Eco-based Pavement Lifecycle Maintenance Scheduling Optimization for Equilibrated Networks

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ABSTRACT

This paper proposes a bi-level mathematical programming framework for pavement maintenance to minimize fuel consumption in equilibrated networks. The proposed model extends research in the area by formulating the interaction between network equilibrium and various maintenance activities. The volume of traffic, age of the pavement, initial conditions, and interference due to maintenance are considered in developing this long-term deterioration model. The fuel consumption induced by roughness and traffic disruption is further investigated in the optimization process. A modified active set algorithm with nested sub-programming is developed to generate the detailed solutions. The performance of the proposed model was tested by comparing it with two other mainstream strategies: worst first and threshold control. The results show that eco-based method outperformed prevalent models by reducing extra fuel consumption by 20%. They thus show that eco-based optimal scheduling has the potential to aid in long-term maintenance decisions and reduce the energy cost.

Keywords: maintenance scheduling, fuel consumption, equilibrated network, optimal deployment

1. INTRODUCTION

Fuel consumption by automobiles is a major obstacle to sustainable development. Many fledgling fuel-efficient measures; such as the Atkinson cycle, EcoBoost-equipped engines, and dual variable valve timing; have been implemented by automobile manufacturers. Pavement roughness influences vehicle fuel use and emissions as well as dynamic pavement loading. Loading affects pavement durability, and maintenance investment determines the resulting pavement condition (Gosse & Clarens, 2013). A review by Hiersche (Hiersche, 1985) showed that increasing the roughness of a road intensifies its corresponding fuel consumption. Delanne (Delanne, 1994) claimed that unevenness in the pavement can affect fuel consumption by up to 6%. Chesher and Harrison (Chesher & Harrison, 1987) found that an increase of 1 m/km in the international roughness index (IRI) raises fuel cost by approximately 6% for a unit car in India and 5.5% for an equivalent vehicle in Brazil.

Given the impact of traffic flow, periodic maintenance is often required to mitigate discomfort, safety hazards, and accompanying delays (Cheu, Wang, & Fwa, 2004). Many pavement maintenance scheduling strategies have been investigated in the last few years, with emphasis on the worst-first (WF), threshold control (TC), and optimization (OPT) methods:

a) WF scheduling rehabilitates a pavement based on its existing condition. In each maintenance period, roads in the worst conditions are preferred to first repair, and maintenance covers as many routes as possible until depleting the budget (J. C. Chu & Huang, 2018). WF is intuitive and very easy to implement, and thus is predominantly used by road agencies. Abaza et al. (Abaza et al., 2004) developed an optimum maintenance and rehabilitation model for the WF strategy based on the discrete-time Markovian deterioration process. Zimmerman and Peshkin (Zimmerman & Peshkin, 2003) assessed the WF and pavement preservation strategies for a network in North Carolina, US, and found that the benefits of the preservation strategy take time to become evident, but their eventual impact on average network conditions is much more significant than the WF. Even so, there is a perception that the public will not support a move away from the WF strategy (Chan et al., 2011). However, WF yields limited benefits in the long run because it is often used on a reactive basis and does not consider the lifespan of the asset.

b) The TC method conducts maintenance activities if a pavement in some link deteriorates to a specific threshold. Pavement maintenance is scheduled based on standards that define the minimum allowable levels of service capability (Tsunokawa & Schofer, 1994). The threshold can be set based on various indices, such as the international roughness index (IRI) (J. C. Chu & Chen, 2012), pavement condition index (PCI) (Sharaf et al., 1987), and critical rut depth (Fwa T. F. et al., 2012). Wang et. al (T. Wang et al., 2014) developed optimal roughness values for triggering treatments to minimize GHG considering both treatment and use phase emission. In practice, this method fits the workflow of transportation agencies well and, thus, has been widely adopted (J. C. Chu & Huang, 2018). One problem induced by TC is that for some periods of maintenance, the budget is redundant as all pavements remain in good condition. On the contrary, in other periods, the budget may be insufficient as too many roads have reached the given threshold and require rehabilitation at the same time. Moreover, the criteria for the threshold are often determined empirically, and may not be universally applicable to all scenarios.

c) The OPT strategy generates maintenance plans to optimize the objective function (minimal travel time, maximal revenue, etc.) within budgetary constraints by using optimization methods. A number of studies have investigated this strategy for several objectives using multiple algorithms. For example, Ng et al. (Ng et al., 2009) proposed a mixed-integer bi-level program to create an optimal long-term maintenance scheduling that simultaneously accounts for traffic dynamics. Ouyang and Madanat (Ouyang & Madanat, 2006) studied a mathematical programming model for a finite horizon involving multiple activities and facilities. Memarzadeh and Pozzi (Memarzadeh & Pozzi, 2016) proposed an approach to integrating adaptive maintenance planning based on the Markov decision process. Most OPT-based methods consider the deterioration process of the pavement, the maintenance period, budget, and various categories of maintenance activities together to generate detailed plans, which leads to a considerable improvement in the long term compared with other strategies.

The maintenance schedule not only determines the timing of maintenance, but also selects the kind of activity that should be performed on each link. Various categories of maintenance activities have been defined and are being used at present, such as preventive and corrective maintenance (P&C), capital preventive maintenance (CAPM), and major rehabilitation and replacement (R&R) (Lea & Harvey, 2002) (X. Zhang & Gao, 2012). According to the 2015 State of the Pavement Report of California, P&C (e.g., crack seal and slurry seal) can extend a pavement's service life by four to seven years at $115,000 per lane mile. CAPM (e.g., pavement grinding, isolated slab replacements, and asphalt concrete overlay) can provide a service life of five to ten years with $326,000 per lane mile. R&R replaces the structure of the pavement rather than only its surface, which is supposed to provide 20 years or more of service life with $894,000 per lane mile (Kim et al., 2015). Santero et.al (Santero et al., 2011) evaluated the current literature across four key methodological attributes, such as functional unit comparability, system boundary comparability, data quality and uncertainty and environmental metrics. Chu (C.-Y. Chu & Durango-Cohen, 2008) used the dynamic performance modeling method to analyze the effect of maintenance activities on the performance of dynamic infrastructure facilities, and incorporated the effectiveness of maintenance in their estimation. Rashid and Tsunokawa (Rashid & Tsunokawa, 2012) proposed an optimization approach based on the trend curve optimal control model to obtain optimal strategies consisting of many diverse maintenance activities. Gao et al. (L. Gao et al., 2012) investigated multiple treatment methods at a network level using bi-leveling optimization.

The optimal scheduling of rehabilitation activities has been extensively researched, and objectives of maintenance scheduling vary among different methodologies, most of them are aimed to minimize the total travel time or capital cost. Gu et al. (Gu et al., 2012) proposed the joint optimization of pavement maintenance to reduce overall lifecycle cost using a continuous pavement state model. Gao et al. (2012) discussed bi-objective pavement maintenance and the rehabilitation-scheduling problem that aims to simultaneously optimize the objectives of improving the condition of the pavement and appropriately using the budget. Given the uncertainty of deterioration in the condition of the pavement, Chootinan et al. (Chootinan et al., 2006) used a stochastic simulation-based genetic algorithm to handle the combinatorial nature of network-level pavement maintenance programming. Gao and Zhang (H. Gao & Zhang, 2013) developed a multi-objective Markov-based model to minimize user cost constrained by annual budget and performance requirements. In recent years, several studies have targeted to minimize the greenhouse gas (GHG) emissions or fuel consumption from pavement rehabilitation polices. Reger et al. considered an agency whose main goal is to reduce its carbon footprint while operating under a constrained financial budget and proposed the optimal timing along with the optimal actions for every road segment in the network (Reger et al., 2015). Lee et al. proposed an efficient solution to solve the maintenance scheduling problem under a GHG emissions constraint (J. Lee et al., 2016). Lee and Madanat (J. Lee & Madanat, 2017) further developed an optimization problem to minimize GHG emissions by determining joint management strategies for a range of heterogeneous interventions, including maintenance, rehabilitation and reconstruction. Wang et al. described a pavement life cycle assessment model to evaluate energy use and GHG emissions from pavement rehabilitation strategies (T. Wang, 2012). Wang et al. further developed a life cycle approach to assess changes in total GHG emissions from strategic management of pavement roughness (T. Wang et al., 2014). However, most researchers have either conducted lifecycle analysis or studied network impact on maintenance scheduling, and have shed little light on the interactions between them.

Pavement roughness has a distinct effect on drivers' choice of route, especially for pavements in poor condition. This is the major reason for why we include the condition of the pavement when formulating a travel cost function. Kerali (Kerali, 2003) has indicated that road roughness is the most significant component of pavement condition used to estimate the user cost. Hawas (Hawas, 2004) used a neuro-fuzzy model to analyze factors affecting drivers' perceptions of route utility, such as travel time, pavement condition, and queuing time. Moreno (Moreno-Quintero, 2006) proposed a general equation that incorporates speed, pavement roughness, and slope into perceived route utility in the process of choosing a route. Ouyang (Ouyang, 2007) used a practical formula with two components, roughness cost and the cost of travel time, to calculate total user cost. The status of deterioration of the pavement is also affected by traffic flow (L. Sun, 2016). Massive traffic results in the rapid deterioration of pavement conditions. In turn, roads in poor condition cause drivers to reroute.

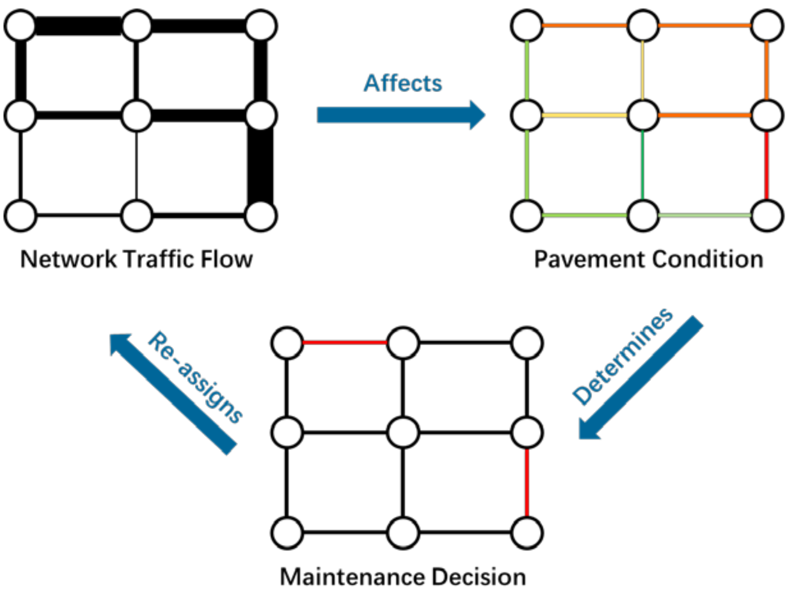


Figure 1. Interactions among traffic flow, pavement condition and maintenance decision

This paper extends literature on pavement maintenance along three directions: (1) An eco-based scheme is proposed to explicitly formulate the interactions between maintenance activities and network equilibrium from the perspective of the lifecycle of the pavement to minimize fuel consumption by the network. Multiple maintenance treatments are quantized and evaluated in the optimization process. (2) The volume of traffic, age of pavement, initial conditions, and interference due to pavement maintenance are considered in developing a long-term deterioration model that provides a dynamic connection with the user's choice of route. (3) Fuel consumption induced by roughness and traffic disruption during construction is investigated by developing a generalized travel cost function and equivalent link capacity.

