SENSITIVITY ANALYSIS OF PERFORMANCE METRICS TO DIFFERENT PARAMETERS IN PAVEMENT MANAGEMENT SYSTEM

Fengdi Guo, Corresponding Author
Research Assistant
Department of Civil & Environmental Engineering*
Phone: 845-772-0350
Email: guofd@mit.edu

Omar Swei
U.S. Fulbright Scholar to Jordan
Department of Civil & Environmental Engineering *
Phone: 617-699-0906
oaswei@mit.edu

Jeremy Gregory
Research Scientist
Department of Civil & Environmental Engineering *
Phone: 617-324-5639
jgregory@mit.edu

Randolph Kirchain
Principal Research Scientist
Institute for Data, Systems and Society*
Phone: 617-253-4258
kirchain@mit.edu

*Materials Systems Laboratory
Massachusetts Institute of Technology
Building E19-695
Cambridge, MA 02139
Fax: 617-258-7471

Word count: 4,449 words text + 9 tables/figures x 250 words (each) = 6,699 words

Submission Date
July 31, 2017

ABSTRACT
A pavement management system is a useful tool for departments of transportation to address the problems of limited budget and aging infrastructures. Previous research focuses mainly on the budget allocation process, trying to improve the optimization algorithms and consider the uncertainty of predictions for pavement deterioration. In any given pavement management system, there are usually many parameters. However, analysis has not been performed to determine the influence of different parameters on the pavement network performance. In this paper, the sensitivity of performance metrics to different parameters is explored based on the interstate pavement network in the U.S. state of Virginia by a probabilistic allocation network model developed at MIT. A statistical method is applied to conduct the sensitivity analysis. The sensitivity of performance metrics to different parameters is decided by p values, and the relative significance of different parameters is compared and ordered by z-score statistics.

Keywords: Pavement management system, Sensitivity, Virginia

1. INTRODUCTION

Limited budget has been a serious problem faced by transportation agencies for quite a long time. According to the Infrastructure Report Card by ASCE, the gap between available and required funding to improve pavement network condition through 2010 is about 1.6 trillion dollars (*1*). Meanwhile, the enactment of the Moving Ahead for Progress in the 21st Century (MAP-21) Act also requires that transportation agencies move towards performance oriented design. Hence, every state in the United States has been considering cost-effective ways to improve the performance of its pavement network. One promising approach is the pavement management system. It is broadly concerned with the evaluation of current conditions, prediction of the deterioration process and planning of maintenance, rehabilitation and reconstruction (MRR) actions for a segment or a pavement network (*2*).

Since its concept was first proposed in the 1960s, pavement management systems have witnessed tremendous developments (*3*). The earliest pavement management systems typically followed a top-down approach, where the pavement network was first segmented into a small set of homogeneous groups and subsequent subprocesses determined the MRR actions for individual projects (*4*, *5*). Although computationally efficient, pavement specific information for individual segments, such as the material type and pavement structure, was omitted from the analysis. One well-known example of this approach is Arizona Department of Transportation Pavement Management System (*6*). Recent computational advances, however, have prompted researchers to increasingly follow a bottom-up approach to capture heterogeneity across a pavement network (*7–10*). It preserves the basic information of different segments, but at the same time it increases computational complexity and requires more computational resources. This approach has been adopted by some transportation agencies in the United States (*11*).

In a pavement management system, budget allocation is a key consideration. Essentially, it is an optimization process during which optimization methods, objectives, constraints, performance metrics and stochastic characteristics should be in consideration. The optimization methods include the prioritization method (*12*, *13*); mathematical methods, such as linear (*6*, *14*), nonlinear (*15*, *16*), integer and dynamic programming (*17*, *18*); heuristic methods, such as evolutionary algorithms (*9*), and genetic algorithms (*8*); and other methods, such as fuzzy logic systems (*19*). The choice among different methods is mainly based on the complexity of a given pavement network. Optimization objectives aim to either minimize costs (agency and/or user) or maximize network performance. The objective can be single or multiple (*20*, *21*). Performance metrics are used to assess the condition of pavement segments, including international roughness index (IRI), remaining service life (RSL), pavement surface rating (PSR), combined condition index (CCI), and so on. Optimization constraints are usually related to available budget, labor (*22*), and performance threshold (*21*).

During the allocation process, an important consideration is the future uncertainty. Right now most papers only focus on the uncertainty of pavement deterioration via Markov chain (*5*, *6*, *23*). It models pavement degradation as a whole, and considers several states that represent the pavement conditions. The Markovian probability matrix is mainly constructed by using historical data. Another way is to add an error item in the deterioration prediction equation. Errors usually satisfy normal distribution with zero mean and the variance is obtained from the historical data (*24*). Besides the uncertainty of deterioration, the uncertainty of MRR cost variation, future budget, traffic volume and other factors should also be considered.

The scales of the pavement management systems proposed in current papers are relatively small. The number of segments in the network is usually less than 100, the analysis period is less than 10 years and the number of MRR actions is less than 5 (*25*). It is necessary to enlarge their scales to put them into practice.

