

11th International Conference of the International Institute for Infrastructure Resilience and
Reconstruction (I3R2)
: Complex Disasters and Disaster Risk Management

Optimization of Pavement Inspection Schedule with Traffic Demand Prediction

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Abstract

In order to improve the current pavement inspection systems, many studies have attempted to produce a flexible inspection schedule by minimizing the lifecycle cost of pavement management system. However, these methods do not incorporate the risk of untimely inspection nor adopt the state-of-art intelligent transportation resources, such as traffic data from various infrastructures, flow prediction models with high accuracy, and empirical-mechanistic models for pavement deterioration process. Therefore, this paper proposes a framework to optimize a flexible inspection schedule within a risk boundary defined by pavement state prediction with traffic flow data and a more mechanistic deterioration model. The results validate the outperformance of the optimized inspection over two conventional inspection schemes – 1-year and 2-year regular inspection. Also the optimized inspection is comparably more robust than the regular inspections with different traffic scenarios due to the uncertainty risk taken by regular inspections.

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Peer-review under responsibility of Dept of Transportation Engineering, University of Seoul.

Keywords: Pavement Inspection; Traffic Demand; Maintenance Optimization

1. Introduction

As more and more vehicles accumulate on the road, traffic flow on the highway network creates rapid deterioration of pavements. Achieving the quality of pavements to a sufficient level therefore becomes critical as this affects safety on the road, as well as congestion and air pollution indirectly [1]. The government usually takes control of managing this public good. Frequently observed are the ad-hoc, regular inspection systems that sample a portion of the total road network, mostly with an interval of 1 or 2 years. However these methods do not incorporate risks of untimely inspection for the sake of simplicity. Some examples are the inspection system by the Department of Transportation of Wisconsin and Minnesota both regularly inspect a portion of the total road network [2], [3]. Korean highway is also sampled on 20% of the road every two years [4].

Only a few systems actually incorporate the risk and estimate the pavement deterioration rate to determine the inspection schedule before hazardous situation. One example is the case of Washington, where new or rehabilitated roads are inspected regularly with 2-year interval with 50% sampling, and others with intervals based on their deterioration rate estimated from simple regression [5], [6]. However, the time input of regression estimation is not the most efficient measure when an abundant source of traffic data is available from various infrastructures. For instance, traffic demand on the road measured from loop detectors by may be a better variable to estimate the deterioration of pavement, as vehicle passage is the primary contributor of the deterioration mechanism.

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Not many papers have studied pavement inspection optimization alone, though many of those that have included inspection within optimization of pavement management system claim that flexible inspection performs better than regular inspection [7]–[13]. These papers used the Markov decision process for the deterioration model of pavement links and considered the inspection schedule together with maintenance and rehabilitation, while designing the maintenance schedule flexibly with uncertainty of inspection measurement. These papers all perform well in producing flexible inspection schedule and reducing the lifecycle cost of pavement management system. However, they have certain limitations. First, they lack to consider the risk associated with untimely inspection of pavement state. The objective functions of these only involve the lifecycle cost of management and do not have a risk measure that could act as a guidance to avoid potential problems arising from malfunctioning pavements or show how much risk the management system is willing to take with the final schedule. Second, though Markov Decision Process in the deterioration models of pavements was proven to be efficient, this does not consider the mechanism of how the pavements gets degraded, for example different wearing of pavements with weather and weight of vehicles.

From the traffic flow data from roadside infrastructure and accurate traffic prediction techniques, it is possible to more directly and accurately estimate the deterioration of pavements. Therefore the boundary condition for the inspection based on risk can be defined with predicted deterioration state from the demand and a more reliable pavement inspection system that considers both safety on the road and efficiency of management can be developed. In order to improve the current inspection systems in field and the current literature on optimization of pavement inspection schedule, this paper proposes an inspection scheduling framework that minimizes the lifecycle cost of inspection within a pre-defined risk boundary, based on the predicted pavement state from an empirical-mechanistic model. Then this optimized inspection schedule is evaluated with comparison to two other inspection systems.