The remainder of this paper is organized as follows: Section 2 presents a bi-level model of the optimal network fuel consumption and Section 3 introduces a solution and methods of approximation for it. Section 4 describes a case study based on the Sioux-Fall network, and Section 5 offers the conclusions of this study and implications for future research on pavement maintenance.

2. MODEL FORMULATION

The primary objective of this model is to minimize fuel consumption in a network constrained by an annual maintenance budget. The lower-level model follows user equilibrium (UE) conditions, under which the travel cost function complies with a generalized BPR function. The influence of pavement roughness is also considered part of travel cost.

2.1 Pavement Deterioration Model

Pavement conditions deteriorate naturally over time. Without maintenance, the process follows an exponential distribution. Our first assumption is that the pavement deterioration process follows a Markov property, which means that the shape of the deterioration curve depends on only the maintenance activities attained in the previous period. The second assumption concerns the exclusiveness of multiple activities, indicating that no more than one maintenance treatment is implemented on the same link at the same year. We use the riding quality index (RQI) as indicator of pavement status, measured from 5 to 0 (initial status to worst condition). We discretize the continuous time span into one-year intervals and use a binary variable to describe decisions regarding the maintenance activities. Let $t \in [0, T]$ denote the discrete time points and T the projected lifetime. The following figure illustrates a model of the deterioration and rehabilitation of a highway network. $R_i(t^+)$ denotes the RQI of the $i \in L$ link immediately after year t, and $R_i(t^-)$ denotes the RQI of the $i \in L$ link immediately before year t. If a maintenance activity is conducted in year t, a gap arises between $R_i(t^+)$ and $R_i(t^-)$, representing an improvement in performance. Otherwise, $R_i(t^+)$ and $R_i(t^-)$ remain the same.

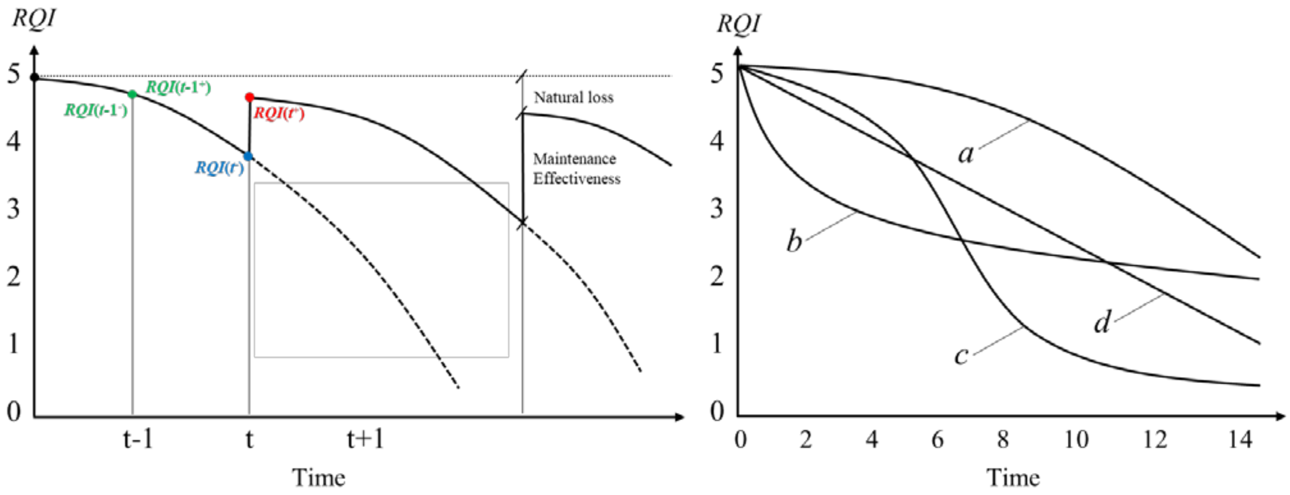


Figure 2. Deterioration process in the maintenance (left) and the typical deterioration modes (right)

Pavement roughness increases exponentially over time between adjacent maintenance activities (Ouyang & Madanat, 2006). Given the complexity of influential factors and the diversity of road structures, the deterioration in pavements follows multiple patterns that can be divided into four main types, as shown in Figure 2 (L. J. Sun, 2005):

(a) Convex curve: slow deterioration followed by fast deterioration until the pavement is destroyed, which is the most common shape of a natural deterioration curve;

(b) Concave curve: fast deterioration followed by slow deterioration until destroyed. This usually appears if the surface of the road cannot provide sufficient shear stress while in service;

(c) Reverse S curve: slow deterioration followed by fast deterioration, and slow again until destroyed, which is actually a combination of curves *a* and *b*.

(d) Linear curve: linear deterioration until destroyed. This usually happens in cases with small volumes of traffic.

Therefore, a unified deterioration model is required to describe the different modes. We propose a negative exponent deterioration model with lifetime factor *A* and shape factor *B* (L. J. Sun, 2005), as follows:

$$R = R_0 \left\{ 1 - \exp[-(A/t)^B] \right\} \quad , \tag{1}$$

where

R_0 = initial RQI

A = lifetime factor (related to traffic volume, structural strength, etc.)

B = shape factor (related to traffic volume, structural strength, etc.)

$$\begin{Bmatrix} A \\ B \end{Bmatrix} = \begin{Bmatrix} f_1(volume, strengh, thickness, environment...) \\ f_2(volume, strengh, thickness, environment...) \end{Bmatrix}$$

t = discrete time.

The first-order derivative is thus as follows:

$$\frac{\partial R}{\partial t} = -R_0 \cdot \exp[-(A/t)^B] \cdot B \cdot A^B / t^{B+1} \quad . \tag{2}$$

The second-order derivative is as follows:

$$\frac{\partial^2 R}{\partial^2 t} = R_0 (B+1) B \cdot A^B \cdot \exp[-(A/t)^B] / t^{B+2} - R_0 \cdot \left(B \cdot A^B / t^{B+1} \right)^2 \cdot \exp[-(A/t)^B] \tag{3}$$

$$t_e = \left(\frac{B \cdot A^B}{B+1} \right)^{-B} \tag{4}$$

Eq. (2) shows that Sun's model monotonically decreases. Eq. (3) and (4) show that if the time is in the interval $(t_e, +\infty)$, the function is concave; otherwise, the function within $(0, t_e)$ is convex. Different values of *A* and *B* may lead to distinct deterioration patterns (curves *a*, *b*, *c*, and *d* in Figure 1). For simplicity, the environmental factors are fixed, and thus coefficients *A* and *B* can be regarded as piecewise functions representing traffic flows *v*, *A*(*v*) and *B*(*v*), respectively. This model is constructed by a long-term dataset collected by field tests. It is tested and proved to be effective in many countries and district. The model coefficients A and B are determined by the traffic flows and pavement structure itself. The detailed number of A and B under various conditions can be referred to the Table 6.3-10 (Sun, 2005)

2.2 Representing Network Fuel Consumption

The objective of eco-based optimal maintenance scheduling is to minimize network-wide consumption for *T* years. Two principle inducements for extra fuel cost are considered: pavement roughness and traffic disruption when maintenance is conducted.

Bumpy roads increase the amount of resistance a vehicle experiences as it drives down the road. A vehicle's fuel consumption has a significant positive correlation with pavement roughness. Many empirical models have been developed to estimate the cost of fuel under various conditions.

Most relevant literatures focus on the quantification of environmental impact of pavement condition in terms of some typical vehicle types (Medium car, SUV, light truck), speed (Gangaram, 2014), and typical treatment techniques (Han et al., 2018; H. Wang et al., 2019) using Motor Vehicle Emission Simulator (MOVES). The results can be used to evaluate the fuel cost and GHG in some case-specific scenarios. In this paper, we consider the vehicular fuel cost from a perspective of network optimization, in which the driving speed on each link is assumed to be the same and the volume of all types of vehicles is transformed into the equivalent passenger car volume. The World Bank's HDM-4 may be the most extensively used one, where the relationship between fuel consumption and international roughness index (IRI) follows a linear regression (Zaabar & Chatti, 2010). The IRI is converted into RQI using the formula developed by the Minnesota Department of Transport (H. Gao & Zhang, 2013; Janisch, 2006; H. Wang et al., 2020). Thus, the fuel consumption induced by roughness can be formulated as follows:

$$O_i(t) = a + b \cdot \left(\frac{6.122 - R_i(t)}{1.963} \right)^2, \quad \forall i \in \mathbf{I}, t \in \mathbf{T}, \tag{5}$$

where

$O_i(t)$ = fuel cost per passenger car unit per hour on link i in year t (gallon/h)

$R_i(t)$ = RQI value of link i in year t

a, b = model regression coefficients

The model parameters a and b are calibrated by field tests. As the traffic flow and pavement conditions both dynamically vary over a year, we use the trapezoid formula to approximately calculate network-wide cost on the planning horizon, as shown in Fig. 3 and Eq. (6):

$$Obj = \sum_{i=1}^{N} \sum_{t=1}^{T} [v_i(t^+) \cdot O_i(t^+) \cdot \tau_i(t^+) + v_i((t+1)^-) \cdot O_i((t+1)^-) \cdot \tau_i((t+1)^-)] \Big/ 2 \tag{6}$$

where

Obj = total fuel consumption induced by the roughness of N links over time span T