Due to the gaps of existing pavement management systems, such as the aspects of uncertainty and scale weaknesses, an MIT probabilistic allocation network model has been proposed (*24*). It applies bottom-up approach and considers the heterogeneity of a pavement network. It considers the uncertainty for both pavement deterioration and the cost variation of MRR actions (*26*). Also, it can be used to analyze a pavement network containing thousands of segments and the analysis period can be several decades. This model can provide project managers and pavement engineers with some guidance for future MRR actions. It has been successfully used to analyze the current condition for the Virginia pavement network system (*27*).

Existing pavement management systems in papers focus mainly on the allocation process. For a given pavement network system, there are usually many parameters, like material type, age, traffic volume, etc. However, exploration of these parameters in the system is often ignored. Analysis of these parameters can help to better understand the factors that have an important influence on the pavement network performance. Some parameters have been discussed during the formulation of pavement deterioration models (*28–32*), including current IRI, age, structural number, etc. In addition, the influence of different climate factors on the pavement distresses has also been explored (*33*). However, there is still a lack of systematic and comprehensive analysis for different parameters in the pavement network system. Therefore, by taking the Virginia pavement network system as an example, the authors are trying to figure out the influence of different parameters based on the MIT allocation model.

2. METHODOLOGY

2.1 MIT probability allocation network model

The MIT probabilistic allocation network model can be used to analyze a large-scale pavement network system in consideration of the uncertainty during the deterioration process as well as MRR cost variation. It consists of an optimization module, a deterioration module, and a cost module. For the optimization module, the objective is to maximize the cost-effectiveness of the whole pavement network within a limited budget. Many performance metrics can be obtained from this model, such as IRI, RSL, etc. The deterioration module predicts the deterioration process of pavement segments. The deterioration rate of a pavement segment is affected by material type, age, AADTT and equivalent thickness. Corresponding equations are formulated statistically based on the LTPP dataset. The cost module is mainly used to predict the future prices of different MRR actions.

2.2 Parameters

The analyses focus on the interstate pavement network in Virginia. The total length is about 2,000 miles and the number of segments is about 2,800. The analysis period is 20 years and 8 MRR actions are considered as shown in Table 1. Here some common parameters are chosen to be analyzed, which can be divided into three categories:

- Economics: budget, concrete/asphalt cost ratio;
- Deterioration: deterioration rate of HMA, asphalt top composite (ATC), concrete and concrete top composite (CTC) pavements;
- Condition: AADT (Annual Average Daily Traffic), AADTT (Annual Average Daily Truck Traffic), equivalent thickness, age, and current IRI.

Performance metrics that describe the network performance include: traffic weighted IRI (TWIRI, defined as equation (1)), traffic weighted RSL (TWRSL), percentage of pavements of different material types, and the ratio of pavements in different conditions. According to National Performance Management Measure, when IRI is less than 1.50m/km, the segment is in good condition; when IRI is between 1.50 and 2.68m/km, it is in fair condition; and when IRI is greater than 2.68m/km, it is in bad condition. RSL is the period during which a segment's IRI increases from current IRI to 2.68m/km.

$$\text{TWIRI} = \frac{\sum_{i=1}^{N} AADT_i \cdot Area_i \cdot IRI_i}{\sum_{i=1}^{N} AADT_i \cdot Area_i} \quad (1)$$

TABLE 1 MRR Actions

Name	Type	Material	Mean Cost	Standard Deviation
diamond grinding	minor rehabilitation	concrete	6.87	1.37
2" mill and fill	major rehabilitation	asphalt	8.03	1.606
4" asphalt overlay	major rehabilitation	concrete&asphalt	12.18	2.436
4" concrete overlay	major rehabilitation	concrete&asphalt	16.87	3.334
new 8" asphalt	reconstruction	concrete&asphalt	26.1	5.22
new 8" JPCP	reconstruction	concrete&asphalt	33.33	6.666
new 12" asphalt	reconstruction	concrete&asphalt	39.15	7.83
new 12"JPCP	reconstruction	concrete&asphalt	50	10

*The unit is $/(yard)^2.

2.3 Approach

To analyze the influence of different parameters on the pavement network performance, we need to explore the influence of the variation of a single parameter, so a reference scenario is set up first as a baseline to compare the influence of parameters' variation. The reference scenario is based on the original Virginia dataset. The budget is set equal to $80 million per year, which can be used to repair about 10% of the Virginia pavement network. For each parameter, another two scenarios are built, called "Incre Scenario" and "Decre Scenario". The value of the parameters increases or decreases 20% while keeping other parameters unchanged, respectively. We will focus on these three scenarios to analyze the influence of a parameter in the Virginia pavement management system.

For each scenario, the analysis period is 20 years. Considering the uncertainty of deterioration process and MRR cost variation, 100 Monte Carlo simulations are conducted. For each simulation, the mean values of different performance metrics are calculated, thus obtaining three groups of mean values. Each group contains 100 samples.

