Generating Near–Optimal Road Condition–Capacity Improvement Decisions using Monte Carlo Simulations

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Abstract

Road travel cost can be defined as a function of condition and volume:capacity factors. Asset managers intervene on heavily trafficked and poor condition roads based on criteria to optimize network travel and intervention (social) costs. These criteria may involve a trade-off between improving road condition or capacity. Road performance is known through periodic inspection and stochastic modeling to estimate deteriorated future condition. The predicted future condition and traffic growth rates change pavement

section intervention (capacity or condition improvement) priority over time. The optimal road intervention choice can be determined using algorithms including the greedy algorithm and Monte Carlo simulations. Greedy algorithms search through the entire sample space locally and step-wise to approximate global optima, whereas Monte Carlo simulations randomly sample candidate sections to generate more globally optimum interventions. This study proposes a road asset management model using Monte Carlo methods to optimally choose road network interventions considering condition and traffic changes over a planning horizon. The study includes an empirical application using real world data and compares the proposed Monte Carlo simulations approach to the greedy algorithm.

Introduction

Optimum road network intervention decisions involve choices on improving road condition and capacity to shorten travel times from origins to destinations. These decisions should be done over longer planning periods because limited road management budgets may not permit working on all candidate sections at once. Therefore, road managers have to carefully develop intervention decision models that optimise travel and agency (social) costs while ensuring user safety. Intervention decisions for a few sections may be easily determined; however, as the number of sections increases, arriving at an optimum solution becomes computationally more cumbersome.

Effective and efficient road condition and capacity improvement decisions are important to ensure smooth movement. Chandra (2004) elaborated the effect of road condition on capacity and travel cost with condition degenaration leading to capacity reduction and travel cost increase. The Bureau of Public Roads (BPR 1964) function modeling the exponential relationship between travel time and traffic volume: capacity ratio was conveniently modified by Obunguta et al. (2022) to incorporate a condition term to model the joint condition deterioration and congestion effects on travel time. Condition improvement costs less than capacity increase because the latter involves new pavement construction. Higher travel speeds are achievable on good roads which in turn increases flow rates and road capacity (Chandra 2004).

However, road width expansions significantly increase capacity due to the creation of additional lanes, unclogging major road network bottlenecks resulting in greater travel time reduction compared to condition improvement. Chandra and Kumar (2003) empirically showed an increasing linear relationship between capacity and carriageway width for Indian roads attributable to the greater freedom of movement on wider roads. A trade-off exists between capacity increase and condition improvement since the former may contribute to a bigger reduction in social costs, whereas the latter increases travel costs if neglected due to a build up of negative effects (Obunguta et al. 2022).

For sections on the same road link/group, working on sections simultaneously may generate multiple intervention effects due to the interaction between these sections. If a poor condition section is improved, it not only improves traffic flow on the improved section but also on neighboring sections as traffic build up is slowed down. Algorithms such as Monte Carlo simulations that incorporate randomness enable the evaluation of multiple effects (Zhang et al. 2018).

Additionally, intervening on road sections at the same time and in the same workzone reduces total agency costs as spatial and temporal consolidations generate cost savings due to usage of the same equipment and staff, and reduced traffic interruptions as a result of fewer work zone repair instances (Mizutani et al. 2020). Lethanh et al. (2018) determined optimal sets of work zones for large infrastructure networks consisting of multiple objects using a linear optimization model directly linked to a geographical information system framework. To lower social costs while maximizing cost savings, road agencies need to work on more sections in the same work zone and at the same time by developing optimum road section group intervention strategies.

This research extends work by Obunguta et al. (2022) to evaluate the effects of pavement deterioration and traffic volume growth on the condition-capacity intervention choice trade-off and explores the effect of condition improvement on capacity that had been simplified. The past model assumed independence between condition and capacity enhancements. Additionally, the study proposes a Monte Carlo simulation approach to improve the efficiency of optimal solution search and includes a comparison between the proposed Monte Carlo to the greedy algorithm applied in the past.

Research Objectives

The main research objective is to build a road pavement asset management model to optimally determine intervention choice for multiple road sections concurrently over a planning horizon while incorporating network changes at each discrete time point. Specifically, the study objectives are:

1) Develop an asset management model to determine near-optimum road intervention choices by optimizing social costs using Monte Carlo methods over a planning horizon.
2) Compare the proposed Monte Carlo simulations approach to a greedy algorithm in arriving at a close to globally optimal solution.
3) Evaluate traffic growth, budget increase and condition deterioration effects on the condition-capacity intervention choice trade-off for multiple pavement sections.
4) Empirically evaluate intervention effects and show the applicability of the model in obtaining socially optimum intervention policies on an actual road network.

To the best of the authors' knowledge, no past study builds a model that evaluates the effects of stochastic pavement deterioration on the intervention (capacity or condition improvement) choice for multiple sections simultaneously for a large network over a finite planning horizon. The rest of the paper is organized as follows. Related literature is reviewed in the next section. The following section develops the road pavement intervention model after which an empirical application is described. Lastly, the conclusions, future work and other possible model applications are presented.

Related Literature

Road asset management involves optimizing the usage of road assets including pavements, bridges and tunnels to maximize their value. In the optimization, intervention planning is preceded by deterioration estimation for which stochastic models such as the probabilistic Markov hazard model are popular due to pavement deterioration uncertainty (Tsuda et al. 2006, Kobayashi et al. 2010, Obunguta and Matsushima 2020). For optimum pavement intervention planning; the usage, risk, travel and agency costs may be optimized (Kobayashi et al. 2013, Mizutani et al. 2020, Obunguta et al. 2022, Moghtadernejad et al. 2022).

Optimal solution search algorithms can be broadly divided into exact and approximate algorithms. Exact methods include iterative approaches, whereas approximate methods include randomized, heuristic and meta-heuristic algorithms. Approximate solution search algorithms involve randomness and arrive at near optimal solutions in a comparatively shorter computational time compared to exact methods (Moghtadernejad et al. 2022). Obunguta et al. (2022) applied a greedy algorithm at one time-point to simultaneously optimize multiple road section interventions by proposing works on a given section while fixing all other section states and generated section specific social costs. Their study then selected candidate sections based on total social cost minimization. Marzouk and Osama (2017) developed a fuzzy-based Monte Carlo methodology to perform integrated infrastructure management through failure risk prediction and life cycle cost (LCC) optimization. Monte Carlo simulations were utilized to assess road infrastructure project risk considering cost, time and quality as the main parameters in LCC analysis (Arba et al. 2019) and to evaluate the benefits of battery swapping services in comparison to electric vehicle charge stations (Zhang et al. 2018). Research by Zhang et al. (2018) encouraged swapping as it was more profitable for large electric vehicle populations. Likewise, Monte Carlo simulations could be used to evaluate the trade-off between two competing road infrastructure management alternatives such as condition and capacity improvement. Greedy algorithms (Rinnooy Kan et al. 1993) search through the entire sample space to evaluate all intervention possibilities locally and step-wise to determine social cost minimization actions approximating global optima, whereas Monte Carlo simulations randomly sample candidate road section works to generate more globally optimum interventions without having to search the entire sample space and so could be more efficient for significantly large road networks.

Kuhn (2009) determined optimal policies for simple infrastructure management problems with value functions for a Markov decision problem and Nozhati et al. (2019) generated near-optimal post-hazard actions for electrical infrastructure considering action interconnectedness and cascading effects. Both studies applied approximate dynamic programming. Similarly, road sections are interconnected and actions on one section may affect the travel time on sections on the same road link. Hackl et al. (2018) employed simulated annealing (SA) to determine near-optimal transportation asset restoration programs after destructive events such as natural disasters by minimizing direct and indirect costs. SA is a meta-heuristic procedure that searches for the global optimum of a discrete optimization problem similar to the physical annealing process of finding low energy states of a heated solid. Moghtadernejad et al. (2022) applied discrete particle swarm optimization (DPSO) to generate optimal post disaster interventions for transportation networks. DPSO searches for an optimal solution through agents (particles) mimicking a flying swarm of birds in search for food, whose trajectories are adjusted stochastically and deterministically. Yeo et al. (2013) looked at selecting the optimum, first or second best alternative intervention for facilities in a planning horizon within a budget constraint.

Road travel cost is dependent on condition and traffic volume:capacity ratio as their degradation increases congestion and travel time (Obunguta et al. 2022). Chandra (2004) showed that road capacity is influenced by condition, geometry and driver behaviour through an empirical study that concluded that a 1,000 mm/km increase in road surface roughness resulted in the decrease of capacity by 300 Passenger Car Units per hour (PCU/h) for two-lane Indian roads using regression analysis. If condition improves, traffic flow increases improving road capacity, and vice versa. Ravi et al. (2017) generated adjustment factors using regression models considering carriageway width, road condition (roughness), shoulder condition and the effect of rise and fall as the key factors affecting Indian road capacity.

Asset management involves sequencing infrastructure interventions for optimum usage over the lifetime of the infrastructure. Such problems may be solved through dynamic programming (Bellman 1954). Bellman developed an efficient optimum intervention sequence (policy) generation model that does not require the cumbersome process of evaluating every possible policy. For a dynamic system, Bellman noted that sequencing decisions could be broken down into solvable sub tasks because of the optimality principle which states that ‘an optimal policy has the property that whatever the initial state and initial decisions are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decisions (Bellman 1954)’. This principle is applicable in finding optimal decisions in shorter time periods and summing them up to obtain the aggregate optimum decision for the entire time horizon.

