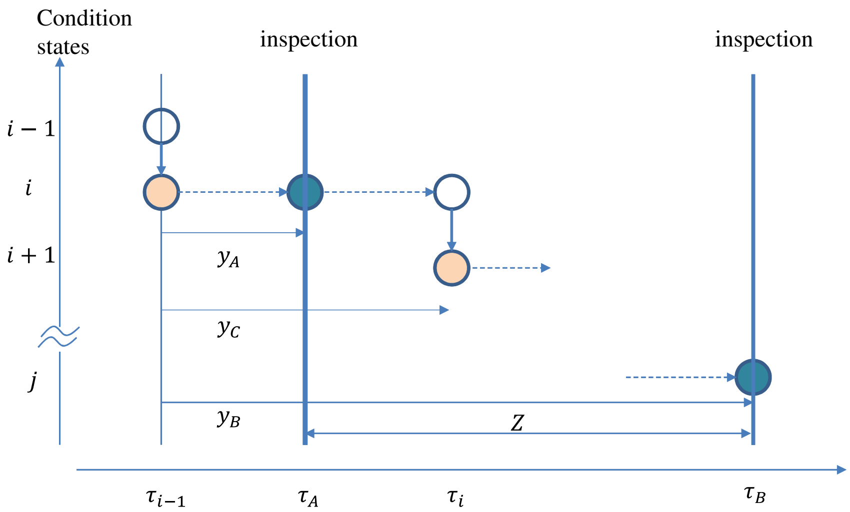


FIGURE 2.5: Manifest deterioration and inspection times

It is noted that the m.t.p defined in Eq. (2.20) is used to represent the manifest deterioration process. To estimate the m.t.p from inspection data, one of the best mode can be used is of Tsuda et al. (2006). The explicit form of estimating the m.t.p in the research of Tsuda et al. (2006) is summarized as follows

$$p_{ij}(z) = \sum_{k=i}^{j} \prod_{m=i}^{k-1} \frac{\theta_m}{\theta_m - \theta_k} \prod_{m=k}^{j-1} \frac{\theta_m}{\theta_{m+1} - \theta_k} \exp(-\theta_k z) \tag{2.21}$$

where, θ_i is hazard rate of conditions state i. Functional form of θ_i can be defined through the characteristic variable $x^{\,k}$ and unknown parameter $\beta_i = (\beta_{i,1}, \cdots, \beta_{i,M})$ (M is number of characteristic variables and $k(k = 1, \cdots K)$ is index of inspection data)in following equation

$$\theta_i^k = f(x^{\,k} : \beta_i) \tag{2.22}$$

Assuming that the m.t.p of each object n is available, the next important step is to define the m.t.p that considers both manifest deterioration process and latent deterioration process [2].

The latent process might trigger faster transition among condition states in the manifest process. In addition, it can result in certain damages on the civil infrastructure that is not explicitly defined by using condition states of the manifest process. For instance, if condition state $i = 5$ is considered as absorbing states of a road section, it could mean that the value of roughness index or percentage of surface cracks have reach to certain level that requires major repair, but do not necessary mean the road section is no longer function. In another words, the road section has not failed its functionality.

It is necessary to define additional condition states or damage level, which can account for the states of a civil infrastructure when it is in critical states that exposes extremely high risks (or impacts) to society. An example of such state is failure states, where the civil structure collapses due to ground shaking triggered by a high magnitude earthquake.

One possible way to overcome the limitation is by introducing an additional discrete scale of states, which not only encompasses the condition states described in manifest process but also the new condition states representing the higher damage level to absolutely failure state. Let denote damage level as $l = (1, \cdots, L)$, where 1 means the smallest damage state and L is absolute failure states. It is important to note that the occurrence of l is assumed only when having natural hazards. Under consideration of natural hazard, within a specific time interval, the actual m.t.p is no longer a manifest m.t.p alone (Eq. (2.21)), but include also any possible transition from each condition state i to damage level l. Thus, the dimension of the new m.t.p increase from $I \times I$ to $(I + L) \times (I + L)$, which can be represented as follows:

$$Q = q_{ij} = \left[\begin{array}{cccc|cccc} p_{11} & p_{12} & \cdots & p_{1I} & e^p_{11} & e^p_{12} & \cdots & e^p_{1L} \\ 0 & p_{22} & \cdots & p_{2I} & e^p_{21} & e^p_{22} & \cdots & e^p_{2L} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & p_{11} & e^p_{I1} & e^p_{I2} & \cdots & e^p_{IL} \\ \hline 0 & 0 & \cdots & 0 & e_{11} & e_{12} & \cdots & e_{1L} \\ 0 & 0 & \cdots & 0 & 0 & e_{22} & \cdots & e_{2L} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & \cdots & 1 \end{array}\right] \tag{2.23}$$

[2]latent deterioration is process caused by sudden occurrence of natural hazards (e.g. earthquakes and avalanches) and likely leads the object to failure state

Where e_{il}^{p} is transition probability from condition state i to damage level l. The sign p indicates the changes of transition probability from manifest process to latent process. The transition probability e_{lm} appears in the third quadrant reflects only the transition probability among the damage level $l, m = (1, \cdots, L)$.

Eq. (2.23) represents the m.t.p under the assumption that no intervention has been carried out. As a matter of fact, the cumulative transition probability with respect to a condition state i to the failure state L must be equal to 1.

$$\sum_{i=1}^{I} (p_{ij} + e_{il}^{p}) = 1 \tag{2.24}$$

However, this condition is conflict with condition in Eq. (2.21) under the manifest m.t.p, where the summation of properties in the row of the m.t.p (first quadrant of Eq. (2.24)) also equal to 1. The condition of Eq. (2.21) will be true if we ignore the latent process. In another words, $e_{lm} = 0$. Theoretically, we can still use the same methodology of Tsuda et al. (2006) estimate the m.t.p of Eq. (2.23). In such a case, we need to consider the occurrences of natural hazards as one of observable characteristic variables in Eq. (2.22). However, it is impossible to process such data as natural hazards such as earthquake rarely happen (extreme distribution) and its consequences (damage level) is not always well documented like condition states in the manifest process. Therefore, it is necessary to adjust the m.t.p p_{ij} based on the given transition probability concerning the damage states e_{lm} and its own m.t.p obtained from the manifest process. In order to estimate the m.t.p Q (Eq. (2.23)), three steps of estimation are required.

- Step 1: Estimate the m.t.p p_{ij} of manifest process based on monitoring data (Eq. (2.21)).
- Step 2: Estimate the transition probability e_{lm} concerning the damage states from condition states of manifest process.
- Step 3: Adjust the m.t.p p_{ij} so as to satisfy the condition in Eq. (2.24).

In this report, we assume that the transition prob-ability e_{lm} can be estimated from the fragility curve, which considers all possible risks due to latent process. The concept of deriving the risk can be referred to study of Mayet and Madanat (2002) for the case of earthquake, and Graf et al. (2009) for the other hazards. After having the values of e_{lm}, the values of p_{ij} in the first quadrant of matrix Q (Eq. (2.23) will be proportionally adjusted

2.5.2 Strategy evaluation part of the MAMOHA model

Given the developed m.t.p in subsection 2.5.1, an intervention model can be constructed for decision making. In this subsection, we present a linear optimization model. The model is developed in favor of the model of Mayet and Madanat (2002), which was published nearly a decade ago. In the cited paper, the author developed an optimization model, which considers the seismic incurred by earthquake events. However, there is a limitation of the model that discussed only for the case of single facility (a bridge). The author argues that it can be used for network management under the assumption of homogeneity in bridge characteristics. In our paper, we apply the same structure of the cited model, but introduce multiple objects in optimization model and each object has different discrete scale of condition states, and differences probability of going to damage or failure states. The structure of the model is given as:

- **Objective function**

$$MIN \sum_{n=1}^{N} \sum_{a_n=1}^{A_n} \sum_{i_n}^{I_n+L_n} \pi_{n,a_n,i_n} \cdot S_{n,a_n,i_n} \tag{2.25}$$

where,
$n = (1, \cdots, N)$: are objects in the system (e.g. road link)
$a_n = (1, \cdots, A_n)$: are intervention actions on object n.
$i_n, j_n = (1, \cdots, I_n + L_n)$: are running indexes of object n (if $i_n = (1, \cdots, I_n)$ then i_n is condition states of manifest deterioration), (if $i_n = (I_n + 1, \cdots, I_n + L_n)$ then i_n is damage level due to latent deterioration).
π_{n,a_n,i_n}: are state transition probability of object n, receiving action a_n on condition state i_n. within one time transition, which is also the variables of the models.
S_{n,a_n,i_n}: Total social cost incurred to different stakeholders under intervention action a_n on state i_n, of object n.

- **Constraints**

+ Total of social cost

$$S_{n,a_n,i_n} = \sum_{s=1}^{S} c^s_{n,a_n,i_n} \tag{2.26}$$

s is index of stakeholders (owner, users, directly affected public, indirectly affected public), c^s_{n,a_n,i_n} is incurred cost from object n to stakeholder s by per-forming intervention action a_n on state i_n.

+ Non-negative constraint

$$\pi_{n,a_n,i_n} \geq 0, \forall \text{n}, \forall a_n, \forall i_n \tag{2.27}$$

+ Balance constraint

$$\sum_{a_n=1}^{A_n} \sum_{i_n=1}^{I_n+L_n} \pi_{n,a_n,i_n} \cdot Q_{n,a_n,i_n,j_n} = \sum_{i_n=1}^{I_n+L_n} \pi_{n,a_n,j_n} \tag{2.28}$$

+ Impact constraint

$$\sum_{n=1}^{N} \frac{1}{1-E_n} \sum_{a_n=1}^{A_n} \sum_{i_n=1}^{I_n} \pi_{n,a_n,i_n} c^s_{n,a_n,i_n} \leq B^s \tag{2.29}$$

B^s is maximum (or limit) of impact incurred to stakeholders s (e.g. owner's annual budget con-straint).

It is noted that the running index in Eq. (2.29) is only up to absorbing state . This is due to the fact that intervention costs on damage states should be used from emergency fund rather than annual budget (Mayet and Madanat, 2002).

2.6 Semi Markov (SM) model

This section describes a deterioration-intervention model followed the semi-Markov chain process. And therefore, the name of the model is semi Markov (SM) model. The model was proposed by Gertsbakh (1997).

It is assumed that the transition in the Markove model (section 2.5) takes place at equal time interval $t = 1, 2, 3, ...$ One can think of that after the condition of the object enter state i, the Markov chain is staying in state i exactly one unit of time and then move to state j.

In SM model, the interval between such transition is randomly distributed. And also, the random transition is not dependent on the past trajectory of the object, in another words, it only depends on the present state. We use the same denotation of condition state $i, j = 1, \cdots, I$ in Markov chain for the SM model. It is assumed that at time $t = 0$, the object is in condition state i. As the transition follows Markov chain, in the next time, the object is in condition state j with the m.t.p p_{ij}. Noted that the index n concerning the number of object is omitted for ease of mathematical expression. We denote τ_{ij} as the time that the object is in condition state i and becomes j and its has a distribution defined as

$$Pro\,(\tau_{ij} \leq t|transitioni \rightarrow j) = F_{ij}(t) \tag{2.30}$$

The trajectory of the SM model can be described as follows: take the initial state i, choose randomly the next state according to the distribution P_{ik}, $k = 1, \cdots, I$. Assuming that the next state is s, then it is understood that the time of staying in state i before moving to state s is $\tau_{is} \approx F_{is}(t)$. The limiting probability Q_j of state j can be defined as

$$Q_j = \lim_{t \to \infty} P(\zeta_t = j) \tag{2.31}$$

where ζ_t is representation of the semi Markov process. In fact, Q_j can be expressed as the long-run proportion of time which the SM spends on state j.

$$Q_j = \lim_{t \to \infty} \frac{time\ in\ j\ on\ [0, t]}{t} \tag{2.32}$$

Denote L_{jj} as the first-passage (return) time from state j to state j. The mean one-step transition time v_i for state i is defined as

$$v_i = \sum_{j=1}^{I} p_{ij} \int_0^\infty t dF_{ij}(t) \tag{2.33}$$

According to Gertsbakh (1997), following conditions hold true.

$$Q_j = \frac{\pi_j v_j}{\sum\limits_{i=1}^{I} \pi_j v_j} \tag{2.34}$$

$$L_{jj} = \frac{\sum\limits_{i=1}^{I} \pi_j v_j}{\pi_j} \tag{2.35}$$

Now, considering the reward or costs associated with the transitions in the semi Markov process. During the transition time τ_{ij}, an amount of reward $\psi_{ij}(\tau_{ij})$ is accumulated. Then, we can define the average ward ω_i for one-step transition from i by averaging $\psi_{ij}(t)$ over all possible destination j.

$$\omega_i = \sum_{j=1}^{I} p_{ij} \int\limits_0^\infty \psi_{ij}(t) dF_{ij}(t) \tag{2.36}$$

and thus, the long-run mean reward per unit time can be defined

$$g = \frac{\sum\limits_{i=1}^{I} \pi_i \omega_i}{\sum\limits_{i=1}^{I} \pi_i v_i} \tag{2.37}$$

Chapter 3

Empirical Analysis

3.1 Example Objects

For the empirical analysis, a 760 m long stretch of the A19 Cantonal Road near Grengiols, Switzerland is regarded which consists of 11 infrastructure objects (bridges: blue, roads: yellow). This road link is narrowed and located in hilly condition. If intervention of any object on the link, it is likely that the entire link will be closed for traffic. Cars and trucks might have to be detoured to a small road (highlighted in red in Figure 3.1). The detour road has a relatively length of 800 m length. However, it is much narrower in comparison with the road link under intervention, and therefore, a considerable amount of extra delay time could be incurred by drivers.

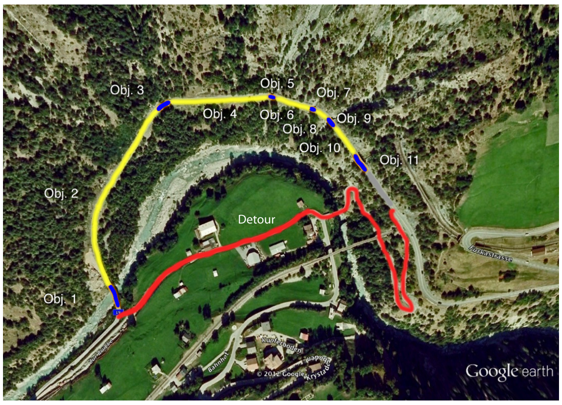


FIGURE 3.1: A19 aerial image

Table 3.1: Infrastructure objects and intervention strategies.

Objects	Name	Description	Width (m)	Length (m)
1	Bridge *Neue Kupferbodenbrücke*	Steel-concrete hybrid	9.6	85
2	Bridge over *Spielbach*	Reinforced concrete	6.5	25
3	Bridge *Lehnenbrücke Grengiols*	Reinforced concrete	6.5	25
4	Road section 1	Asphalt concrete	5.7	290
5	Road section 2	Asphalt concrete	5.7	160
6	Road section 3	Asphalt concrete	5.7	45
7	Road section 4	Asphalt concrete	5.7	20
8	Road section 5	Asphalt concrete	5.7	65
9	Culvert *Bader 1*	Reinforced concrete	6.5	10
10	Culvert *Bader 2*	Reinforced concrete	6.5	10
11	Culvert *Bader 3*	Reinforced concrete	6.5	25

In order to apply the proposed models in the case of road link in Cantonal Wallis, Switzerland. It is important to estimate values of impacts (or cost) incurred by stakeholders and deterioration parameters of the objects based on relevant historical information and performance of the objects over the past operational period.

In each of the following sections, we present the input values of impacts used for each proposed model. Input values such as preventive intervention cost, corrective intervention cost, deterioration parameters of each object are calculated based on historical information.

3.2 Description of the empirical example

3.2.1 Condition states and Deterioration

In order to apply the proposed models in the real case, it is important from the outset to define the range of condition states of each object. The object can be in a simple 2 condition states (or binary state) or multiple condition states. For the case of BR, PGR, PIMR, and AR models, physical condition of each object is necessarily to be in two condition states $CS1$ and $CS2$ ($CS1$ can be though of fully operational state, while $CS2$ is regarded as non-full operational state). The representation of the two condition state can be interpreted from Fig. 3.2.

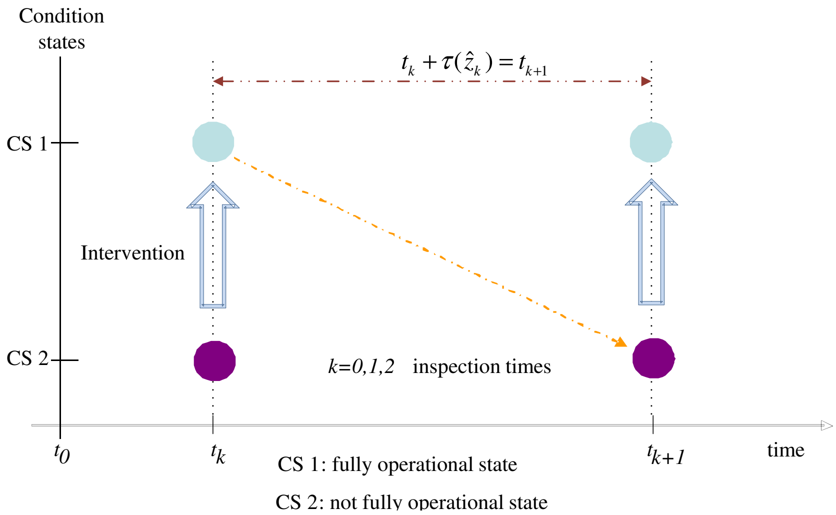


FIGURE 3.2: Condition state definition, deterioration and intervention

In the figures, CS 1 can be thought of condition state that the object is in the state that can provide adequate level of service, whilst, CS 2 is regarded as when the object cannot provide adequate level of service. When the object is found to be in CS 2, intervention action shall be executed in order to bring it back to CS 1.

In order to relate CS 1 and CS 2 to the physical changes (or deterioration) of the objects, it is necessary to define the a range of values concerning a typical performance indicator of the object. The performance indicator is the one that can be measured through inspection data. For instance, in PMS, roughness is often used as performance indicator. Overtime, due to deterioration, roughness increases in its value. At some certain value of roughness, i.e, 100 mm/m, the road section could be considered as heavily damage and it is recommended to perform resurfacing so that the riding comfort of drivers can be assured. The performance indicator can also be defined as a composite or weighted index, which is estimated based on several performance indicator such as the Pavement Service Index (PSI), which is commonly used in the America (Shahin, 2005).

In the case of Swiss Cantonal roads, an individual I-value or a composite index defined by means of several I-values can be used. According to the definition of aggregate performance index shown in Table 1.2 of Chapter 1, three critical levels (states) of road sections and bridges are defined to represent CS 2 in this study (Table 1.2 and Table 1.3). For example, if value of any I-values is within the range $[0, 2]$, the road sections are considered in CS 1, beyond that range, the road sections are considered in CS 2 $(I \geq 2)$.