Next, the average values of three groups will be compared in a statistical way to explore the influence of a parameter. After examining their variances using Levene's Test, the variances are shown to be different with a significant level equal to 5%. Therefore, analysis of variance (ANOVA) cannot be applied. Instead, we are using another statistical method based on z-score statistics. The null hypothesis is that the difference between the means of two samples is 0. Since the sample size in our analysis is quite large (≥30), standard normal z-score statistics is used, which can be calculated by the following equations:

$$\sigma_{x_1-x_2} = \sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}} \quad (2)$$

$$z = \frac{(x_1-x_2)-0}{\sigma_{x_1-x_2}} \quad (3)$$

Where, n_1 and n_2 represent the sample sizes, x_1 and x_2 are the sample means, and s_1 and s_2 are the standard deviations.

Based on the z-score statistics, we can calculate the corresponding p value, and then to check the influence of a parameter on the pavement network performance.

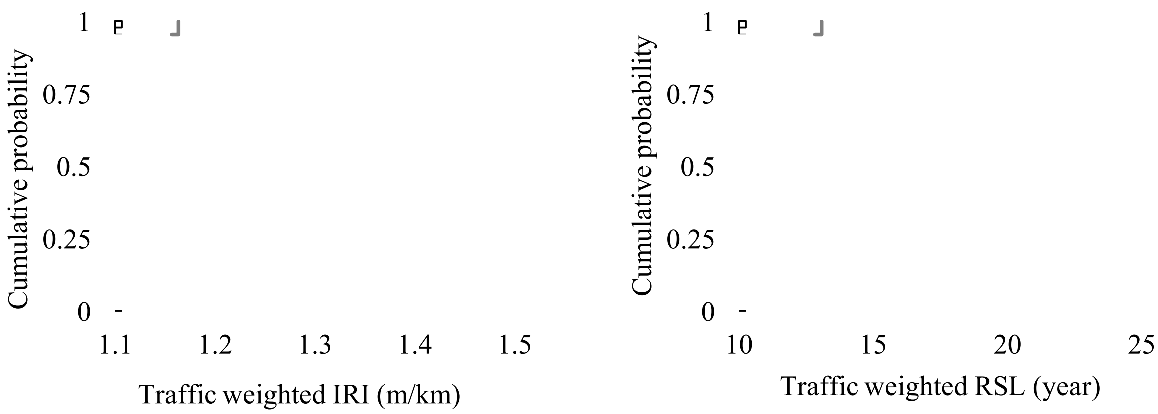
3. RESULTS AND DISCUSSIONS

3.1 Reference scenario

The reference scenario is based on the original Virginia dataset and the annual budget is $80 million. Figure 1 shows the cumulative probability of traffic weighted IRI and RSL during the analysis period. The position of the curves can reflect the condition of the pavement network. For example, when the TWIRI curve lies on the left side of the figure, it corresponds to a lower TWIRI value and a better pavement network performance.

Figure 2 shows the variation of pavement type distribution during the analysis period. The ratio of HMA pavements decreases while the ratio of concrete top composite pavements increases dramatically. The allocation process tends to make the pavement network contain more concrete type pavements.

Figure 3 shows the variation of pavement condition distribution. The ratio of pavements in poor condition stays quite stable. The ratio of pavements in good condition decreases first and then increases due to the limitation of budget. At the beginning of the analysis period, the deterioration rate is quicker than the maintenance rate, leading to the decrease of pavements in good condition. With the increase of maintenance year by year, the ratio of pavements in good condition grows gradually.



(1) **(2)**

FIGURE 1 Cumulative probability of traffic weighted IRI (1) and traffic weighted RSL (2) over 20-year analysis period