Other works such as Martani et al. (2022) quantitatively evaluated highway designs incorporating uncertainties in future mobility patterns including autonomous vehicles, and management flexibility using real options. Adey et al. (2020) looked at maximizing net benefits of infrastructure asset management through appropriate definitions of road service taking into account how relevant stakeholders including owners, users and the public are impacted. Similarly, this study aims to maximize social benefits by efficiently determining close-to-optimal interventions for numerous road network sections concurrently.

Road Pavement Intervention Model

Model Definition

Consider a road network with a total of K^G road sections and each $k^g = 1^g, \dots, K^G$ belongs to group $g = 1, \dots, G$ which could be road links. Each k^g has pavement condition $i_t^{k^g}$, and traffic volume:capacity ratio $v_t^{k^g}/c_t^{k^g}$ at time point t $(t = 0, 1, 2, \dots, T)$ defined by functions $f(.)$. The travel time $\tau_t^{k^g}$, condition $i_t^{k^g}$, traffic volume $v_t^{k^g}$ and capacity $c_t^{k^g}$ of a section k^g at every time point t vary due to deterioration and improvement effects. The transition of condition state $i_t^{k^g}$ $(i_t^{k^g} = 1, \dots, J_t^{k^g})$, with $J_t^{k^g}$ as the absorbing state, follows the Markov deterioration process after time interval r. Road managers decide the appropriate action $A_t^{k^g}$ $(A_t^{k^g} = A_i, A_c, A_0)$ on a section with $\boldsymbol{A}_t$ being the vector of interventions at t. Action A_i improves condition, A_c increases capacity, and A_0 is no action which attracts an intervention unit cost $C^{A_t^{k^g}}$ that increase monotonically as $C^{A_0} = 0 < C^{A_i} < C^{A_c}$ and are discounted using a discount rate ρ (**Fig. 1**). Let $\boldsymbol{A} = (A_{t=0}^{1^1}, \dots, A_T^{K^G})$ be the string of interventions, policy, for all sections in the network over the entire planning horizon T. The goal is to find a set of optimum interventions $\boldsymbol{A}^*$, an optimum policy, that minimizes total social costs $\sum_{t=0}^{T} \xi_t$. Interventions for all K^G should reduce annual social costs ξ_t within budget limit Ω_t. If the entire budget is spent on improving condition, a total of $N_{A_i} = \Omega_t / C^{A_i}$ sections will be chosen and if it is spent on enhancing capacity, a total of $N_{A_c} = \Omega_t / C^{A_c}$ sections will be selected. The management goal is to select η_{A_i} condition and η_{A_c} capacity improvement candidates within Ω_t optimally while preserving road user safety. A safety threshold is set based on condition in which sections in the worst state have their condition improved (batch 1) after which optimization which involves near-optimal condition and capacity enhancement (batch 2) is carried out within Ω_t following Obunguta et al. (2022). The social cost is defined as a summation of the travel and intervention cost and incorporates savings accrued due to spatial and temporal consolidations by interconnecting/ grouping sections on the same road link.

Working on sections has the effect of improving the general road link condition because a single deteriorated section affects traffic flow on the entire road link. This phenomenon is modeled by obtaining a representative group section with the worst condition, average congestion and average travel time. In **Fig. 2**, road section $k^g = 2^1$ belonging to group $g = 1$ is inaccessible despite being in good condition due to the poorer condition of neighboring $k^g = 1^1$and $k^g = 3^1$; hence, it is of no value. To make road link $g = 1$ more valuable, the worse condition neighboring sections need improvement. If road link $g = 1$ has more traffic compared to $g = 2$, it is more optimal to repair $k^g = 3^1$ instead of $k^g = 1^2$ despite the latter being in poorer condition than the former as repairing $k^g = 3^1$ accrues more social benefits.

Problem Description

The infrastructure planning problem posed in this paper involves determining near-optimum intervention decisions for multiple interconnected road sections over planning horizon T. In the general framework (**Fig. 3**), condition data including explanatory variables such as traffic loading are input into the Markov deterioration model to output the expected pavement life. Intervention planning is then proposed with the greedy or Monte Carlo algorithm utilized for optimal solution search with the infrastructure state updated at each t. The model output comprises of total social costs, optimum policy and selection of an appropriate solution algorithm. The road network has state $\boldsymbol{S}_t$ in which each section k^g has a unique state $s_t^{k^g}(i_t^{k^g}, v_t^{k^g}, c_t^{k^g})$. Road managers have to take optimal actions for all road sections simultaneously at t. The road system then attains a new state at each subsequent t due to condition or capacity improvement, condition deterioration and traffic volume growth. The goal of the managers is to decide actions $\boldsymbol{A}_t$ for the entire road system to improve the next state $\boldsymbol{S}_{t+r}$ within Ω_t after every time interval r.

Travel Time Function

Travel time is important in the estimation of travel costs and intervention effects. The adopted travel time function incorporates a condition term in the original BPR function (Obunguta et al. 2022)

$$\tau_t^{k^g} = \tau^{k^g,0}\left[\left\{1+\alpha_1 f(i_t^{k^g})\right\}\left\{1+\alpha_2\left(f(v_t^{k^g}/c_t^{k^g})\right)^n\right\}\right] \tag{1}$$

$$f(i_t^{k^g}) = \begin{cases} 0 & if\ \ IRI_t^{k^g} \le i^{k^g*} \\ (i_t^{k^g} - i^{k^g*})^y & if\ \ IRI_t^{k^g} > i^{k^g*} \end{cases}$$

$$f(v_t^{k^g}/c_t^{k^g}) = \begin{cases} 0 & if\ \ (v^{k^g}/c_t^{k^g}) \le (v^{k^g}/c^{k^g})^* \\ (v_t^{k^g}/c_t^{k^g}) - (v^{k^g}/c^{k^g})^* & if\ \ (v_t^{k^g}/c_t^{k^g}) > (v^{k^g}/c^{k^g})^* \end{cases}$$

where α_1 and α_2 = unknowns collected in parameter $\boldsymbol{\alpha}$; $\tau^{k^g,0}$ = free-flow travel time on k^g when traveling at free-flow speed (FFS); $IRI_t^{k^g}$ = International Roughness Index (IRI) for k^g at t; $f(i_t^{k^g})$ and $f(v_t^{k^g}/c_t^{k^g})$ = condition and volume:capacity functions, respectively; y = index; and i^{k^g*} and $(v^{k^g}/c^{k^g})^*$ = condition and volume:capacity significant values.

Pavement section capacity is affected by condition and traffic as discussed earlier. The capacity in PCU/h is defined linearly as (Ravi et al. 2017)

$$c_t^{k^g} = f\left(i_t^{k^g}\right) \tag{2}$$

$$= c_0 - \gamma_0 i_t^{k^g}$$

where c_0 = basic two-lane road capacity; and γ_0 = model coefficient.

Road Pavement Intervention

Condition betterment improves both condition and capacity as highlighted before due to travel time reduction which increases traffic flow and road capacity. Capacity improvements were assumed to improve only the road capacity. When intervention $A_t^{k^g} \in [A_0, A_i, A_c]$ is performed, the condition and capacity improve based on

$$i_t^{k^g} = \begin{cases} i_t^{k^g} - \nabla \\ c_t^{k^g} = f\left(i_t^{k^g} - \nabla\right) & if\ A_i\ on\ k^g\ at\ t \\ i_t^{k^g} \\ c_t^{k^g} & otherwise \end{cases} \tag{3}$$

$$c_t^{k^g} = \begin{cases} mc_t^{k^g} & if \quad A_c\ on\ k^g\ at\ t \\ c_t^{k^g} & otherwise \end{cases} \tag{4}$$

where m = percentage capacity increase; and ∇ = condition improvement.

Markov Transition Process

The stochastic Markov deterioration model is suitable to estimate future road condition because it is probabilistic and appropriately models uncertain pavement deterioration processes. The Markov Transition Probability (MTP) from condition state $h(t) = i_t^{k^g}$ observed at discrete time t to condition state $h(t+r) = j_{t+r}^{k^g}$ at a future time $t+r$ assuming no repair is (Madanat 1993 and Tsuda et al. 2006)

$$Prob\left[h(t+r) = j_{t+r}^{k^g} \,\middle|\, h(t) = i_t^{k^g}, A_t^{k^g}\right] = \begin{cases} \pi_{i_t^{k^g}, j_t^{k^g}} & if\ A_t^{k^g} = A_0 \\ 0 \quad if\ A_t^{k^g} \in [A_i, A_c] \end{cases} \tag{5}$$

The MTP from $i_t^{k^g}$ to $j_t^{k^g}$ is explicitly expressed as a function of hazard rates (Tsuda et al. 2006)

$$\pi_{i_t^{k^g}, j_t^{k^g}} = \sum_{\tilde{k}=i_t^{k^g}}^{j_t^{k^g}} \prod_{\tilde{m}=i_t^{k^g}}^{\tilde{k}-1} \frac{\theta_{\tilde{m}}}{\theta_{\tilde{m}} - \theta_{\tilde{k}}} \prod_{\tilde{m}=\tilde{k}}^{j_t^{k^g}-1} \frac{\theta_{\tilde{m}}}{\theta_{\tilde{m}+1} - \theta_{\tilde{k}}} exp(-\theta_{\tilde{k}} r) \tag{6}$$

$$i_t^{k^g} \le \tilde{k} \le \tilde{m} \le j_t^{k^g}$$

where $\theta_{i_t^{k^g}}$ = hazard rate; and $\tilde{k}$ and $\tilde{m}$ = indices.