$\tau_i(t)$ = travel time on link i in year t

$v_i(t)$ = traffic volume on link i in year t

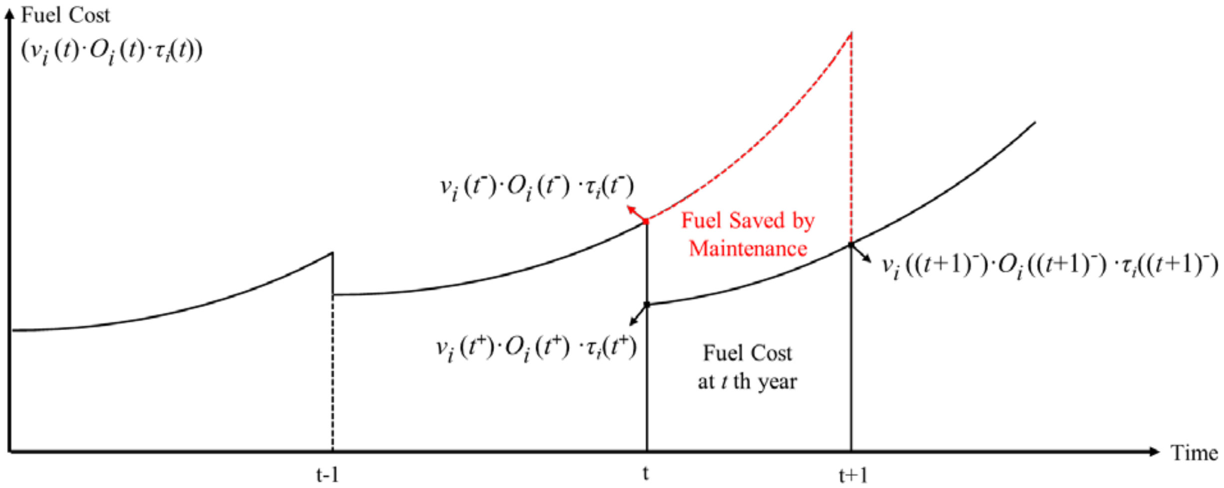


Figure 3 The objective function

Apart from roughness, traffic disruption during construction is a primary factor that increases fuel consumption. Link capacities are temporarily reduced due to the closure of lanes, leading to increased travel time in Eq. (6) and accordingly higher fuel costs. A highway link is often repaired lane by lane in order to not excessively disrupt traffic. Many literatures have investigated the work-zone impacts caused by lanes closure (E.-B. Lee et al., 2005). However, most quantitative results are based on the actual data statistics and simulation, which are quite hard to directly apply in the bi-level programming modelling. To simplify the formulation, we consider the influence of construction as a piecewise function, as shown in Eq. (7):

$$C_i(t_m)=\begin{cases}\dfrac{(L_i-1)}{L_i}\cdot C_i^0, & t_m\in[0,\min(m_p\cdot L_i,365)]\\ C_i^0, & t_m\in(\min(m_p\cdot L_i,365),365]\end{cases}, \tag{7}$$

where

$C_i(t_m)$ = traffic capacity of link i at discrete time (day) in a year

C_i^0 = initial capacity of link i

p = maintenance activity type, $p = \begin{cases} 1: & P\&C \\ 2: & CAPM \\ 3: & R\&R \end{cases}$

m_p = construction time for maintenance activity p

$y_{i,p}(t)$ = a binary decision variable that is one if and only if maintenance activity p is conducted on link i in year t

L_i = the total number of lanes on link i

t_m = discrete time (day) in a year, $t_m \in [0, 365]$

As most preventive and corrective maintenance activities are conducted at night, its m_p (p = 1) can be regarded as zero.

2.3 Effectiveness and Cost of Maintenance

The marginal effectiveness of maintenance expenditures depends on the conditions of the facility when maintenance is performed (Ouyang & Madanat, 2004). The effectiveness and cost of maintenance according to the 2015 State of the Pavement Report of California (Kim et al., 2015) are listed in Table 1. This table is summarized using a large number of data obtained from practice, which is instructive to other cases.

Table 1. Average cost per lane mile of maintenance activities

Activities	**Cost per Mile**	**Extended Service Life**	**Road Condition**
P&C (p=1)	$115,000	4-7 years	RQI⩾4.195
CAPM (p=2)	$326,000	5-10 years	4.195 < RQI ≤ 2.435
R&R (p=3)	$894,000	20+ years	RQI<2.435

* P&C: preventive and corrective maintenance;
CAPM: capital preventive maintenance;
R&R: rehabilitation and replacement.

In practice, the extended service life of the pavement varies according to the condition of the pavement when the activity is performed. This difference is affected by multiple factors, such as time, weather condition, pavement materials, traffic load, etc. To simplify the formulation, we transform the extend service life into effectiveness index ΔR(p) to approximately represent the impact of maintenance activities on pavement conditions. The extended service life of activity *p* is denoted by $\Delta l(p)$. The effectiveness index indicates the change in RQI due to a maintenance activity, as shown in Fig. 4. Eq. (8) reveals the relationship between Δl and ΔR.

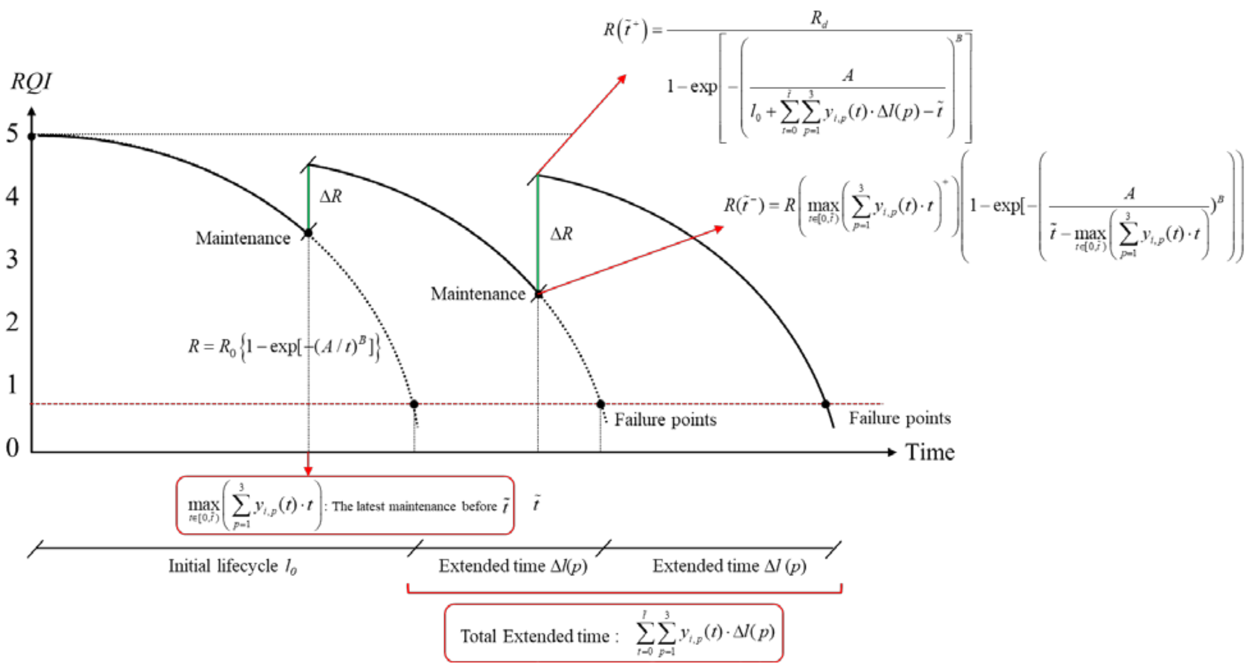


Figure 4. Effectiveness index ΔR

Given R_d as the lower bound of acceptable pavement performance, the initial lifecycle l_0 can be calculated as in Eq. (8). The extended service life for each maintenance activity is indicated in Table 1. Thus, the real service life following maintenance is $l_0 + \Delta l$. Assuming that $\tilde{t}$ is the elapsed time from the recent reconstruction, the deterioration function is represented by Eq. (9). As the new deterioration curve is supposed to reach failure when RQI decreases to R_d, and the $R\left(\tilde{t}^+\right)$ cannot exceed R_0, the effectiveness index ΔR can be derived by Eq. (10).

$$l_0 = \frac{A}{\sqrt[B]{\ln R_0 - \ln(R_0 - R_d)}} \tag{8}$$

$$R(t|\tilde{t}) = \left(R_0\left(1-\exp[-(A/\tilde{t})^B]\right) + \Delta R\right)\left(1-\exp[-(A/t)^B]\right) \tag{9}$$

$$\Delta R(p,\tilde{t}) = \min\left\{\begin{array}{l} \dfrac{R_d}{1-\exp\left[-\left(\dfrac{A}{l_0 + \sum_{t=0}^{\tilde{t}}\sum_{p=1}^{3} y_{i,p}(t)\cdot \Delta l(p) - \tilde{t}}\right)^B\right]} - \\ R\left(\max_{t\in[0,\tilde{t})}\left(\sum_{p=1}^{3} y_{i,p}(t)\cdot t\right)^+\right)\left(1-\exp[-\left(\dfrac{A}{\tilde{t} - \max_{t\in[0,\tilde{t})}\left(\sum_{p=1}^{3} y_{i,p}(t)\cdot t\right)}\right)^B]\right), R_0 - R(\tilde{t}) \end{array}\right\} \tag{10}$$

2.4 Bi-level Model Formulation

Given the hierarchical relationship between maintenance activities and drivers' choice of route, a bi-level optimization model is proposed to describe the two-layer process where the levels correspond to the layers. The upper level program can be formulated as follows:

$$\min\ Obj = \sum_{i=1}^{N}\sum_{t=1}^{T}[v_i(t^+)\cdot O_i(t^+)\cdot \tau_i(t^+) + v_i((t+1)^-)\cdot O_i((t+1)^-)\cdot \tau_i((t+1)^-)] \Big/ 2 \tag{11}$$

$$\text{s.t.} \quad \sum_{p=1}^{3} y_{i,p}(t) \le 1, \quad \forall i \in \mathbf{I}, t \in \mathbf{T} \tag{12}$$

$$\Delta R(p,\tilde{t}) = \frac{R_d}{1-\exp\left[-\left(\dfrac{A}{l_0 + \Delta l(p)}\right)^B\right]} - R_0\left(1-\exp[-(A/\tilde{t})^B]\right) \tag{10}$$

$$R_i(t^+) = R_i(t^-) + \sum_{p=1}^{3} y_{i,p}(t)\cdot \Delta R(p,t), \quad \forall i \in \mathbf{I}, t \in \mathbf{T} \tag{13}$$

$$R_i(t^-) = R_i((t-1)^+) \cdot \left(\frac{1-\exp\left[-\left(\frac{A(v_i(t))}{t} \right)^{B(v_i(t))} \right]}{1-\exp\left[-\left(\frac{A(v_i(t-1))}{t-1} \right)^{B(v_i(t-1))} \right]} \right), \quad \forall i \in \mathbf{I}, t \in \mathbf{T} \tag{14}$$

$$O_i(t) = a + b \cdot \left(\frac{6.122 - R_i(t)}{1.963} \right)^2, \quad \forall i \in \mathbf{I}, t \in \mathbf{T}, \tag{5}$$

$$\sum_{i=1}^{N} \sum_{t=1}^{T-1} \sum_{p=1}^{3} L_i \cdot y_{i,p}(t) \cdot c_p(t) \cdot e^{-rt} \le B_g, \quad \forall i \in \mathbf{I}, t \in \mathbf{T} \tag{15}$$

$$-\sum_{p=1}^{3} y_{i,p}(t) \cdot M \le R(t^-) - R_s \le \left(1 - \sum_{p=1}^{3} y_{i,p}(t) \right) \cdot M + R_0 \tag{16}$$

$$y_{i,2}(t) = 0,\ y_{i,3}(t) = 0,\ \text{if } R(t^-) \in (4.195, 5], \quad \forall i \in \mathbf{I}, t \in \mathbf{T} \tag{17}$$

$$y_{i,3}(t) = 0,\ \text{if } R(t^-) \in (2.435, 4.195], \quad \forall i \in \mathbf{I}, t \in \mathbf{T} \tag{18}$$

$$y_{i,p}(t) \cdot \left(1 - y_{i,p}(t) \right) = 0, \forall i \in \mathbf{I}, t \in \mathbf{T} \quad , \tag{19}$$

where

$y_{i,p}(t)$ = a binary decision variable that is one if and only if maintenance activity *p* is conducted on link *i* in year *t*