2. Inspection Optimization Framework

The inspection optimization framework is described in Figure 1. First, the traffic flow information from sensors installed on highway is gathered. Using traffic flow forecasting techniques, such as historical average, future traffic flow is predicted over the time horizon for which inspection will be scheduled. Second, an empirical-mechanistic model of pavement deterioration based on the predicted traffic demand on the road is used to predict the future pavement state of each link of total road network. This defines the risk boundary for each pavement link, indicated by the time due of an inspection before that pavement link drops below a threshold level of dangerous pavement state. Third, within the risk boundary, a flexible inspection schedule is found from genetic algorithm that minimizes the lifecycle cost of inspection in terms of total inspection efficiency. In the following discusses the empirical-mechanistic model adapted to predict the pavement state in the future and the objective function to minimize the lifecycle cost of inspection in detail.

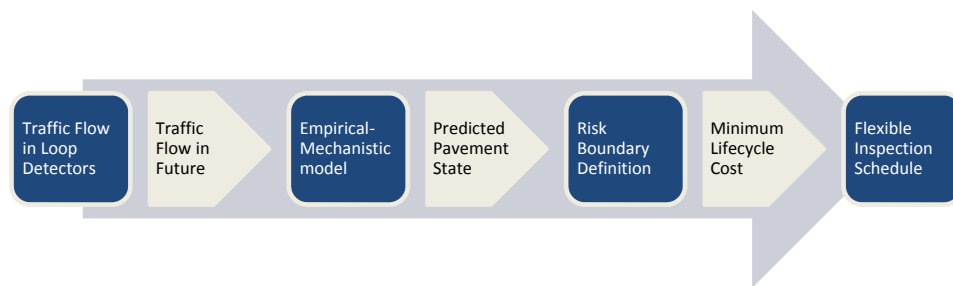


Fig. 1. The Proposed Inspection Optimization Framework

3. Methodology

First, the prediction method for pavement state is discussed. Usually, the Markov decision process is often used in pavement state prediction when optimizing the lifecycle cost of pavement management [7]–[13]. However, studies on pavement state estimation show that a mechanistic perspective of pavement deterioration can be also developed for example the AASHTO Road Test data [14]–[19]. These models produce a serviceability of pavement as a function of variables that directly affect and better describe the deterioration process of pavements. Examples of these variables are traffic characteristics, pavement structural properties and environmental conditions, which is described as below.

$$P_t = P_0 + \alpha \sum_{s=0}^{t-1} N_s^\delta \Delta N_{s+1} \quad (1)$$

where

P_t = pavement serviceability at time t ,

N_t = cumulative traffic up to time t

ΔN_t = traffic increment from time $t - 1$ to time t

α, δ = parameters to be estimated

This is an empirical-mechanistic model, since the parameters of the model with mechanically related variables are found empirically. When this model is adapted, the inspection schedule can describe the deterioration process in more detail than the Markov chain process, by using the future traffic flow predicted with the data from loop detectors. Among a number of serviceability prediction studies, the Random Effect method to estimate the parameters by Prozzi and Madanat [14] is chosen for its superior performance as a serviceability prediction model [20]. Therefore, this paper uses the Random Effect method and its parameters to predict the future serviceability of a pavement link i at time t , with assumed knowledge on initial serviceability P_0 and data such as historical cumulative traffic flow, and the future traffic flow. The result from this model acts as an input to define the risk boundary of inspection for each pavement link, which describes the due time of inspection for that link against a certain serviceability threshold.