Table 3.2: Condition states and critical levels

Obj.	Name	Critical levels (CS)		
		1	2	3
1	Bridge *Neue Kupferbodenbrücke*	I > 2.0	I > 3.0	I > 4.0
2	Bridge over *Spielbach*	I > 2.0	I > 3.0	I > 4.0
3	Bridge *Lehnenbrucke Grengiols*	I > 2.0	I > 3.0	I > 4.0
4	Road section 1	I > 2.0	I > 3.0	I > 4.0
5	Road section 2	I > 2.0	I > 3.0	I > 4.0
6	Road section 3	I > 2.0	I > 3.0	I > 4.0
7	Road section 4	I > 2.0	I > 3.0	I > 4.0
8	Road section 5	I > 2.0	I > 3.0	I > 4.0
9	Culvert *Bader 1*	I > 2.0	I > 3.0	I > 4.0
10	Culvert *Bader 2*	I > 2.0	I > 3.0	I > 4.0
11	Culvert *Bader 3*	I > 2.0	I > 3.0	I > 4.0

With the model using two condition state $CS1$ and $CS2$, one of best fitted model for deterioration prediction is Weibull distribution (Kobayashi et al., 2010; Lethanh and Adey, 2012). The Weibull analysis represents the memory of how object has been in each condition state over time. Given the fact that, nowadays, inspection data on object is accumulated year by year, the appropriateness in the use of probabilistic Weibull analysis on two condition states system can be assured. For the rest of this report, Weibull analysis will be used for the model with two condition state. Following functions describe the hazard function, probability density function, and cumulative distribution function of Weibull distribution.

$$\lambda(\tau) = \alpha m \tau^{m-1}, \tag{3.1}$$

$$f(\tau) = \alpha m \tau^{m-1} \exp(-(\alpha\tau)^m), \tag{3.2}$$

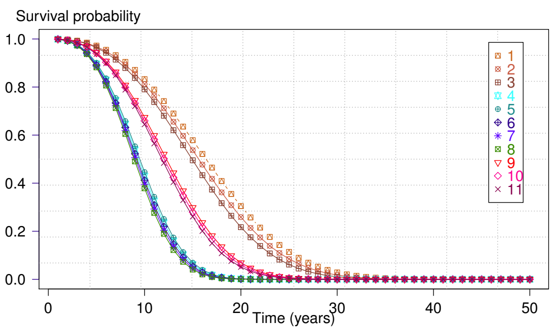
$$\tilde{F}(\tau) = \exp(-(\alpha\tau)^m). \tag{3.3}$$

It is note that it is up to the decision makers to define the critical levels that can be used for the analysis. Also, at each critical level, it requires to define the values of model's parameters. Following table gives an overview on the Weibull-parameters of the 11 different objects. Values of Weibull parameters α and m shown in the table are assumed to be estimated based on the critical levels defined in Table 3.2 and the concerning historical data recorded as results of inspection activities.

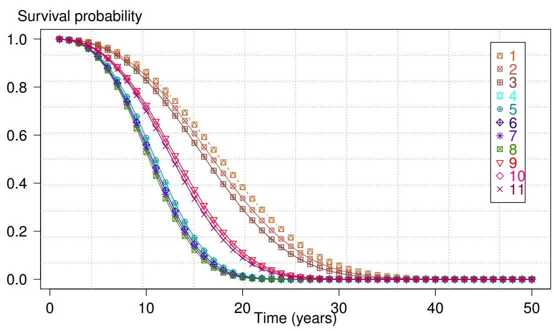
TABLE 3.3: Weibull parameters for all 11 different objects for 3 critical levels

Object	Critical levels					
	1		2		3	
	α	m	α	m	α	m
1	0.0533	2.70	0.0492	2.70	0.0410	2.70
2	0.0559	2.70	0.0516	2.70	0.0430	2.70
3	0.0585	2.70	0.0540	2.70	0.0450	2.70
4	0.0945	2.95	0.0819	2.95	0.0630	2.95
5	0.0930	2.95	0.0806	2.95	0.0620	2.95
6	0.0960	2.95	0.0832	2.95	0.0640	2.95
7	0.0975	2.95	0.0845	2.95	0.0650	2.95
8	0.0990	2.95	0.0858	2.95	0.0660	2.95
9	0.0714	2.76	0.0663	2.76	0.0510	2.76
10	0.0728	2.76	0.0676	2.76	0.0520	2.76
11	0.0742	2.76	0.0689	2.76	0.0530	2.76

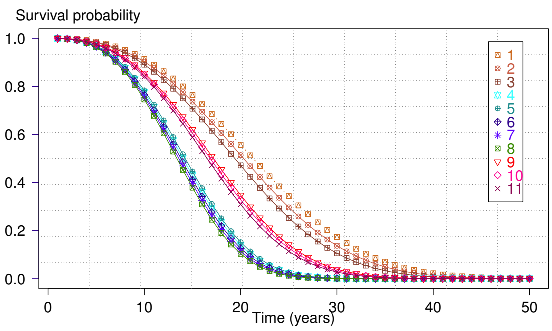
Values of model's parameters can be used to plot the deterioration curves that represent the evolution of survival probability over time under respective critical levels. Figure 3.3



(a)-critical level 1



(b)-critical level 2



(c)-critical level 3

FIGURE 3.3: Deterioration curves (Weibull distribution)

presents 3 plots of deterioration curves correponding to 3 critical levels defined in Table

3.3. The curves represent the gradual decreassing of survival probability over time. In each plot, there are three different groups of objects. The first group is concrete bridges (three curves in upper part of the plot), the second group is for road sections (5 curves in lower part of the plot), and the third group is for culverts (3 curves in the middle). If the conditions of objects are classified in critical level 1, durations of the objects staying in condition state 1 are relatively 30, 15, and 25 years for bridges, roads, and culverts, respectively. While, they are 40, 20, and 30 years for critical level 2 and 50, 25, and 35 years for critical level 3.

If condition of each object is defined with more than 2 condition states, the Markov model can be used. For this example, it is assumed that a discrete scale of 5 condition states is used to model the deterioration of each object. The definition of condition states of each object is given in Table 3.4.

Table 3.4: Condition states vs. performance index ranges for roads

Condition state	I-values	Definition German	English translation
1	$[0; 1]$	gut	good
2	$(1; 2]$	mittel	medium
3	$(2; 3]$	ausreichend	sufficient
4	$(3; 4]$	kritisch	critical
5	$(4; 5]$	schlecht	bad

In order to have a relative and sound comparison between Markov model and other models using two condition states. It is necessary to estimate the Markov transition probability (m.t.p) for each object. Using the model developed by Tsuda et al. (2006), the m.t.p of each object is estimated (shown in Tables 3.5, 3.6, and Table 3.7). The hazard rates θ_i and the duration of transition in each condition state are also presented in the tables.

Table 3.5: Markov transition probability, deterioration rate, duration (bridges)

Objects	Condition	Condition states					Hazard rate	Duration
(Bridges)	states	1	2	3	4	5	θ_i	(years)
1	1	0.84951	0.14587	0.00451	0.00011	0.00000	0.1631	6.13
	2	0	0.94082	0.05710	0.00202	0.00006	0.0610	16.39
	3	0	0	0.93128	0.06577	0.00295	0.0712	14.04
	4	0	0	0	0.91631	0.08369	0.0874	11.44
	5	0	0	0	0	1	NA	
2	1	0.84696	0.14826	0.00466	0.00011	0.00000	0.1661	6.02
	2	0	0.93988	0.05795	0.00211	0.00006	0.0620	16.13
	3	0	0	0.92941	0.06753	0.00305	0.0732	13.66
	4	0	0	0	0.91576	0.08424	0.0880	11.36
	5	0	0	0	0	1	NA	
3	1	0.84366	0.15138	0.00484	0.00012	0.00000	0.1700	5.88
	2	0	0.93894	0.05888	0.00211	0.00006	0.0630	15.87
	3	0	0	0.93034	0.06660	0.00306	0.0722	13.85
	4	0	0	0	0.91448	0.08552	0.0894	11.19
	5	0	0	0	0	1	NA	

Table 3.6: Markov transition probability, deterioration rate, duration (roads)

Objects	Condition	Condition states					Hazard rate	Duration
(Roads)	states	1	2	3	4	5	θ_i	(years)
4	1	0.73118	0.25304	0.01514	0.00061	0.00003	0.3131	3.19
	2	0	0.89039	0.10311	0.00611	0.00040	0.1161	8.61
	3	0	0	0.88586	0.10389	0.01025	0.1212	8.25
	4	0	0	0	0.82911	0.17089	0.1874	5.34
	5	0	0	0	0	1	NA	
5	1	0.73853	0.24627	0.01459	0.00058	0.00003	0.3031	3.30
	2	0	0.89128	0.10234	0.00601	0.00038	0.1151	8.69
	3	0	0	0.88692	0.10313	0.00995	0.1200	8.33
	4	0	0	0	0.83244	0.16756	0.1834	5.45
	5	0	0	0	0	1	NA	
6	1	0.72542	0.25790	0.01598	0.00066	0.00003	0.3210	3.12
	2	0	0.88683	0.10630	0.00645	0.00041	0.1201	8.33
	3	0	0	0.88338	0.10624	0.01038	0.1240	8.06
	4	0	0	0	0.83077	0.16923	0.1854	5.39
	5	0	0	0	0	1	NA	
7	1	0.72108	0.26182	0.01633	0.00073	0.00004	0.327	3.06
	2	0	0.88595	0.10660	0.00700	0.00045	0.1211	8.26
	3	0	0	0.87459	0.11414	0.01127	0.134	7.46
	4	0	0	0	0.82936	0.17064	0.1871	5.34
	5	0	0	0	0	1	NA	
8	1	0.71821	0.26438	0.01662	0.00075	0.00004	0.3310	3.02
	2	0	0.88506	0.10732	0.00715	0.00047	0.1221	8.19
	3	0	0	0.87284	0.11561	0.01155	0.1360	7.35
	4	0	0	0	0.82770	0.17230	0.1891	5.29
	5	0	0	0	0	1	NA	

TABLE 3.7: Markov transition probability, deterioration rate, duration (culverts)

Objects (Culverts)	Condition states	Condition states 1	2	3	4	5	Hazard rate θ_i	Duration (years)
1	1	0.84282	0.14944	0.00749	0.00024	0.00001	0.1710	5.85
	2	0	0.90574	0.08971	0.00434	0.00020	0.0990	10.10
	3	0	0	0.90665	0.08727	0.00608	0.0980	10.20
	4	0	0	0	0.87459	0.12541	0.1340	7.46
	5	0	0	0	0	1	NA	
2	1	0.83946	0.15217	0.00810	0.00027	0.00001	0.1750	5.71
	2	0	0.90032	0.09482	0.00462	0.00023	0.1050	9.52
	3	0	0	0.90574	0.08755	0.00671	0.0990	10.10
	4	0	0	0	0.86329	0.13671	0.1470	6.80
	5	0	0	0	0	1	NA	
3	1	0.83694	0.15392	0.00882	0.00030	0.00001	0.1780	5.62
	2	0	0.89315	0.10143	0.00515	0.00027	0.1130	8.85
	3	0	0	0.90213	0.09068	0.00719	0.1030	9.71
	4	0	0	0	0.85899	0.14101	0.1520	6.58
	5	0	0	0	0	1	NA	

It is noted that the valuve of expected durations of transition in each condition state are estimated by inverting the value of deterioration rate θ_i. To illustrate the differences in term of deterioration, following deterioration curves were plotted. If we compare

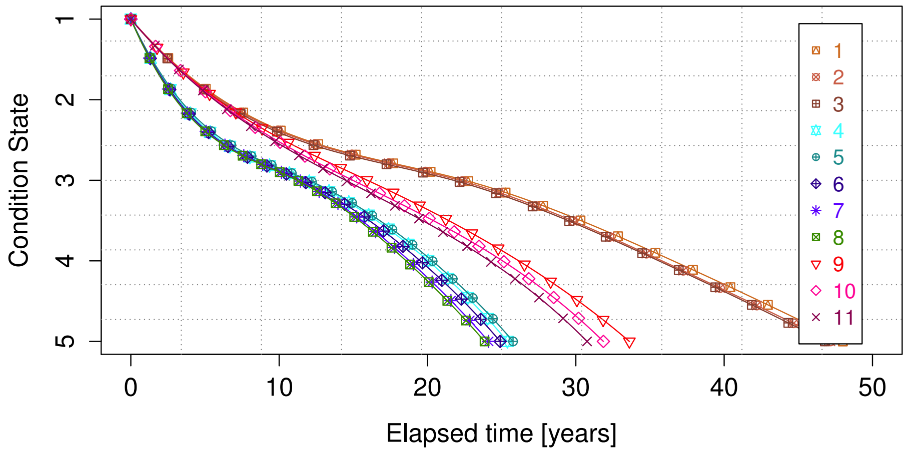


FIGURE 3.4: Deterioration curves (Markov)

the deterioration curves between Fig. 3.3 and 3.4, we can notice that relatively, same speed of deterioration can be assumed. However, a perfect fit is not possible because in the models using Weibull function for only two condition state, we oversimplify the condition states. The $CS1$ in Fig. 3.3 is somehow corresponding to a range of condition state from 1 to 4 in Markov model (Fig. 3.4). Fig. 3.3 presents the decrease of survival probability over time, while Fig.3.4 demonstrates the deterioration curves, which shows the duration of each condition state.

In a nutshell, again, it is emphasized that the overall service life of road sections and bridges are about 30 years and 50 years, respectively. These values are acceptable and realistic enough for the demonstration of the proposed model.

3.2.2 Intervention types and intervention strategies

The intervention types (ITs) for each object are defined according to critical levels. With 3 critical level, we introduce 3 different ITs, which are early repair, major repair, and renewal.

- IT 1 - Early repair: This strategy type is assumed when the condition of the object reaches critical level 1 in Weibull model and condition state 3 in Markov model. In IT 1, a corrective intervention is triggered at a very low level of damage. This keeps the amount of repair relatively low, however it increases the number of repairs. The trigger CS is a level of 3. For the road sections, IT 1 can be a combination of intervention actions such as: crack sealing and patching. For the bridge, IT 1 is something like crack sealing and patching for the top asphalt layers of the bridges, while replace concrete cover of damaged areas of the deck and girders without exposing to the steel frames.
- IT 2 - Major repair: This strategy type is assumed when the condition of the object reaches critical level 2 in Weibull model and condition state 4 in Markov model. In IS 1, a corrective Intervention is triggered at a medium level of damage. This increases the amount of repair in comparison to IT 1, however it decreases the number of repairs. The trigger CS is a level of 4. Example of IT 4 for the road sections can be a extensive combination of actions such as cracking sealing, patching, partial depth repair. For the bridge section, IT 2 can be a combination of cracking sealing, partial depth repair for the top asphalt layers of the bridges and replacing concrete covers in damage areas of decks and girders, making new handrails and drainage system.
- IT 3 - Renewal: This strategy type is assumed when the condition of the object reaches critical level 3 in Weibull model and condition state 5 in Markov model. In IT 3, a corrective intervention is triggered at a very high level of damage. This sets the amount of repair equal resurfacing for pavement section and rebuilding for bridge, however this means that the number of interventions is very low. The trigger CS is a level of 5.

The intervention strategies (ISs) will be the combination of intervention types with the bundle of objects. For instance, concrete bridge often has longer service life than road sections and therefore, it is expected that arrival of intervention on road section will come earlier than the bridge. However, if doing intervention on a road section alone in this year and doing intervention on bridge after a few years, it might be costly with regard to set up cost (e.g. bidding process, mobilization of resources, and interruption of traffic). It is therefore important to consider the possibility of grouping or bundling objects in a single intervention packages (hereinafter referred as intervention strategies). The investiaged intervention strategies (ISs) are further illustrated in following tables.

TABLE 3.8: Investigated intervention strategies

Critical level	ISs	Bridge			Road sections					Culverts		
		1	2	3	4	5	6	7	8	9	10	11
1	1	-	-	-	-	-	-	-	-	-	-	-
1	2	x	x	x	-	-	-	-	-	-	-	-
1	3	-	-	-	x	x	x	x	x	-	-	-
1	4	x	x	x	x	x	x	x	x	-	-	-
1	5	x	x	x	-	-	-	-	-	x	x	x
1	6	-	-	-	x	x	x	x	x	x	x	x
1	7	x	x	x	x	x	x	x	x	x	x	x
2	8	-	-	-	-	-	-	-	-	-	-	-
2	9	x	x	x	-	-	-	-	-	-	-	-
2	10	-	-	-	x	x	x	x	x	-	-	-
2	11	x	x	x	x	x	x	x	x	-	-	-
2	12	x	x	x	-	-	-	-	-	x	x	x
2	13	-	-	-	x	x	x	x	x	x	x	x
2	14	x	x	x	x	x	x	x	x	x	x	x
3	15	-	-	-	-	-	-	-	-	-	-	-
3	16	x	x	x	-	-	-	-	-	-	-	-
3	17	-	-	-	x	x	x	x	x	-	-	-
3	18	x	x	x	x	x	x	x	x	-	-	-
3	19	x	x	x	-	-	-	-	-	x	x	x
3	20	-	-	-	x	x	x	x	x	x	x	x
3	21	x	x	x	x	x	x	x	x	x	x	x

Table 3.8 shows 21 combinations of possible intervention strategies. The sign “x” infer the bundle of objects and the sign “-” infers no bundle of the objects. As a matter of fact, the combination of bundles will be exponentially grows together with the number of the object. Also, it is also possible to define the ISs based up on combination of three dimensions: the critical level of deterioration, the numbers of objects, and the bundle of object. However, for demonstration of the methodology, only 21 ISs are investigated.

3.2.3 Impact hierarchy and unit values of impact types

Under each IS, it is expected that various impact types would incur to different stakeholders. As previously discussed in section 1.3 of Chapter 1, impacts needs to be calculated taking into account of owner, users, and environment. In order to discuss such types of impacts, it is necessary to describe them in term of impact hierarchy or structure that would allows us to correctly measure and quantify them as well as to avoid double counting of the impacts.

In this research work, we employ the impact hierarchy developed by Adey et al. (2012). In the cited paper, the authors classified stakeholders into four basic groups: owner, users, directly affected public (DAP), and indirectly affected public (IAP). The definition of the stakeholders groups is described in Table 3.9.

TABLE 3.9: Stakeholder groups (adopted from Adey et al. (2012))

Stakeholder group	**Definition**	**Examples**
Owner	The persons who are responsible for decisions with respect to physically modifying the infrastructure	A federal road authority
Users	The persons who are using the roads	A driver and passengers of a vehicle on a road.
Directly affected public (DAP)	the persons who are in the vicinity of the road but are not using it	Persons in a house next to the road that hear vehicles driving on the road.
Indirectly affected public (IAP)	The persons who are not in the vicinity of the road but are affected by its use	Persons in a house far away from the road that do not hear vehicles driving on the road, but are affected by a changing climate due to the emissions produced by vehicles driving on the road.

Under each stakeholders group, the benefit hierarchy has several levels (or branches) representing impact types (e.g. Intervention cost consisting of labour, material, and equipment is impact type incurred by the owner. For the users, a typical impact type is vehicle operation cost that he/she must pay in using the road in a given particular condition states. The lists of impact types and the way to quantify them are discussed in the paper of Adey et al. (2012).

3.2.4 Unit values of impact types

According to Adey et al. (2012), unit values of impact types can be measured by historical records or by stakeholders willingness to pay.

In this section, the mean impact and time (hereafter referred as unit impact and unit time) incurred by each stakeholder under a particular IS are shown. The values of impacts and time are considered as a base or benchmark value for comparison and also for directly use to estimate the actual impacts and time incurred when performing intervention on each of the actual objects in the investigated road link.

The unit impact and unit time of carrying each of IS are estimated based on historical data and shown in following table 3.10.

TABLE 3.10: unit impact and time of ISs

Object type	IS 1		IS 2		IS 3	
	c	t	c	t	c	t
RC bridge	2'100	0.65	2'800	1.42	3'500	2.8
Asphalt road	25	0.35	35	0.76	45	1.5
Culvert	1'260	0.55	1'680	1.13	2'100	2.1

Note: c stands for impact in mu/m^2 and time in $hour/m^2$.

The unit impact incurred to stakeholders other than the owner is summarized in Table 3.11.

TABLE 3.11: Unit impact incurred by user, DAP, and IAP

Item	Stakeholders	Description	Unit	Value
1		Operation cost per passenger car, personal use	mu/hour	11
2	User	Operation cost per passenger car, professional use	mu/hour	38
3		Operation cost per heavy-weight vehicle or bus	mu/hour	75
4		Cost per accident	mu/Person	32'420
5		Cost per injured	mu/Person	241'140
6	DAP	Cost per deaths	mu/Casualty	3'181'900
7		Cost per accident	mu/Person	13'900
8		Cost per injured	mu/Person	60'280
9		Cost per deaths	mu/Casualty	561'510
10	IAP	Pollution cost per passenger car	mu/km	0.02
11		Pollution cost per heavy-weight vehicle or bus	mu/km	0.15
12		Pollution cost for construction	mu/$_{Owner}$ spent	0.01

3.2.5 Summary of impacts

The impacts incurred by the four types of stakeholders (Owner, Users, DAP, and IAP) under planned interventions and unplanned interventions are illustrated in Table 3.12, Table 3.13, and Table 3.14.