L_i = length of link *i*

$c_p(t)$ = maintenance cost of *p* activity per mile at *t* year

r = discount rate

B_g = planning capital budget

t^+ = immediate time after year *t*

t^- = immediate time before year *t*

R_s = the lowest RQI requirement for driving safety

M = a sufficiently large number

Eq. (11)–(19) describe the decision making process. The decision variables $y_{i,p}(t)$ determines the maintenance time t and activity p that should by applied on link i. The constraint (12) ensure that no more than one activity is conducted on the same link each year. Eq. (13) and (14) reflect the impact of maintenance-related decisions on variations in the condition of the pavement. In each year, (e.g., $t, t+1, ...$), if a maintenance activity is conducted ($y_{i,p}(t)=1$), the pavement status recovers according to its effectiveness. On the contrary, $y_{i,p}(t)=0$ means that no measures have been taken and the RQI in the next year remains the same as at the end of the last year. Between time segments (e.g., $[t, t+1]$), RQI deteriorates exponentially as shown in Eq. (14). Eq. (14) is effective as the variable unit is year, thus vi(t) can be regarded as a constant within each year. Eq. (5) defines the cost of fuel on each link based on HDM-4. Eq. (15) indicates budget limitations and the multiplier e^{-rt} discounts costs into values at the given time. Eq. (16) means that maintenance is compulsory if a road deteriorates to below the safety requirements. Eq. (17)–(18) make it clear that maintenance activities are to be determined by pavement status. No major maintenance or replacement is undertaken when the roads are in good conditions. Eq. (19) indicates that the variable $y_{i,p}(t)$ is binary. The coefficients a, b, r, and R_d are derived from field tests and empirical studies.

Once the maintenance decision concerning a given network has been made, the flow of traffic on each link may change according to the UE conditions. We formulate this as follows:

$$v_i(t) \in \arg\min \sum_{i \in \mathbf{I}} \int_0^{v_i(t)} tc(v_i(t))dv \tag{20}$$

$$\sum_{k \in \mathbf{K}_{rs}} f_k^{rs}(t_m) = q_{rs}(t_m), \quad \forall r \in \mathbf{R}, s \in \mathbf{S} \tag{21}$$

$$v_i(t_m) = \sum_{r\in\mathbf{R}}\sum_{s\in\mathbf{S}}\sum_{k\in\mathbf{K}_{rs}} \delta_{i,k}^{rs} f_k^{rs}(t_m), \quad \forall i \in \mathbf{I} \tag{22}$$

$$f_k^{rs}(t_m) \geq 0, \quad \forall r \in \mathbf{R}, s \in \mathbf{S}, k \in \mathbf{K}_{rs} \tag{23}$$

$$C_i(t_m) = \begin{cases} \dfrac{(L_i - 1)}{L_i} \cdot C_i^0, \; t_m \in [0, \min(m_p \cdot L_i, 365)] \\ C_i^0, \qquad t_m \in (\min(m_p \cdot L_i, 365), 365] \end{cases}, \tag{7}$$

$$\tau_i(t_m) = tco_i \left[1 + \alpha \left(\frac{v_i(t_m)}{C_i} \right)^{\beta} \right] \tag{24}$$

$$tc(v_i(t_m)) = \gamma R_i(t_m) \cdot L_i + \varphi \cdot \tau_i(t_m), \tag{25}$$

where

$tc(v_i(t))$ = generalized travel cost function on link i at year t

$v_i(t)$ = the traffic flow on link i at year t, which can be estimated by the average traffic volume for a year,

$$\frac{L_i \cdot m_p \cdot v_i\left(t_m \in [0, \min(m_p \cdot L_i, 365)]\right) + \left(365 - L_i \cdot m_p\right) \cdot v_i\left(t_m \in (\min(m_p \cdot L_i, 365), 365]\right)}{365}$$

$f_k^{rs}(t)$ = flow on path $k \in \mathbf{K}_{rs}$ between origin – destination (OD) pair r-s at year t

$\mathbf{K}_{rs}$ = set of paths between OD pair r-s

$\mathbf{R}$ = set of origin nodes in the network

$\mathbf{S}$ = set of destination nodes in the network

$q_{rs}(t)$ = fixed travel demand for OD pair r-s

$\delta_{i,k}^{rs}$ = a binary coefficient that equals one if path $k \in \mathbf{K}_{rs}$ between OD pair r-s uses link i and 0 otherwise

γ = RQI value coefficient: operating cost per unit length under a fixed RQI

φ = time value coefficient

tco_i = free-flow travel time on link *i*

$\tau_i(t_m)$ = travel time on link *i* at *m* day in year *t*

α, β = model constant, generally $\alpha = 0.15$, $\beta = 4$ for BPR function

Constraints (20)-(25) present the UE conditions. Constraint (19) shows the travel demand for the OD pairs. Constraint (22) defines the relationship between link flow and path flow. Constraint (23) ensures that path flow is nonnegative.

As previously mentioned, travel time and pavement condition both influence drivers' perceptions of route utility (Kerali, 2003) (Hawas, 2004) (Moreno-Quintero, 2006) (Ouyang, 2007). Therefore, the travel cost function $tc(v_i(t))$ follows a generalized BPR equation as shown in Eq. (25). The first part of the function denotes losses due to pavement roughness, and the second part is the estimated travel time formulated in Eq. (24). γ , φ help unify the units and translate their values into equivalent monetary values. The details are introduced later in a case study.

Eq. (5)–(25) represent a challenging bi-level problem owing to the implicit relationship between the maintenance decision variable $y_{i,p}(t)$ and link flow $v_i(t)$. They also constitute a mixed nonlinear integer and an NP-hard problem, which is challenging to articulate. Therefore, we proposed a modified active set method to solve the bi-level problem.

3. ACTIVE SET METHOD

The eco-based maintenance problem is a typical discrete network design problem (DNDP). Multiple solutions have been developed in the literature, such as branch and bound (Leblanc, 1975), simulated annealing (Friesz et al., 1992), and SO relaxation (S. Wang et al., 2013), etc. The most common procedure to solve a bi-level program is to reformulate it as an equivalent single-level one.

Given the complexity of nonlinear and complementary constraints, the single-level model of this problem still requires a prodigious amount of calculation. We employ the active set method (L. Zhang et al., 2009) to obtain a strongly stationary solution.

The active set algorithm starts by setting an initial feasible solution. The binary variables, $y_{i,p}(t)$, representing the initial solution are grouped into two active sets:

$$\Omega_0 = \left\{(i,p,t) : y_{i,p}(t) = 0\right\} \tag{26}$$

$$\Omega_1 = \left\{(i,p,t) : y_{i,p}(t) = 1\right\}, \tag{27}$$

where $\Omega_0 \cap \Omega_1 = \phi$ and $\Omega_0 \cup \Omega_1 = \bigcup$.

With the active sets in Eq. (26) and (27), the maintenance scheme is fixed and the pavement condition for every year can be derived accordingly. We can then easily solve the UE problem to calculate traffic flow on each link of each year. Let $(\bar{\boldsymbol{y}}, \bar{\boldsymbol{v}})$ be the solution set to the UE model. Because the BPR function increases monotonically, $\bar{\boldsymbol{v}}$ must be unique. Therefore, $(\bar{\boldsymbol{y}}, \bar{\boldsymbol{v}})$ must be the optimal solution to the original model with the constraints expressed in Eq. (26) and (27) because $(\bar{\boldsymbol{y}}, \bar{\boldsymbol{v}})$ is the only feasible solution to the lower-level model.

The basic idea underlying the active set algorithm is to exchange elements between Ω_0 and Ω_1 to reduce the overall fuel consumption in each iteration until optimization has been achieved. The elements to be exchanged are determined by calculating the Lagrange function of the original model. Given the optimal solution $(\bar{\boldsymbol{y}}, \bar{\boldsymbol{v}})$, the Lagrangian multipliers associated with Eq. (26) and (27) are denoted by $\lambda_{i,p}(t)$ and $\mu_{i,p}(t)$, respectively. The following theorems were proved by Zhang et al. (L. Zhang et al., 2009), and can be used to adjust active sets:

Theorem 1: Given that Ω_0 and Ω_1 are feasible solution sets, if $\lambda_{i,p}(t) < 0$ for some $(i', p', t') \in \Omega_0$, switching (i', p', t') from Ω_0 to Ω_1 yields less objective function value. If $\mu_{i,p}(t) > 0$ for some $(i', p', t') \in \Omega_1$, switching (i', p', t') from Ω_1 to Ω_0 yields less objective function value.

Theorem 2: The active set method converges after a finite number of iterations.

To ensure the feasibility of the solution achieved in every iteration, an embedded program is developed to confine the solution to an area that is feasible according to the available budget, as follows:

$$\min \sum_{(i,p,t)\in\Omega_0} \lambda_{i,p}(t) g_{i,p}(t) - \sum_{(i,p,t)\in\Omega_1} \mu_{i,p}(t) h_{i,p}(t) \quad (28)$$

$$\text{s.t} \sum_{(i,p,t)\in\Omega_0} L_i \cdot y_{i,p}(t) \cdot c_p(t) \cdot g_{i,p}(t) \cdot e^{-rt} + \sum_{(i,p,t)\in\Omega_1} L_i \cdot y_{i,p}(t) \cdot c_p(t) \cdot \left(1 - h_{i,p}(t)\right) e^{-rt} \le B \quad (29)$$

$$\sum_{(i,p,t)\in\Omega_0} \lambda_{i,p}(t) g_{i,p}(t) - \sum_{(i,p,t)\in\Omega_1} \mu_{i,p}(t) h_{i,p}(t) \ge \theta \quad (30)$$

$$g_{i,p}(t), h_{i,p}(t) \in \{0,1\}, \forall i \in \mathbf{I}, t \in \mathbf{T}. \quad (31)$$

where $g_{i,p}(t) = 1$ records a shift in $(i, p, t) \in \Omega_0$ to Ω_1 and $h_{i,p}(t) = 1$ represents the opposite. θ is set to guarantee a decrease in the objective function. In the first iteration, $\theta = -\infty$. In the next iteration, θ can be calculated using Eq. (32) in each step:

$$\theta = \varepsilon + \sum_{(i,p,t)\in\Omega_0} \lambda_{i,p}(t) g^1_{i,p}(t) - \sum_{(i,p,t)\in\Omega_1} \mu_{i,p}(t) h^1_{i,p}(t), \quad (32)$$

where ε is a sufficiently small constant. Initially, θ is $-\infty$ and solving (28)-(31) would yield an adjustment plan ($g^1_{i,p}(t)$, $h^1_{i,p}(t)$) with negative change, then a better solution can be found. However, the KKT multipliers are only estimates of the change of the objective function, ($g^1_{i,p}(t)$,

$h_{i,p}^{1}(t)$) may not lead to an actual decrease. The constraint shown in Eq. (32) prevents the solution from degenerating back to that in the previous iteration. The objective of Eq. (28) is to minimize the estimated decrease, a high negative value of which implies a significant reduction in objective value. If Eq. (28) is zero, no better solution can be found.