Second, the objective function that minimizes the lifecycle cost of inspection is described. Under the constraint of risk boundary, the genetic algorithm searches for the best flexible inspection schedule for the entire pavement network on the subject budget year, minimizing the lifecycle cost. The setup of this paper is that budget year has an interval of a year while inspection on pavements can be done quarterly, though these parameters can be changed easily in the overall framework. The planning horizon of the system is assumed thirty years. Note that all inspections schedules are subjected to the soft risk boundary from pavement state prediction after optimization, with penalty on the untimely inspection in monetary terms. The objective function of optimization is as follows.

$$\text{max(Total Efficiency)} = \text{max(Interval Efficiency + Distribution Efficiency)} \quad (2)$$

The total efficiency to be optimized is composed of interval efficiency and distribution efficiency. First, the interval efficiency is the efficiency from flexibly modulating the inspection schedule of a pavement link within the budget year, in other words, ‘winning or gaining’ more time without inspection. This affects the lifecycle cost-to-go of inspection of that link. Assume a regular inspection done on pavement link i every second quarter with a regular interval of one year. The inspection cost is assumed constant with no inflation. The cost-to-go of the pavement link i in present value before optimization is described as below, and we call this the cost-to-go with no deference of intervals.

$$\sum_{t=1}^{120} \text{inspection cost of link } i \times (1+r)^{-(t-\text{current quarter})} \quad (3)$$

where,

t = the number of quarters left in the planning horizon, from 1 to 120 quarters

r = discount rate (quarterly)

Now by optimizing the inspection schedule, flexible inspection may create deference of intervals and result in two cases of cost-to-go. One is where inspection is delayed, for example a link with inspection on second quarter last year is schedule on the fourth quarter this year with 2 quarter. Another is where it is shifted earlier, for example a link inspected on the second quarter of last year is now done on the first quarter. The first case of delayed inspection will then decrease the cost-to-go, since it reduces the present value of lifecycle cost-to-go or even reduce the number of inspections done in the planning horizon in total. On the contrast, the second case of earlier inspection increases the cost-to-go in the present value. Therefore, the cost-to-go with flexibly modulated inspection schedule of link i in present value can be expressed as:

$$\sum_{t=1}^{t=120} \text{cost of link } i \times (1+r)^{-(t-\text{inspected quarter})} \quad (4)$$

For instance, inspected quarter here takes value 4 for the inspection on fourth quarter. This we call the cost-to-go with deference of intervals. By subtracting the cost-to-go with deference seen in equation 4 from that without deference seen in equation 3, we can find the interval efficiency of flexibly scheduling the inspection, described in detail as the following:

$$\text{Interval Efficiency} = \sum_{i=1}^{\text{\# of links}} \sum_{k=1}^m \frac{L_i \times S^{-1} \times w}{(1+r)^{Q_{k,i}}} - \sum_{k=1}^n \frac{L_i \times S^{-1} \times w}{(1+r)^{q_{k,i}}} \quad (5)$$

where,

k = number of inspections left in the lifecycle for link i .

For regular schedule $k = [1, m]$ and for flexible schedule, $k = [1, n]$

L_i = length of link i

S = speed of inspection vehicle, $\frac{20\text{km}}{\text{hr}}$

w = wage for inspection, 8\$/hr

r = quarterly rate of discount

$Q_{k,i}$ = number of quarters elapsed for the k th inspection of link i with flexible schedule.

For example, $Q_{k,i} = (4, 8, 12, 16, \dots)$. $0 \leq Q_{k,i} \leq \text{planning horizon in quarters}$

$q_{k,i}$ = number of quarters elapsed for the k th inspection of link i with regular schedule

For example, $q_{k,i} = (2, 6, 10, 14, \dots)$. $0 \leq q_{k,i} \leq \text{planning horizon in quarters}$

Second, the distribution efficiency is the efficiency from evenly distributing the inspection load over the quarters in the budget year, when there assumed to be a fixed inspection capacity that can be done in normal working hours. If the inspection load of each quarter exceeds the capacity, then the efficiency of inspection decreases and must be done in overtime hours. The reference schedule which to compare the performance of the flexible inspection has the most even distribution of total required inspections, with the least inspection load in overtime. The distribution efficiency can be expressed as below:

$$\begin{aligned} &\text{Distribution Efficiency} \\ &= w_{\text{over}}(L_{\text{over,even}} - L_{\text{over,GA}}) + w_{\text{normal}}(L_{\text{normal,even}} - L_{\text{normal,GA}}) \end{aligned} \quad (6)$$

where,

w_{over} = overtime wage, 16\$/hr

w_{normal} = normal wage, 8\$/hr,

$$L_{\text{over},X} = \sum_{s=1}^4 (L_{s,X} - C)$$

= sum of lengths of links inspected in overtime with schedule X .