For a given set $(i_t^{k^g} = 1, \dots, J_t^{k^g})$, the MTP matrix $\mathbf{\Pi}$ can be defined using transition probabilities between $(i_t^{k^g}, j_t^{k^g})$ pairs.

$$\mathbf{\Pi} = \begin{bmatrix} \pi_{11} & \cdots & \pi_{1J_t^{k^g}} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \pi_{J_t^{k^g} J_t^{k^g}} \end{bmatrix} \tag{7}$$

Because $\mathbf{\Pi}$ follows Markov process properties and due to the nature of pavement deterioration, all the conditions below must be met. The first ensures non-negativity, the second specifies no transition to better state for no repair and the third ensures all probabilities sum to 1.

$$\left. \begin{array}{l} \pi_{i_t^{k^g}, j_t^{k^g}} \ge 0 \\ \pi_{i_t^{k^g}, j_t^{k^g}} = 0 \; (when \; i_t^{k^g} > j_t^{k^g}) \\ \sum_{j_t^{k^g}=1}^{J_t^{k^g}} \pi_{i_t^{k^g}, j_t^{k^g}} = 1 \end{array} \right\} \tag{8}$$

The Markov transition from t to $t + r$ depends only on $h(t)$ and not on earlier history (is memoryless). To predict future pavement condition, MTP at $t + r$ is

$$\mathbf{\Pi}(r) = \mathbf{\Pi}^r \tag{9}$$

To ensure non-negative hazard rates and subsequently expected life expectancies, the hazard rate for each k^g and $i_t^{k^g}$ is expressed in exponential form

$$\theta_{i_t^{k^g}}^{k^g} = exp(\boldsymbol{x}^{k^g} \boldsymbol{\beta}'_{i_t^{k^g}}) \tag{10}$$

$$(i_t^{k^g} = 1, \dots, J_t^{k^g} - 1)$$

where $\boldsymbol{\beta}_{i_t^{k^g}} = (\beta_{i_t^{k^g},1}, \dots, \beta_{i_t^{k^g},M})$ = row vector of unknown parameters with symbol [′] signifying the transpose; and $\boldsymbol{x}^{k^g}$ = row vector of explanatory variables.

The parameters can be determined by expressing the log-likelihood function

$$ln[\boldsymbol{L}(\boldsymbol{\beta})] = ln\left[\prod_{i_t^{k^g}=1}^{J_t^{k^g}-1} \prod_{j_t^{k^g}=i_t^{k^g}}^{J_t^{k^g}} \prod_{k^g=1^g}^{K^G} \left\{\pi_{i_t^{k^g},j_t^{k^g}}(\bar{r}^{k^g}, \overline{\boldsymbol{x}}^{k^g} : \boldsymbol{\beta})\right\}^{\delta_{i_t^{k^g},j_t^{k^g}}^{k^g}}\right] \tag{11}$$

$$= \sum_{i_t^{k^g}=1}^{J_t^{k^g}-1} \sum_{j_t^{k^g}=i_t^{k^g}}^{J_t^{k^g}} \sum_{k^g=1^g}^{K^G} \delta_{i_t^{k^g},j_t^{k^g}}^{k^g} ln\left[\pi_{i_t^{k^g},j_t^{k^g}}\left(\bar{r}^{k^g}, \overline{\boldsymbol{x}}^{k^g} : \boldsymbol{\beta}\right)\right]$$

$$\delta_{i_t^{k^g},j_t^{k^g}}^{k^g} = \begin{cases} 1 & when\ h(t) = i_t^{k^g}\ and\ \ h(t+r) = \ j_t^{k^g} \\ 0 & otherwise \end{cases}$$

where $\delta_{i_t^{k^g},j_t^{k^g}}^{k^g}$ = dummy variable; and the symbol [¯] denotes a measured quantity.

The $\boldsymbol{\beta}_{i_t^{k^g}}$ parameters are obtained by maximising the log-likelihood using iterative methods.

$$\frac{\partial ln\left[\boldsymbol{L}(\widehat{\boldsymbol{\beta}})\right]}{\partial \beta_{i_t^{k^g},m}} = 0 \tag{12}$$

$$(i_t^{k^g} = 1, \dots, J_t^{k^g} - 1; m = 1, \dots, M)$$

The optimal $\widehat{\boldsymbol{\beta}}$ can be obtained through approximating optimality using Newton's method (Tsuda et al. 2006) or Bayesian methods such as Markov Chain Monte Carlo (MCMC) using the Metropolis-Hastings (MH) algorithm (Kobayashi et al. 2010). The MCMC method randomly samples $\boldsymbol{\beta}_{i_t^{k^g}}$ from a probability distribution using the MH algorithm until equilibrium where the Markov chain converges.

The life expectancy ($RMD_{i_t^{k^g}}^{k^g}$) in $i_t^{k^g}$ for k^g is obtained as the inverse of the hazard rate (Lancaster 1990)

$$RMD_{i_t^{k^g}}^{k^g} = \frac{1}{\theta_{i_t^{k^g}}^{k^g}} \tag{13}$$

The average life expectancy $ET^{k^g}_{j^{k^g}_t}(j^{k^g}_t = 2, \dots, J^{k^g}_t)$ is obtained by summing up life expectancies from $i^{k^g}_t = 1$ to $j^{k^g}_t$.

$$ET^{k^g}_{j^{k^g}_t} = \sum_{i^{k^g}_t=1}^{j^{k^g}_t} \frac{1}{\theta^{k^g}_{i^{k^g}_t}} \tag{14}$$

The estimated MTPs and life expectancies can be used to predict future condition $j^{k^g}_t$ as $i^{k^g}_t$ transitions to $i^{k^g}_t + 1$ at the end of pavement life.

Social Cost Optimization

The social cost $\xi_t(\boldsymbol{A}_t)$ at time t, also simply represented as ξ_t, is presented as a summation of travel and intervention cost. Assuming repair was done once a year

$$\xi_t = \sum_{g=1}^{G} (1+\rho)^{-t} \left\{ \left(\omega k^g \overline{v^{k^g}_t} * \overline{\tau^{k^g}_t} \right) + \sum_{k^g=1^g}^{K^g} \sum_{A_t} a^{k^g}_t C^{A^{k^g}_t} \right\} \tag{15}$$

where ω = unit travel time monetary value; $\overline{\tau^{k^g}_t}$ = average travel time on k^g sections in g; $\overline{v^{k^g}_t}$ = average volume on k^g sections in g; $C^{A^{k^g}_t}$ = unit cost of $A^{k^g}_t$; $a^{k^g}_t$ = section area improved; and ρ = discount rate.

The objective is to minimize the total social costs $\sum_{t=0}^{T} \xi_t$ over planning horizon T. The optimum set of actions, policy, can be obtained by optimizing

$$\boldsymbol{A}^* = \underset{\boldsymbol{A}_t}{arg\,min} \sum_{t=0}^{T} \xi_t \tag{16}$$

$$Subject\ to$$

$$\boldsymbol{A} \in \boldsymbol{\Gamma} \tag{17}$$

$$\sum_{g=1}^{G} \sum_{k^g=1^g}^{K^g} \sum_{A_t} a^{k^g}_t C^{A^{k^g}_t} \in \Omega_t \qquad \forall t \tag{18}$$

where $\boldsymbol{\Gamma}$ = set of all feasible actions; and Ω_t = budget limit.

Solution Algorithms

Greedy Algorithm

The optimal solution for the above sequential optimization problem can be determined by obtaining the social costs for all possibilities and then using a greedy algorithm to select interventions with the biggest social cost reduction first (**Fig. 4**). The greedy algorithm searches for a globally optimal solution locally and step-wise. When one section intervention is proposed, the state of all other sections is fixed and total social costs at t estimated. This proposal step is done for all sections considering all possible interventions after which candidates are selected using a social cost minimization greedy algorithm with steps:

Step 1: Propose A_i, A_C and A_0 for each k^g at every t and fix the state $s_t^{k^g}$ of all other sections.

Step 2: Estimate social costs $\xi_t(A_t^{k^g})$ each time an action is proposed.

Step 3: From all $\xi_t(A_t^{k^g})$ estimates, determine the social cost reduction $\Delta\, \xi_t(A_t^{k^g})$ by subtracting $\xi_t(A_t^{k^g})$ from previous social cost ξ_{t-r}.

Step 4: Use a greedy algorithm to select candidates with the biggest $\Delta\, \xi_t(A_t^{k^g})$ and update $\boldsymbol{S}_t$.

Step 5: Lastly, estimate the total social costs $\sum_{t=0}^{T} \xi_t$ that include spatial-temporal consolidations, determine final state $\boldsymbol{S}_T$ and optimum policy $\boldsymbol{A}^*$.

The solution to this problem is quite complex and the evaluation of all possible actions is inefficient. For a network consisting of 2,000 road sections with three interventions over a 15 year planning period, there are 90,000 possible interventions in the first year, then 84,000 in the second year and so on. This becomes cumbersome if inputs including number of elements, actions and length of the analysis period are increased. Methods that incorporate sampling such as Monte Carlo simulations may be more efficient.

Monte Carlo Algorithm

The more efficient Monte Carlo simulations approach involves randomly sampling interventions $\boldsymbol{A}_t$ without having to scan through the entire sample space. The algorithm applies Bellman's principle of optimality by determining optimal annual interventions and then summing up to generate total optimal interventions for the entire planning horizon.