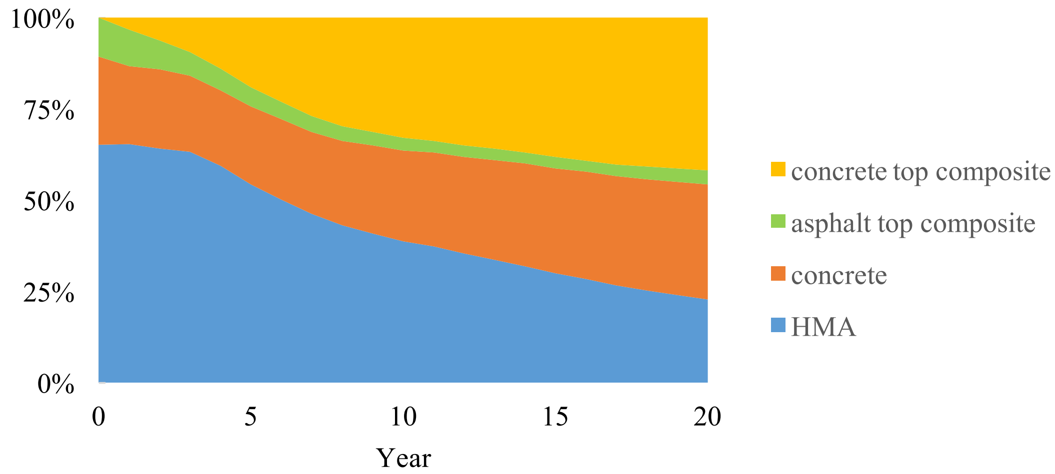


FIGURE 2 Pavement type distribution over 20-year analysis period

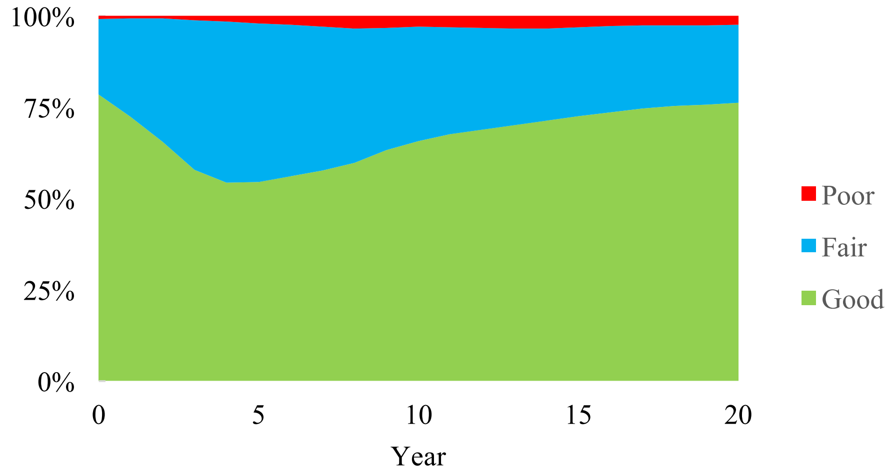


FIGURE 3 Pavement condition distribution over 20-year analysis period

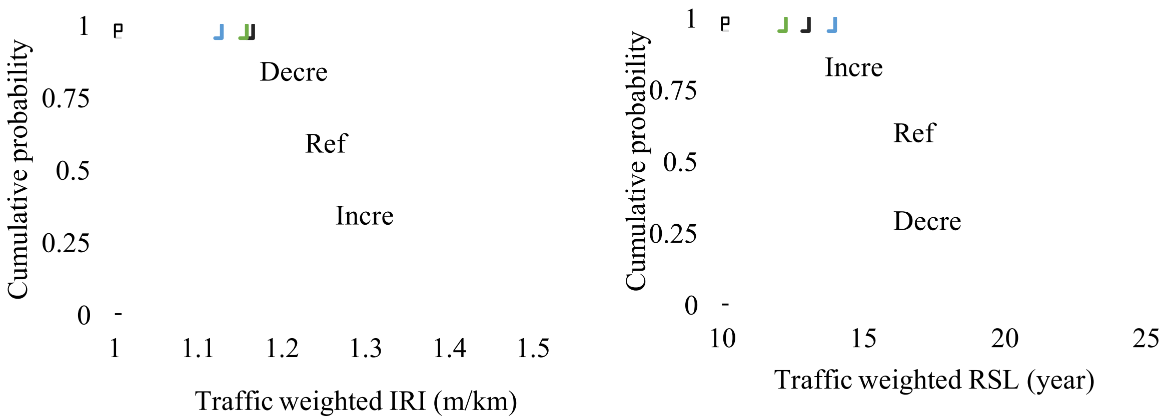
3.2 Sensitivity analysis - AADTT

Since the analysis processes are similar for different parameters, AADTT is chosen as an example for the explanation. There are two comparisons for each performance metrics, ‘Indre’ vs ‘Reference’ and ‘Decre’ vs ‘Reference’, and two pairs of z-score statistics and p values can be obtained, of which the larger z-score statistics is used as the sensitivity metrics. The z-score statistics and p values for different performance metrics are listed in Table 2. If the significance level is 5%, then only the ratio of CTC pavements is insensitive to AADTT.

Figure 4 shows the cumulative probability of traffic weighted IRI and RSL. The differences between these three scenarios are obvious, in accordance with the z-score statistics. Also, traffic weighted IRI increases and traffic weighted RSL decreases with the increase of AADTT since its growth can speed up the deterioration rate of pavements. Figure 5 describes the pavement type distribution for different AADTT scenarios. The growth of AADTT increases the ratios of HMA and concrete pavements while decreases the ratios of ATC and CTC pavements at the same time, but the variation for the ratios of different material types are quite small, which is reflected in the relatively smaller z-score statistics in Table 2. Figure 6 shows the pavement condition distribution for different AADTT scenarios. Similar to previous results, the growth of AADTT decreases the ratio of pavements in good condition and increases the ratio of pavements in fair condition. The ratio of pavements in poor condition does not change much, but the z statistics for the ratio of poor pavements is quite large. This is because the ratio of poor pavements is so small that even a small change can cause a huge difference.