Schedule X can take either the even reference schedule

or the schedule from GA.

$L_{s,X}$ = sum of lengths of links inspected in s th quarter in the budget year with schedule X

C = quarterly capacity, which is the sum of lengths of links that can be done in normal working time within a quarter

$$L_{\text{normal},X} = \sum_{i=1}^{\text{number of links}} L_i - L_{\text{over},X}$$

= sum of lengths of links inspected in normal hours with schedule X

Note from the distribution efficiency is that even if the current inspection system has a sufficiently large quarterly capacity and allows inspection to be concentrated in a short period of time within the budget year, this efficiency measure still gives us ability to gradually reduce the inspection capacity to the optimal level in the future. This helps find the required level of inspection capacity at a minimum from considering how the inspection load can be distributed.

Summing the interval efficiency and the distribution efficiency, which are both in monetary terms, we have the total efficiency function as follows:

$$\begin{aligned} & \text{Total Efficiency} \\ &= \sum_{i=1}^{\text{number of links}} \sum_{k=1}^m \frac{L_i \times S^{-1} \times w}{(1+r)^{Q_{k,i}}} - \sum_{k=1}^n \frac{L_i \times S^{-1} \times w}{(1+r)^{Q_{k,i}}} \\ &+ w_{\text{over}}(L_{\text{over,even}} - L_{\text{over,GA}}) + w_{\text{normal}}(L_{\text{normal,even}} - L_{\text{normal,GA}}) \end{aligned} \quad (7)$$

Within the risk boundary developed from the serviceability model of each link, the genetic algorithm seeks for a flexible inspection schedule of the budget year for the entire set of pavement links that maximize the total efficiency.

4. Results

The result from the flexible inspection is assessed in comparison to two other conventional inspection methods – regular inspection schedule with interval of one year and two years. These three inspection schedules are evaluated against three criteria - interval efficiency, distribution efficiency and penalty for untimely inspection. Interval efficiency and distribution efficiency are evaluated with the functions identical to equation (5) and (6), which will grade the three inspection schedules in monetary terms. Penalty for untimely inspection is an additional criterion to evaluate the risk associated with regular inspections that disregard the predicted state of pavements. A penalty of 20 dollars per link is assumed and given to each quarter that inspection is scheduled late for, compared to the time serviceability prediction drops below the threshold value of 3.0.

Furthermore, there are four different traffic scenarios, which are every possible combination of high or low average traffic flow and high or low concentrated traffic flow over the entire road network. Refer to Figure 2. It shows how a sample of 100 pavement links may have a different traffic flow per quarter. The codes, HH, LH, LL, and HL, denote different traffic scenarios, for example, HL denotes high average load and low concentrated load. On the left in Figure 2, we can observe that a road network with HH traffic scenario has higher average traffic flow than LL. On the center in Figure 2, we can observe that road networks with HH and HL have similar average traffic flow, but HH has a higher frequency of concentrated traffic load than HL. This is similar for the right of Figure 2, where a road network with LH has higher frequency of concentrated traffic load than LL, while having similar average traffic flow.