The steps of the algorithm are as follows:

Step 1. Set the iteration variable $\eta = 1$, $TO^{0} = +\infty$, $TD^{0} = -\infty$ and the initial feasible fixed solutions $\left(\Omega_0^{\eta}, \Omega_1^{\eta}\right)$.

Step 2. Solve (5)–(25) with $\left(\Omega_0^{\eta}, \Omega_1^{\eta}\right)$ by Frank and Wolfe algorithm and derive $\lambda_{i,p}^{\eta}(t)$ and $\mu_{i,p}^{\eta}(t)$. Calculate total fuel consumption TO^{η}. If $TO^{\eta} \geq TO^{\eta-1}$, then $\eta = \eta - 1$; go to step 3.

Step 3. Solve (28)–(32) and $\theta = \varepsilon + TD^{\eta-1}$.

a) If the optimal objective value is zero, $\left(\Omega_0^{\eta}, \Omega_1^{\eta}\right)$ is the best solution and the iteration ends;

b) if not, derive $\left(g_{i,p}(t), h_{i,p}(t)\right)$ by the derivative of the Lagrangian function, and the objective value TD^{η} and go to step 4.

Step 4. Obtain a new solution to $\left(\Omega_0^{\eta+1}, \Omega_1^{\eta+1}\right)$:

$$\Omega_0^{\eta+1} = \Omega_0^{\eta} - \left\{(i,p,t) \in \Omega_0^{\eta} : g_{i,p}(t) = 1\right\} + \left\{(i,p,t) \in \Omega_1^{\eta} : h_{i,p}(t) = 1\right\},$$

$$\Omega_1^{\eta+1} = \Omega_1^{\eta} - \left\{(i,p,t) \in \Omega_1^{\eta} : h_{i,p}(t) = 1\right\} + \left\{(i,p,t) \in \Omega_0^{\eta} : g_{i,p}(t) = 1\right\},$$

then $\eta = \eta + 1$; go to step 2.

---

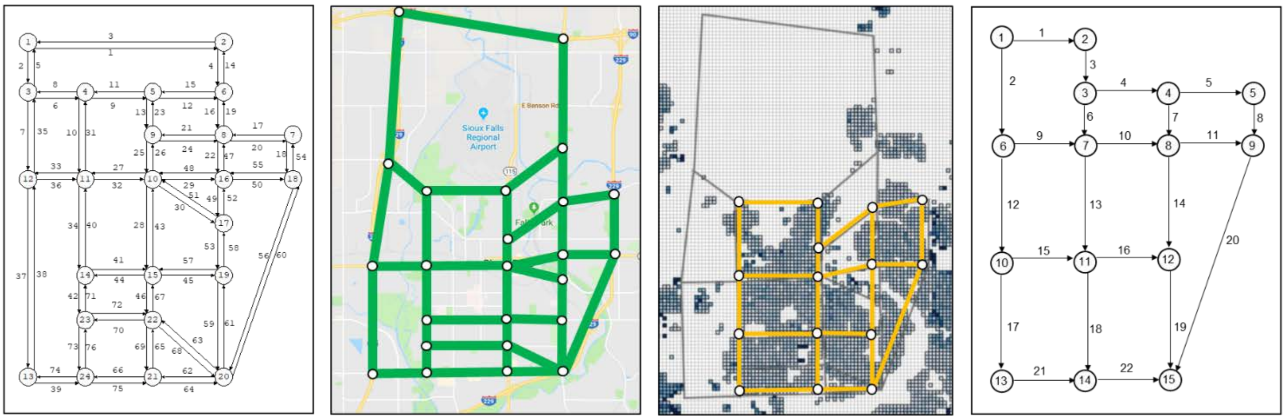
*TO^{η} and TD^{η} both represents the value of the objective function in the η^{th} iteration.

4. NUMERICAL EXAMPLES

This section reports a case study based on the Sioux Falls Network in South Dakota (Morlok, 1973). The aim is to understand the capability of this combined OPT & TC method in various environments. Figs. 5(a) and 5(b) show the topology and geographical patterns of the Sioux Falls network, and Fig. 5(c) shows the population distribution in the area (Chakirov & Fourie, 2014). For the sake of simplicity, we consider only a part of the original network based on population density, shown in Fig. 5(c), the topology of which is illustrated in Fig. 5(d).

4.1 Basic Setting

The basic characteristics of the selected Sioux Falls network are listed in Table 2 and the origin–destination trip matrix is given in Table 3. The other default parameters were as follows: (1) The capacity of each lane was approximately is 1500 pcu/h. (2) The number of lanes on each link was estimated by dividing link capacity by lane capacity. (3) The initial RQI = 5. (4) The discount rate r = 0.08. (5) The maintenance planning period T = 10 (years). (6) The BPR function: $\alpha = 0.15, \beta = 4$. (7) The lowest RQI requirement for safety R_s was set to 2.0. (8) The maintenance cycle l_0 =10 (years). (9) The average construction time m_p for three types of maintenance activities was assumed to be 0, 30, and 60 days/mile/lane respectively (Ram & Peshkin, 2014). In practice, these parameters are supposed to be estimated according to the local situation. (10) The price of maintenance of each activity c_p is shown in Table 1. (11) A and B were the deterioration parameters as referred to in Sun(L. Sun, 2016).



(a) (b) (c) (d)

Figure 5 The highway network of Sioux Falls: (a) the original network topology; (b) the geographical network; (c) the population distribution; (d) the redrafted topology

Table 2 Network characteristics of Sioux Falls network

Link	Free flow time (min)	Length (mile)	Capacity (10^3pcu/h)	Link	Free flow time (min)	Length (mile)	Capacity (10^3pcu/h)
1	1.2	1	7.5	12	2.4	0.9	6.5
2	3.3	1.5	6.0	13	3.6	1.1	7.5
3	3	1.1	7.0	14	2.4	1	6.7
4	2	1.9	6.7	15	3	1.1	7.0
5	1.8	1.1	10.6	16	2.4	1.1	6.4
6	1.8	0.4	5	17	3.6	1.4	8
7	3	1.2	6.7	18	3.6	1.8	8
8	1.2	1.2	7	19	2.4	1.1	6.6
9	3	0.8	10	20	2.4	2.5	5.3
10	3	1.1	6.8	21	1.8	1	6.5
11	1.8	0.9	7.5	22	3.6	1.3	6.7

Table 3 Network OD demand (10^3 pcu/h)

	1	2	6	7	9	10	11	12	13	14	15
1	0	1.32	1.07	1.08	1.21	0.9	0.84	0.8	0.8	0.64	1.62
2	0	0	0	1.13	0.88	0	0.81	0.73	0	0.81	0.8
6	0	0	0	1.5	0.79	1.32	1.11	0.95	1.05	0.61	0.74
7	0	0	0	0	1.02	0	1.32	1.17	0	0.9	0.95
9	0	0	0	0	0	0	0	0	0	0	0.99
10	0	0	0	0	0	0	1.32	2.13	1.13	0.87	0.95

11	0	0	0	0	0	0	0	1.32	0	1.14	1.27
12	0	0	0	0	0	0	0	0	0	0	1.32
13	0	0	0	0	0	0	0	0	0	1.32	0.61
14	0	0	0	0	0	0	0	0	0	0	1.32
15	0	0	0	0	0	0	0	0	0	0	0

4.2 Parameter Calibration

Many field tests have been conducted to calibrate the coefficients of the model in Eq. (5). Analysis of a sample of Virginia Department of Transportation pavements indicates that the fuel consumption grows about 2.6235 gal/h along with the increase of the 1m/mile IRI (Gillespie & McGhee, 2007). These data were applied to calibrate the model coefficients, as shown in Eq. (33):

$$O_i(t) = 27.661 + 2.6235 \cdot \left(\frac{6.122 - R_i(t)}{1.963} \right)^2, \quad \forall i \in \mathbf{I}, t \in \mathbf{T} \tag{33}$$

The generalized BPR function in Eq. (25) has two components: the cost incurred by pavement roughness and that incurred by travel time. The former leads to extra fuel consumption and a corresponding loss of comfort. The fuel consumption per vehicle mile is assumed to rise by 0.13% for every 1% increase in pavement roughness, as reported from Florida (Jackson, 2004), and the price at the time of the study was approximately $2.64 /gallon, that is about $0.0398 /(RQI·mile). The world bank estimated that users' operation costs rise at a rate of two to four percent per IRI unit of roughness as roughness increases (Paterson, 1987), that is approximately $0.0007 /(RQI·mile). In sum, the RQI value coefficient γ was $0.0405 /(RQI·mile).

To transform travel time into monetary units, a method based on the gross domestic product (GDP) was used to calculate the equivalent temporal values (Zong et al., 2009), as follows:

$$\varphi = \eta \cdot \frac{GDP}{P \cdot T}, \tag{34}$$

where φ is the time value coefficient, GDP indicates regional GDP, P represents the local population, T represents average working hours per year, and η is the time factor, set to 0.5 for transportation. Sioux Falls has a population of 174,360 and a GDP of RMB $15,768 million (U.S. Bureau of Economic Analysis, 2018), with most citizens working 8.1 hours per day. φ was $15.49 /h. Then Eq. (25) can be calibrated as:

$$tc(v_i(t)) = 0.3 \cdot L_i - 0.04 \cdot R_i(t) \cdot L_i + 15.49 \cdot \tau_i(t) \tag{35}$$

Although the multiplier of pavement roughness (−0.04) was considerably smaller than that for travel time, it had a similarly significant impact on drivers if the pavement conditions were poor ($R_i(t)$ was large) and the road was very long.