TABLE 3.12: Impacts under IS1 - Critical level 1 (x100 mu)

Object group	Objects name	Planned impact (pi)				Unplanned impact (ci)			
		Owner	User	DAP	IAP	Owner	User	DAP	IAP
Bridge	1	17,136	75.89	1.71	54.14	34,272	151.78	3.42	71.27
	2	3,413	22.32	0.50	40.41	6,825	44.64	1.01	43.82
	3	3,413	22.32	0.50	40.41	6,825	44.64	1.01	43.82
Road	4	413	258.91	5.84	37.41	744	466.05	10.51	37.74
	5	232	142.85	3.22	37.23	418	257.13	5.80	37.42
	6	64	40.18	0.91	37.06	115	72.32	1.63	37.11
	7	29	17.86	0.40	37.03	51	32.14	0.72	37.05
	8	93	58.03	1.31	37.09	167	104.46	2.35	37.17
Culvert	9	819	8.93	0.20	37.82	1,556	16.96	0.38	38.56
	10	819	8.93	0.20	37.82	1,556	16.96	0.38	38.56
	11	2,048	22.32	0.50	39.05	3,890	42.41	0.96	40.89

TABLE 3.13: Impacts under IS8 - Critical level 2 (x100 mu)

Object group	Objects name	Planned impact (pi)				Unplanned impact (ci)			
		Owner	User	DAP	IAP	Owner	User	DAP	IAP
Bridge	1	22,848	80.35	1.81	59.85	35,414	124.55	2.81	72.41
	2	4,550	23.63	0.53	41.55	7,053	36.63	0.83	44.05
	3	4,550	23.63	0.53	41.55	7,053	36.63	0.83	44.05
Road	4	579	274.14	6.18	37.58	752	356.39	8.03	37.75
	5	325	151.25	3.41	37.32	422	196.63	4.43	37.42
	6	90	42.54	0.96	37.09	117	55.30	1.25	37.12
	7	40	18.91	0.43	37.04	52	24.58	0.55	37.05
	8	130	61.45	1.39	37.13	169	79.88	1.80	37.17
Culvert	9	1,092	9.45	0.21	38.09	1,529	13.23	0.30	38.53
	10	1,092	9.45	0.21	38.09	1,529	13.23	0.30	38.53
	11	2,730	23.63	0.53	39.73	3,822	33.09	0.75	40.82

TABLE 3.14: Impacts under IS15 - Critical level 3 (x100 mu)

Object group	Objects name	Planned impact (pi)				Unplanned impact (ci)			
		Owner	User	DAP	IAP	Owner	User	DAP	IAP
Bridge	1	28,560	89.28	2.01	65.56	39,984	124.99	2.82	76.98
	2	5,688	26.26	0.59	42.69	7,963	36.76	0.83	44.96
	3	5,688	26.26	0.59	42.69	7,963	36.76	0.83	44.96
Road	4	744	304.61	6.87	37.74	1,190	487.37	10.99	38.19
	5	418	168.06	3.79	37.42	668	268.89	6.06	37.67
	6	115	47.27	1.07	37.11	185	75.63	1.70	37.18
	7	51	21.01	0.47	37.05	80	32.56	0.73	37.08
	8	167	68.27	1.54	37.17	267	109.24	2.46	37.27
Culvert	9	1,365	10.50	0.24	38.36	1,979	15.23	0.34	38.98
	10	1,365	10.50	0.24	38.36	1,979	15.23	0.34	38.98
	11	3,413	26.26	0.59	40.41	4,948	38.08	0.86	41.95

Values of impacts shown in Table 3.12, Table 3.13 and Table 3.14 were estimated for IS 1, IS 8, and IS 15, which does not consider bundling of objects. As can be seen from the table, for the bridges and culverts, dominant impacts are mostly incurring to the owner. For the road sections, impacts incurred by users account for about 50% of the total impact. This is due to the fact that cost to resurface the road section is significantly less than the cost to repair the bridge, while the detour route is more or less the same for all objects.

It is assumed that under bundling strategies, impacts incurred by stakeholders will change proportionally to the length or area of the objects. For instance, if executing interventions on all three bridges within a period of time, an amount of X% (refer as reduction factor) of impacts will be either decreased or increased. In this research, following assumption of reduction factor maded for each bundle intervention strategy.

TABLE 3.15: Reduction of impact

Critical level	ISs	Bridge			Road sections					Culverts		
		1	2	3	4	5	6	7	8	9	10	11
1	1	1	1	1	1	1	1	1	1	1	1	1
1	2	0.98	0.98	0.98	1	1	1	1	1	1	1	1
1	3	1	1	1	0.97	0.97	0.97	0.97	0.97	1	1	1
1	4	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	1	1	1
1	5	0.95	0.95	0.95	1	1	1	1	1	0.95	0.95	0.95
1	6	1	1	1	0.94	0.94	0.94	0.94	0.94	0.94	0.94	0.94
1	7	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93
2	8	1	1	1	1	1	1	1	1	1	1	1
2	9	0.97	0.97	0.97	1	1	1	1	1	1	1	1
2	10	1	1	1	0.96	0.96	0.96	0.96	0.96	1	1	1
2	11	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	1	1	1
2	12	0.94	0.94	0.94	1	1	1	1	1	0.94	0.94	0.94
2	13	1	1	1	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93
2	14	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
3	15	1	1	1	1	1	1	1	1	1	1	1
3	16	0.95	0.95	0.95	1	1	1	1	1	1	1	1
3	17	1	1	1	0.93	0.93	0.93	0.93	0.93	1	1	1
3	18	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	1	1	1
3	19	0.91	0.91	0.91	1	1	1	1	1	0.91	0.91	0.91
3	20	1	1	1	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
3	21	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90

Values in Table 3.15 is used to multiply with the values of impacts shown in Table 3.12, Table 3.13, and Table 3.14 gives the values of impact for other ISs. For instance, under IS2, as three briges are grouped for intervention, the impacts incurred by stakeholders by executing these 3 objects will be proportionally decreased by 5% (reduction factor is 0.95). This table is used as a simple example to show the effects of bundling strategies in different ways. In reality, it is necessary to estimate accurately the value of reduction factor for each IS and each stakeholders under both planned intervention and unplanned intervention.

Chapter 4

Estimation Results

This section presents the estimation results for the target road link. The OIS for each object and the link under specific ISs are shown in the tables, respectively for each model. In addition, a brief comparison on several import aspects of the proposed models is highlighted.

4.1 The BR model

TABLE 4.1: Annual impact and optimal intervention time-BR model

ISs	Bridges			Road sections					Culverts			Annual Impact	Reduction
	1	2	3	4	5	6	7	8	9	10	11		
1	1,685	363	363	109	62	21	12	30	111	113	282	3,151	0
	16	15	15	10	10	10	11	10	12	12	12		
2	2,363	0	0	109	62	21	12	30	111	113	282	3,103	-48
	16	16	16	10	10	10	11	10	12	12	12		
3	1,685	363	363	227	0	0	0	0	111	113	282	3,144	-7
	16	15	15	10	10	10	10	10	12	12	12		
4	2,545	0	0	0	0	0	0	0	111	113	282	3,051	-100
	15	15	15	15	15	15	15	15	12	12	12		
5	2,770	0	0	109	62	21	12	30	0	0	0	3,003	-148
	15	15	15	10	10	10	11	10	15	15	15		
6	1,685	363	363	699	0	0	0	0	0	0	0	3,110	-41
	16	15	15	11	11	11	11	11	11	11	11		
7	2,933	0	0	0	0	0	0	0	0	0	0	2,933	-218
	15	15	15	15	15	15	15	15	15	15	15		
8	1,651	355	355	95	54	18	10	25	107	109	273	3,052	0
	22	21	21	14	15	14	15	14	17	16	16		
9	2,291	0	0	95	54	18	10	25	107	109	273	2,982	-70
	19	19	19	13	13	13	13	12	15	14	14		
10	1,651	355	355	193	0	0	0	0	107	109	273	3,044	-8
	19	18	18	13	13	13	13	13	15	14	14		
11	2,437	0	0	0	0	0	0	0	107	109	273	2,927	-125
	18	18	18	18	18	18	18	18	15	14	14		
12	2,677	0	0	95	54	18	10	25	0	0	0	2,878	-174
	18	18	18	13	13	13	13	12	18	18	18		
13	1,651	355	355	645	0	0	0	0	0	0	0	3,006	-46
	19	18	18	14	14	14	14	14	14	14	14		
14	2,808	0	0	0	0	0	0	0	0	0	0	2,808	-244
	18	18	18	18	18	18	18	18	18	18	18		
15	1,563	336	336	90	51	17	8	23	98	100	251	2,873	0
	29	27	27	18	19	18	20	18	23	22	22		
16	2,124	0	0	90	51	17	8	23	98	100	251	2,762	-111
	24	0	0	15	16	15	17	15	19	18	18		
17	1,563	336	336	176	0	0	0	0	98	100	251	2,860	-13
	24	23	23	15	15	15	15	15	19	18	18		
18	2,238	0	0	0	0	0	0	0	98	100	251	2,686	-187
	23	23	23	23	23	23	23	23	19	18	18		
19	2,443	0	0	90	51	17	8	23	0	0	0	2,632	-240
	23	23	23	15	16	15	17	15	23	23	23		
20	1,563	336	336	590	0	0	0	0	0	0	0	2,825	-48
	24	23	23	17	17	17	17	17	17	17	17		
21	2,592	0	0	0	0	0	0	0	0	0	0	2,592	-281
	22	22	22	22	22	22	22	22	22	22	22		

Estimation results on the optimal intervention return periods and annual impacts under respective ISs using BR model are shown in Table 4.1. The table is divided into 3 main parts, the first part shows the values of annual impacts on each object and its optimal intervention return period, for example, under IS-1, interventions on object 1 (the bridge) has annual impact of 1'685 mu and has optimal intervention return period of 16 years. The second part of the table shows the total annual impacts under each strategy. The total annual impacts are the sum of annual impacts incurred by executing interventions on each object. The third part of the table shows the comparison of annual impacts among ISs assuming that the reference strategies are IS-1, IS-8, and IS-15.

The reasons to use 3 reference strategies are mainly due to the fact that the physical conditions of each object can be assumed with 3 critical damage states (earlier discussed in Table 3.2), and thus, it is important at first to compare the differences in annual costs among different ISs using the same critical levels.

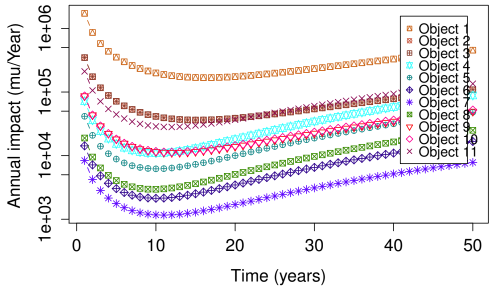
As can be seen from the table, among ISs from 1 to 7, reference strategy (IS-1) has the highest annual impact (3'151 mu) comparing to that of other ISs. The strategy has the lowest annual impacts is IS-7 (2'933 mu) with a reduction of 218 mu (about 7%) in comparison with the reference strategy. This results show the importance of execution of interventions simultaneously on the grouping of objects. The grouping of objects will likely reduce the set up cost during intervention period and eventually reduce the annual cost.

It is also realized that under the grouping of intervention, the optimal intervention return period become shorter for the bridges and longer for the road sections and culverts in comparison with no grouping intervention strategies. For example, under IS-1, object 1 and object 4 have optimal intervention return period of 16 and 10 years, respectively, while under IS-7, the optimal intervention return period of both objects are 15. Reasons behind this change are mainly due to the differences in deterioration processes. The bridges often has longer service life in comparison with that of the road sections and culverts. When combining them into a single intervention packages, mathematically, the optimal intervention return period shall be somewhere in between of the two periods under no grouping interventions.

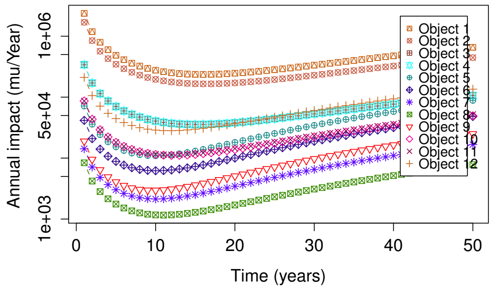
Similar findings and conclusions are realized for the comparison of ISs from 8 to 14 and from 15 to 21. However, it is important to see that under critical level 2 (ISs from 8 to 14), the annual impacts incurred keep decreasing for each object and thus the annual accumulative impacts are also decreased in comparison with that under critical level 1 (IS-1 to IS-7). The decreasing in annual impacts is also observable under critical level 3 (IS-15 to IS-21).

If managers consider only critical level 1 as the level to trigger intervention, it is obvious from the finding that the optimal IS is IS-7. Also, if managers consider the critical level 2 and 3, IS-14 and IS-21 are the optimal strategies, respectively. However, from the results, if managers compare all ISs, the optimal one will be IS-21 since it has the lowest annual impacts (2'592 mu). Taking IS-1 as reference strategy for comparison against IS-7, IS-14 and IS-21, the reductions in annual impacts are 218 mu, 343 mu, and 559 mu, respectively. This means that by choosing the IS-21, the benefits that stakeholders expect to have are 559 mu in comparison with IS-1.

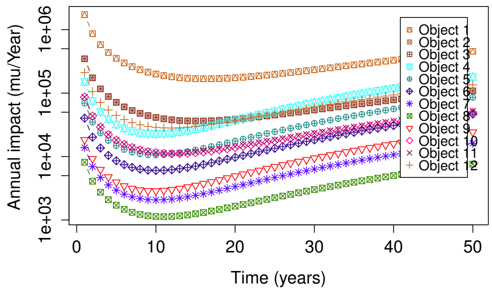
The impact curves corresponding to each object or a group of objects are given in Figs. 4.1, 4.2, and 4.3. The mimimum points of the curves show the optimal intervention return period on the horizontal axis and the annual impact on the vertical axis. It can be clearly seen from these figures that if the optimal intervention return period of a object is too short, it will incurs a considerable huge amount of impacts. These impacts will slowly go down if intervention time become longer, but it will goes up again if intervention time become too long. This is because if it is too long, there will be a risk for the object to be in adequate level of services and therefore the expected numbers of corrective interventions will increase and eventually cause the annual impacts to increase.



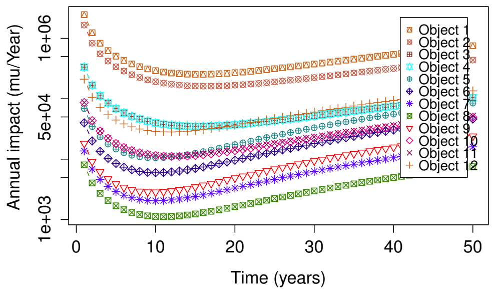
(a)-IS1



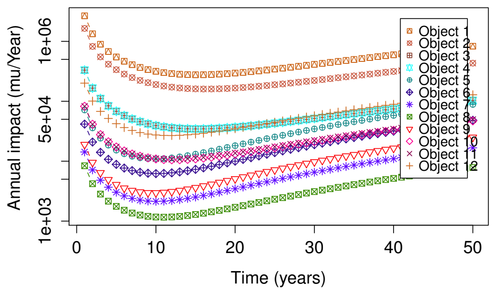
(b)-IS2



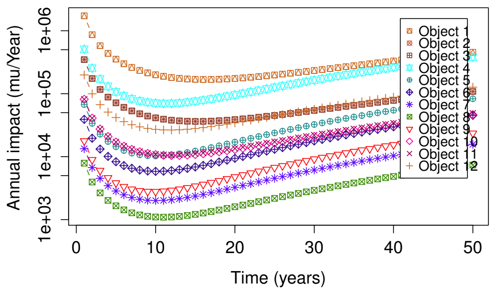
(c)-IS3



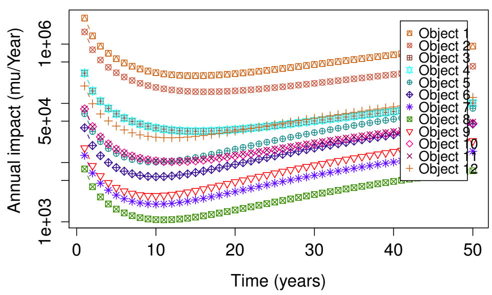
(d)-IS4



(e)-IS5

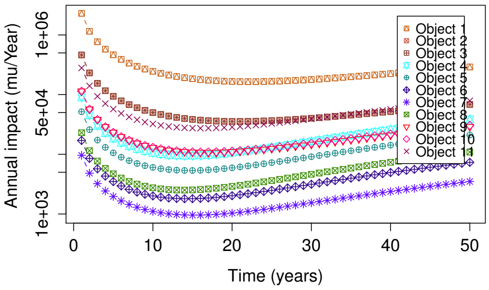


(f)-IS6

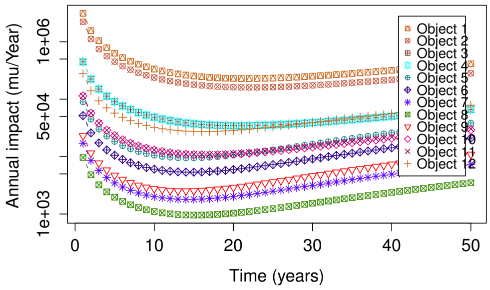


(g)-IS7

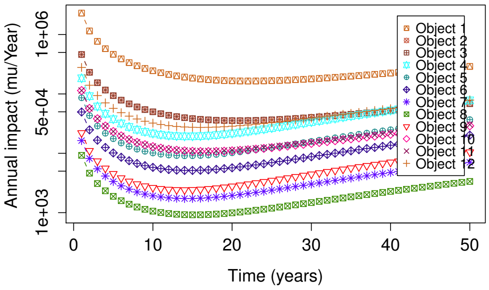
FIGURE 4.1: Impact curves-BR model (IS1-IS7)



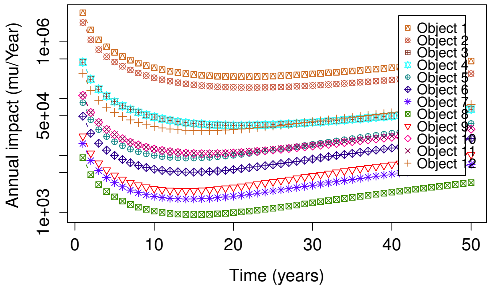
(a)-IS8



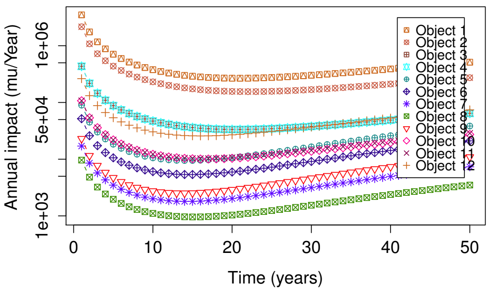
(b)-IS9



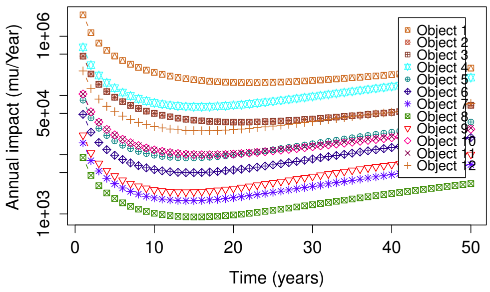
(c)-IS10



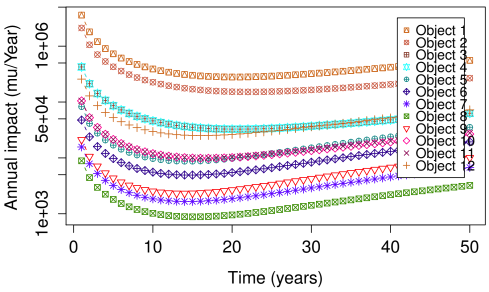
(d)-IS11



(e)-IS12

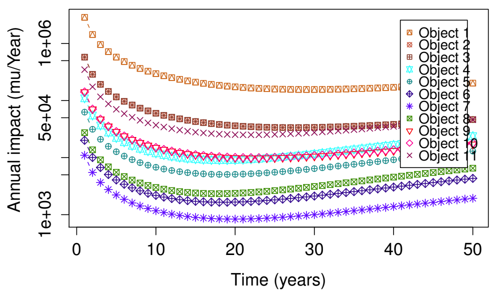


(f)-IS13

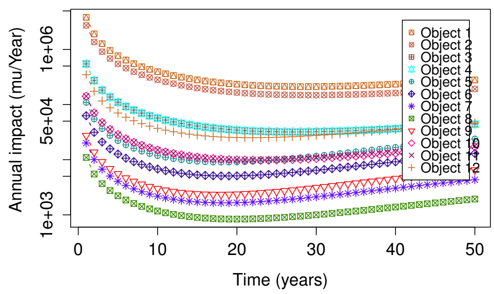


(g)-IS14

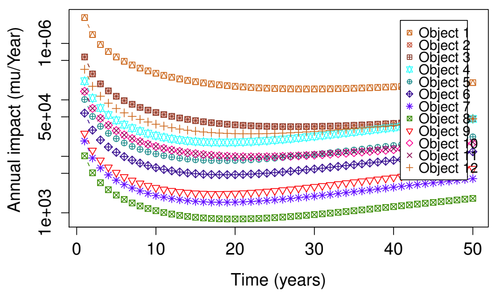
FIGURE 4.2: Impact curves-BR model (IS8-IS14)