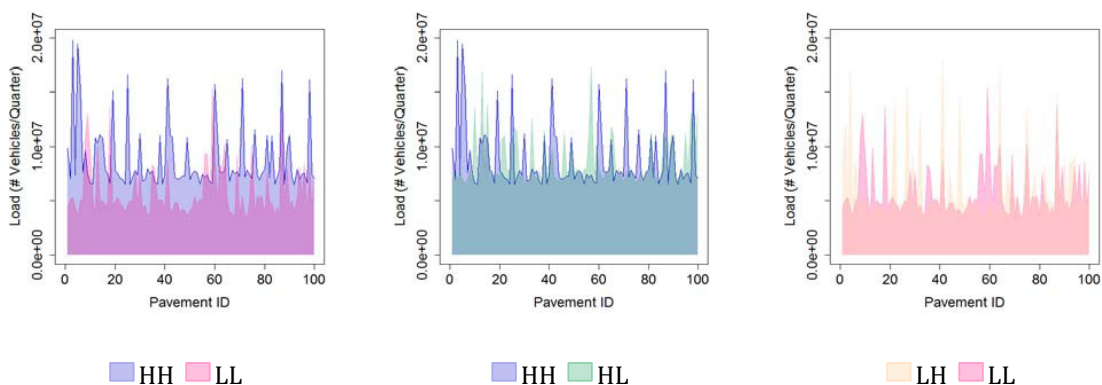


Fig. 2. An example of different traffic scenarios

A sample of a hundred pavements links have been randomly generated a hundred times for four different scenarios, which makes 40,000 pavement links tested in total. To start, we analyze the performance of three inspection schedules according to the total efficiency loss, which comprises of interval efficiency, distribution efficiency, and risk penalty for untimely inspection. The density graph is drawn in Figure 3. As seen, the total efficiency is the highest for the optimized inspection from the genetic algorithm, followed by the regular inspection with 1-year interval, then the regular inspection with 2-year interval. To analyze why the optimized inspection schedule has outperformed the other two, a table is presented to show the mean values of each efficiency values for the three inspection schemes.

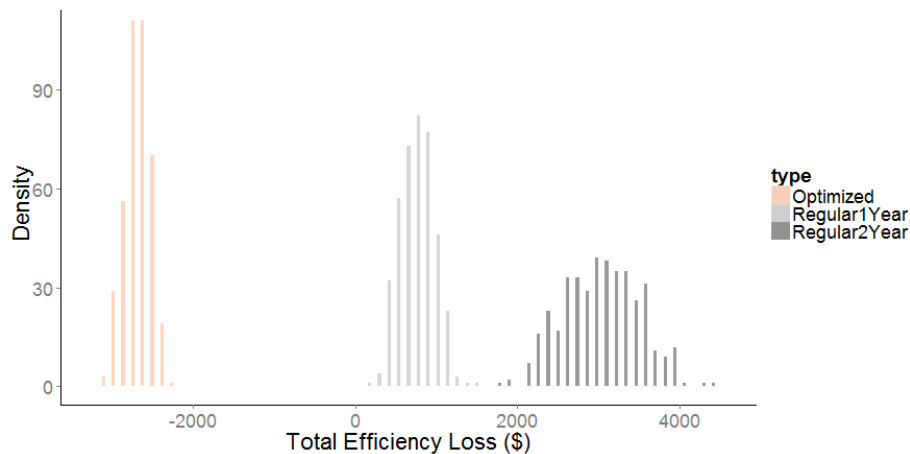


Fig. 3. Comparison of Total Efficiency Loss between Three Inspections

Refer to Table 1, where negative efficiency loss means efficiency gain and positive efficiency loss means poorer performance of the inspection. First, the regular inspection with 2-year interval has the best performance, followed by optimized inspection, then regular with 1-year interval. The regular inspection with 1-year interval has zero interval efficiency loss, since it was the reference inspection schedule with which to compare the interval efficiency of the other two inspection schedules. In other words, the regular inspection with 1-year interval was used to calculate the portion represented by the equation (3), which is a sub-part of equation (5). It is obvious that the regular inspection with 2-year interval performs better than the optimized schedule, since all pavements links have 2-year intervals between inspections, while in optimized inspection schedule, pavements have inspection intervals distributed between 1-year and 2-years.