TABLE 2 Z-score statistics and p values for different performance metrics (AADTT)

Performance metrics	z-score statistics	p value
TWIRI	3.95	0
TWRSL	4.90	0
Ratio of HMA pavements	3.76	0
Ratio of ATC pavements	2.18	0.015
Ratio of concrete pavements	2.60	0.005
Ratio of CTC pavements	1.29	0.099
Ratio of good pavements	3.91	0
Ratio of fair pavements	3.64	0
Ratio of poor pavements	5.79	0



(1) **(2)**

FIGURE 4 Cumulative probability of traffic weighted IRI (1) and traffic weighted RSL (2) for different AADTT scenarios

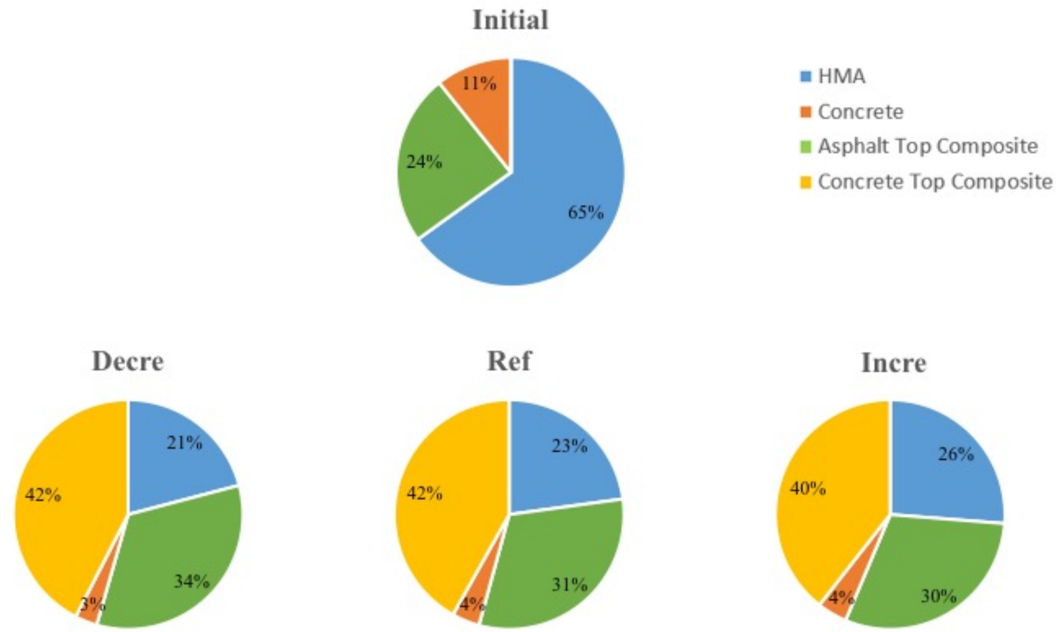


FIGURE 5 Pavement type distribution for different AADTT scenarios at the beginning and at the end of analysis period

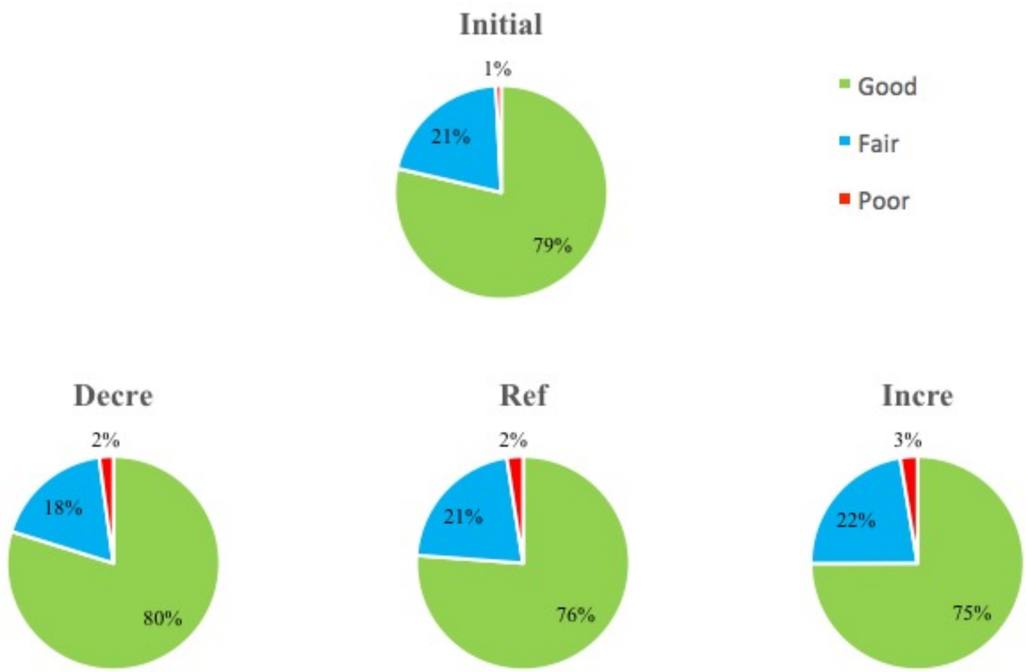


FIGURE 6 Pavement condition distribution for different AADTT scenarios at the beginning and at the end of analysis period

3.3 Summary

Table 3 shows the z-score statistics and p values of different parameters for different performance metrics. Assuming a significance level of 5%, when the p value is larger than the significance level, the performance metric is not sensitive to the parameter. For example, all performance metrics are insensitive to AADT since all p values are larger than 0.05. In addition, for a single performance metric, we can compare its sensitivity to different parameters based on the z-score statistics. The parameter with a high z-score value means that it has a more important influence on the performance metrics. Taking TWIRI as an example, the z-score value of budget is the largest, so budget has the largest influence on the TWIRI.