4.3 Comparison of Strategies

In this section, we compare three maintenance strategies. The network defaults and parameters have been introduced in the last two sections. The budget was set to $0–$70 million for 10 years. The first strategy tested was worst first, which is designed to first repair roads in the worst condition without considering its effects on traffic flow. In most cases, the budget for each year was assigned on average. Maintenance decisions were made separately each year within the lifecycle. The budget remaining at the end of a year was added to the budget for the next year. The WF method can be summarized as follows:

$t = 1 \leftarrow$ initial year

$j(t) = 0 \leftarrow$ number of maintained links in year t

$B_a(t) = B \times \frac{1-e^{-r}}{1-e^{-rT}} \leftarrow$ annual budget, T $\leftarrow$projected lifetime

$B_r(t) = B_a(t) \leftarrow$ remaining budget in year t

$C_{\tilde{i}}(t) = 0 \leftarrow$ maintenance cost in year t

while $t < 10$

while $C_{\tilde{i}}(t) \leq B_r(t)$

solve lower model (20)-(25) and calculate $R_i(t^-)$ using Eq. (14)

The maintained link $\tilde{i} = \left\{ \forall i \in \underset{\left\{\forall i \in \mathbf{I}, s.t. y_{i,p}(t)=0, \forall p\right\}}{\arg\min} \left[R_i(t^-)\right] \right\} \underset{}{\arg\min} [v_i(t)]$

Calculate maintenance cost $C_{\tilde{i}}(t)$ based on Table 1

$B_r(t) = B_r(t) - C_{\tilde{i}}(t)$

$y_{\tilde{i},p}(t) = 1 \leftarrow$ parameter p refers to Table 1

$j(t) = j(t) + 1$

calculate $R(t^+)$ using Eq. (13)

end

$B_a(t+1) = B_a(t+1) + B_r \cdot e^r \leftarrow$ the unused budget flows to the next year

$t = t + 1$

end

The second strategy was threshold control, where the thresholds (Table 1) were set as triggers for the maintenance activities. For the early years, the maintenance threshold is normally set as 90%

of the initial condition, which is about 4.5 for RQI. In practice, many links may reach their thresholds simultaneously, because of which we need to pick the "more urgent" links among them owing to the limited annual budget. An "urgent" link is the one with a higher rate of deterioration, and can be calculated by Eq. (2). The TC method can be summarized as follows:

$t = 1 \leftarrow$ initial year

$B_a(t) = B \times \frac{1-e^{-r}}{1-e^{-rT}} \leftarrow$ annual budget, T ←projected lifetime

$B_r(t) = B_a(t) \leftarrow$ remaining budget in t year

while $t < T$

solve lower model (20)–(25) and calculate $R_i(t^-)$ using Eq. (14)

Calculate the deterioration rate $Dr(i)$ of each link based on Eq. (2).

$\pi_1 = \{ i \mid R_i(t^-) \in (R_{trd},\ 5] \} \leftarrow$ divide links into two components

$\pi_2 = \{ i \mid R_i(t^-) \in [0,\ R_{trd}] \} \leftarrow$where R_{trd} denotes the controlled threshold

Set π_2 contains links requiring maintenance

Solve the following program:

$\max \sum_{i \in \mathbf{I}} \sum_{p=1}^{3} Dr(i) \cdot y_{i,p}(t) \leftarrow$ choose the most urgent links

s.t. $\sum_{\substack{p=1 \\ i \in \pi_2}}^{3} y_{i,p}(t) \cdot C_p(t) \leq B_a(t) \leftarrow$ annual budget constraint

$C(t) = \sum_{\substack{p=1 \\ i \in \pi_2}}^{3} y_{i,p}(t) \cdot C_p(t) \leftarrow$ calculate the maintenance cost

calculate $R(t^+)$ using Eq. (13)

$B_r(t) = B_a(t) - C(t)$

$$B_a(t+1) = B_a(t+1) + B_r \cdot e^r$$

$t = t+1$

end

Constraints (12), (19) are still valid in WF and TS. The fuel consumption of these three methods is shown in Figure 6. The network fuel consumption decreased with an increase in the budget. This trend followed a quasi-linear pattern before the $20 million budget. Following it, this decreasing tendency diminished along with continued investment. Compared with the other two methods, the eco-based strategy always had the lowest network fuel consumption, and saved 20% in fuel cost more than WF and almost 40% more than TC. When the budget was very high, the fuel cost of the eco-based strategy and WF converged as every road in the network had been repaired. However, the result for TC was still relatively high, indicating that no other roads could reach the threshold if all roads had been maintained in the early years.

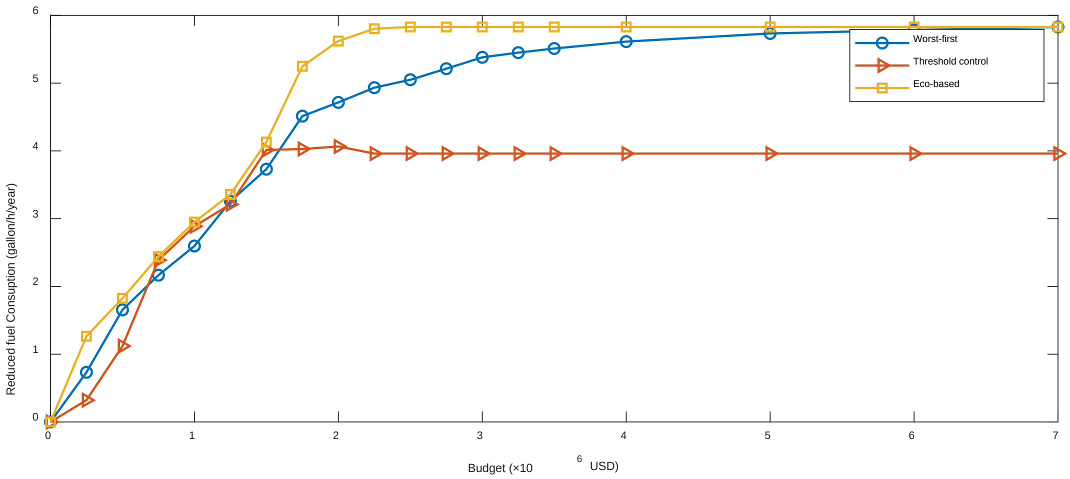
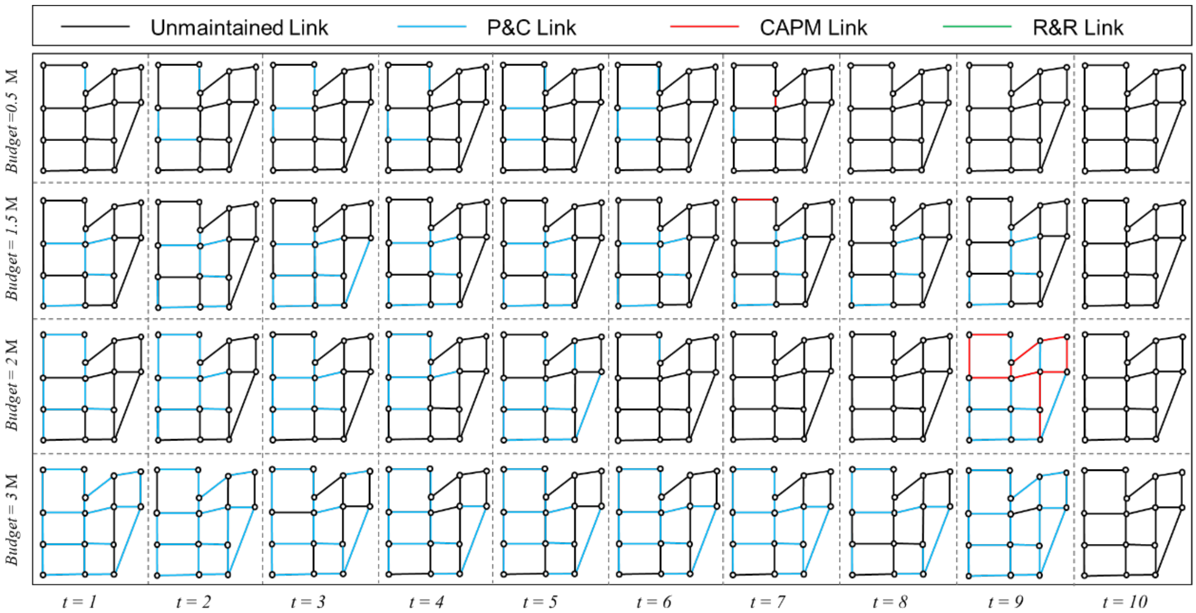
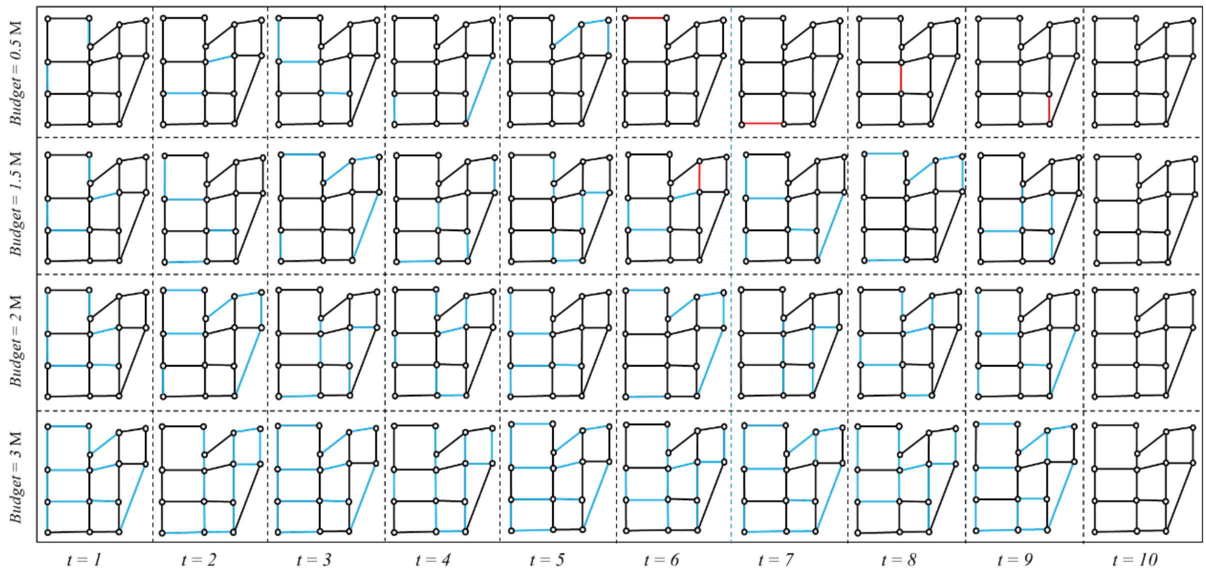


Figure 6. Changing patterns of network fuel cost with budget for the newly-built network