Table 1. Mean Values of the Efficiency Criterion for Three Inspections

	Regular 1 year	Regular 2 year	Optimized
Interval Efficiency Loss (\$)	0	-3279.14	-2803.09
Distribution Efficiency Loss (\$)	97.05	97.05	157.97
Risk Penalty (\$)	667.80	6173.45	0
Total Efficiency Loss (\$)	764.85	2991.36	-2645.12

Second, the distribution efficiency of regular inspections is better than that of the optimized inspection. Note that inspection schedule for the regular inspection in previous year was assumed evenly distributed already, hence a high efficiency. Also, the distribution efficiency of regular inspections is the same, since they have identical inspection schedule except for the difference in years, for example the same schedule applies to 2015 for the regular inspection with 1-year interval and to 2016 for the regular inspection with 2-year interval. The reason why the optimized inspection has a poorer performance is that this system must obey the risk boundary preset by the pavement serviceability predictions, despite the inefficiency caused by concentrated a higher load in one specific quarter. Third, the risk penalty is greatest for the regular inspection with 2-year intervals and has the worst performance. This is because this schedule plans inspections much later than the other two inspections, creating more risks for untimely inspection. Since the genetic algorithm finds a solution strictly within the risk boundary, the optimized schedule has a zero risk penalty.

In total, we observe that the optimized inspection has the highest efficiency overall, from deferring inspection intervals of pavements without creating risks. The regular inspections do have a strong advantage in the ease of implementation, but have a risk associated with blindly planning the inspection schedule without considering the pavement states. Especially for the regular inspections with 2-year interval, the risk for untimely inspection seems critical, despite its efficiency gain in deferring inspections the longest.

In addition to the efficiency comparison, the robustness of three systems with different traffic scenarios can be observed. The analysis of the unique advantages and disadvantages of three inspections in different traffic scenarios could give us a deeper insight and guide us in selecting the appropriate inspection schedule in practical application. Therefore, the total efficiency for three inspection schemes for different traffic scenarios is presented. Refer to Figure 4. The total efficiency for three inspection schedules is presented with different traffic scenarios – HH, HL, LH, and LL. The first look of the three graphs tell us that with different traffic scenarios, the efficiency cost differs considerably for the 1-year and 2-year regular inspections. This indicates that the optimized inspection schedule is the least variability with different traffic scenarios. More specifically, the standard deviations of the total efficiency loss for 1-year regular, 2-year regular, and optimized inspections are 209.61, 464.26, and 155.36 in dollars, respectively. The smallest standard deviation of the optimized inspection again shows that the optimized inspection schedule has a narrower distribution than the regular inspections. This is a strength of the optimized inspection schedule since it provides pavement managers a better idea to conduct inspections within a certain level of budget constraint.

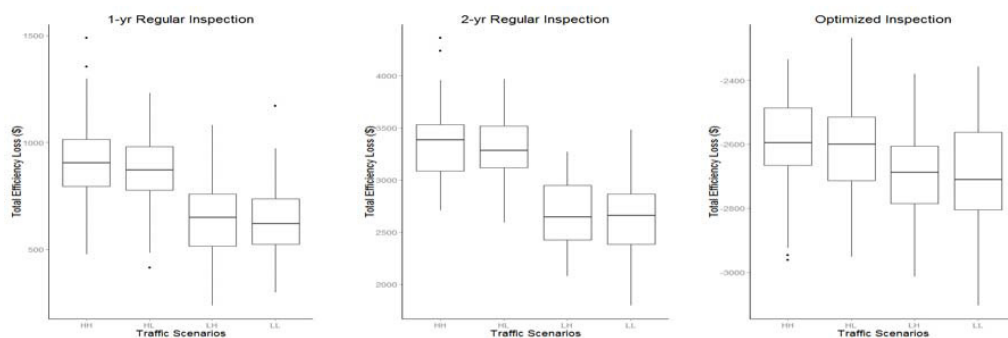


Fig. 4. Total Efficiency of Inspection Schedules with Different Traffic Scenarios