TABLE 3 Z-score statistics and p values for different parameters

		TWIRI	**TWRSL**	**HMA**	**ATC**	**concrete**	**CTC**	**good**	**fair**	**poor**
AADT	z	0.26	0.15	0.58	0.42	0.26	0.18	0.25	0.23	0.57
	p	0.396	0.439	0.281	0.336	0.398	0.430	0.401	0.408	0.285
AADTT	z	3.95	4.90	3.76	2.18	2.60	1.29	3.91	3.64	5.79
	p	0	0	0	0.015	0.005	0.099	0	0	0
age	z	6.21	4.87	6.03	4.81	1.85	0.64	6.38	5.75	11.11
	p	0	0	0	0	0.032	0.262	0	0	0
budget	z	11.74	8.40	12.90	0.59	1.04	7.68	10.42	9.73	11.99
	p	0	0	0	0.278	0.149	0	0	0	0
concrete/ asphalt ratio	z	3.29	2.96	23.19	6.71	17.40	14.75	3.32	3.18	4.31
	p	0	0.002	0	0	0	0	0	0.001	0
composite deterioration	z	0.89	3.78	19.63	12.97	4.44	7.45	1.97	1.72	3.67
	p	0.187	0	0	0	0	0	0.024	0.043	0
concrete deterioration	z	0.10	0.70	0.85	4.86	10.23	0.29	0.67	0.66	0.69
	p	0.460	0.242	0.199	0	0	0.386	0.253	0.255	0.245
HMA deterioration	z	2.70	2.36	24.90	11.13	6.14	12.08	1.10	1.08	2.52
	p	0.003	0.009	0	0	0	0	0.135	0.141	0.006
current IRI	z	8.41	3.28	1.90	1.50	1.13	0.98	7.20	6.64	11.38
	p	0.000	0.001	0.029	0.067	0.129	0.163	0	0	0
equivalent thickness	z	7.47	6.80	1.53	0.92	3.36	0.88	6.16	5.00	10.90
	p	0	0	0.063	0.180	0	0.191	0	0	0

* (1) "HMA", "ATC", "concrete", "CTC" in the first line represent the ratio of HMA, ATC, concrete, and CTC pavements, respectively;
(2) "good", "fair", "poor" in the first line represent the ratio of pavements in good, fair and poor condition, respectively.

The summary of the sensitivity analysis is shown in Table 4. The order of different parameters in each cell is based on the z-score statistics, namely from large to small values. Ratios of four pavement material types are grouped into one metrics called pavement type. The largest z-score statistics of the ratios of four pavement material types is used to represent the z-score statistics of pavement type. Similarly, ratios of three pavement condition distribution are consolidated into one group called pavement condition.

Obviously, budget has the largest influence, which is a key factor to improve the pavement network performance. Parameters that are related with the deterioration process, like AADTT, equivalent thickness, age, and deterioration rate for different materials, play a significant role in the network performance. One exception is the deterioration rate of concrete pavements, which is due to the small ratio of concrete pavements. Current IRI is also significant because we tend to maintain the pavements in bad condition first. The influence of AADT is quite trivial since only heavy truck traffic affects the deterioration process.

TABLE 4 Sensitivity analysis results

	Traffic weighted IRI	Traffic weighted RSL	Pavement type	Pavement condition
Sensitive	budget, current IRI, equivalent thickness, age, AADTT, concrete/asphalt cost ratio, deterioration of HMA	budget, equivalent thickness, AADTT, age, deterioration of composite, current IRI, concrete/asphalt cost ratio, deterioration of HMA	deterioration of HMA, concrete/asphalt cost ratio, deterioration of composite, budget, deterioration of concrete, age, AADTT, equivalent thickness, current IRI	budget, current IRI, age, equivalent thickness, AADTT, concrete/asphalt cost ratio, deterioration of composite, deterioration of HMA
Insensitive	deterioration of composite, AADT, deterioration of concrete	deterioration of concrete, AADT	AADT	deterioration of concrete, AADT

4. CONCLUSIONS

Taking the interstate pavement network in Virginia as an example, the influences of different parameters on the performance metrics have been explored based on the MIT allocation network model. The sensitivity of performance metrics to different parameters is described by z-score statistics and p values. The relative significance of different parameters on a single performance metrics is compared by the z-score statistics.