Firstly, the optimum intervention in the initial year

$$\boldsymbol{A}_{t=0}{}^{*} \in \underset{\boldsymbol{A}_{t=0}}{arg\,min} J_0(\boldsymbol{A}_{t=0}) \tag{19}$$

where the cost-to-go function J_0 is defined as

$$J_0(\boldsymbol{A}_{t=0}) = \underset{\boldsymbol{A}_0,\dots,\boldsymbol{A}_T}{min} \sum_{t=0}^{T} \xi_t$$

Next, the optimum intervention after the first year

$$\boldsymbol{A}_1{}^{*} \in \underset{\boldsymbol{A}_1}{arg\,min} J_1(\boldsymbol{A}_{t=0}{}^{*}, \boldsymbol{A}_1) \tag{20}$$

where

$$J_1(\boldsymbol{A}_{t=0}{}^{*}, \boldsymbol{A}_1) = \underset{\boldsymbol{A}_1,\dots,\boldsymbol{A}_T}{min} \sum_{t=0}^{T} \xi_t$$

Following the above procedure incrementally T times, the optimum intervention $\boldsymbol{A}_T{}^{*}$ at T is

$$\boldsymbol{A}_T{}^{*} \in \underset{\boldsymbol{A}_T}{arg\,min} J_T(\boldsymbol{A}_{t=0}{}^{*}, \boldsymbol{A}_1{}^{*}, \dots, \boldsymbol{A}_T) \tag{21}$$

where

$$J_T(\boldsymbol{A}_{t=0}{}^{*}, \boldsymbol{A}_1{}^{*}, \dots, \boldsymbol{A}_T) = \underset{\boldsymbol{A}_T}{min} \sum_{t=0}^{T} \xi_t$$

with

$$J_t(\boldsymbol{A}) = \sum_{t=0}^{T} \xi_t$$

The optimum policy $\boldsymbol{A}^{*}$ over T can then be determined as the combination of all the optimum solutions to the annual sub problems.

$$\boldsymbol{A}^{*} = (\boldsymbol{A}_{t=0}{}^{*}, \boldsymbol{A}_1{}^{*}, \dots, \boldsymbol{A}_T{}^{*}) \tag{22}$$

The Monte Carlo solution steps are detailed in **Fig. 5**.

Empirical Application

Model Inputs

The road pavement intervention model was empirically applied to Uganda's surveyed national road network. Obunguta et al. (2022) obtained α_1 and α_2 as 0.3331 and 0.3481, respectively with n fixed to 1 as the best loss minimizing result; and the significant values $i^{k^g *}$ and $(v^{k^g}/c^{k^g})^*$ were fixed at 4.00 mm/m IRI and 0.5, respectively for Ugandan national roads. This study applied Ugandan national road life expectancies for 1,993 sample 1 km road sections shown in **Table 7** in the Appendix (Obunguta and Matsushima 2020). The estimated benchmark life expectancy was 10.69 years for the sampled roads with IRI (in mm/m) discretized as 1. Good (0 – 3.50), 2. Fair (3.51 – 5.00), 3. Poor (5.01 – 6.50), and 4. Bad (> 6.50) according to the Ministry of Works and Transport (MoWT 2017). Based on Obunguta et al.'s (2022) evidence-based study, Ugandan road sections were categorized as non-congested (NC), moderately congested (MC), congested (CO) and heavily congested (HC) as shown in **Table 1**.

The costs C^{A_i} and C^{A_c} were set to US$280,000 per km (here after $ is used) and $1,652,000 per km, respectively; variable ω was set to $34.56/PCU/h, and the initial annual budget was fixed at $75.06 million following Obunguta et al. (2022). According to traffic levels measured in PCU/h in 2017 and 2018, the estimated traffic growth rate fluctuated with traffic increasing, decreasing, or remaining stagnant on a given route (see **Table 7** in the Appendix). In this study application, the traffic growth rate was set to 0.1% to minimize A_c selection bias. The free flow travel time (FFT) was assumed to be the minimum achievable within a given road group because this may approximate free flow conditions. The budget was considered to increase by 20% each year to create more optimization space by increasing the candidate pool and a 10% discount rate was considered (Bank of Uganda 2018). Following Ravi et al. (2017), the parameters c_0 and γ_0 were set to 2,956 and 199, for two-lane roads and 5,082 and 275, for four-lane roads, respectively, assuming similarity between Indian and Ugandan roads. If a section underwent condition improvement, the condition improved to good with IRI randomly sampled assuming a uniform distribution in the condition state IRI range. Capacity was assumed to double if increased. In case of no action, the condition state deteriorated based on life expectancy and the section attained a randomly sampled IRI in the next state assuming a uniform distribution. Section volume:capacity ratio changed according to condition change and traffic volume growth rates. The greedy algorithm searched through the entire search space, whereas the Monte Carlo algorithm sampled *N* candidates in worse state. Both algorithms were run in Python 3.10.9 using a computer with processor: 13th Gen Intel(R) Core(TM) i9-13900K CPU @ 3.00 GHz, memory (RAM): 64.0 GB and operating system: Windows 11 Pro (64-bit).

Model Results

Estimated Social Costs

The **Table 2** and **Table 3** show results of the estimated social costs; annual undiscounted and aggregate discounted, respectively; using the greedy and Monte Carlo algorithm with traffic growth fixed or considered for a 15 year planning horizon. For the Monte Carlo algorithm, 10 and 1 iteration were set for computational reasons. With traffic growth fixed, estimated annual social costs decreased for both algorithms due to social cost optimization and previous work effects. The Monte Carlo simulation with one iteration generated larger social costs in comparison to the greedy algorithm because of fewer optimal solution search instances. However, the greedy algorithm was suboptimal and resulted in larger social costs compared to the Monte Carlo simulation approach with 10 iterations. This showed the efficiency of Monte Carlo methods in arriving at more optimal solutions considering more iterations despite this requiring a higher computational time cost (**Table 4**). The Monte Carlo algorithm was extensive and robust in its optimal solution search with higher exploration abilities and incorporated multiple intervention effects as it proposed interventions for several road sections simultaneously and randomly. On the other hand, the greedy algorithm was myopic and restricted as it proposed intervention for a given section while fixing the states of other sections which limited the evaluation of multiple intervention work effects concurrently. The greedy algorithm produced locally optimal choices step-wise that did not approximate global optima.

The change in social costs for either algorithm is graphically shown in **Fig. 6** considering fixed traffic. As expected, the agency costs were lower (less than 2% of total social costs) compared to travel costs. To show the impact of intervention works, undiscounted social costs without the influence of discount factors were applied. The fluctuation in social costs between the initial and third year was due to model adjustments as capacity was defined as a function of condition and because of randomness in determination of condition and volume: capacity ratio after intervention. The greedy algorithm (**Fig. 6** a) showed a general reduction in social costs with steeper reductions in the third and eleventh year after which the costs stagnated. This stagnation was probably due to the algorithm getting trapped in local optima as mentioned above. The Monte Carlo simulations approach (**Fig. 6** b) achieved a huge reduction in social costs in the third year after which the social costs gradually reduced over time. This result shows that timely interventions for vital sections optimally selected unblocks critical bottlenecks in the road network that lowers total social costs even with limited budgets, which highlights the importance of timely and decisive network interventions before the build up of negative effects.

The Appendix shows how the incorporation of multiple interventions for group $g = 1$ by the random Monte Carlo algorithm makes it superior to the greedy algorithm. The Monte Carlo algorithm selected vital combinations of condition or capacity improvement works each year that unclogged road network bottlenecks unlike the greedy algorithm that deferred condition and capacity interventions to the 11th and 7th to 9th year, respectively (**Table 8** and **Table 9** in the Appendix). It should be noted that, the Monte Carlo methods were unstable especially for much fewer iterations compared to the greedy algorithm. This instability is attributable to the randomness of Monte Carlo simulations.

Similar results were shown considering traffic growth, however, the total social costs exponentially increased due to the enormous increase in travel costs. The enormous social costs were due to the fixed network length and limited budget assumptions. As a result, with traffic growth, the social costs exponentially increased due to larger section volume: capacity ratios. Additionally, the limited budget did not permit working on all critical sections hence the joint negative effects of higher volume: capacity and condition for many critical sections not intervened on further increased the social costs exponentially. In future, the case of network length extension through the construction of entirely new routes could be studied.

Algorithm efficiency was examined through computational time comparison with one iteration set for the Monte Carlo algorithm as computational costs increase with increase in iterations despite the greater possibility of generating more optimal solutions (**Table 4**). The greedy algorithm needed about 24 minutes, whereas Monte Carlo simulations required about 11 minutes (53.38% shorter) for a single iteration for a 15 year planning horizon. The Monte Carlo algorithm didn't have to search through the entire sample space as probable candidates were randomly sampled in a more defined sample space which optimized computational time. However, the program run time was about an hour longer when 10 iterations were set for the Monte Carlo simulations compared to the greedy algorithm. The greedy algorithm presented a locally optimal solution in a relatively shorter time despite this not closely approximating the globally optimal solution because it was stuck in local optima. As iterations increased, optimal solution search instances for the Monte Carlo algorithm were increased with higher probability of lowering social costs to generate a more stable true global optima; however, this required a larger computational cost.

Section Intervention

The **Table 5** and **Table 6** show the number of candidates selected for intervention by the greedy and Monte Carlo algorithm for a 15 year planning horizon with traffic growth rate fixed and considered, respectively. The first batch contains candidates in terminal state that need improvement to ensure road user safety and the second batch contains sections selected for condition and or capacity enhancement through social cost optimization. For both algorithms, batch 1 decreased after the first year due to significant improvement of sections in the worst to the best state and the subsequent annual works that prevented section deterioration preserving road safety. For batch 2, heavily deteriorated sections were selected for condition improvement and highly trafficked sections were prioritized for capacity increase to optimize social costs. The greedy algorithm was suboptimal to the Monte Carlo simulations as the greedy algorithm was trapped in local optima. The increase in batch 2 over the years was due to budget increment.