Furthermore, we can identify which types of traffic scenarios influence the efficiency of inspections significantly. Table 2 shows the result of hypothesis testing of different means of four traffic scenarios for each inspection. The first value 0.3652, for example, is the p-value for the difference between mean efficiency losses of HH case and HL case of regular 1-year interval with t-test statistics given as:

$$T = \frac{\text{Total Cost of 1 - year Regular Inspection (HH)} - \text{Total Cost of 1 - year Regular Inspection (HL)}}{\text{Standard Error} / \sqrt{\text{Sample Size}}}$$

Table 2. P-values for the Hypothesis Testing for the Difference in Means of Inspection Performances

		Regular 1 year	Regular 2 year	Optimized
Between <i>similar</i> average traffic flow	HH and HL	0.3652	0.2016	0.4272
	LL and LH	0.4921	0.2218	0.8137
Between <i>different</i> average traffic flow	HH and LL	2.2e-16	2.2e-16	2.675e-06
	HH and LH	2.2e-16	2.2e-16	8.919e-07
	HL and LL	2.2e-16	2.2e-16	1.024e-04
	HL and LH	2.2e-16	2.2e-16	6.216e-05

It is clear that between similar average traffic flows, i.e. between HH and HL, all inspection schedules have similar performance with high p-values. On the contrary, between different average traffic flows, for instance between HL and LL, all inspection schedules have efficiency means very different from each other with low p-values. Therefore, we can conclude that when a network of pavements is subjected to a higher average traffic load, the inspection efficiency drops significantly.

In summary, we have found from comparison between 1-year regular inspection, 2-year regular inspection and the optimized inspection that a) the optimized inspection performs better than the regular inspections in

terms of the total efficiency that is comprised of interval efficiency, distribution efficiency, and risk penalty, b) the total efficiency for the optimized inspection is comparably more robust than the regular inspections with different traffic scenarios, and c) the total efficiency for three different inspections is influenced heavily by the average traffic flow of the road network.

5. Conclusion

Despite many studies have attempted to improve the current inspection system of pavement management that is ad-hoc and require subjective judgment; they do not consider to evaluate the risk of untimely inspection nor incorporate a physical reasoning in prediction of pavement state. This paper has a goal to fully utilize the large pool of traffic information from ITS technologies and flow prediction models with high accuracy. With these resources, we can implement a more mechanistic model to predict the pavement state, which adapts variables that actually come into play of deterioration process, such as traffic characteristics, structural properties of pavements and environmental factors.

This paper proposes a framework for optimizing a flexible inspection schedule, which has a primary objective to avoid the risk of untimely inspection from pavement state prediction while minimizing the lifecycle cost of inspection. The lifecycle cost is a function of efficiency that comprises of interval efficiency and distribution efficiency, which measures the efficiency from flexibly adjusting the inspection schedule. Also, an in-depth performance analysis is conducted on the optimized inspection schedule, in comparison to two conventional inspection systems – regular inspection systems with 1-year interval and 2-year interval. In this analysis, we confirm on the superior performance of the optimized inspection to regular inspections. In addition, different traffic scenarios influence performance of pavement inspection schedules; however, the optimized inspection seems to be comparably more robust than the regular inspections. The risk penalty given to the regular inspections may be the key to the robustness of the inspection performances.

The evaluation of three inspection systems in this paper opens up a wide door for possible experiments in search of the best inspection schedule. In addition to different traffic scenarios, the performance of inspection schedules may be assessed with many other factors, such as initial state of pavement, weather, and pavement age represented by the initial cumulative traffic demand and initial pavement state. Especially with changing pavement age, one may attempt to assess the trend of cost-to-go and test the robustness of a flexible inspection, compared to the 1-year and 2-year regular inspections that may be advantageous for old and young pavements, respectively. Also the deterministic prediction of pavement condition in this paper could be developed to reflect a stochastic process of deterioration, giving room to experiment the flexibility of inspection schedule even further. Moreover, this paper is limited in that the maintenance cost has not been included in the assessment of lifecycle cost in the objective function.

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