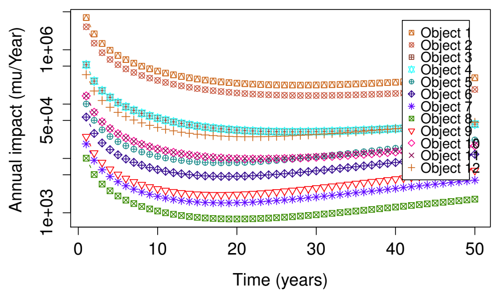
(a)-IS15



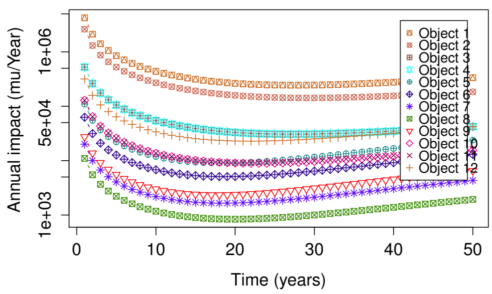
(b)-IS16



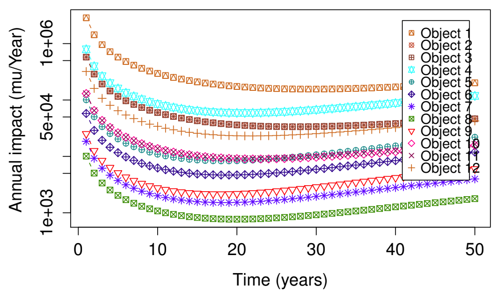
(c)-IS17



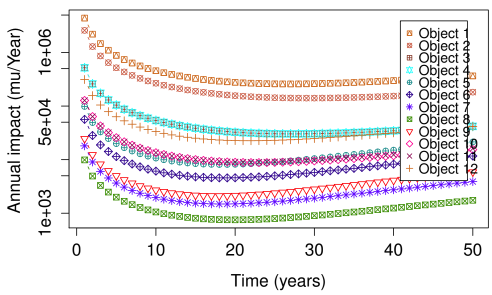
(d)-IS18



(e)-IS19



(f)-IS20



(g)-IS21

Figure 4.3: Impact curves-BR model (IS15-IS21)

4.2 The PGR model

Estimation results on optimal intervention return periods and annual impact using the PGR model are presented in Table 4.2. For ease of comparison with the estimations results using the BR model and other models, which will be shown in later parts of this chapter, the structure of Table 4.2 is designed to be similar to that of Table 4.1.

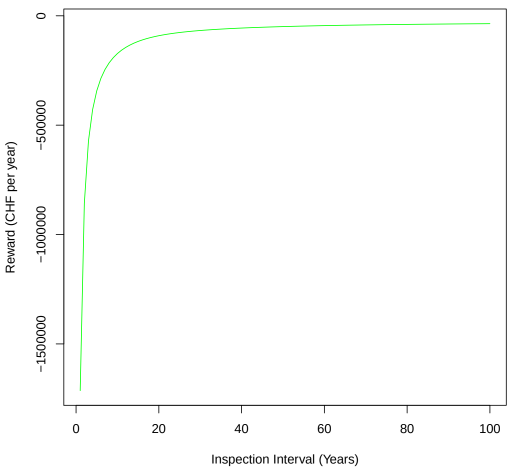
Under the PGR model, instead of estimating annual impact, the optimal intervention return period is estimated (Eq. (2.7)) so as to maximize the operational time or the service of the entire road link. In another words, it is aimed in PGR model to minimize the benefit of using the link (Section 2.2 of chapter 2).

The findings from the results of using PGR model can be highlighted as follows:

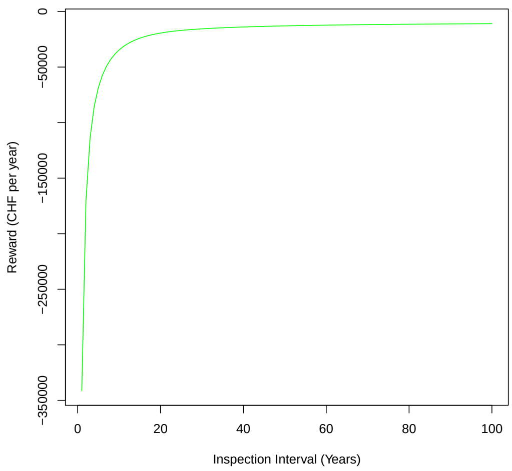
- under critical level 1 (IS-1 to IS-7), optimal intervention return period is 100 years for objects 1, 2, 3, 9, 10, 11; 6 years for objects 4, 5, 6, 8 and 5 years for object 7. This results in an annual accumulative impact of 979 mu;
- results under grouping strategies (IS-2 to IS-7, IS-9 to IS-14 and IS-16 to IS-21) are higher than the results from the non-grouping strategies (IS-1, IS-8, IS-15). This is due to the different objects have contrasting optimal points, as can be seen in the figures 4.4 and 4.5. This leads to interventions at suboptimal times for some of the objects if choosing a fixed interval for all objects.
- under no grouping strategies (e.g IS-1), the optimal intervention return period for the road sections are much shorter than that under grouping strategies. This is because the road objects do show a distinct optimal point, whereas the other objects do not. (see fig. 4.4 and 4.5)
- If comparing between IS-1, IS-8, and IS-15, the optimal one is IS-1 as it yields the lowest annual impact (979 mu) (about 13% decreased in comparison with the annual benefit of IS-15.

Table 4.2: Annual impact and optimal intervention time-PGR model

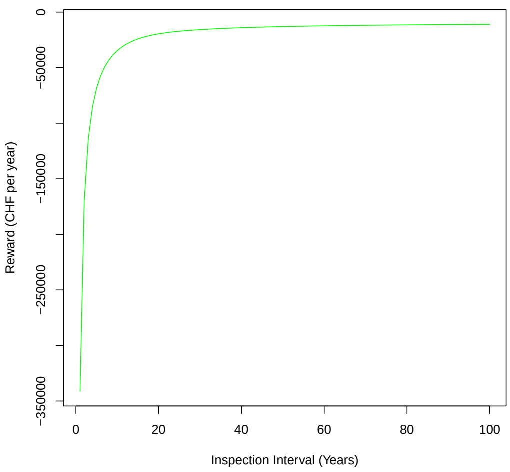
ISs	Bridges			Road sections					Culverts			Annual	Reduction
	1	2	3	4	5	6	7	8	9	10	11	Impact	
1	360	109	110	92	52	16	8	23	57	57	95	979	0
	100	100	100	6	6	6	5	6	100	100	100		
2	826	0	0	92	52	16	8	23	57	57	95	1,225	247
	100	0	0	6	6	6	5	6	100	100	100		
3	360	109	110	217	0	0	0	0	57	57	95	1,006	27
	100	100	100	5	0	0	0	0	100	100	100		
4	1,929	0	0	0	0	0	0	0	57	57	95	2,138	1,160
	19	0	0	0	0	0	0	0	100	100	100		
5	1,209	0	0	92	52	16	8	23	0	0	0	1,399	421
	100	0	0	6	6	6	5	6	0	0	0		
6	360	109	110	693	0	0	0	0	0	0	0	1,272	294
	100	100	100	9	0	0	0	0	0	0	0		
7	2,201	0	0	0	0	0	0	0	0	0	0	2,201	1,222
	18	0	0	0	0	0	0	0	0	0	0		
8	392	113	114	99	56	17	9	25	56	56	92	1,029	0
	100	100	100	8	8	7	6	7	100	100	100		
9	824	0	0	99	56	17	9	25	56	56	92	1,235	205
	100	0	0	8	8	7	6	7	100	100	100		
10	392	113	114	236	0	0	0	0	56	56	92	1,059	30
	100	100	100	6	0	0	0	0	100	100	100		
11	2,030	0	0	0	0	0	0	0	56	56	92	2,234	1,205
	25	0	0	0	0	0	0	0	100	100	100		
12	1,169	0	0	99	56	17	9	25	0	0	0	1,375	346
	100	0	0	8	8	7	6	7	0	0	0		
13	392	113	114	744	0	0	0	0	0	0	0	1,363	334
	100	100	100	11	0	0	0	0	0	0	0		
14	2,322	0	0	0	0	0	0	0	0	0	0	2,322	1,293
	25	0	0	0	0	0	0	0	0	0	0		
15	446	122	123	107	60	18	9	26	59	59	101	1,130	0
	100	100	100	10	10	9	8	9	100	100	100		
16	871	0	0	107	60	18	9	26	59	59	101	1,310	180
	100	0	0	10	10	9	8	9	100	100	100		
17	446	122	123	317	0	0	0	0	59	59	101	1,227	97
	100	100	100	6	0	0	0	0	100	100	100		
18	2,165	0	0	0	0	0	0	0	59	59	101	2,384	1,254
	28	0	0	0	0	0	0	0	100	100	100		
19	1,229	0	0	107	60	18	9	26	0	0	0	1,449	319
	100	0	0	10	10	9	8	9	0	0	0		
20	446	122	123	769	0	0	0	0	0	0	0	1,460	330
	100	100	100	13	0	0	0	0	0	0	0		
21	2,477	0	0	0	0	0	0	0	0	0	0	2,477	1,347
	27	0	0	0	0	0	0	0	0	0	0		



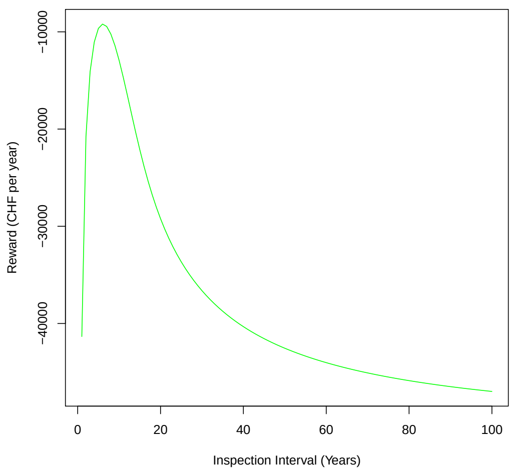
(a)-Object 1



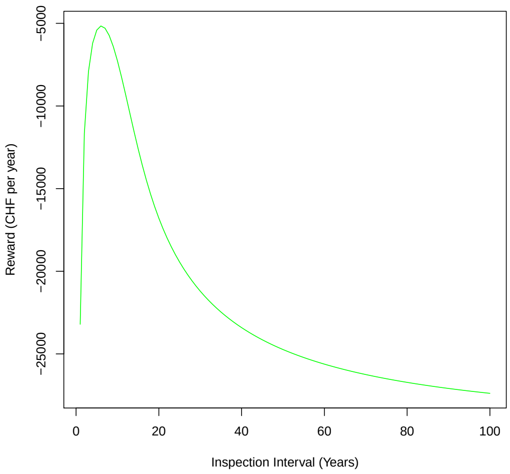
(b)-Object 2



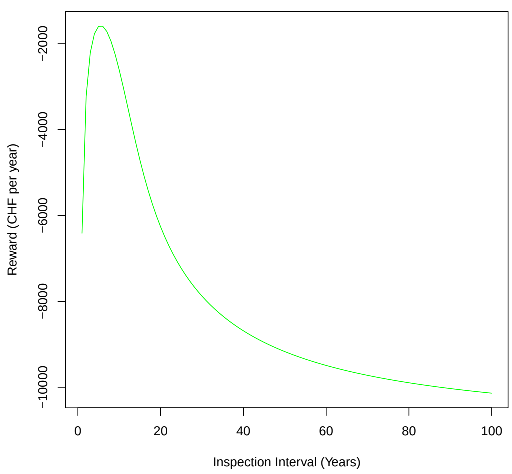
(c)-Object 3



(d)-Object 4

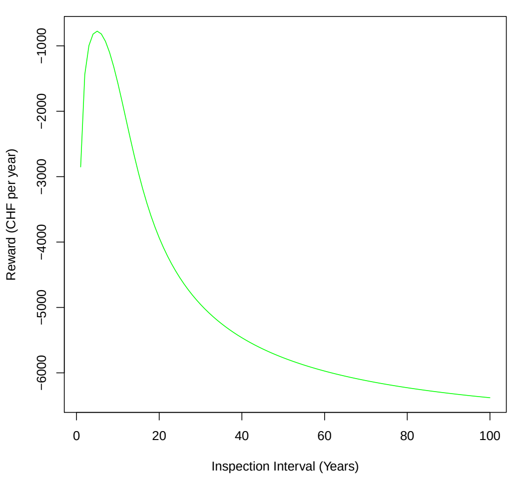


(e)-Object 5

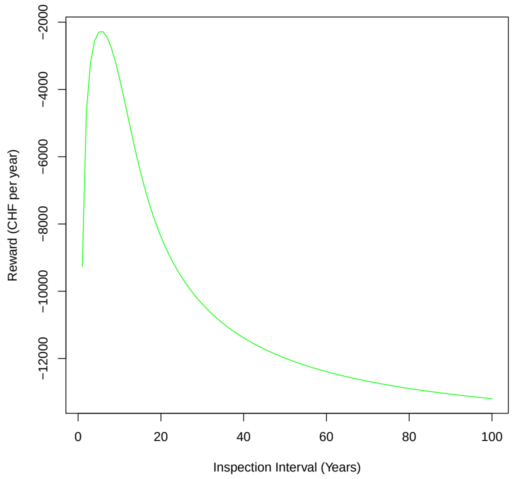


(f)-Object 6

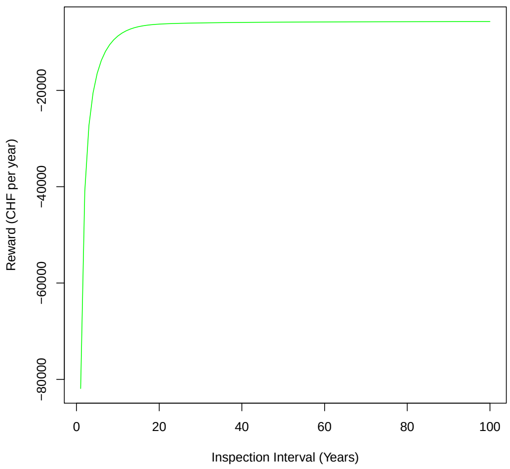
FIGURE 4.4: Impact curves-PGR model (Objects 1-6)



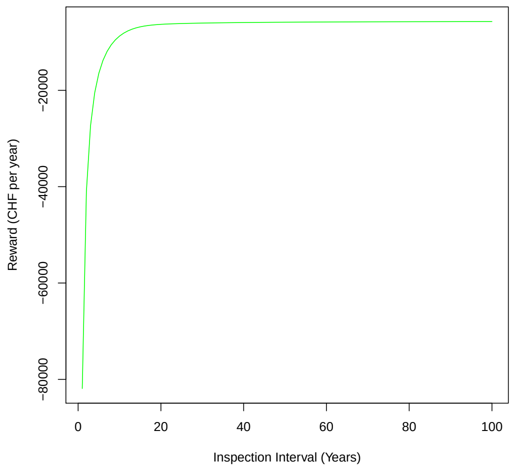
(a)-Object 7



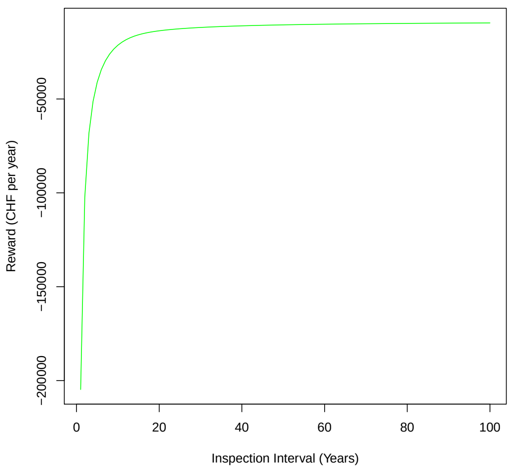
(b)-Object 8



(c)-Object 9



(d)-Object 10



(e)-Object 11

FIGURE 4.5: Impact curves-PGR model (Objects 7-11)

The conclusion is the PGR model is not suitable to be used for determination of the intervention strategies for the road link. The reasons are briefly described as follows:

- The PGR Model is based on the assumption, that all objects behave more or less the same, i.e. the deterioration parameters are close to each other, which is not the case for the examined road link.
- The consequence is, that the costs rise if one combines different object types. This is because they have very unalike optimal points which leads to having one group of objects repaired at a very suboptimal stage - may it be too early or too late.

4.3 The PIMR-1 model

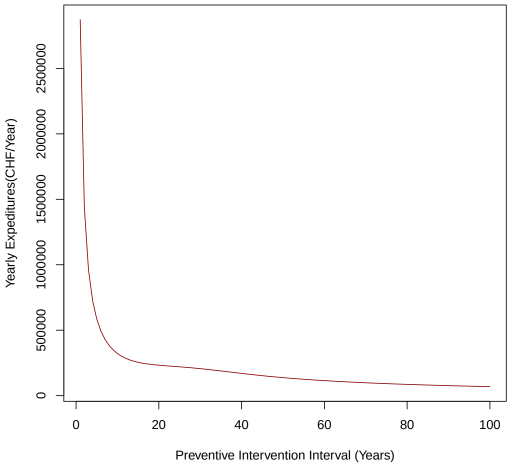
The estimation results on optimal intervention return periods and annual impacts using the PIMR-1 model are shown in Table 4.3. The optimal ISs under critical level 1, 2, and 3 are IS-7, IS-14, and IS-21, respectively. However, the annual impacts are not decreasing like in the case of the BR model, in PIMR-1 model, the annual impacts keep increasing as the critical level goes higher. Also, the optimal intervention return periods of each objects or of a grouping of objects are too long (100 years), which is too far from the expectation.

Reasons for the annual impacts to keep going up as critical level goes higher and for the optimal intervention return period to be too far off are mainly due to:

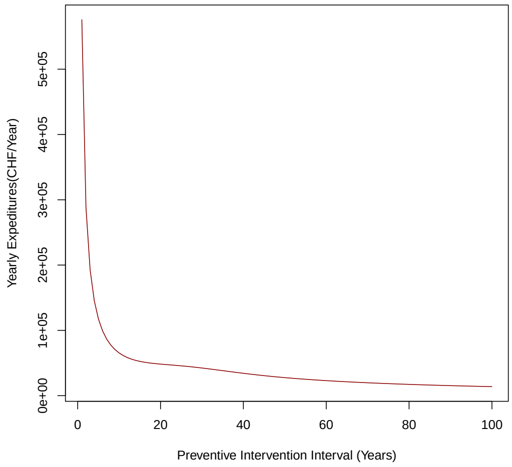
- The mean number of failures on a given period [0,T] (see Eq. (2.8)) is hard to be obtained. The mean number of failures for object 1 is 1.042 per 100 years, which is not actually reflected in the deterioration curve (Fig. 3.3))
- Also, in the formulation of the model, it is assumed that all objects are more or less having the same characteristics (e.g. size and attribute). Meanwhile, for the road link under investigation, such homogeneity is not existed, making somewhat unrealistic to relate the value of model's parameters into real situation.