The trade-off between condition improvement and capacity increase was shown by the variation in the number of candidates each year and the η_{A_i}/η_{A_c} ratio. If η_{A_i}/η_{A_c} is greater than 1, more sections were selected for condition improvement than for capacity increase, and vice versa. The greedy algorithm selected more sections for condition improvement in batch 2 in year 2 and 11 due to their deteriorated state, whereas capacity enhancements optimized social costs in the other years considering fixed traffic. The increase in condition improvement candidates in the eleventh year was due to a build up of deteriorated sections not selected in earlier years probably due to the confinement of the greedy algorithm in local optima. With traffic growth, the condition improvement peak in the eleventh year disappeared as it was more optimal to select sections for capacity increase because of relatively higher traffic levels. For the Monte Carlo simulations, candidate selection for either improvement showed a gradual η_{A_i}/η_{A_c} decrease and the advantage of timely interventions on critical sections that lower social costs while maintaining road safety. This result demonstrates the supremacy of the Monte Carlo algorithm in generating more optimal interventions even within limited budgets.

Condition and Congestion of Network Sections

Network section condition over the fifteen-year planning period was obtained comparing the greedy and Monte Carlo algorithm with traffic growth fixed or considered (**Fig. 7**). For both algorithms, the entire network condition improved to good at the end of the planning horizon save for the greedy algorithm with traffic growth. The greedy algorithm generated poorer condition as 29.25% of the network stayed in fair to bad condition until the tenth year with traffic fixed (**Fig. 7** a1) and 29.35% of the network was in fair to bad condition until the end of the planning horizon with traffic considered (**Fig. 7** a2). The latter case showed a stagnating trend which suggested that better network condition was unachievable in the foreseeable future unless the budget was significantly increased to accommodate more works including condition improvement. On the other hand, the Monte Carlo algorithm resulted in a gradual improvement in road pavement condition in that by the seventh year, 90% of the network had achieved good state regardless of traffic growth (**Fig. 7** b1, b2). This result shows the superiority of the Monte Carlo algorithm in determining intervention works that better road condition and safety despite incurring a higher computational cost compared to the myopic greedy algorithm whose optimal solution search gets trapped in local optima.

Also, network section congestion over the fifteen-year period applying either algorithm was estimated with traffic growth fixed or considered (**Fig. 8**). The initial drop in moderately congested sections was due to condition deterioration. The gradual reduction in congestion thereafter is attributable to capacity increase due to the combined effects of capacity and condition improvement. With traffic fixed, both algorithms achieved about 68% of the network in moderate and non-congested state at the end of the planning period (**Fig. 8** a1, b1). However, with traffic growth, 40.44% and 33.86% of the network degenerated to congested and heavily congested state for the greedy (**Fig. 8** a2) and Monte Carlo algorithm (**Fig. 8** b2), respectively. This 6.58% improvement in network congestion by the Monte Carlo algorithm showed its superiority in optimal solution search with positive cascading impacts of timely condition improvement resulting in road capacity gains.

Conclusions

This study built a model to generate near-optimal intervention decisions for a road infrastructure group while incorporating network state variability over time. The proposed model incorporated road infrastructure and traffic conditions through a modified BPR travel time function to optimally decide intervention decisions for an infrastructure group over a planning horizon using Monte Carlo simulations.

The model included the variability of infrastructure and traffic conditions over time through condition deterioration estimation using the Markov hazard model, traffic growth rate and intervention effects. The modified BPR function enabled the evaluation of the trade-off of intervention works; i.e., capacity increase and condition improvement for multiple road sections within a planning horizon, and the generation of more optimal interventions. The evaluation of capacity and condition improvement trade-off is an important tool for road managers due to competing management decisions and budget limitations. The convenience of the model in generating close-to-optimal intervention decisions while evaluating the trade-off between competing alternatives and the incorporation of infrastructure and traffic condition variability represented real situations which makes the model highly applicable in the real world. The model betterment using Monte Carlo methods permitted the evaluation of competing alternative interventions effortlessly with the modeler having autonomy to decide model accuracy levels, robustness and computational cost through setting appropriate iterations and solution space size.

The empirical results showed the superiority of the Monte Carlo in generating much lower social costs due to the incorporation of multiple intervention effects compared to the greedy algorithm despite the Monte Carlo methods incurring a higher computational cost for more iterations. The Monte Carlo simulations approach supremacy was also shown by better network condition and congestion state. The results also showed the importance of traffic level in making road infrastructure decisions which highlights the need for regulators to control traffic growth rates to avoid the exponential increase in social costs (negative effects) as a result of more traffic congestion.

The Monte Carlo algorithm's solution search could be improved by defining a better search space and increasing the number of iterations. Model outputs may change if the exogeneous parameters are adjusted; therefore, the accuracy of model inputs should be carefully ensured through detailed historical data analysis and probably expert recommendations.

This proposed decision model can be applied to other civil infrastructures including bridges, tunnels and water distribution systems to evaluate the trade-off between multiple interventions and in other fields such as health that require the generation of optimal choices for competing treatments over a given time horizon. In future, it will be interesting to investigate and improve the instability of Monte Carlo methods for fewer iterations and evaluate the case of construction of entirely new network routes.

Data Availability Statement

Some or all data, models, or code used during the study were provided by a third party. Direct requests for these materials may be made to the provider as indicated in the Acknowledgments. The restricted data include Ugandan pavement condition, travel time, traffic volume, and inventory data.

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Declaration of Interest Statement

There was no conflict of interest reported by the authors.

Notation

The following symbols are used in this paper:

g = road group

k^g = section in g

t = time point

r = time interval

T = analysis period

$\tau_t^{k^g}$ = travel time on k^g at t

$i_t^{k^g}$ = condition of k^g at t

$v_t^{k^g}$ = traffic volume on k^g at t

$c_t^{k^g}$ = capacity of k^g at t

$J_t^{k^g}$ = absorbing state at any t

$A_t^{k^g}$ = intervention on k^g at t

$\boldsymbol{A}_t$ = vector of interventions at t

$C^{A_t^{k^g}}$ = unit cost of intervention on k^g at t

$a_t^{k^g}$ = area of k^g improved at t

ρ = discount rate

$\boldsymbol{A}$ = string of all interventions over T

$\boldsymbol{A}^*$ = optimum set of interventions/ policy over T

η_{A_i} = number of candidates for condition improvement

η_{A_c} = number of candidates for capacity increase

ξ_t = social cost at t

Ω_t = budget limit at t

$\boldsymbol{S}_t$ = road network state at t

$s_t^{k^g}$ = state of k^g at t

$\tau^{k^g,0}$ = free-flow travel time

α_1 = condition parameter

α_2 = volume: capacity parameter

$IRI_t^{k^g}$ = IRI of k^g at t

$f(.)$ = function

$J_t(.)$ = cost-to-go function

$\pi_{i_t^{k^g}, j_t^{k^g}}$ = Markov transition probability

$\theta_{i_t^{k^g}}^{k^g}$ = hazard rate for k^g in $i_t^{k^g}$

$\boldsymbol{\Pi}$ = Markov transition probability matrix

$RMD_{i_t^{k^g}}^{k^g}$ = life expectancy for k^g in $i_t^{k^g}$

z = iterations

ω = monetary value of one unit of travel time

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Table 1. Volume:capacity grouping for Ugandan roads.

Category	v^{k^g}/c^{k^g}
NC	0 – 0.50
MC	0.51 – 1.00
CO	1.01 – 1.50
HC	> 1.50

Table 2. Estimated undiscounted annual social costs considering the greedy and Monte Carlo algorithm.

t	Social cost (millions of $)			
	with traffic growth		with traffic fixed	
	Greedy	Monte	Greedy	Monte
0	4.6350×10^4	4.6350×10^4	4.6350×10^4	4.6350×10^4
1	4.5682×10^4	4.7740×10^4	4.1846×10^4	4.2045×10^4
2	3.8180×10^4	5.8594×10^4	5.0201×10^4	4.9777×10^4
3	3.6820×10^4	4.5488×10^4	4.1855×10^4	1.4346×10^4
4	3.5677×10^4	4.3566×10^4	4.0306×10^4	1.2201×10^4
5	3.5969×10^4	3.7274×10^4	3.8845×10^4	9.2666×10^3
6	4.2842×10^4	3.7293×10^4	3.7900×10^4	8.6321×10^3
7	9.3505×10^4	4.1063×10^4	3.7038×10^4	8.6007×10^3
8	4.4738×10^5	7.9496×10^4	3.6218×10^4	9.2609×10^3
9	3.0688×10^6	4.2234×10^5	3.5838×10^4	8.5934×10^3
10	2.2363×10^7	2.9465×10^6	3.5199×10^4	9.2461×10^3
11	1.6716×10^8	2.1454×10^7	2.2767×10^4	8.5721×10^3
12	1.2018×10^9	1.5712×10^8	2.2723×10^4	9.2309×10^3
13	8.9991×10^9	1.1516×10^9	2.2879×10^4	8.5408×10^3
14	6.4644×10^{10}	8.4412×10^9	2.2668×10^4	9.1836×10^3
15	4.8194×10^{11}	6.1876×10^{10}	2.2776×10^4	8.5066×10^3

Table 3. Estimated total discounted social costs considering the greedy and Monte Carlo algorithm.