Parameters such as budget, current IRI, equivalent thickness, age, AADTT, cost ratio between concrete and asphalt, and deterioration rate of HMA pavements have a significant influence on the traffic weighted IRI. The deterioration rate of composite and concrete pavements, as well as AADT have little influence on the traffic weighted IRI. Similarly, except for the deterioration rate of concrete pavements, parameters with high influence on traffic weighted RSL are nearly the same as those on traffic weighted IRI. Both performance metrics are the most sensitive to budget.

Pavement type distribution is sensitive to most parameters except AADT. Compared to other parameters, the deterioration rates of different materials play a more significant role. Pavement condition distribution is only insensitive to AADT and the deterioration rate of concrete pavements and is the most sensitive to budget.

In general, the approach proposed and the results presented in the paper can help to determine the influence of different parameters and provide guidance in better applying the pavement management system.

ACKNOWLEDGEMENTS

This research was conducted as part of the Concrete Sustainability Hub at the Massachusetts Institute of Technology, which is supported by the Portland Cement Association and the Ready Mixed Concrete Research and Education Foundation.

REFERENCES

1. De La Garza, J. M., S. Akyildiz, D. R. Bish, and D. A. Krueger. Network-Level Optimization of Pavement Maintenance Renewal Strategies. Advanced Engineering Informatics, Vol. 25, No. 4, 2011, pp. 699–712. https://doi.org/10.1016/j.aei.2011.08.002.
2. Madanat, S., S. Park, and K. Kuhn. Adaptive Optimization and Systematic Probing of Infrastructure System Maintenance Policies under Model Uncertainty. Vol. 12, No. September, 2006, pp. 192–198.
3. Markow, M. J. Highway Management Systems: State of the Art. Journal of Infrastructure Systems, Vol. 1, No. 3, 1995, pp. 186–191. https://doi.org/10.1061/(ASCE)1076-0342(1995)1:3(186).
4. Kuhn, K. D., and S. M. Madanat. Model Uncertainty and the Management of a System of Infrastructure Facilities. Transportation Research Part C: Emerging Technologies, Vol. 13, No. 5–6, 2005, pp. 391–404. https://doi.org/10.1016/j.trc.2006.02.001.
5. Abaza, K. A. Expected Performance of Pavement Repair Works in a Global Network Optimization Model. Journal of Infrastructure Systems, Vol. 13, No. June, 2007, pp. 124–134. https://doi.org/doi:10.1061/(ASCE)1076-0342(2007)13:2(124).
6. Golabi, K., R. B. Kulkarni, and G. B. Way. A Statewide Pavement Management System. Interfaces, Vol. 12, No. 6, 1982, pp. 5–21.
7. Chan, W., T. Fwa, and C. Tian. Road-Maintenance Planning Using Genetic Algorithm. I: Formulation. Journal of Transportation Engineering, Vol. 120, No. 5, 1994, pp. 693–709. https://doi.org/10.1093/isle/ist137.
8. Fwa, T., W. Chan, and C. Tan. Genetic-Algorithm Programming of Road Maintenance and Rehabilitation. Vol. 122, No. 3, 1996, pp. 246–253.
9. Yeo, H., Y. Yoon, and S. Madanat. Maintenance Optimisation for Heterogeneous Infrastructure Systems: Evolutionary Algorithms for Bottom-up Methods. Structure and Infrastructure Engineering, No. June 2015, 2012, pp. 1–12. https://doi.org/10.1080/15732479.2012.657649.
10. Sathaye, N., and S. Madanat. A Bottom-up Optimal Pavement Resurfacing Solution Approach for Large-Scale Networks. Transportation Research Part B: Methodological, Vol. 46, No. 4, 2012, pp. 520–528. https://doi.org/10.1016/j.trb.2011.12.001.
11. Hong, F., E. Perrone, M. Mikhail, and A. Eltahan. Planning Pavement Maintenance and Rehabilitation Projects in the New Pavement Management System in Texas. 2017.
12. Kulkarni, R. B., D. Miller, R. M. Ingram, C.-W. Wong, and J. Lorenz. Need-Based Project Prioritization: Alternative to Cost-Benefit Analysis. Journal of Transportation Engineering, Vol. 130, No. April, 2004, pp. 150–158. https://doi.org/10.1061/(ASCE)0733-947X(2004)130:2(150).
13. Shah, Y. U., S. S. Jain, and M. Parida. Evaluation of Prioritization Methods for Effective Pavement Maintenance of Urban Roads. International Journal of Pavement Engineering, Vol. 15, No. 3, 2014, pp. 238–250. https://doi.org/10.1080/10298436.2012.657798.
14. Wang, F., Z. Zhang, and R. Machemehl. Decision-Making Problem for Managing Pavement Maintenance and Rehabilitation Projects. Transportation Research Record: Journal of the Transportation Research Board, Vol. 1853, No. 3, 2003, pp. 21–28. https://doi.org/10.3141/1853-03.
15. Abaza, B. K. A., S. A. Ashur, S. A. Abu-eisheh, and A. Rabay. Macroscopic Optimum System for Management of Pavement Rehabilitation. Vol. 127, No. 6, 2001, pp. 493–500.
16. Gao, L., C. Xie, Z. Zhang, and S. T. Waller. Network-Level Road Pavement Maintenance and Rehabilitation Scheduling for Optimal Performance Improvement and Budget Utilization. Computer-Aided Civil and Infrastructure Engineering, Vol. 27, No. 4, 2012, pp. 278–287. https://doi.org/10.1111/j.1467-8667.2011.00733.x.
17. Durango-Cohen, P. L., and P. Sarutipand. Capturing Interdependencies and Heterogeneity in the