Table 4.3: Annual impact and optimal intervention time-PIMR-1 model

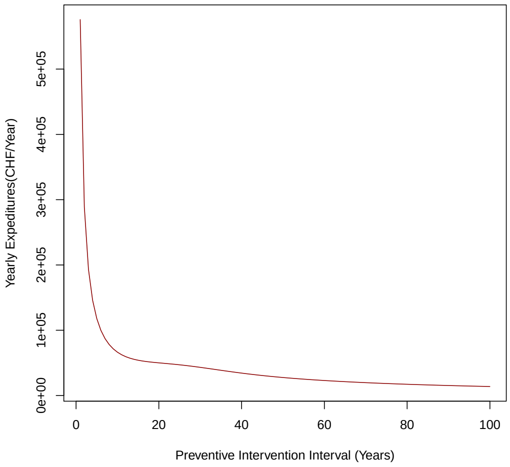
ISs	Bridges			Road sections					Culverts			Annual	Reduction
	1	2	3	4	5	6	7	8	9	10	11	Impact	
1	518	104	104	20	11	4	2	5	25	25	61	878	0
	100	100	100	100	100	100	100	100	100	100	100		
2	711	0	0	20	11	4	2	5	25	25	61	863	-15
	100	0	0	100	100	100	100	100	100	100	100		
3	518	104	104	41	0	0	0	0	25	25	61	876	-1
	100	100	100	100	0	0	0	0	100	100	100		
4	737	0	0	0	0	0	0	0	25	25	61	847	-31
	100	0	0	0	0	0	0	0	100	100	100		
5	794	0	0	20	11	4	2	5	0	0	0	836	-42
	100	0	0	100	100	100	100	100	0	0	0		
6	518	104	104	143	0	0	0	0	0	0	0	869	-9
	100	100	100	100	0	0	0	0	0	0	0		
7	816	0	0	0	0	0	0	0	0	0	0	816	-61
	100	0	0	0	0	0	0	0	0	0	0		
8	586	117	117	21	12	4	2	5	27	27	67	986	0
	100	100	100	100	100	100	100	100	100	100	100		
9	796	0	0	21	12	4	2	5	27	27	67	961	-25
	100	0	0	100	100	100	100	100	100	100	100		
10	586	117	117	42	0	0	0	0	27	27	67	984	-2
	100	100	100	100	0	0	0	0	100	100	100		
11	821	0	0	0	0	0	0	0	27	27	67	942	-43
	100	0	0	0	0	0	0	0	100	100	100		
12	886	0	0	21	12	4	2	5	0	0	0	929	-57
	100	0	0	100	100	100	100	100	0	0	0		
13	586	117	117	153	0	0	0	0	0	0	0	974	-12
	100	100	100	100	0	0	0	0	0	0	0		
14	907	0	0	0	0	0	0	0	0	0	0	907	-79
	100	0	0	0	0	0	0	0	0	0	0		
15	689	138	138	28	16	5	3	7	34	34	85	1,178	0
	100	100	100	100	100	100	100	100	100	100	100		
16	917	0	0	28	16	5	3	7	34	34	85	1,130	-48
	100	0	0	100	100	100	100	100	100	100	100		
17	689	138	138	55	0	0	0	0	34	34	85	1,174	-4
	100	100	100	100	0	0	0	0	100	100	100		
18	942	0	0	0	0	0	0	0	34	34	85	1,096	-82
	100	0	0	0	0	0	0	0	100	100	100		
19	1,018	0	0	28	16	5	3	7	0	0	0	1,077	-101
	100	0	0	100	100	100	100	100	0	0	0		
20	689	138	138	196	0	0	0	0	0	0	0	1,161	-17
	100	100	100	100	0	0	0	0	0	0	0		
21	1,060	0	0	0	0	0	0	0	0	0	0	1,060	-118
	100	0	0	0	0	0	0	0	0	0	0		



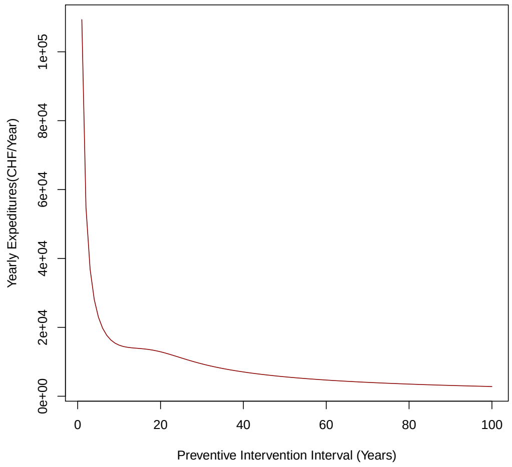
(a)-Object 1



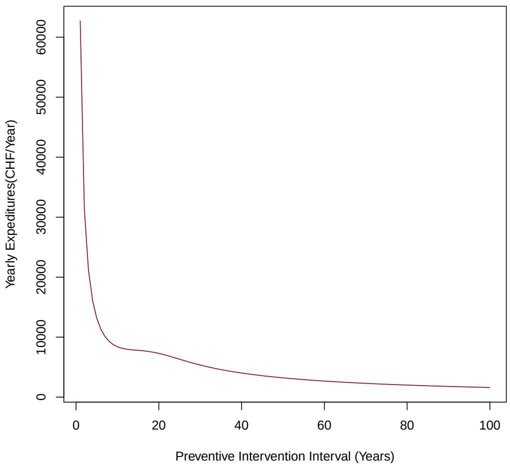
(b)-Object 2



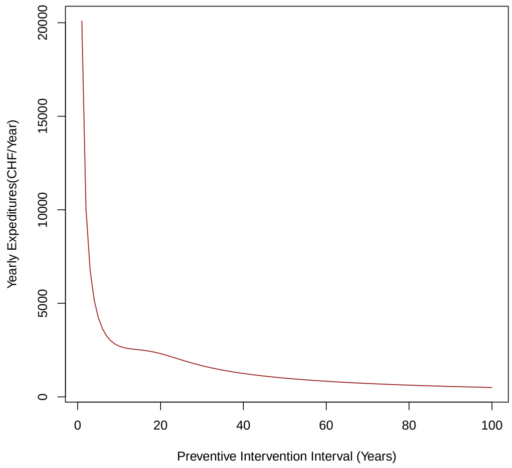
(c)-Object 3



(d)-Object 4

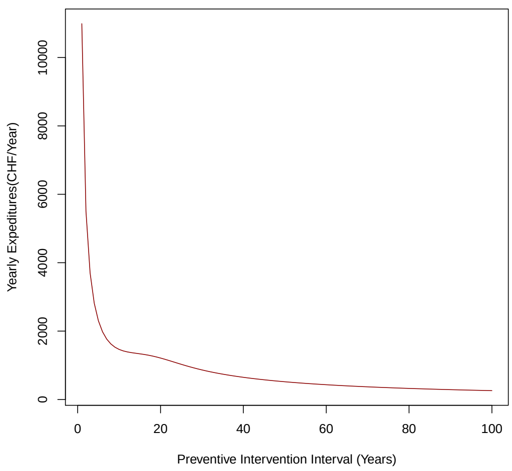


(e)-Object 5

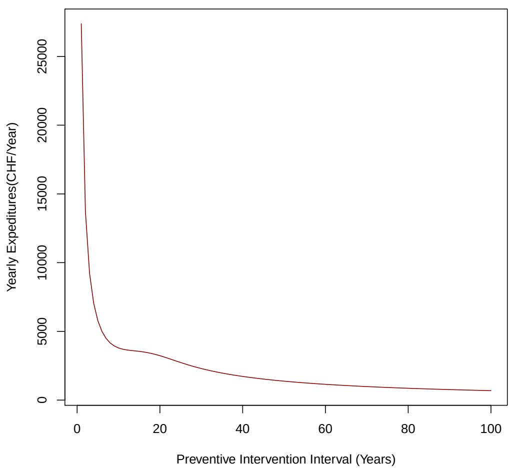


(f)-Object 6

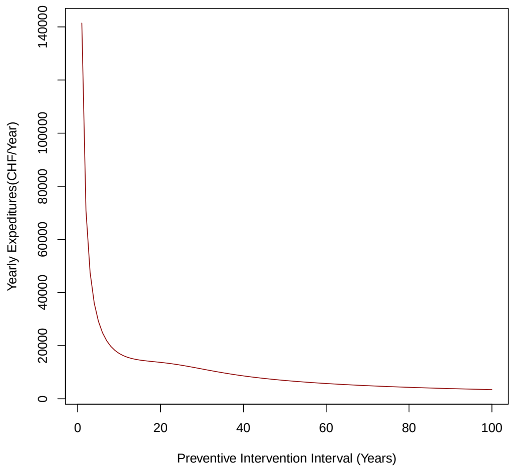
FIGURE 4.6: Impact curves-PIMR-1 model (Objects 1-6)



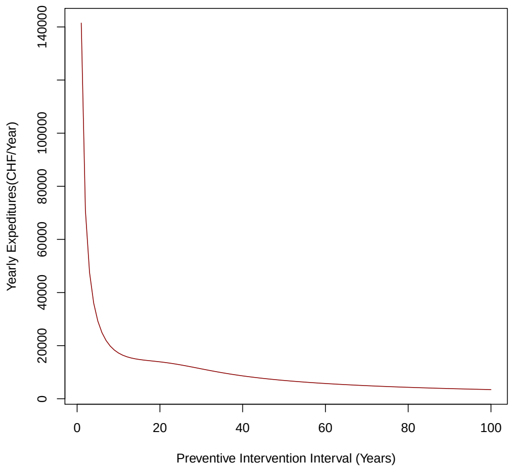
(a)-Object 7



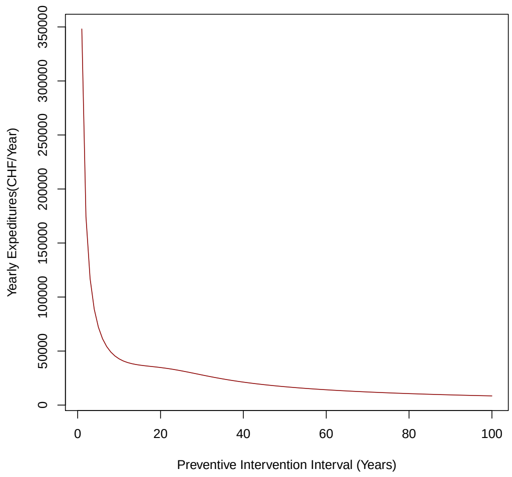
(b)-Object 8



(c)-Object 9



(d)-Object 10



(e)-Object 11

FIGURE 4.7: Impact curves-PIMR-1 (Objects 7-11)

It is concluded that the PIMR-1 model is not suitable to be used for determination of intervention strategies for the road link under investigation.

4.4 The PIMR-2 model

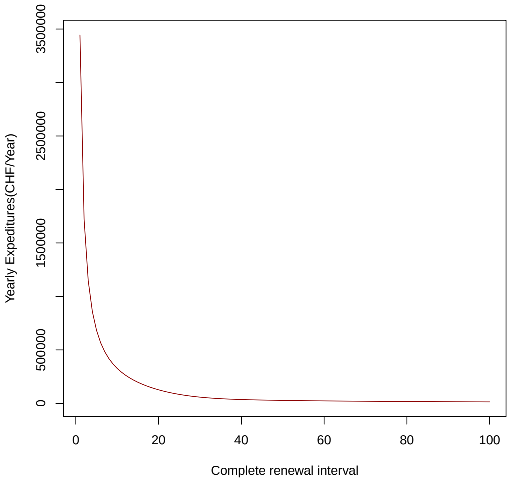
The estimation results on optimal intervention return periods and annual impacts using the PIMR-2 model are shown in Table 4.4. The optimal ISs under critical level 1, 2, and 3 are IS-7, IS-14, and IS-21, respectively. However, the annual impacts are not decreasing like in the case of the BR model, in PIMR-1 model, the annual impacts keep increasing as the critical level goes higher. Also, the optimal intervention return periods of each objects or of a grouping of objects are too long (100 years), which is too far from the expectation. This finding is similar to the findings in using the PIMR-1 model.

Reasons for the annual impacts to keep going up as critical level goes higher and for the optimal intervention return period to be too far off are mainly due to:

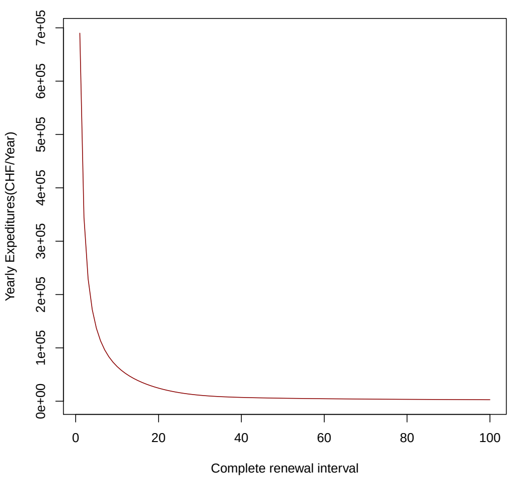
- The mean number of failures on a given period [0,T] (see Eq. (2.8)) is hard to be obtained. The mean number of failures for object 1 is 1.042 per 100 years, which is not actually reflected in the deterioration curve (Fig. 3.3))
- Also, in the formulation of the model, it is assumed that all objects are more or less having the same characteristics (e.g. size and attribute). Meanwhile, for the road link under investigation, such homogeneity is not existed, making somewhat unrealistic to relate the value of model's parameters into real situation.
- Note that the reasons are the same for the PIMR-1 model

Table 4.4: Annual impact and optimal intervention time-PIMR-2 model

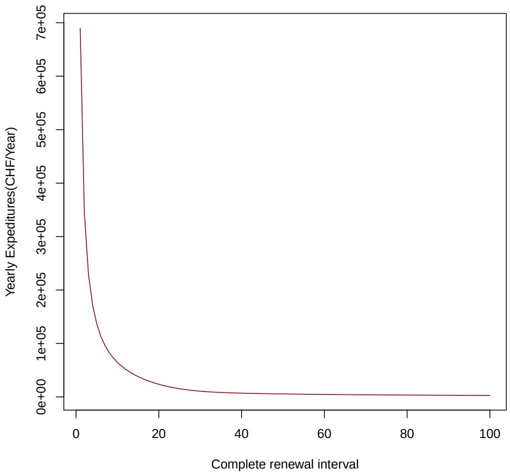
ISs	Bridges			Road sections					Culverts			Annual	Reduction
	1	2	3	4	5	6	7	8	9	10	11	Impact	
1	82	16	16	3	2	1	0	1	4	4	10	139	0
	100	100	100	100	100	100	100	100	100	100	100		
2	112	0	0	3	2	1	0	1	4	4	10	137	-2
	100	0	0	100	100	100	100	100	100	100	100		
3	82	16	16	7	0	0	0	0	4	4	10	139	0
	100	100	100	100	0	0	0	0	100	100	100		
4	117	0	0	0	0	0	0	0	4	4	10	134	-5
	100	0	0	0	0	0	0	0	100	100	100		
5	126	0	0	3	2	1	0	1	0	0	0	133	-7
	100	0	0	100	100	100	100	100	0	0	0		
6	82	16	16	23	0	0	0	0	0	0	0	138	-1
	100	100	100	100	0	0	0	0	0	0	0		
7	129	0	0	0	0	0	0	0	0	0	0	129	-10
	100	0	0	0	0	0	0	0	0	0	0		
8	110	22	22	4	2	1	0	1	5	5	13	188	0
	100	100	100	100	100	100	100	100	100	100	100		
9	150	0	0	4	2	1	0	1	5	5	13	183	-5
	100	0	0	100	100	100	100	100	100	100	100		
10	110	22	22	9	0	0	0	0	5	5	13	187	0
	100	100	100	100	0	0	0	0	100	100	100		
11	156	0	0	0	0	0	0	0	5	5	13	180	-8
	100	0	0	0	0	0	0	0	100	100	100		
12	168	0	0	4	2	1	0	1	0	0	0	177	-11
	100	0	0	100	100	100	100	100	0	0	0		
13	110	22	22	31	0	0	0	0	0	0	0	186	-2
	100	100	100	100	0	0	0	0	0	0	0		
14	173	0	0	0	0	0	0	0	0	0	0	173	-15
	100	0	0	0	0	0	0	0	0	0	0		
15	139	28	28	5	3	1	1	1	7	7	17	236	0
	100	100	100	100	100	100	100	100	100	100	100		
16	185	0	0	5	3	1	1	1	7	7	17	227	-10
	100	0	0	100	100	100	100	100	100	100	100		
17	139	28	28	10	0	0	0	0	7	7	17	236	-1
	100	100	100	100	0	0	0	0	100	100	100		
18	190	0	0	0	0	0	0	0	7	7	17	220	-16
	100	0	0	0	0	0	0	0	100	100	100		
19	205	0	0	5	3	1	1	1	0	0	0	216	-20
	100	0	0	100	100	100	100	100	0	0	0		
20	139	28	28	38	0	0	0	0	0	0	0	233	-3
	100	100	100	100	0	0	0	0	0	0	0		
21	213	0	0	0	0	0	0	0	0	0	0	213	-24
	100	0	0	0	0	0	0	0	0	0	0		



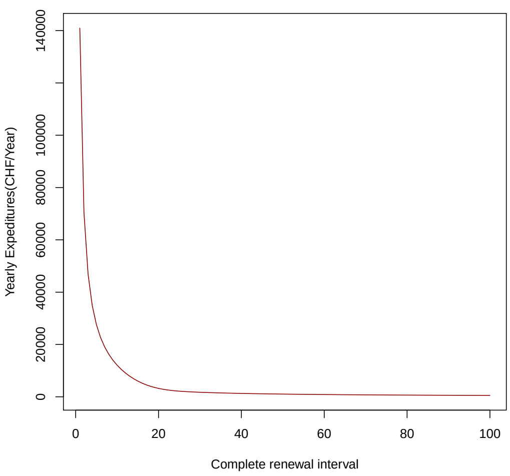
(a)-Object 1



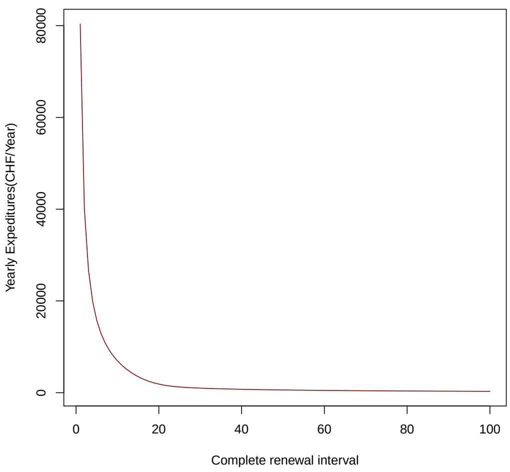
(b)-Object 2



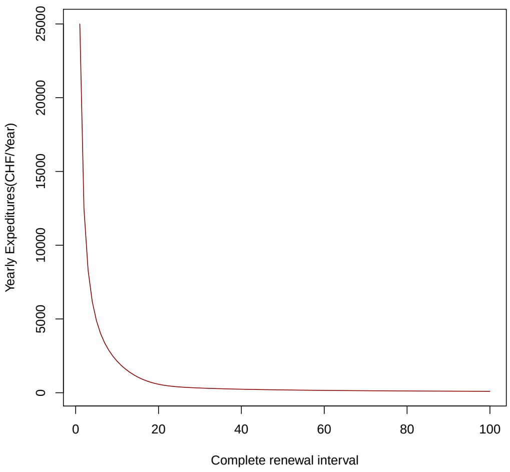
(c)-Object 3



(d)-Object 4

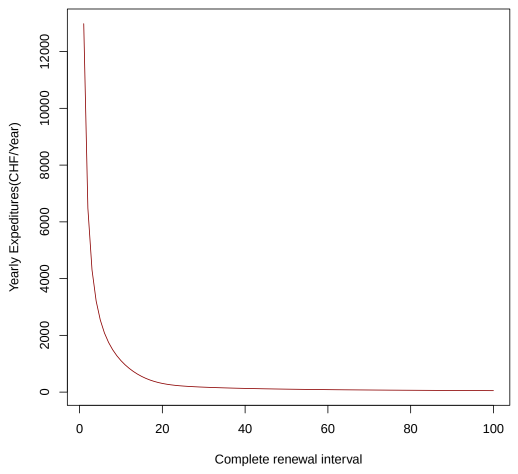


(e)-Object 5

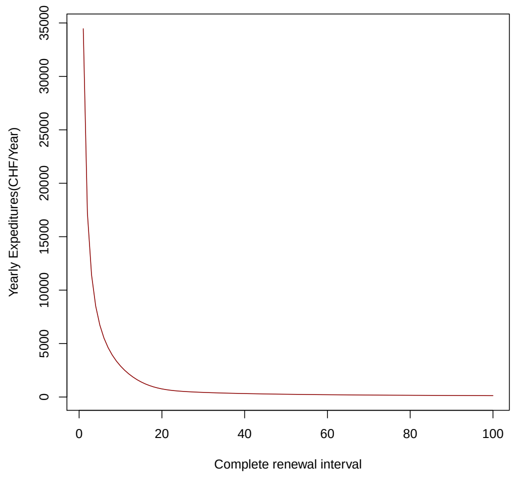


(f)-Object 6

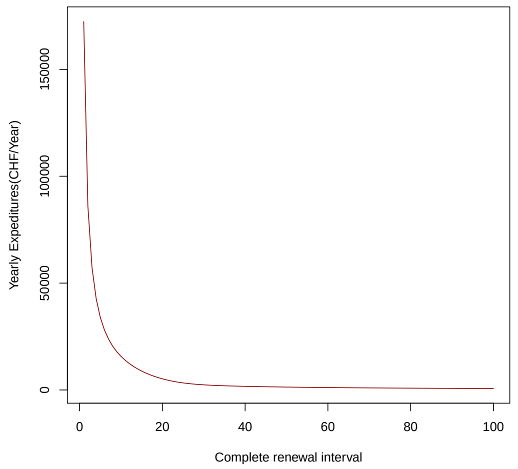
Figure 4.8: Impact curves-PIMR-2 model (Objects 1-6)