Total social cost (millions of $)					
with traffic growth			with traffic fixed		
Greedy	Monte (10 iterations)	Monte (1 iteration)	Greedy	Monte (10 iterations)	Monte (1 iteration)
1.3545×10^{11}	1.7428×10^{10}	1.9483×10^{10}	3.2831×10^{5}	1.8427×10^{5}	3.8871×10^{5}

Table 4. Algorithm computation time.

computation time (s)			%
Greedy	Monte (10 iterations)	Monte (1 iteration)	reduction in time
1,399.8678	5,118.0281	652.6725	53.38

Table 5. Number of sections selected for intervention with traffic fixed.

t	Greedy				Monte			
	*Batch 1	**Batch 2		η_{A_i}/η_{A_c}	Batch 1	Batch 2		η_{A_i}/η_{A_c}
	A_i	A_i	A_c		A_i	A_i	A_c	
1	61	10	23	3.09	61	52	16	7.06
2	3	312	0	infinite	3	124	32	3.97
3	0	3	63	0.05	0	121	44	2.75
4	0	4	72	0.06	0	115	54	2.13
5	0	4	81	0.05	0	95	66	1.44
6	0	5	90	0.06	0	106	73	1.45
7	0	5	99	0.05	0	83	86	0.97
8	0	6	108	0.06	0	79	96	0.82
9	0	6	117	0.05	0	51	110	0.46
10	0	7	126	0.06	0	44	120	0.37
11	0	583	37	15.76	0	33	131	0.25
12	0	0	145	0.00	0	25	142	0.18
13	0	1	154	0.01	0	11	153	0.07
14	0	0	163	0.00	0	6	163	0.04
15	0	1	172	0.01	0	0	173	0.00

**Batch 1: Sections in the absorbing state worked on for safety reasons.*

***Batch 2: Candidate sections selected through optimization.*

Table 6. Number of sections selected for intervention with traffic growth.

t	Greedy				Monte			
	*Batch 1	**Batch 2		η_{A_i}/η_{A_c}	Batch 1	Batch 2		η_{A_i}/η_{A_c}
	A_i	A_i	A_c		A_i	A_i	A_c	
1	61	10	23	3.09	61	70	13	10.08
2	3	312	0	infinite	3	148	28	5.39
3	0	3	63	0.05	0	154	38	4.05
4	0	4	72	0.06	0	113	54	2.09
5	0	4	81	0.05	0	105	64	1.64
6	0	5	90	0.06	0	91	76	1.20
7	0	5	99	0.05	0	79	87	0.91
8	0	6	108	0.06	0	62	99	0.63
9	0	0	118	0.00	0	49	110	0.45
10	0	1	127	0.01	0	27	123	0.22
11	0	1	136	0.01	0	15	134	0.11
12	0	2	145	0.01	0	15	143	0.10
13	0	2	154	0.01	0	9	153	0.06
14	0	3	163	0.02	0	8	163	0.05
15	0	3	172	0.02	0	0	173	0.00

Appendix

The **Table 7** shows a summary of Ugandan national roads data from Obunguta and Matsushima (2020), **Table 8** and **Table 9** show the selection of candidates from group A001 ($g = 1$) for intervention using a greedy and Monte Carlo algorithm; respectively, with traffic fixed.

Table 7. Summary of Ugandan national roads data (Obunguta and Matsushima 2020).

g	Road group	No. of sections	FFT (s)	Average traffic ('000 PCU/h)		Traffic growth rate (%)	Life expectancy (years)			
							Condition state			
				2017	2018		1	2	3	Total
1	A001	87	54.55	5.46	4.92	-9.81	3.20	3.02	4.41	10.64
2	A002	355	46.15	2.25	1.72	-23.34	3.64	2.60	3.35	9.60
3	A003	11	67.92	8.03	5.48	-31.66	3.09	1.07	2.20	6.36
4	A004	77	52.17	1.34	1.35	0.79	4.09	3.81	4.18	12.08
5	A005	94	46.75	0.75	0.89	18.78	4.22	3.91	4.53	12.66
6	A006	348	49.32	1.11	1.31	17.90	3.95	3.40	3.92	11.27
7	A007	93	50.70	1.15	1.15	0.00	4.01	3.42	4.02	11.45
8	A008	235	48.65	0.56	0.82	45.57	3.96	3.56	3.86	11.38
9	B100	23	64.29	2.90	3.01	3.91	2.98	2.05	2.04	7.07
10	B103	9	54.55	0.28	1.04	276.77	3.44	2.99	2.90	9.33
11	B150	77	50.70	0.40	0.47	19.30	4.19	4.01	4.37	12.57
12	B151	41	52.94	0.27	0.58	117.93	3.23	2.69	2.53	8.46
13	B152	49	51.43	0.27	0.41	53.48	3.84	3.55	3.73	11.13
14	B153	77	52.94	0.27	0.46	73.02	3.61	3.20	3.21	10.02
15	B200	41	51.43	0.24	0.24	0.00	4.20	4.04	4.37	12.61

16	B300	63	50.70	0.12	0.16	32.71	4.14	3.99	4.28	12.41
17	B303	8	120.00	0.81	0.73	-9.39	2.49	1.73	1.29	5.51
18	B307	55	53.73	0.64	0.64	0.75	3.44	2.87	2.90	9.21
19	B308	17	52.17	0.87	0.87	0.00	3.69	3.12	3.44	10.25
20	C004	19	65.45	0.87	0.47	-45.20	3.12	2.33	2.22	7.67
21	C157	3	189.47	0.47	0.47	0.00	2.36	1.55	1.12	5.03
22	C158	1	103.40	0.47	0.47	0.00	2.37	1.56	1.14	5.06
23	C170	2	87.80	0.47	0.47	0.00	2.86	2.13	1.80	6.80
24	C198	3	102.86	0.47	0.47	0.00	2.66	1.90	1.52	6.08
25	C199	1	356.16	0.47	0.47	0.00	2.28	1.47	1.04	4.79
26	C210	1	189.47	0.20	0.20	0.00	2.40	1.63	1.17	5.19
27	C232	1	281.65	0.15	0.15	0.00	2.34	1.57	1.10	5.01
28	C308	11	54.55	0.11	0.11	0.00	3.93	3.69	3.82	11.44
29	C309	7	72.00	0.11	0.11	0.00	3.16	2.58	2.29	8.03
30	C350	52	56.25	0.46	0.55	21.28	3.68	3.27	3.29	10.24
31	C354	2	61.02	0.21	0.21	0.00	3.46	2.98	2.85	9.28
32	C356	14	56.25	0.22	0.36	65.15	3.71	3.36	3.36	10.44
33	C410	17	46.75	0.31	0.36	15.08	3.56	3.16	3.23	9.95
34	C412	10	55.38	0.07	0.21	212.69	3.79	3.50	3.55	10.84
35	C420	2	180.00	0.07	0.07	0.00	2.43	1.67	1.20	5.30
36	C457	4	60.00	0.07	0.07	0.00	3.27	2.77	2.56	8.61
37	C511	9	53.73	0.13	0.13	0.00	3.46	3.07	3.02	9.55
38	C517	1	137.52	0.13	0.13	0.00	2.43	1.67	1.20	5.30
39	C540	63	53.73	0.38	0.38	0.00	3.61	3.22	3.21	10.03

40	C684	4	90.00	0.30	0.30	0.00	2.82	2.11	1.74	6.67
41	C744	6	57.14	0.43	0.43	0.00	3.75	3.36	3.44	10.55

Table 8. Selection of candidates from group A001 ($g = 1$) for intervention using a greedy algorithm.

k^g	Greedy (with traffic fixed)														
	Year														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
2^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
3^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
4^1	**1,0**	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
5^1	**1,0**	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
6^1	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
7^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
8^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
9^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
10^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
11^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
12^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
13^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
14^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
15^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
16^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
17^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
18^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
19^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
20^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
21^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
22^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
23^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
24^1	**1,0**	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
25^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
26^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
27^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
28^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
29^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
30^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
31^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
32^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
33^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
34^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
35^1	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
36^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
37^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
38^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
39^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
40^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	**1,0**	0,0	0,0	0,0	0,0
41^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
42^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0

43[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
44[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
45[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
46[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
47[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
48[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
49[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
50[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
51[1]	**1,0**	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
52[1]	**1,0**	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
53[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
54[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
55[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
56[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
57[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
58[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
59[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
60[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
61[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
62[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
63[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
64[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
65[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
66[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
67[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
68[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
69[1]	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
70[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
71[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
72[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
73[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
74[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
75[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
76[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
77[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
78[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
79[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
80[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
81[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**1,0**	0,0	0,0	0,0	0,0
82[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
83[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0
84[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
85[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
86[1]	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
87[1]	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0
No. A_i	8	0	0	0	0	0	0	0	0	0	34	0	0	0	0

No. A_c	0	0	0	0	0	0	51	27	28	0	0	0	1	0	0

Note: Action A_0 = (0,0); A_i = (1,0); A_c = (0,1); A_i and A_c = (1,1). Bold highlights sections worked on.