Management of Multifacility Transportation Infrastructure Systems. Journal of Infrastructure Systems, Vol. 13, No. 2, 2007, pp. 115–123. https://doi.org/10.1061/(ASCE)1076-0342(2007)13:2(115).
18. Ouyang, Y. Pavement Resurfacing Planning for Highway Networks : Parametric Policy Iteration Approach. Vol. 13, No. 1, 2007, pp. 65–71.
19. Moazami, D., H. Behbahani, and R. Muniandy. Pavement Rehabilitation and Maintenance Prioritization of Urban Roads Using Fuzzy Logic. Expert Systems with Applications, Vol. 38, No. 10, 2011, pp. 12869–12879. https://doi.org/10.1016/j.eswa.2011.04.079.
20. Mbwana, J. R. A Framework for Developing Stochastic Multi-Objective Pavement Management Systems. First Road Transportation Technology Transfer Conference in Africa, 2001, pp. 339–352.
21. Meneses, S., and A. Ferreira. Pavement Maintenance Programming Considering Two Objectives: Maintenance Costs and User Costs. International Journal of Pavement Engineering, Vol. 14, No. 2, 2012, pp. 206–221. https://doi.org/10.1080/10298436.2012.727994.
22. Fwa, T., W. Chan, and C. Tan. Genetic-Algorithm Programming of Road Maintenance and Rehabilitation. Journal of Transportation Engineering, 1996.
23. Medury, a, and S. Madanat. Simultaneous Network Optimization Approach for Pavement Management Systems. Journal of Infrastructure Systems, Vol. 20, No. July, 2014, pp. 1–7. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000149.
24. Swei, O. Material Diversification in Pavement Management: A Technique to Proactively Deal with an Uncertain Future. 2016.
25. Torres-Machi, C., A. Chamorro, C. Videla, E. Pellicer, and V. Yepes. An Iterative Approach for the Optimization of Pavement Maintenance Management at the Network Level - ProQuest. Hindawi Publishing Corporation The Scientific World Journal Article, Vol. Volume 201, No. ID 524329, 2014, p. 11.
26. Swei, O., J. Gregory, and R. Kirchain. Probabilistic Approach for Long-Run Price Projections : Case Study of Concrete and Asphalt. J.Constr.Eng.Manage, 2016, pp. 1–11. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001211.
27. Akbarian, M., S. S. Moeini-Ardakani, F.-J. Ulm, and M. Nazzal. Mechanistic Approach to Pavement-Vehicle Interaction and Its Impact on Life-Cycle Assessment. Transportation Research Record: Journal of the Transportation Research Board, Vol. 2306, No. 1, 2012, pp. 171–179. https://doi.org/10.3141/2306-20.
28. Attoh-Okine, N. O., S. Mensah, and M. Nawaiseh. A New Technique for Using Multivariate Adaptive Regression Splines (MARS) in Pavement Roughness Prediction. Proceedings of the Institution of Civil Engineers - Transport, Vol. 156, No. 1, 2003, pp. 51–55.
29. Loizos, a., and C. Plati. An Alternative Approach to Pavement Roughness Evaluation. International Journal of Pavement Engineering, Vol. 9, No. 1, 2008, pp. 69–78. https://doi.org/10.1080/10298430600949894.
30. Terzi, S. Modeling for Pavement Roughness Using ANFIS Approach. Advances in Engineering Software, Vol. 57, 2013, pp. 59–64. https://doi.org/10.1177/0019793915592375.
31. Kargah-Ostadi, N., S. M. Stoffels, and N. Tabatabaee. Network-Level Pavement Roughness Prediction Model for Rehabilitation Recommendations. Transportation Research Record: Journal of the Transportation Research Board, Vol. 2155, 2010, pp. 124–133. https://doi.org/10.3141/2155-14.
32. Mazari, M., and D. D. Rodriguez. Prediction of Pavement Roughness Using a Hybrid Gene Expression Programming-Neural Network Technique. Journal of Traffic and Transportation Engineering (English Edition), Vol. 3, No. 5, 2016, pp. 448–455. https://doi.org/10.1016/j.jtte.2016.09.007.
33. Qiao, Y., G. W. Flintsh, D. R. Andrew, and P. Tony. Examining the Effects of Climatic Factors on Flexible Pavement Performance and Service Life. Transportation Research Record: Journal of the Transportation Research Board, Vol. 2349, 2013, pp. 100–107. https://doi.org/10.3141/2349-12.