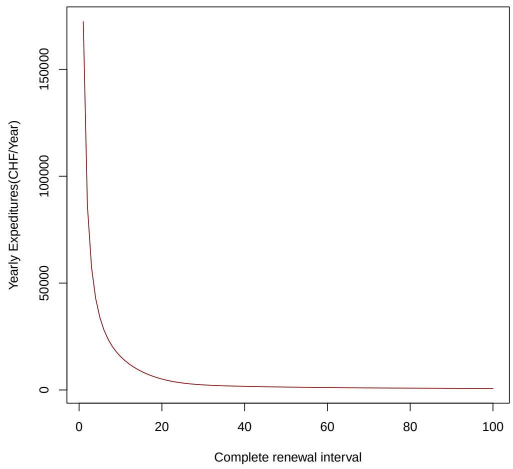
(a)-Object 7



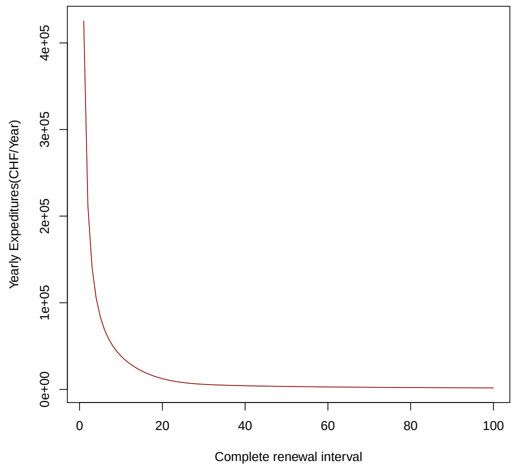
(b)-Object 8



(c)-Object 9



(d)-Object 10



(e)-Object 11

FIGURE 4.9: Impact curves-PIMR-2 (Objects 7-11)

It is concluded that the PIMR-2 model is not suitable to be used for determination of intervention strategies for the road link under investigation.

4.5 The AR model

Estimation results on the optimal intervention return periods and annual impacts under respective ISs using the AR model are shown in Table 4.5.

As can be seen from the table, among ISs from 1 to 7, reference strategy (IS-1) has the highest annual impact (3'483 mu) comparing to that of other ISs. The strategy has the lowest annual impacts is IS-7 (3'243 mu) with a reduction of 240 mu (about 7%) in comparison with the reference strategy. This results show the importance of execution of interventions simultaneously on the grouping of objects. The grouping of objects will likely reduce the set up cost during intervention period and eventually reduce the annual cost.

It is also realized that under the grouping of intervention, the optimal intervention return period become shorter for the bridges and longer for the road sections and culverts in comparison with no grouping intervention strategies. For example, under IS-1, object 1 and object 4 have optimal intervention return period of 16 and 10 years, respectively, while under IS-7, the optimal intervention return period of both objects are 15. Reasons behind this change are mainly due to the differences in deterioration processes. The bridges often has longer service life in comparison with that of the road sections and culverts. When combining them into a single intervention packages, mathematically, the optimal intervention return period shall be somewhere in between of the two periods under no grouping interventions.

Similar findings and conclusions are realized for the comparison of ISs from 8 to 14 and from 15 to 21. However, it is important to see that under critical level 2 (ISs from 8 to 14), the annual impacts incurred keep decreasing for each object and thus the annual accumulative impacts are also decreased in comparison with that under critical level 1 (IS-1 to IS-7). The decreasing in annual impacts is also observable under critical level 3 (IS-15 to IS-21).

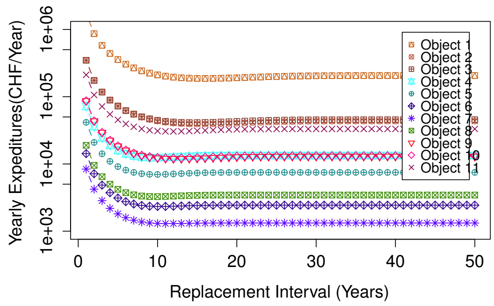
If managers consider only critical level 1 as the level to trigger intervention, it is obvious from the finding that the optimal IS is IS-7. Also, if managers consider the critical level 2 and 3, IS-14 and IS-21 are the optimal strategies, respectively. However, from the results, if managers compare all ISs, the optimal one will be IS-21 since it has the lowest annual impacts (3'055 mu). Taking IS-1 as reference strategy for comparison against

IS-7, IS-14 and IS-21, the reductions in annual impacts are 240 mu, 252 mu, and 428 mu, respectively. This means that by choosing the IS-21, the benefits that stakeholders expect to have are 428 mu in comparison with IS-1.

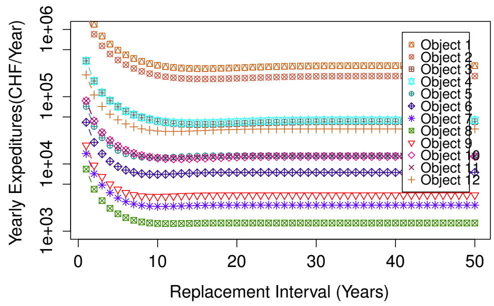
TABLE 4.5: Annual impact and optimal intervention time-AR model

ISs	Bridges 1	Bridges 2	Bridges 3	Road sections 4	Road sections 5	Road sections 6	Road sections 7	Road sections 8	Culverts 9	Culverts 10	Culverts 11	Annual Impact	Reduction
1	1,870	394	412	124	70	23	13	33	119	122	304	3,483	0
	16	15	15	10	10	10	11	10	12	12	12		
2	2,622	0	0	124	70	23	13	33	119	122	304	3,430	-53
	15	15	15	10	10	10	11	10	12	12	12		
3	1,870	394	412	255	0	0	0	0	119	122	304	3,475	-8
	16	15	15	10	10	10	10	10	12	12	12		
4	2,823	0	0	0	0	0	0	0	119	122	304	3,368	-115
	15	15	15	15	15	15	15	15	12	12	12		
5	3,060	0	0	124	70	23	13	33	0	0	0	3,322	-161
	15	15	15	10	10	10	11	10	15	15	15		
6	1,870	394	412	760	0	0	0	0	0	0	0	3,435	-47
	16	15	15	11	11	11	11	11	11	11	11		
7	3,243	0	0	0	0	0	0	0	0	0	0	3,243	-240
	15	15	15	15	15	15	15	15	15	15	15		
8	1,918	403	422	105	59	20	11	28	117	119	299	3,500	0
	22	21	20	16	17	17	19	16	19	18	18		
9	2,661	0	0	105	59	20	11	28	117	119	299	3,418	-82
	22	22	22	16	17	17	19	16	19	18	18		
10	1,918	403	422	214	0	0	0	0	117	119	299	3,491	-9
	22	21	20	16	16	16	16	16	19	18	18		
11	2,824	0	0	0	0	0	0	0	117	119	299	3,358	-142
	21	21	21	21	21	21	21	21	19	18	18		
12	3,085	0	0	105	59	20	11	28	0	0	0	3,308	
	21	21	21	16	17	17	19	16	21	21	21		
13	1,918	403	422	705	0	0	0	0	0	0	0	3,449	-52
	22	21	20	17	17	17	17	17	17	17	17		
14	3,231	0	0	0	0	0	0	0	0	0	0	3,231	-269
	21	21	21	21	21	21	21	21	21	21	21		
15	1,835	385	403	117	66	21	11	30	115	117	295	3,394	0
	30	29	28	16	16	17	18	16	23	22	22		
16	2,492	0	0	117	66	21	11	30	115	117	295	3,262	-131
	30	30	30	16	16	17	18	16	23	22	22		
17	1,835	385	403	227	0	0	0	0	115	117	295	3,377	-17
	30	29	28	16	16	16	16	16	23	22	22		
18	2,639	0	0	0	0	0	0	0	115	117	295	3,165	-228
	28	28	28	28	28	28	28	28	23	22	22		
19	2,866	0	0	117	66	21	11	30	0	0	0	3,110	-284
	28	28	28	16	16	17	18	16	28	28	28		
20	1,835	385	403	710	0	0	0	0	0	0	0	3,333	-61
	30	29	28	20	20	20	20	20	20	20	20		
21	3,055	0	0	0	0	0	0	0	0	0	0	3,055	-338
	27	27	27	27	27	27	27	27	27	27	27		

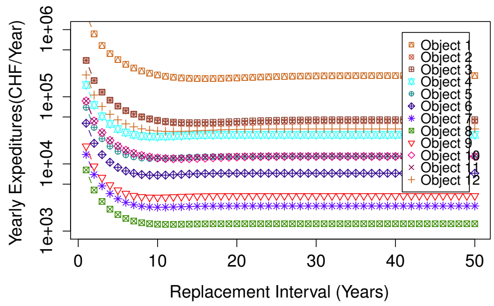
The above findings and conclusions are almost identical to the case of the BR model (section 4.5). Differences can be seen only in the increasing values of annual impacts or slightly different of the optimal intervention return period for respective objects. This is an interesting finding, which shows a close relationship between the two models. An exploration on the differences between the two models will be described in later part of this chapter.



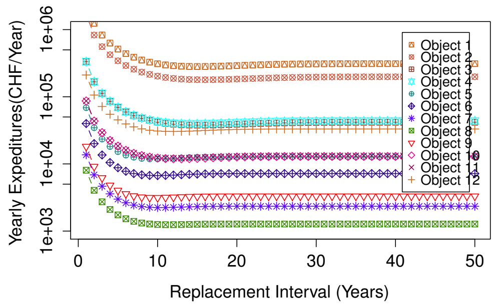
(a)-IS1



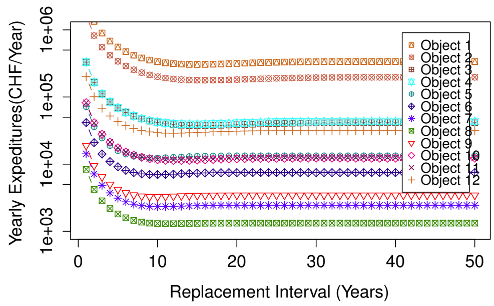
(b)-IS2



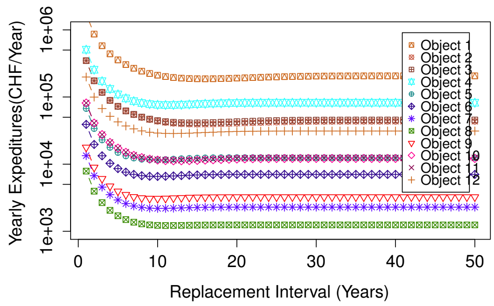
(c)-IS3



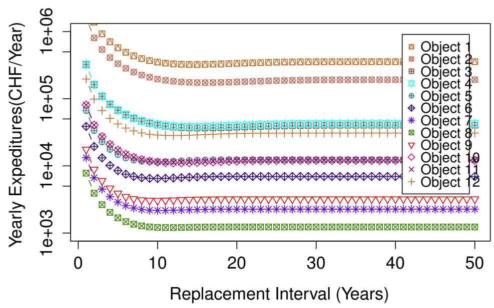
(d)-IS4



(e)-IS5

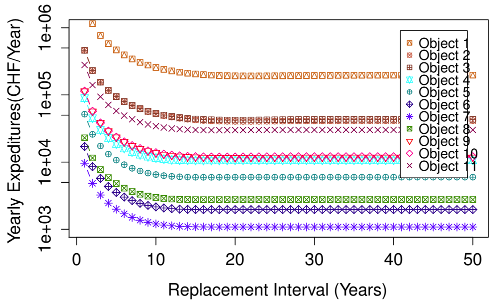


(f)-IS6

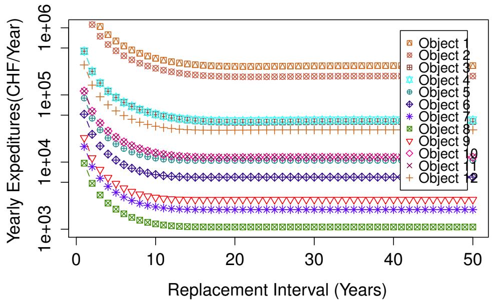


(g)-IS7

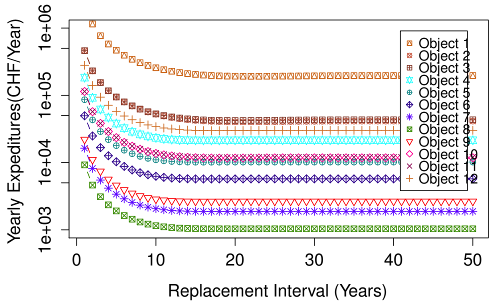
FIGURE 4.10: Impact curves-AR model (IS1-IS7)



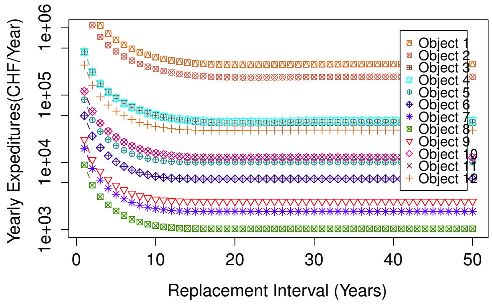
(a)-IS8



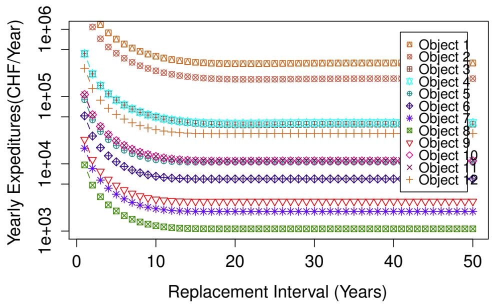
(b)-IS9



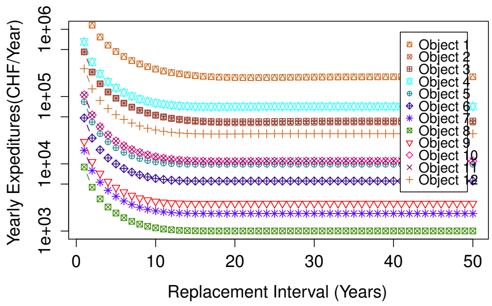
(c)-IS10



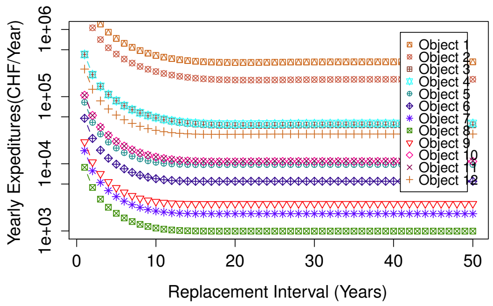
(d)-IS11



(e)-IS12

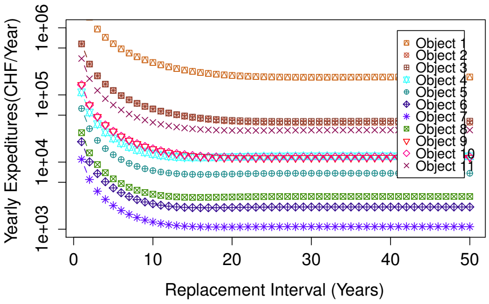


(f)-IS13

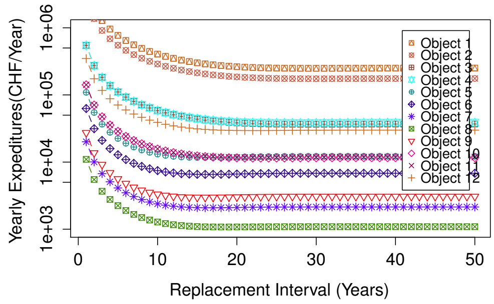


(g)-IS14

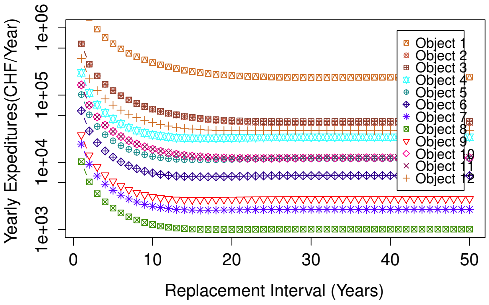
Figure 4.11: Impact curves-AR model (IS8-IS14)



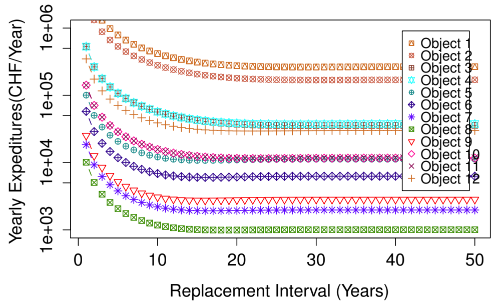
(a)-IS15



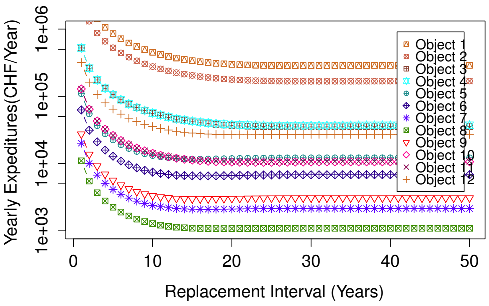
(b)-IS16



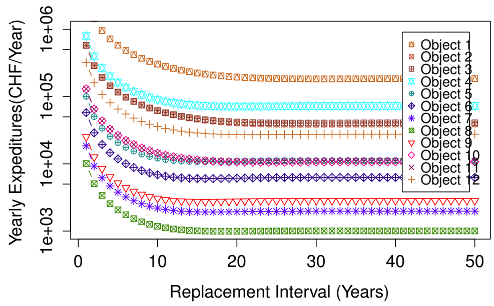
(c)-IS17



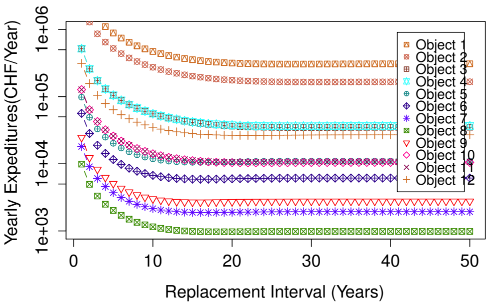
(d)-IS18



(e)-IS19



(f)-IS20



(g)-IS21

FIGURE 4.12: Impact curves-AR model (IS15-IS21)

The impact curves corresponding to each object or a group of objects are given in Figs. 4.10, 4.11, and 4.12. The mimimum points of the curves show the optimal intervention return period on the horizontal axis and the annual impact on the vertical axis. It can be clearly seen from these figures that if the optimal intervention return period of a object is too short, it will incurs a considerable huge amount of impacts. These impacts will slowly go down if intervention time become longer, but it will goes up again if intervention time become too long. This is because if it is too long, there will be risker for the object to be in adequate level of services and therefore the expected numbers of corrective interventions will increase and eventually cause the annual impacts to increase. This conclusion is similar to that of the BR model. However, there is a significant difference between the two models. As can be seen from the tails of the curves, in BR model, after the minimum points the tails go up with gradual increasing in the values of impacts. However, in AR model, the tails keep increaseing with much smaller incremence in the value of impacts and thus the curves have flat tails. Reasons for such differences will be further explained in the later part of this chapter.