Table 9. Selection of candidates from group A001 ($g = 1$) for intervention using Monte Carlo methods.

k^g	Monte (with traffic fixed)														
	Year														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
2^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0
3^1	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0
4^1	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
5^1	**1,0**	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0
6^1	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
7^1	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
8^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0
9^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0
10^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0
11^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
12^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0
13^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0
14^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
15^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0
16^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0
17^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0
18^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
19^1	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
20^1	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
21^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
22^1	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
23^1	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
24^1	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0
25^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
26^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0
27^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
28^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0
29^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
30^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	**0,1**	0,0
31^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
32^1	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
33^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
34^1	0,0	0,0	0,0	0,0	**1,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
35^1	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
36^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
37^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0
38^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0
39^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0
40^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	**0,1**	**0,1**
41^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
42^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0

43^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**
44^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0
45^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0
46^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
47^1	0,0	0,0	**0,1**	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
48^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
49^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0
50^1	0,0	**1,0**	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
51^1	**1,0**	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0
52^1	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
53^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0
54^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
55^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
56^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0
57^1	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
58^1	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**
59^1	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
60^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
61^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	**0,1**
62^1	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
63^1	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
64^1	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0
65^1	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
66^1	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
67^1	0,0	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
68^1	0,0	0,0	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**
69^1	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
70^1	**1,0**	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0
71^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0
72^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**
73^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
74^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0
75^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	**0,1**
76^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
77^1	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0
78^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0	0,0	0,0
79^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0
80^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
81^1	0,0	0,0	0,0	**1,0**	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0
82^1	**1,0**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
83^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**1,0**	0,0	**0,1**	0,0	0,0	0,0	0,0	0,0
84^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	0,0	0,0	0,0
85^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**	0,0
86^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	**0,1**	**0,1**
87^1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
No. A_i	10	3	3	1	7	5	0	6	4	2	0	1	0	0	0

No. A_c	0	0	1	0	2	3	4	3	4	5	6	15	7	11	8

Fig. 1. Layout of pavement sections over time.

Fig. 2. Road sections in two road groups (links).

Fig. 3. General framework.

Fig. 4. Flow diagram of the greedy algorithm.

Fig. 5. Monte Carlo solution algorithm.

Fig. 6. Undiscounted social costs over planning horizon for greedy (a) and Monte Carlo (b) algorithm with traffic fixed.

Fig. 7. Condition of Ugandan road network for greedy (a) and Monte Carlo (b) algorithm.

Fig. 8. Congestion of Ugandan road network for greedy (a) and Monte Carlo (b) algorithm.

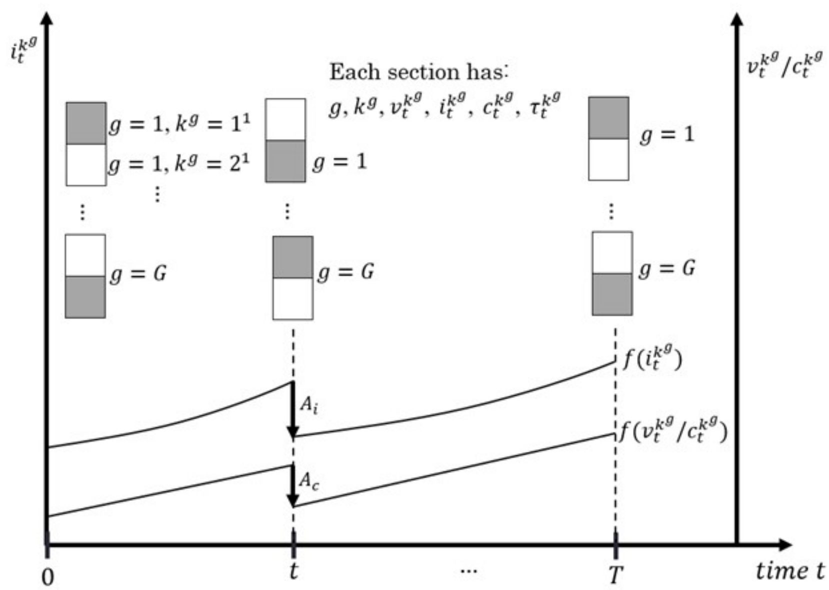

Fig. 1. Layout of pavement sections over time.

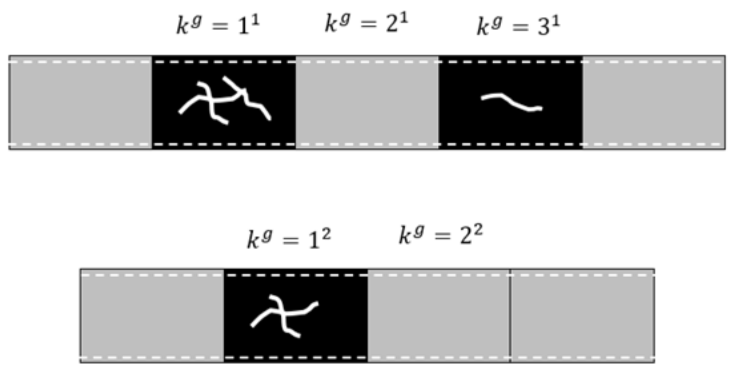

Fig. 2. Road sections in two road groups (links).

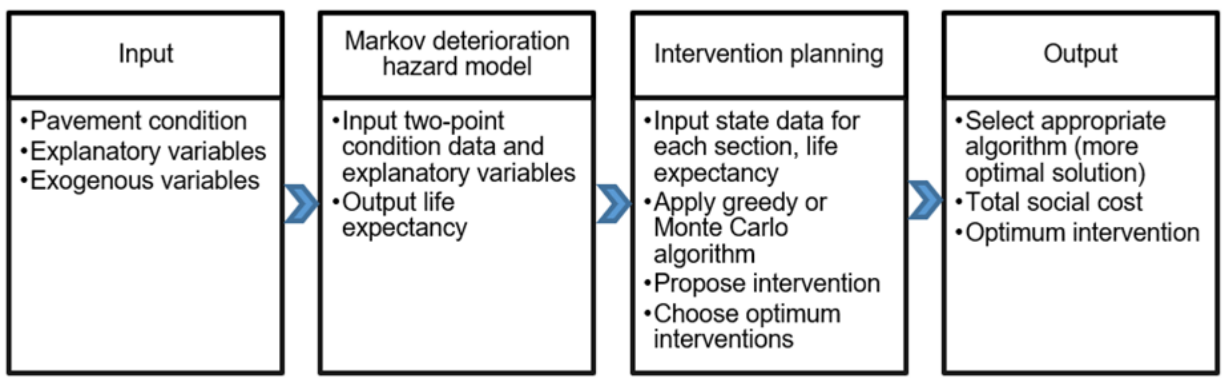

Fig. 3. General framework.

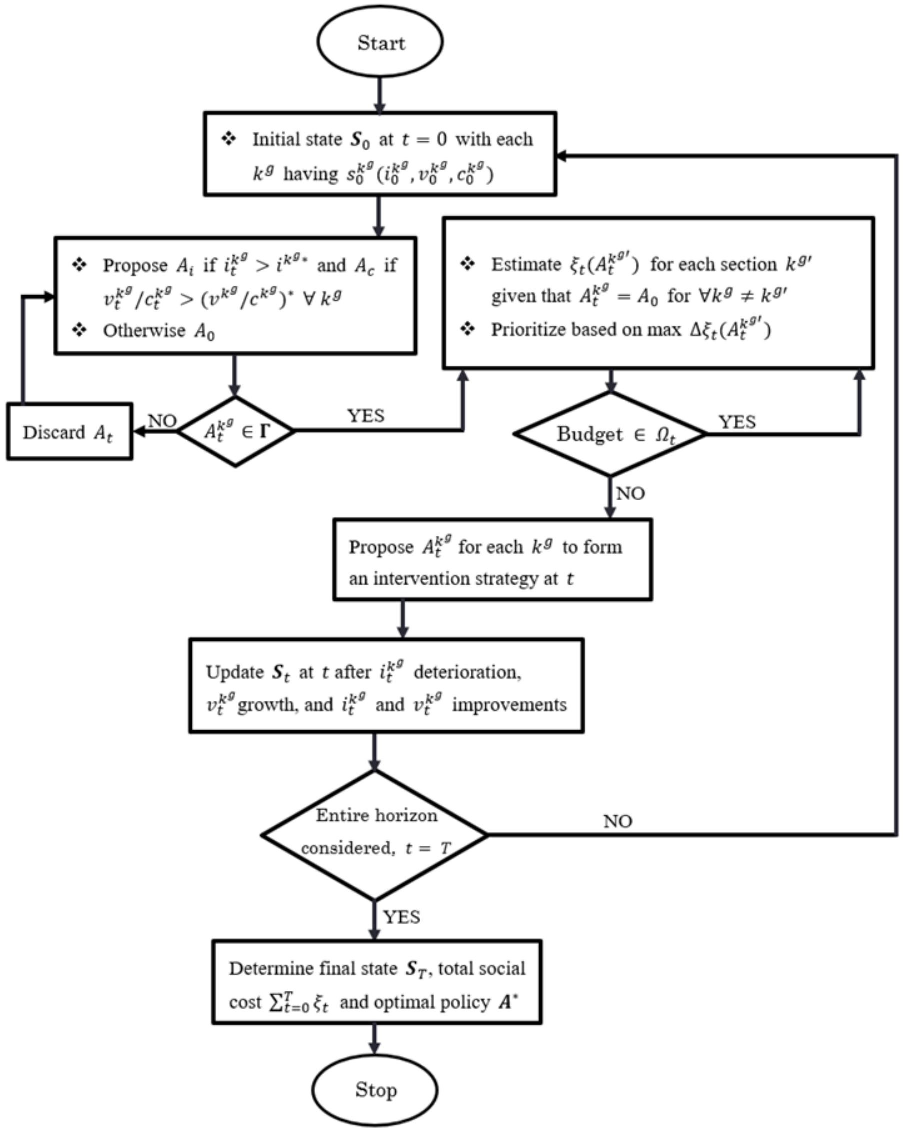

Fig. 4. Flow diagram of the greedy algorithm.

Algorithm: Monte Carlo simulation

Start

Input: $RMD_{i_t^{k^g}}^{k^g}$, Ω_t, $s_{t=0}^{k^g}(i_0^{k^g}, v_0^{k^g}, c_0^{k^g})$, $FFT_t^{k^g}$, g, v_{rate}, $C^{A_t^{k^g}}$ and initialization

Step 1: Determine the initial state $s_{t=0}^{k^g}(i_0^{k^g}, v_0^{k^g}, c_0^{k^g})$ for each k^g and calculate the initial social cost $\xi_{t=0}$ considering g data.