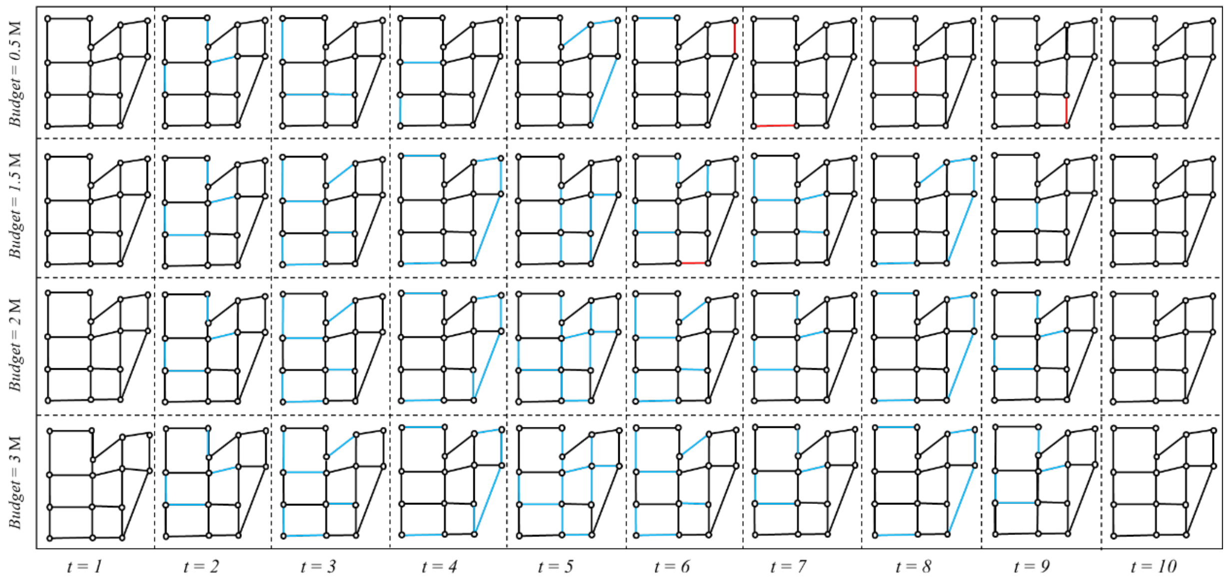
Fig. 7 shows the detailed schemes with budgets of 0.5, 1.5, 2, and 3 million USD. For eco-based strategy, most maintenance activities were scheduled in the early years of the lifecycle, indicating the benefits of preventive maintenance. In general, roads with high traffic volumes were more inclined to be repaired continually. The others were likely to be maintained every other year or even a more extended period. When the budget was $2 million, no measures were taken in the seventh and eighth year. Sequentially, all links were rehabilitated in ninth year, which implied that maintaining roads every year might not have been the optimal solution in terms of fuel consumption. For worst-first strategy, when the budget is relatively low, the maintained roads are exclusive for the adjacent years, which is consistent with the features of WF algorithm. For threshold control strategy, no maintenance activities would be conducted at fifth and sixth years, because all the links in the network are in good conditions. Thus, there might be some budget left during the designed lifecycle for TC algorithm. This also explained why the maintenance schemes are constant for the budget > $1.5 million.



(a) Eco-based Strategy



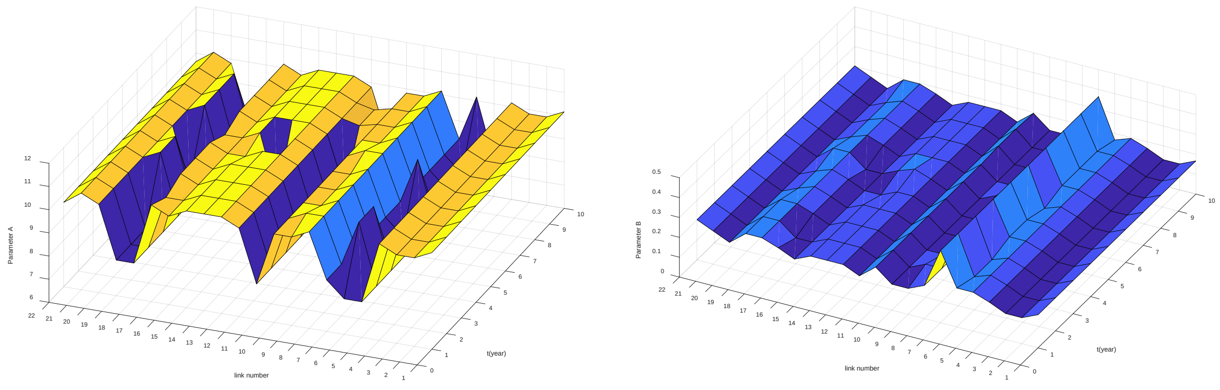
(b) Worst-first Strategy



(c) Threshold Control Strategy

Figure 7 Maintenance schedule under different budgets for the newly-built network

As the functions A(v) and B(v) are piecewise functions, their values are relatively stable in most cases. However, there are some vulnerable links whose deteriorating trends are easily affected by traffic redistribution, such as links 6, 11 and 19, as shown in Fig. 8. In general, the traffic loads on these roads are not heavy, and they are adjacent to the main-volume links. The impact of maintenance activities on these links is interactive and simultaneous. Once some maintenance is conducted, the A and B of some links become larger, and the others become smaller due to the transfer of the traffic.



(a) The changes of parameter A (b) The changes of parameter B

Figure 8 The changes of parameters A and B under two million budgets

We further compared these strategies in terms of the average pavement condition and total travel time. Fig. 9 shows the average condition of the network using different schemes. The three strategies yielded similar effects on average road condition while the maintenance budget remained relatively small (<1.75×10^6 USD). Under such a circumstance, the TC strategy exhibited greater capabilities in terms of restoring pavement roughness, as this method was designed to maintain the overall network condition. When the budget was higher (>1.75×10^6 USD), the eco-based method yielded a significant improvement, especially as the budget ranged from 1.75 to 4×10^6 USD.

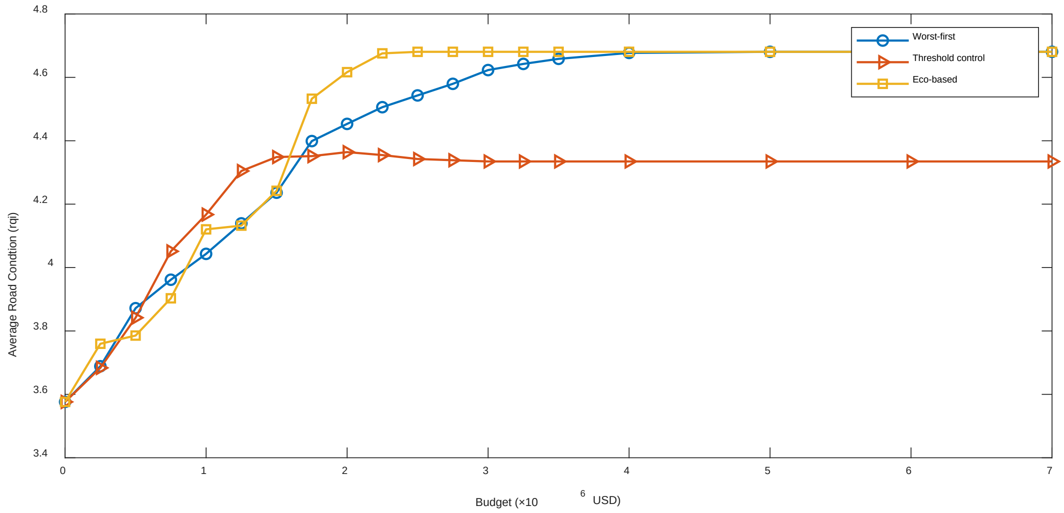


Figure 9 Average road conditions under different budgets for the newly-built network

Travel time was another crucial factor that needed to be considered when scheduling maintenance activities. Fig. 10 shows the total travel time with different approaches. It fluctuated drastically with lower budgets. This impact dropped off with an increase in the maintenance budget. None of these strategies was scheduled to minimize travel time. However, as the maintenance activities can redistribute traffic flow by changing the roughness of the pavement, these strategies bring about an additional impact on network travel time in turn. Overall, the eco-based scheme exhibited the lowest total travel time and the best capability of improving the road conditions.

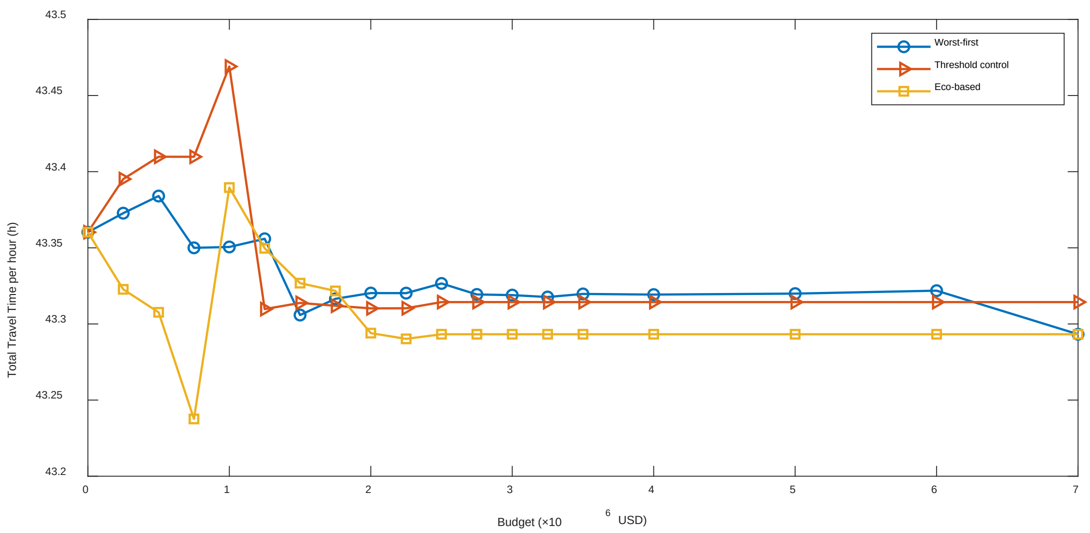


Figure 10 Total travel time under different budgets for the newly-built network

Fig. 6-10 illustrates the effectiveness of the proposed model for a newly-built network. Therefore only the P&C and CAPM are applied on the deteriorated roads during the planning period. In the second case, we considered the network had not been maintained in the last ten years, whose RQIs have deteriorated down to about 3.0. The planning period is set as five years. Fig.11-13 shows a comparison between the three maintenance scheduling strategies. As the RQIs in the network stay at a low level, there is no essential difference between WF and TC. Fig.11 shows that the eco-based method can reduce fuel consumption by 0.2% ~ 29.7% more than WF/TC. The eco-based strategy is also superior to the other two methods in terms of total travel time and average road conditions. Compared with the newly-built roads scenario, the benefits of eco-based approach in the old roads scenario are more stable and less volatile. However, the differences between three methods in terms of fuel consumption, travel time, and road condition are not as significant as in the scene of new roads due to the poor road conditions in the network and short planning cycle, as shown in Fig. 12 and Fig. 13. Fig. 14 demonstrates the maintenance schedule under different budgets for three optimization methods.