4.6 The Markov model

Estimation results on the annual impacts under respective ISs using the proposed Markov model are shown in Table 4.6.

Under the Markov model, a discrete condition states are used instead of binary states used in the BR, PGR, PIMR, and AR models. Also, it is assumed that interventions on each object or on a group of objects can be executed anytine within one year interval if the physical condition of the object or a part of the object reaching the condition states that triggers the intervention. For example, if condition state of the object is 3, it will be renewed to be 1 with the probability associated with the transition from other states to condition state 3.

Results obtained from using the Markov model are understood as optimal intervention strategies under steady state condition, which means the intervention types can be repeated every interval (of 1 year). Therefore, in Table 4.6, values shown in the second row of each IS is 1 and not higher than that. The annual impacts are shown on the first row under each IS and the annual accumulative impacts and reduction are shown in the last two columns of the table.

TABLE 4.6: Annual impact-Markov model

ISs	Bridges			Road sections					Culverts			Annual Impact	Reduction
	1	2	3	4	5	6	7	8	9	10	11		
1	1,578 1	349 1	354 1	135 1	77 1	26 1	15 1	36 1	104 1	108 1	266 1	3,047	0
2	2,184 1	0 1	0 1	135 1	77 1	26 1	15 1	36 1	104 1	108 1	266 1	2,951	-96
3	1,578 1	349 1	354 1	276 1	0 1	0 1	0 1	0 1	104 1	108 1	266 1	3,035	-12
4	2,461 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	104 1	108 1	266 1	2,939	-108
5	2,529 1	0 1	0 1	135 1	77 1	26 1	15 1	36 1	0 1	0 1	0 1	2,818	-229
6	1,578 1	349 1	354 1	717 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	2,997	-50
7	2,792 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	2,792	-255
8	1,190 1	295 1	296 1	100 1	58 1	21 1	13 1	28 1	74 1	76 1	176 1	2,327	0
9	1,703 1	0 1	0 1	100 1	58 1	21 1	13 1	28 1	74 1	76 1	176 1	2,249	-78
10	1,190 1	295 1	296 1	211 1	0 1	0 1	0 1	0 1	74 1	76 1	176 1	2,318	-9
11	1,914 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	74 1	76 1	176 1	2,240	-87
12	1,928 1	0 1	0 1	100 1	58 1	21 1	13 1	28 1	0 1	0 1	0 1	2,147	-180
13	1,190 1	295 1	296 1	511 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	2,291	-36
14	2,128 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	2,128	-199
15	1,001 1	242 1	243 1	88 1	50 1	16 1	9 1	23 1	65 1	67 1	166 1	1,969	0
16	1,496 1	0 1	0 1	88 1	50 1	16 1	9 1	23 1	65 1	67 1	166 1	1,979	9
17	1,001 1	242 1	243 1	188 1	0 1	0 1	0 1	0 1	65 1	67 1	166 1	1,972	2
18	1,683 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	65 1	67 1	166 1	1,981	12
19	1,704 1	0 1	0 1	88 1	50 1	16 1	9 1	23 1	0 1	0 1	0 1	1,889	-80
20	1,001 1	242 1	243 1	461 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	1,947	-22
21	1,882 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	0 1	1,882	-87

The annual impacts of an object or a group of objects were estimated based on Eq. (2.25) for each IS. The Markov transition probability (m.t.p) (Eq. (2.21)) used for each object were those given in Tables 3.5, 3.6, and 3.7. The m.t.p used for a grouping of objects were assumed to be the average m.t.p of the m.t.p of the objects. This assumption is realistic enough to reflect the average deterioration of the group of objects, especially if they shares a similar characteristics (e.g. a group of 3 bridges, a group of 5 road sections). However, the average m.t.p might exposes to higher significance of bias when a grouping of objects with different characteristics such as a group of bridge and road section. This is very important point to be kept in mind in the later exploration of analytical results.

Under critical level 1 (IS1-IS7), there are 3 condition states. The last two condition states (4 and 5) are considered as condition state 3 and their m.t.p are added up to be a part of the m.t.p of condition state 3. Example of the m.t.p of object 1 under IS1 is given in Table 4.7:

TABLE 4.7: Markov transition probability of object 1 under IS1

Condition states	1	2	3
1	0.84951	0.14587	0.00462
2	0	0.94082	0.05918
5	0	0	0

As can be seen from the Table 4.7, the m.t.p of CS1 and CS2 are identical to that of the object 1 shown in Table 3.5. However, the m.t.p of CS3 is the sum of m.t.p CS3, CS4, and CS5 in Table 3.5. The same ways of forming the m.t.p for ISs under critical level 2 were made, except there will be 4 condition states in ISs of critical level 2 (IS8-IS14) instead of 3 condition states in ISs of critical level 1 (IS1-IS7).

It is also important to highlight the fact that estimation results shown in Table 4.6 were calculated based on the assumptions that there are impacts incurred when the objects are still in adepquate level of services beside the impacts incurred when the objects are at inadequate level of services. This assumption can be clearly seen in Eq. (2.26) and this assumption is very much different from the use of other models described in this report. Under this assumption, the Markove model allows us to capture a large spectrum of impacts, which could possibily incurred by stakeholders. For instance, under condition state 1, the bridge is still in good condition and the incurred impacts to users is 10 mu, but if it is in condition state 2, the impacts shall be, in principle, higher. However, in models used binary states (e.g. BR and AR models), impacts incurred when the objects are at condition state 1 or 2 are essentially the same, which is regarded as over or under estimation of the actual impacts. Following table of using object 1 under IS1 as the case desribes more about the implication of the content in this paragraph.

TABLE 4.8: Impacts incurred by stakeholder (object 1-IS1

State	Owner		Users+DAP+IAP	
	a=1	a=2	a=1	a=2
i=1	0	3'427'200	6'794	22'647
i=2	0	3'427'200	18'117	22'647
i=3	3'427'200	3'427'200	22'647	22'647

As can be seen from the table, under IS1, object 1 has 3 condition states. There are two intervention actions (denoted as a=1 and a=2). Intervention type a=1 infers do nothing on the object and intervention type a=2 infers a major intervention on object 1 (refer also to the mode described in subsection 2.5.2). If a=2, there are impacts incurred by owner, which equals to 3'427'200 mu, and if no intervention (a=1), the impact to owner is 0. Beside impacts incurred by the owner, there are impacts on users, the DAP, and the IAP as well. When a=2, impacts incurred by stakeholders rather than the owner were 22'647 mu, which is similar to input values used also in other models. However, when a=1, such impacts are assumed to be 6'794 mu, 18'117 mu, and 22'647 mu, respectively for 3 condition states. Those values are assumed to be 30%, 80% and 100% of that when a=2. The assumptions on the percentages of those values are believed to be expert opinions or based on empirical models, which are beyond the scope of this report.

Based on the values given on Table 4.7 and 4.8, the optimal solution for the object 1 was estimated to be

TABLE 4.9: optimal solution (object 1-IS1

Intervention type	Variables (π_i)						
	i=1	i=2	i=3	i=4	i=5	l=1	l=2
a=1	0.2766	0.68178	0	0	0	0	0
a=2	0	0	0.04163	0	0	0	0
Objective function	1'578						

As you can see from Table 4.9, the value of object function is 1'578 mu, which is also shown in Table 4.6 under IS1. Values of variables shown in the table implies that the distribution of stead state if intervention types a=1 and a=2 are to be followed. There will be 0.2766 and 0.68178 chances that object 1 will be in condition state 1 and 2 respectively, and no intervention is needed on these two conditions state (a=1). Also, there is 0.04163 chance that the object will be in condition state 3 at the end of every year and that proportion will become 0 right after intervention type a=2 is executed.

In Table 4.9, there are additional information on columns concerning i=4 and 5 and l=1, and 2. Under IS1, object 1 has only 3 condition states (i=1,2, and 3) so eventually the value of m.t.p under these columns shall be 0. Also, in the Markov model, it is allowed to estimate the failure probability due to latent process. However, in this example, the probability of going to condition states where the object is not in adequate level of services is assumed to be 0. This assumption is due to the reason that in other models proposed in this report, latent process is not considered.

4.7 The Semi-Markov model

The use of semi-Markov model is possible for the case study. However, it was finally rejected due to following difficulties

- Semi-Markov model exposes to have multi-dimensional issues, which are hard to program for a road link composed of multiple objects (e.g. numbers of objects are greater than 2);
- It is hard to define in semi-Markov model the transition probability among different states of the road link based on assumptions maded for the BR, PGR, PIMR, AR, and Markov model;
- It is hard to estimate the impacts incurred during the transition time between two condition states of the object.

4.8 Models comparison

In conclusion, a summary of important aspects of the 7 proposed models is given in Table 4.10 for comparison.

TABLE 4.10: Models comparison

Descriptions	Models						
	BR	PGR	PIMR-1	PIMR-2	AR	Markov	Semi-Markov
OIS	21	21	7	7	21	21	NA
Annual impact of OIS	2’592	2’477	816	129	3’055	1’882	NA
Programmability	Easy	Easy	Easy	Easy	Easy	Moderate	Difficult
Type of ISs considered	All	All	All	All	All	All	NA
Ease of determination of model parameters	No	No	Moderate	No	Yes	Yes	NA
Consideration of uncertainties	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Use of historical data for deterioration prediction	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of condition states considered	2	2	2	2	2	>2	>2
Memory	Yes/No	Yes/No	Yes/No	Yes/No	Yes/No	No	Yes
Dimensionality	No	No	No	No	No	Yes	Yes
Applicability	Yes	No	No	No	Yes	Yes	No

Following points can be highlighted:

- With regard to the determination of the OISs, it is likely that the BR model, PGR model AR model, and Markov model give the same OIS (IS21). However, the annual impacts resulted from the BR model is always less than that of the AR model;

- It is easy to program for models using binary states (BR, PGR, PIMR-1, PIMR-2, and AR). However, it is more difficult to program the multi-state models (Markov model and semi-Markov model) due to the problems of dimensionalities;

- It is possible to considered all possible ISs in each model.

- It is difficult and sensitive to determine the parameter values of binary models based on historical data, while, is is less difficult to determine the values of parameters in the Markov model than that of binary model;

- All models take into consideration of uncertainties in manifest deterioration processes of infrastructure objects. The Markov model seems to be more advantegous than the others as it also considers the uncertainties due to latent processes (e.g. failure or collapese of objects due to natural hazards such as earthquakes and avalanche;

- Historical data on condition of the objects can be ultilized in all models for prediction and strategy evaluations. However, the Markov model is considered as memoriless model as it is assumed in the model that condition state of the object in the following period only depending on its condition state at the present, and not depending on the condition states in the past;

- Markov models and semi-Markov model use multiple condition states rather than using only two states (binary). The use of multiple condition states is considered as more suitable to be applied in the management of infrastructures;

- Markov model and semi-Markov model face the issue of dimensionalities as the number of objects in the link increase as well as the increase in the discrete range of condition states;

- The BR, AR, and Markov model yields same OISs and they are quite fit to the actual data. Thus, it is believed that they are applicable to be used.

Chapter 5

Conclusions

This report has proposed 7 models to be used to determine optimal intervention strategies for a road link composed of multiple objects: The block replacement model, the periodic group repair model, the periodic intervention with minimal repair with complete renewal, the periodic intervention with minimal repair with partial renewal, the Markov model, and the semi-Markov model.

The models were based on the work of Gertsbakh (1997) and Mayet and Madanat (2002); Lethanh et al. (2013). The models developed by Gertsbakh (1997) were primarily used for facilities and machinery management. In this research, one of the objective is trying to investigate and realize any possible extensions of the cited models so as they become applicable for use in infrastructure management system. The model developed by citetLethanh2013 is mainly for use in infrastructure systems and thus it is proposed to be used as a benchmark model and for ease of comparison with models proposed by Gertsbakh (1997).

All proposed models are probabilistic model and they are capabele of taking uncertainties of deteriorations and failure of the objects into consideration. They can also be classified into two main groups of models: binary state models (BR, PGR, PIMR1, and PIMR2) and multiple states models (Markov model and semi-Markov model). In binary state models, it is assumed that the infrastructure object can be only in one of two states: state where adequate level of service is provided and state that adquate level of service is not provided. In multiple states models, physical condition of the object can be described in discrete scales such as from 1 to 5 and by doing so, they can capture more behaviours and characteristis of the object or the services that the object offers than that of binary state models.

In order to make a fair comparison of the estimation results of the proposed models, a same case study on a road link composed of 11 objects in the Canton of Wallis was selected. The link is located in a mountainous areas and includes 3 concrete bridges, 5 road sections, and 3 culverts. The objects on the link are exposed with both manifest deteriorations and natural hazard risks such rock falls and avalanches.

To apply the binary state models on the case study, physical conditions of each object were classified into 3 main critical levels, which are correponding to condition state 3, 4 and 5 in multiple state Markov model. Probabilistic distribution parameters of the binary states models were estimated based on the deterioration curves of that used in Markov model.

When the objects are still providing adquate levels of servives, there are impacts and benefits associated with them. When the objects are not providing adquate levels of services, high impacts incurred by stakeholders. In addition, under such situation, corrective interventions and preventive interventions are introduced. The impacts incurred by stakeholders as results of executing preventive and corrective interventions were estimated by using empirical models. For instance, operational costs were estimated using vehicle operation models; accidents were estimated using accident risk models, intervention costs (impacts incurred by the owner) were calculated based on Swiss construction norms.

Based on the estimation results, a comparison of several important aspects of the models is given, with a main conclustion that

- the PRG, PIMR1 and PIMR2 are not applicable to be used as their model parameters are very sentitive and hard to be precisely obtained using historical data.
- the semi-Markov model is computational probablematics as it involves exponential growth of dimensions and thus it was finally not choosen to be investigated.
- the BR, AR, and Markov models are applicable and convenient to be used and fitted with actual data and currently used empirical models for quantifying the impacts. The BR and AR models give the same results of the optimal intervention strategies and they are very closely related with regard to the formulations.
- the Markov model is perharp the most applicable one as it allows the consideration of multiple interventions and multiple condition states, which are both trackable and convenient for management. Also, Markov model allows the better integration of latent process into the model. Moreover, it is possible in the optimization model to have impact constraints (e.g. budget constraint)

- The grouping of intervention on a number of objects instead of intervention on single object could significantly reduce the negative impacts incurred by the stakeholders, especially the users and owners, e.g. owner could mimize the set up cost and impact incurred by setting traffic barriers during execution period.

- The impact hierarchy proposed by Adey et al. (2012) and the MINLP model proposed by Lethanh and Adey (2012) are helpfull and adequate to be used in the course of determination of optimal intervention strategies for public roads. By using the hierarchy, all possible impacts incurred by all stakeholders are quantified and no double-counting could be happen. The proposed MINLP model was developed in the way that it fits with the hierarchy and allow to determine the optimal intervention return period of each interventin type as well as the annual impact of the strategy.

Beside the advanteges of the BR, AR, and Markov models, there are several limitations of these models that shall be highlighted to be considered for future improvements.

- the BR, AR, and Markov models shall includes discount factors for impacts as the estimation involves the future time (e.g. values of impacts need to be discounted to present values for fair comparison).

- The proposed BR and AR model allows the evaluation of intervention strategies that are composed of a single type of intervention (e.g. resurfacing, reconstruction, etc). It is only possible with this model to evaluate intervention strategies that are composed of interventions of more than one type, which is something that often occurs in reality, by updating the model parameters and re-estimate the optimal intervention return period for each new type of intervention follow the execution of an intervention. Further investigation is required to determine a model that will improve the ability of the decision maker to evaluate these intervention strategies.

- the proposed BR and AR models do not allow the consideration of impact constraints (e.g. budget constraint).

- the use of steady state in Markov model is not perfectly show the behaviours of the infrastructure management system. In most of the case, it is hard to believe one type of intervention can be repeated over and over. This problem can be overcomed with the use of Dynamic programing techniques.

Appendix A

Appendix A

```
# This program was coded by Nam LETHANH (lethanh@ibi.baug.ethz.ch) and Clemens KIELHAUSER (kielhauser@ibi.baug.ethz.ch)
#BLOCK REPLACEMENT (BR)
#Run program by copying .source("BR.R")
#------------------------------------------------------
#reading the input.
data <- read.csv("inputdataIS21.csv",header=TRUE)
attach(data)
OBJMAX<-length(data[,1])

#please specify investigation period and discount factor
YearMax<-50 #total no of year to be investigated.
rho<-0   #discount factor
#mfac<-c(0.09,0.09,0.09,0.09,0.09,0.09,0.09,0.09,0.09,0.09,0.09) # factor for correction IS3
#mfac<-c(0.12,0.12,0.12,0.04,0.04,0.04,0.04,0.04,0.12,0.12,0.12) # factor for correction IS2
#mfac<-c(0.14,0.14,0.14,0.14,0.14,0.14,0.14,0.14,0.14,0.14,0.14) # factor for correction IS1
#creating easy-to-read output file
sink("br_output.txt", append=FALSE, split=FALSE)
  cat("Investigated number of Objects: ",OBJMAX,"\n")
  cat("Investigated years: ",YearMax,"\n")
  cat("Discount rate: ",rho*100," %","\n","\n")
  cat("This is the block replacement Method ","\n","\n")
sink()

#creating local variables
rate<-matrix(nrow=YearMax, ncol=OBJMAX)     #hazard rate in respective year
```

```
mcoin<-matrix(nrow=YearMax, ncol=OBJMAX)    #mean number of corrective intervention
eta_cost<-matrix(nrow=YearMax, ncol=OBJMAX)   #cost per unit time (object n, time t)
eta_avail<-matrix(nrow=YearMax, ncol=OBJMAX)  #availability (object n, time t)
cpi<-matrix(nrow=1, ncol=OBJMAX)         #cost for periodic intervention as sum of stakeholder values
cci<-matrix(nrow=1,ncol=OBJMAX)          #cost for critical intervention as sum of stakeholder values
Mineta_cost<-matrix(nrow=1, ncol=OBJMAX)    #minimum of eta_cost
Maxeta_avail<-matrix(nrow=1, ncol=OBJMAX)   #maximum of eta_avail
Optobj_cost<-matrix(nrow=1, ncol=OBJMAX)    #time of Mineta_cost
Optobj_avail<-matrix(nrow=1, ncol=OBJMAX)   #time of Maxeta_avail
colors=c("chocolate","coral3","coral4","cyan1","cyan4","darkblue","blue","chartreuse4","red","deeppink","deeppink4") #colors for plot

#summing up stakeholder costs
for (n in 1:OBJMAX){
  cpi[n]<-owner_cpi[n]+user_cpi[n]+das_cpi[n]+ias_cpi[n]
  }

for (n in 1:OBJMAX){
  cci[n]<-owner_cci[n]+user_cci[n]+das_cci[n]+ias_cci[n]
  }

#calculating hazard rate and eta values - NEW
for (t in 1:YearMax){
  for (n in 1:(OBJMAX))
    {
    rate[t,n]<-m[n]*alpha[n]*(alpha[n]*t)^(m[n]-1)
    mcoin[t,n]<-rate[t,n]*t*mfac[n]
    eta_cost[t,n]<-exp(-rho*t)*(cpi[n]+mcoin[t,n]*cci[n])/t
    eta_avail[t,n]<-t/(t+mcoin[t,n]*tci[n]+tpi[n])
  }
}

##calculating hazard rate and eta values - OLD
#for (t in 1:YearMax){
#  for (n in 1:OBJMAX)
#  {
#    rate[t,n]<-m[n]*alpha[n]*(alpha[n]*t)^(m[n]-1)
#    mcoin[t,n]<-rate[t,n]*t
#    eta_cost[t,n]<-exp(-rho*t)*(cpi[n]+mcoin[t,n]*cci[n])/t
#    eta_avail[t,n]<-t/(t+mcoin[t,n]*tci[n]+tpi[n])
#  }
```

```
#}


print(eta_cost)
print(eta_avail)

#finding the minimum cost year and maximum availability year from the
    estimation results.
for (n in 1:OBJMAX){
  Mineta_cost[n]<-min(eta_cost[,n])
  Optobj_cost[n]<-which.min(eta_cost[,n])
  Maxeta_avail[n]<-max(eta_avail[,n])
  Optobj_avail[n]<-which.max(eta_avail[,n])
}

#writing into easy-to-read output file
sink("br_output.txt", append=TRUE, split=FALSE)
  for (n in 1:OBJMAX){
    cat("optimal intervention time (cost criterion) of object ",n,":",
    Optobj_cost[n]," years, cost:",Mineta_cost[n]," mu per year","\n")
  }
  for (n in 1:OBJMAX){
    cat("optimal intervention time (availability criterion) of object
    ",n,":",Optobj_avail[n]," years, availability:",100*Maxeta_avail[n
    ]," %","\n")
  }
sink()

#generating machine-readable output files
output_cost<-matrix(nrow=OBJMAX, ncol=3)
output_avail<-matrix(nrow=OBJMAX, ncol=3)

for (n in 1:OBJMAX){
  output_cost[n,1]<-n
  output_cost[n,2]<-Optobj_cost[n]
  output_cost[n,3]<-Mineta_cost[n]
  }

for (n in 1:OBJMAX){
  output_avail[n,1]<-n
  output_avail[n,2]<-Optobj_avail[n]
  output_avail[n,3]<-Maxeta_avail[n]
  }