Step 2: Do for $t = 0,1,\dots,T$

Step 3: for iterations $z = 1,\dots,Z$, randomly sample $N = (N_{A_i} + N_{A_c})$ interventions $\boldsymbol{A}_t$ and select $\eta = (\eta_{A_i} + \eta_{A_c})$ candidates within budget Ω_t then estimate the social cost $\xi_t(\boldsymbol{A}_t)$ at time point t

Step 4: The sampled interventions $\boldsymbol{A}_t$ are selected if the social cost is minimized

$$\boldsymbol{A}_t = \begin{cases} \boldsymbol{A}_t \; if \quad \xi_t < \xi_{t-r} \\ otherwise \quad go\ to\ next\ \ z \end{cases}$$

Step 5: By optimizing the cost-to-go function J_t determine $\boldsymbol{A}_t^*$ subject to Ω_t and $A_t^{k^g} \in \Gamma$ constraints

$$\boldsymbol{A}_t^* = \underset{\boldsymbol{A}_t}{argmin}\, \xi_t \qquad \forall z$$

Step 6: Update the state information $s_{t+r}^{k^g}$ for each k^g at time point $t + r$ as follows

$i_t^{k^g} \rightarrow i_{t+r}^{k^g}$ based on $A_t^{k^g} \in [A_0, A_i]$ or $RMD_{i_t^{k^g}}^{g}$

$v_t^{k^g} \rightarrow v_{t+r}^{k^g}$ based on growth rate v_{rate}

$c_t^{k^g} \rightarrow c_{t+r}^{k^g}$ based on $A_t^{k^g} \in [A_0, A_i, A_c]$

Step 7: Go to Step 2

Step 8: Propose $\boldsymbol{A}^*$ for the entire planning horizon T

Output: $\boldsymbol{A}^*$, $s_T^{k^g}(i_T^{k^g}, v_T^{k^g}, c_T^{k^g})$, $\xi_t \quad \forall t$

End

Fig. 5. Monte Carlo solution algorithm.

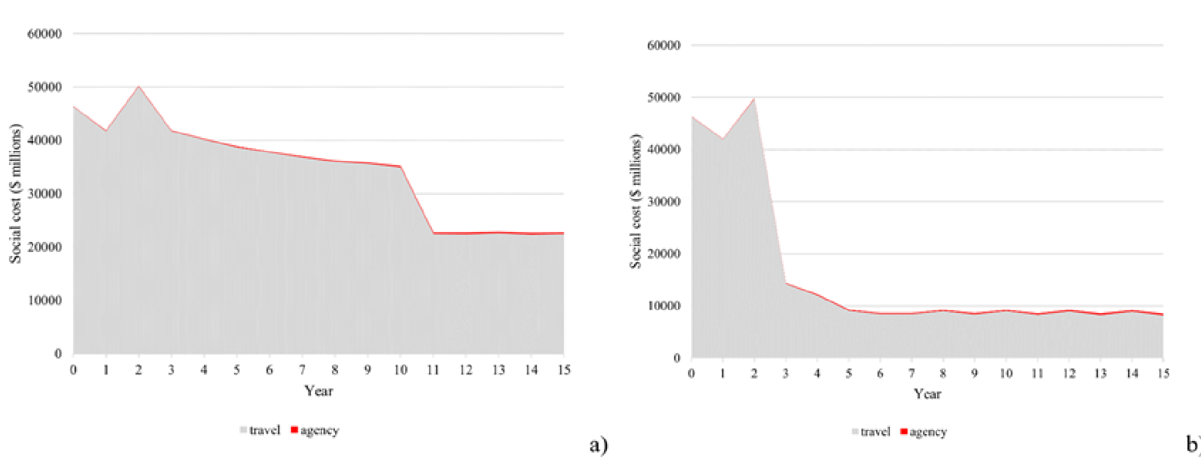

Fig. 6. Undiscounted social costs over planning horizon for greedy (a) and Monte Carlo (b) algorithm with traffic fixed.

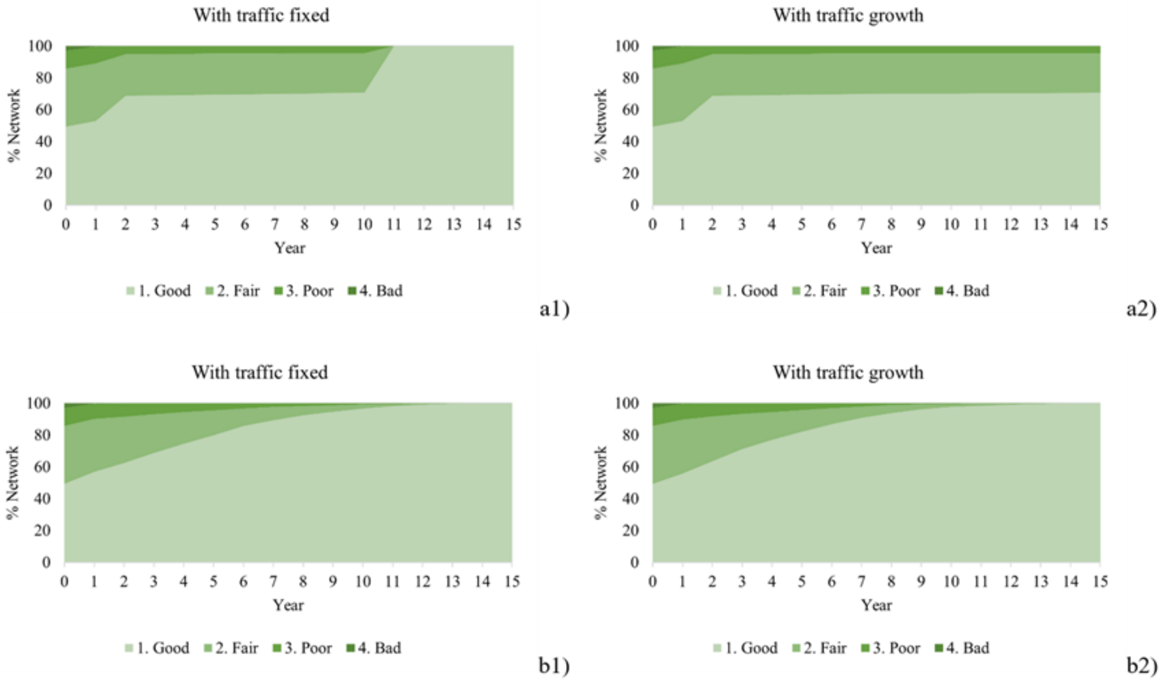

Fig. 7. Condition of Ugandan road network for greedy (a) and Monte Carlo (b) algorithm.

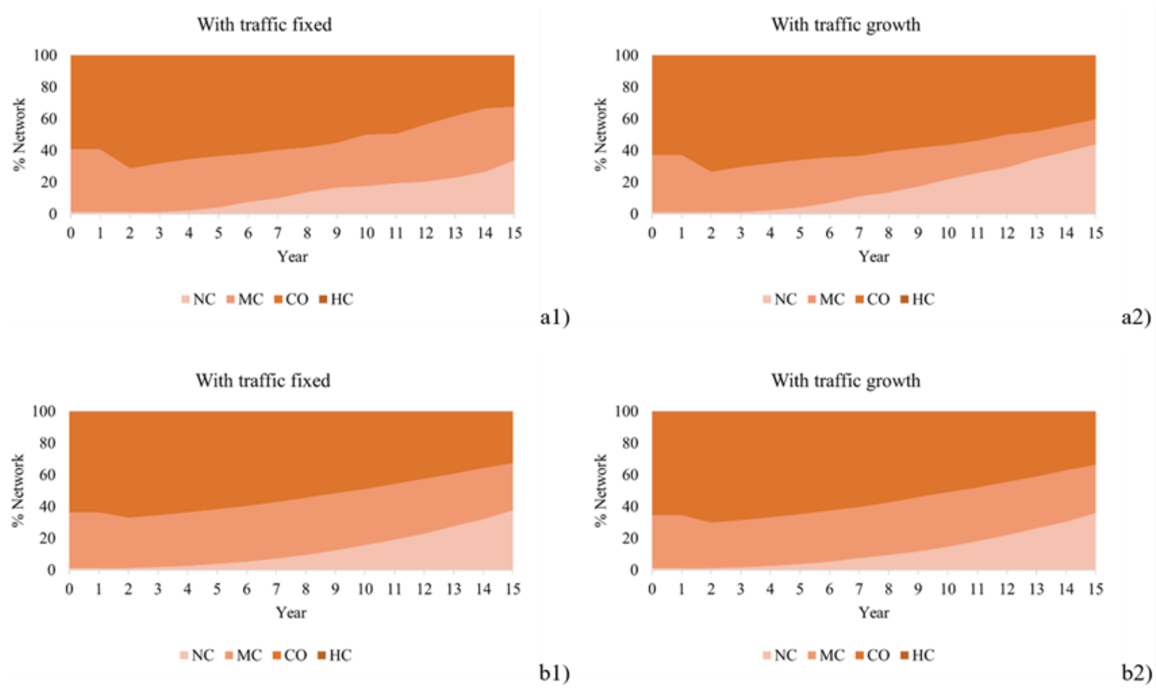

Fig. 8. Congestion of Ugandan road network for greedy (a) and Monte Carlo (b) algorithm.