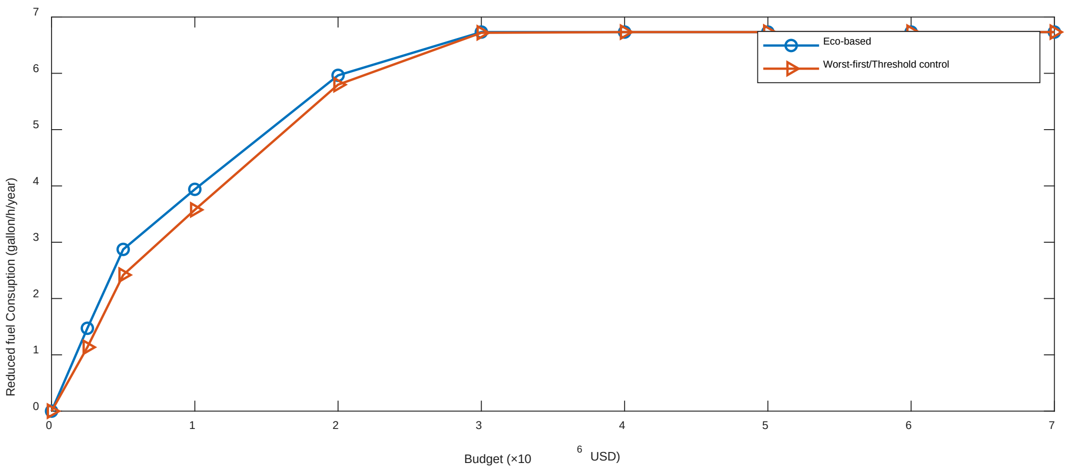


Figure 11. Changing patterns of network fuel cost with budget for the old-road network

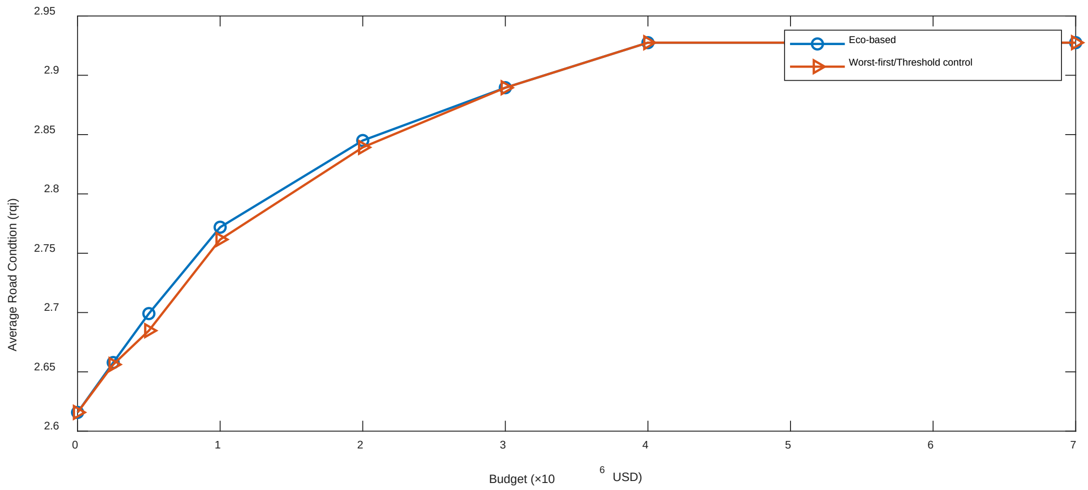


Figure 12 Average road conditions under different budgets for the old-road network

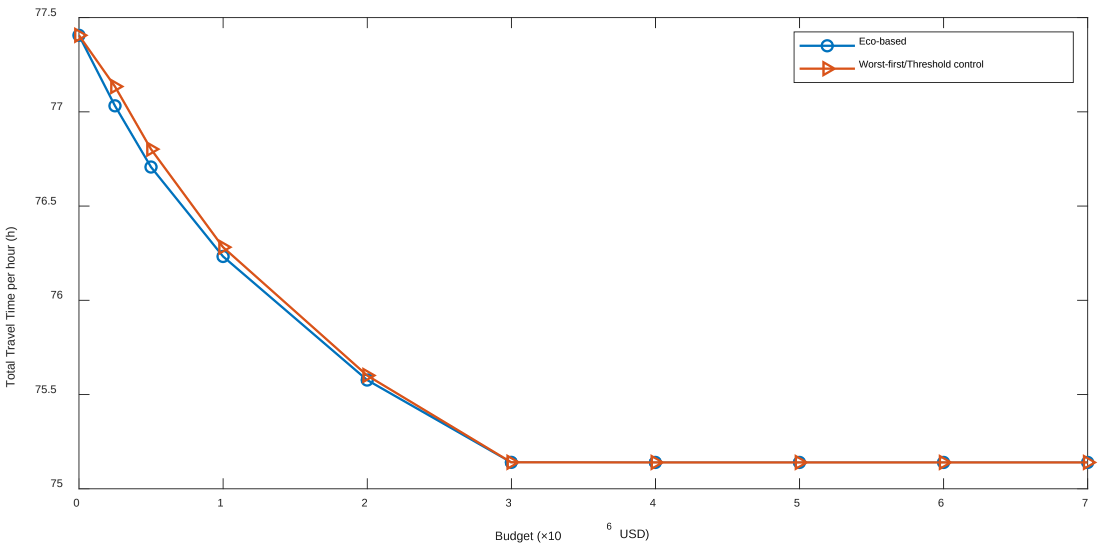
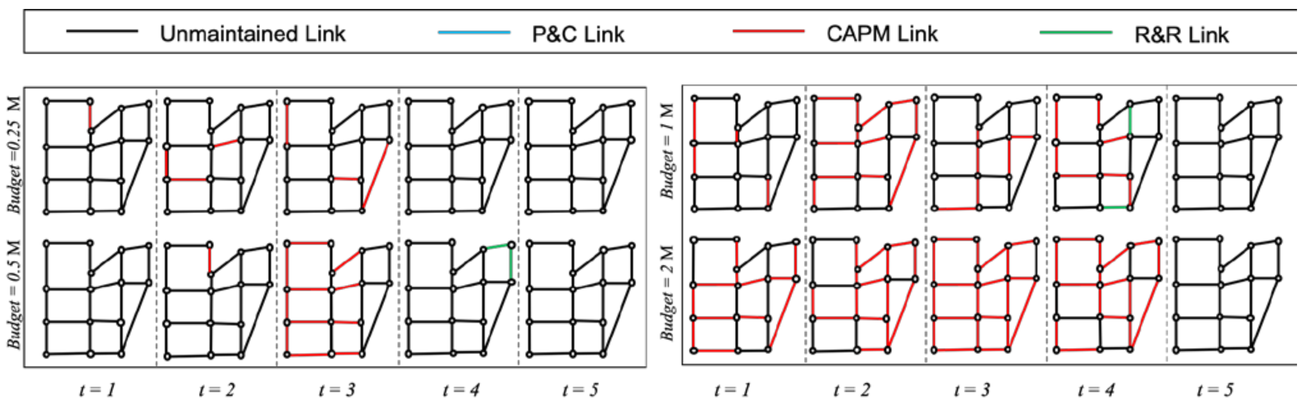
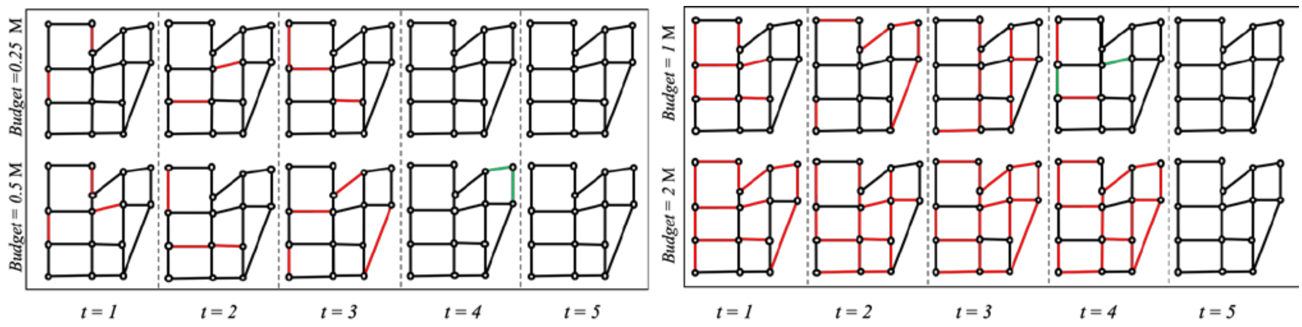


Figure 13 Total travel time under different budgets for the old-roads network



(a) Eco-based Strategy



(b) Worst-first Strategy/ Threshold Control Strategy

Figure 14 Maintenance schedule under different budgets for the old-road network

5. CONCLUSIONS

This paper proposed an eco-based method of optimizing the scheduling of maintenance activities to minimize network fuel consumption from the perspective of the lifecycle of a road network. An integrated bi-level mathematical model that incorporates interactions between maintenance and the driver's choice of route was formulated to optimize a repair scheme. Three major maintenance activities—preventive and corrective maintenance (P&C), capital preventive maintenance (CAPM), and major rehabilitation and replacement (R&R)—were considered. The network fuel consumption incorporated the cost of fuel induced by roughness and traffic disruption during construction. A modified active set algorithm with nested sub-programming was developed to solve the challenging bi-level problem. Two traditional maintenance strategies—worst first and threshold control—were compared. A numerical example based on the Sioux Falls network was investigated to reveal the effects of various budgetary constraints and verify the improvement yielded by the proposed model. A generalized BPR function was built by considering the joint effect of travel time and road roughness. Compared with travel time, unit pavement roughness had a much smaller impact on the driver's choice of route. However, on long roads in fairly poor condition, the effect of pavement roughness would be amplified, leading drivers to reconsider their travel routes. The results show that on the whole, the proposed schemes outperformed two traditional ones under all budgetary constraints from the perspective of fuel consumption. They saved 20% more fuel than the other two methods in different scenarios, which shows the ecological benefits of implementing them. The eco-based strategy also performed well with regard to overall roads conditions and total travel time.

Note that the effectiveness of the proposed bi-level model is based on the fundamental assumptions introduced in section 2.1. In practice, the pavement deterioration process may not strictly follow as Markov property, and sometimes multiple maintenance treatments may be conducted at the same time Under such conditions, we would extend our research from three perspectives in future: (1) To construct a more accurate pavement deterioration model based on data driven methods; (2) To predict the traffic volume and the impact of traffic disruption by a mass of field data; (3) To investigate the real fuel consumption on the road in terms of different vehicles and time variant speed.

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