```

```
write.table(output_cost, file = "output_br_cost.csv", sep = ",", col.
    names = c("Object","optimal year","cost"), qmethod = "double",row.
    names=FALSE)
write.table(output_avail, file = "output_br_avail.csv", sep = ",", col
    .names = c("Object","optimal year","availability"), qmethod = "
    double",row.names=FALSE)
write.table(eta_cost, file = "output_eta_cost.csv", sep = ",", qmethod
     = "double",row.names=FALSE)
#creating legend for plot
leg<-matrix(nrow=OBJMAX, ncol=1)
for (i in 1:OBJMAX){
  leg[i]<-paste("Object",i)
}

#creating pdf graphics
setEPS()
postscript(file="BR-impact-is.eps")
matplot(eta_cost,type="b",col=colors,pch=(15-(1:OBJMAX)) ,xlab="Time (
    years)",ylab="Annual impact (mu/Year)",lwd=1,lty=1,add=F,log="y")
legend("topright", inset=.05,cex=0.8, pch=(15-(1:OBJMAX)),col=colors,
    legend=leg)
#dev.off()
#pdf(file="BR_avail.pdf")
#matplot(eta_avail,type="l",col=rainbow(OBJMAX),xlab="Time (years)",
    ylab="Availability",lwd=1,lty=1,add=F)
#legend("topright", cex=1, pch=16,col=rainbow(OBJMAX), legend=leg)
#dev.off()
print(Optobj_cost)
print(Mineta_cost)
detach(data)
closeAllConnections()

#The End
```

Listing A.1: Program for block replacement (BR)

```
# This program was coded by  Clemens KIELHAUSER (kielhauser@ibi.baug.
    ethz.ch)
#AGE REPLACEMENT (AR)
#Run program by copying .source("AR.R")
#-------------------------------------------------------
#reading the input.
data <- read.csv("inputdataIS21.csv",header=TRUE,sep=",")
attach(data)
OBJMAX<-totaldata<- length(data[,1])

#please specify investigation period and discount factor
```

```
YearMax<-50#total no of year to be investigated
rho<-0#discount rate for costs

#creating easy-to-read output file
sink("ar_output.txt", append=FALSE, split=FALSE)
  cat("Investigated number of Objects: ",OBJMAX,"\n")
  cat("Investigated years: ",YearMax,"\n")
  cat("Discount rate: ",rho*100," %","\n","\n")
  cat("This is the age replacement Method ","\n","\n")
sink()


#creating local variables
cdf<-matrix(nrow=YearMax, ncol=OBJMAX)    #cumulative density function values
surv<-matrix(nrow=YearMax, ncol=OBJMAX)   #survival probability values
int<-matrix(nrow=YearMax, ncol=OBJMAX)    #int stands for integral of surv from 0 to t
cpi<-matrix(nrow=1, ncol=OBJMAX)      #cost for periodic intervention as sum of stakeholder values
cci<-matrix(nrow=1,ncol=OBJMAX)       #cost for critical intervention as sum of stakeholder values
eta_cost<-matrix(nrow=YearMax, ncol=OBJMAX) #cost per unit time (object n, time t)
Mineta_cost<-matrix(nrow=1, ncol=OBJMAX)  #minimum of eta_cost
Optobj_cost<-matrix(nrow=1, ncol=OBJMAX)  #time of Mineta_cost
output_cost<-matrix(nrow=OBJMAX, ncol=3)  #storage variable for output file
colors=c("chocolate","coral3","coral4","cyan1","cyan4","darkblue","blue","chartreuse4","red","deeppink","deeppink4") #colors for plot

#summing up stakeholder costs
for (n in 1:OBJMAX){
  cpi[n]<-owner_cpi[n]+user_cpi[n]+das_cpi[n]+ias_cpi[n]
  }

for (n in 1:OBJMAX){
  cci[n]<-owner_cci[n]+user_cci[n]+das_cci[n]+ias_cci[n]
  }

#defining functions
cdfweib<-function(x,a,b){(1-exp((-(x*b)^a)))}          #Weibull CDF
cdfexp<-function(x,r){1-exp(-(r*x))}                  #exponential CDF
edexp<-function(x,rate){(1-cdfexp(x,rate))}          #extended exponential CDF
```

```
edweibull<-function(x,shape,scale){(1-cdfweib(x,shape,scale))}  # extended Weibull CDF

#calculating hazard rate and eta values
for (t in 1:YearMax){
  for (n in 1:OBJMAX){
    if (funct_type[n]=="exp"){
      cdf[t,n]<-cdfexp(t,rate[n])
      int[t,n]<-integrate(edexp,0,t,rate=rate[n])$val
    }
    if (funct_type[n]=="wei"){
      cdf[t,n]<-cdfweib(t,shape[n],scale[n])
      int[t,n]<-integrate(edweibull,0,t,shape=shape[n],scale=scale[n])$val
    }
    surv[t,n]<-1-cdf[t,n]
    eta_cost[t,n]<-((cdf[t,n]*cci[n]+surv[t,n]*cpi[n])*exp(-(rho*t)))/int[t,n]
  }
}

print(eta_cost)

#finding the minimum cost year and maximum availability year from the estimation results.
for (n in 1:OBJMAX){
  Mineta_cost[n]<-min(eta_cost[,n])
  Optobj_cost[n]<-which.min(eta_cost[,n])
}

#writing into easy-to-read output file
sink("ar_output.txt", append=TRUE, split=FALSE)
  for (n in 1:OBJMAX){
    cat("optimal intervention time (cost criterion) of object ",n,":",Optobj_cost[n]," years, cost:",Mineta_cost[n]," CHF per year","\n")
  }
sink()

#generating machine-readable output files

for (n in 1:OBJMAX){
  output_cost[n,1]<-n
  output_cost[n,2]<-Optobj_cost[n]
  output_cost[n,3]<-Mineta_cost[n]
  }
```

```
write.table(output_cost, file = "output_ar_cost.csv", sep = ",", col.
    names = c("Object","optimal year","cost"), qmethod = "double",row.
    names=FALSE)


#creating legend for plot
leg<-matrix(nrow=OBJMAX, ncol=1)
for (i in 1:OBJMAX){
  leg[i]<-paste("Object",i)
}

#creating pdf graphics
#pdf(file="AR_cost.pdf")
matplot(eta_cost, type="b",col=colors,pch=(15-(1:OBJMAX)),xlab="
    Replacement Interval (Years)",ylab="Yearly Expeditures(CHF/Year)",
    ylim=c(1e3,1000000),log="y",lwd=1,lty=1,add=F)
legend("topright", inset=.05,cex=0.8, pch=(15-(1:OBJMAX)),col=colors,
    legend=leg)
#dev.off()


detach(data)
closeAllConnections()

print(output_cost)
#The End
```

Listing A.2: Program for age replacement (AR)

```
# This program was coded by  Clemens Kielhauser (kielhauser@ibi.baug.
    ethz.ch)
#PERIODIC GROUP REPAIR (PGR)
#Running program by copying .source("program.R")
#----------------------------------------------------
#reading the input.
data <- read.csv("is1.csv",header=TRUE,sep=",")
attach(data)
OBJMAX<-totaldata<- length(data[,1])

#please specify investigation period, discount factor and inspection
    setup costs
YearMax<-100#total no of year to be investigated
rho<-0.0#discount rate for costs
setc<-0#inspection setup costs
```

```
#creating easy-to-read output file
sink("pgr_output.txt", append=FALSE, split=FALSE)
  cat("Investigated number of Objects: ",OBJMAX,"\n")
  cat("Investigated years: ",YearMax,"\n")
  cat("Discount rate: ",rho*100,"%","\n","\n")
  cat("This is the periodic group repair Method ","\n","\n")
sink()

#creating local variables
cidle<-matrix(nrow=1, ncol=OBJMAX)    #cost if object is beyond threshold
cop<-matrix(nrow=1,ncol=OBJMAX)     #cost if object is operational
rn<-matrix(nrow=YearMax, ncol=OBJMAX) #reward for inspection interval
rtu<-matrix(nrow=YearMax, ncol=OBJMAX)    #reward sum per time unit
csu<-matrix(nrow=YearMax, ncol=OBJMAX)    #inspection cost sum per time unit
etac<-matrix(nrow=YearMax, ncol=OBJMAX)
Maxeta<-vector(length=OBJMAX)
Optobj<-vector(length=OBJMAX)

# summing up stakeholder costs
for (n in 1:OBJMAX){
  cop[n]<-owner_op[n]+user_op[n]+das_op[n]+ias_op[n]
}
for (n in 1:OBJMAX){
  cidle[n]<-owner_idle[n]+user_idle[n]+das_idle[n]+ias_idle[n]
}

#defining functions
pdfexp<-function(x,r){r*exp(-(r*x))}                          #exponential PDF
pdfweib<-function(x,a,b){(a*b)*(x*b)^(a-1)*exp(-(x*b)^a)}     #Weibull PDF
cdfweib<-function(x,a,b){(1-exp((-(x*b)^a)))}                 #Weibull CDF
cdfexp<-function(x,r){1-exp(-(r*x))}                          #exponential CDF
epdfexp<-function(x,cop,cidle,t,rho,r){(cop+cidle*(t-x))*pdfexp(x,r)*exp(-rho*t)}   #extended exp. PDF
epdfweib<-function(x,cop,cidle,t,rho,a,b){(cop+cidle*(t-x))*pdfweib(x,a,b)*exp(-rho*t)} #extended Weib. PDF

#calculating hazard rate and eta values
for (t in 1:YearMax){
  for (n in 1:OBJMAX){
    if (funct_type[n]=="exp"){
```

```
      rn[t,n]<-(integrate(epdfexp,0,t,cop=cop[n],cidle=cidle[n],t=t,rho=rho,r=rate[n])$val+cop[n]*t*(1-cdfexp(t,rate[n]))*exp(-(rho*t)))
     }
    if (funct_type[n]=="wei"){
      rn[t,n]<-(integrate(epdfweib,0,t,cop=cop[n],cidle=cidle[n],t=t,rho=rho,a=shape[n],b=scale[n])$val+cop[n]*t*(1-cdfweib(t,shape[n],scale[n]))*exp(-(rho*t)))
    }

  }
}

for (t in 1:YearMax){
  for (n in 1:OBJMAX){
    rtu[t,n]<-rn[t,n]
    csu[t,n]<-setc+cinsp[n]
    etac[t,n]<-(rtu[t,n]-csu[t,n]*exp(-(rho*t)))/t
  }
}


# finding the maximum year from the estimation results.
for (n in 1:OBJMAX){
  Maxeta[n]<-max(etac[,n])
  Optobj[n]<-which.max(etac[,n])

#writing into easy-to-read output file
  sink("pgr_output.txt", append=TRUE, split=FALSE)
  cat("optimal intervention time for periodic group repair:",Optobj," years, reward:",Maxeta,"CHF per year","\n")
  sink()

}



#generating machine-readable output files
output<-matrix(nrow=n, ncol=2)
for (n in 1:OBJMAX){
  output[n,1]<-Optobj[n]
  output[n,2]<-Maxeta[n]
}

write.table(output, file = "output_pgr.csv", sep = ",", col.names = c("optimal year","reward"),
```

```
            qmethod = "double",row.names=FALSE)

#creating eps graphics
setEPS()
postscript(file="PGR_output%d.eps",onefile=F)
for (n in 1:OBJMAX){
plot(etac[,n],type="l",col="green",xlab="Inspection Interval (Years)",
   ylab="Reward (CHF per year)",lwd=1,lty=1)
}
dev.off()

detach(data)
closeAllConnections()
print(output)


#The End
```

Listing A.3: Program for periodic group repair

```
##
##source("markovgiventheta.R")
#This program was coded by Nam Lethanh from Osaka University (2011)
############INPUT PART############################
jmax=4  # road
theta<-c(0.08,0.17,0.3,0)
#jmax=5 #Brige
#theta<-c(0.06,0.09,0.19,0.25,0)
z=1  # Please select the interval or elapsed time in Markov processs
########################################
thetasa<-matrix(double(1),nrow=jmax,ncol=jmax)
probability<-matrix(double(1),jmax,jmax)
##############defining thetasa value################

##############################################
markovprob<-function(jmax,z,theta,probb){
probb<-matrix(double(1),jmax,jmax)
##theta<-matrix(double(1),nrow=1,ncol=jmax)
thetasa<-matrix(double(1),nrow=jmax,ncol=jmax)
################################################
for (i in 1:jmax){
for (j in 1:jmax)
thetasa[i,j]=theta[i]-theta[j]
}
print(thetasa)
###############################################
for (i in 1:jmax){
```

```
for (j in 1: jmax){
prob1=0.0
reserve<-1.0
for (k in i:(j-1)){
if (j<=i) {
reserve=1
} else {
reserve=reserve*theta[k]
}
}
print(reserve)
#################################################
if (i>j){
probb[i,j]=0.0
} else {
for (k in i:j){
prod11=1.0
######################
for (e in i:j){
if(e !=k) {
prod11=thetasa[e,k]*prod11
}
}
#####################
prob1=prob1+exp(-theta[k]*z)/prod11
}
#############
prob1<-prob1*reserve
probb[i,j]=prob1
}
}
}
print(probb)
}
#########################
pro<-markovprob(jmax,z,theta,probb)
# After running this code in R, from R console, you just type down pro
   , results will appear.
```

Listing A.4: Estimation of Markov transition probability

```
# This program is coded by Nam Lethanh, ETH Zurich, Switzerland (
   lethanh@ibi.baug.ethz.ch) .
# this program is coded for the case of multiple object using
   stationary Markov chain model (1 period transition probability).
#Minimization of total cost subject to constrains: finding our optimal
    intervention strategies
```

```
# ... index sets
set objects;      # set of objects
#set r{objects};    # r is action on object n
# ... parameters (constants)
param r{objects};
param I{objects}; #number of condition states
param P {n in objects, a in 1..r[n],i in 1..I[n],j in 1..I[n]}; #
    This is the repair Markovian matrix P_{rij}
param B; #                      #  Budget (CHF)
param Q{objects}; #this is the probability of going to failure (%)
param c {n in objects,a in 1..r[n],i in 1..I[n]}; #agency cost
param u {n in objects,a in 1..r[n],i in 1..I[n]}; #user cost

# ... problem variables
var w {n in objects,a in 1..r[n],i in 1..I[n]} >= 0;# process time of
    state in object
#var Q{n in objects} >= 0;
# ...

# ... objective is to minimize total cost
minimize totalcost: sum{n in objects,a in 1..r[n], i in 1..I[n]} (w[n,
    a,i]*(c[n,a,i]+u[n,a,i]));

subject to
 # ...non-negative of variable
  nonnegative{n in objects,a in 1..r[n],i in 1..I[n]}: w[n,a,i] >= 0;
  # ...balance of state probabilities
 # balance3 {n in objects}: sum{a in 1..r[n],i in (I[n]-1)..I[n]} w[n,
    a,i]=0.00075;
   # ...balance of state probabilities
   balance1 {n in objects}: sum{a in 1..r[n],i in 1..I[n]} w[n,a,i]=1;
  # ... balance of state probabilities
   balance2{n in objects,j in 1..I[n]}: sum{a in 1..r[n],i in 1..I[n
    ]}(w[n,a,i]*P[n,a,i,j]) = sum{a in 1..r[n]}(w[n,a,j]);
  #...constraint on the failure probability
  #failure{n in objects, a in 1..r[n],j in (I[n]-1)..I[n]}: Q[n]=sum{i
     in 1..(I[n]-2)}w[n,a,i]*P[n,a,i,j];
  #...budget constraint
  budget: sum{n in objects}((1/(1-Q[n]))*sum{a in 1..r[n],i in 1..(I[n
    ]-2)} w[n,a,i]*c[n,a,i]) <= B;
#...constraints on value of variables
# binding1 {n in objects, a in 1..(r[n]-1), i in (I[n]-1)..I[n]}: w[n,
    a,i] = 0;
```

Listing A.5: Markov optimization model in AMPL

```
# This data is coded by Nam Lethanh, ETH Zurich, Switzerland (
    lethanh@ibi.baug.ethz.ch) .

#...index sets
set objects:= obj1; #number of object
set r[obj1] := r1_obj1 r2_obj1 r3_obj1;


param I:= obj1 5; #this is number of condition states

param B:= 2000; #budget constraint -million CHF
#....no
# ...transition probability P[n,a,i,j] [CHF]...
param P:=
#....transition probability for object 1


  [obj1,r1_obj1,*,*]: 1   2   3   4   5:=
    1   0.693 0.297 0   0   0.01
    2   0.0   0.792 0.198 0   0.01
    3   0.0   0   0.495 0.495 0.01
    4   0.0   0   0   0.99  0.01
    5   0   0   0   0   1

  [obj1,r2_obj1,*,*]: 1   2   3   4   5:=
    1   0.792 0.198 0   0   0.01
    2   0.0   0.9405  0.0495  0   0.01
    3   0.0   0   0.693 0.297 0.01
    4   0.0   0   0   0.99  0.01
    5   0   0   0   0   1

  [obj1,r3_obj1,*,*]:   1   2   3   4   5:=
    1   0.99  0   0   0   0.01
    2   0.99  0   0   0   0.01
    3   0.99  0   0   0   0.01
    4   0.99  0   0   0   0.01
    5   1   0   0   0   0;


  #.............................



# ...owner cost [CHF]...
param c:=
```

```
  [obj1,*,*]:   1   2   3   4   5 :=
    r1_obj1   0   0   0   0   150
    r2_obj1   5   5   5   5   150
    r3_obj1   150   150   150   150   150;



# ...user cost [CHF]...
param u:=
#...for object 1
  [obj1,*,*]:   1 2 3 4 5:=
    r1_obj1   0 5 15  30  250
    r2_obj1   0 5 15  30  250
    r3_obj1   50  50  50  50  250;

param Q:= obj1 0.01;
```

Listing A.6: Example of data structure in Markov optimization model in AMPL

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