Deterioration Forecasting in Flexible Pavements Due to Floods and Snow Storms

Salar Shahini Shamsabadi, Yasamin Sadat Hashemi Tari, Ralf Birken, Ming Wang

DETERIORATION FORECASTING IN FLEXIBLE PAVEMENTS DUE TO FLOODS AND SNOW STORMS

Salar Shahini Shamsabadi[1], Yasamin Sadat Hashemi Tari[2], Ralf Birken[3], Ming Wang[4]

[1,2,3,4] *Northeastern University, 360 Huntington Ave, Boston, MA, 02115*

[1]shahini.s@husky.neu.edu, [2] hashemitari.y@husky.neu.edu, [3] r.birken@neu.edu, [4] mi.wang@neu.edu

ABSTRACT

Roadway agencies and state DOTs utilize Pavement Management Systems (PMS) to implement cost-effective maintenance strategies. A reliable yet easily applicable model for deterioration process of pavements is an integral part of any Pavement Management System. As pavement condition grows to be one of the crucial problems facing our nation, the reliability of these deterioration prediction models becomes more important. While numerous endevours have been made to capture the effect of the environment, load and pavement's structure on pavement failures, only few have realized the impact of severe events such as Snow Storms and Floods on road infrastructures. First, this impact was quantified using Long Term Pavement Performance (LTPP) and National Oceanic and Atmospheric Administration (NOAA) databases with a dependable natural deterioration model. Then, a regression-based statistical approach has been undertaken to model the effect of snow storms and floods on pavement serviceablilites based on the severity of the events and condition of the pavement prior to these event. Final models rendered more than 90% correlation with the quantified impact values of snow storms and floods.

KEYWORDS : *Deterioration Modeling, Pavement Management, Infrastructure Monitoring, Statistical Analysis, Data Fusion.*

1. INTRODUCTION

Restoring serviceability of roadways has prominent societal and economic benefits. However, insufficient funding often limits timely repairs and rehabilitation of the pavement. As needs continue to outpace the availability of funding, the proper selection of road maintenance and improvements becomes more crucial [1]. To maximize the benefits and minimize the overall costs of maintaining or preserving the transportation systems, highway administration has provided guidelines for developing pavement management systems as early as the 1970s [2]. Hudson et al. [3] describe a pavement management system (PMS) as "…a coordinated set of activities, all directed toward achieving the best value possible for the available public funds in providing and operating smooth, safe, and economical pavements."

Success of planning or project prioritization in the PMSs depends on the accuracy of the predicted future performance and available up to date pavement condition information. Being able to project when a pavement needs to be repaired before the pavement fails is an integral part of any successful PMS. Prediction of pavement deterioration influences the quality of many PMS components such as determining the number of years when rehabilitation will be needed, corresponding treatment alternatives for future years and selecting the most cost-effective maintenance and rehabilitation (M&R) alternatives [4]. A solid deterioration model will not only help road controlling authorities in cost-effective scheduling of maintenance activities and budget allocations, it can also be employed for the design of pavement structures. Consequently, these models can be utilized for evaluation of different design, maintenance, and rehabilitation strategies based on geographical regions, estimated volumes of traffic and other factors [5].

1.1 GENERAL INFLUENCING PARAMETERS ON PAVEMENT PERFORMANCE

Interactions between climate, vehicles and the road result in deformation and deterioration of pavements. Predicting this behaviour is not easy. While deterioration models for rigid pavements have had a decent performance, because of the the high visco-elastic characteristic of the asphalt, current deterioration models for flexible pavements have had limited success so far.
Pavement infrastructure deterioration is an aggregated impact from traffic loading, environmental condition, and other contributors. The behaviour of a pavement under these factors depends on the characteristics of its structure (materials and thickness of each pavement layer), the quality of its construction, and the subgrade (bearing capacity and presence of water) [6]. Each factor causes certain distresses on the pavement. Understanding factors that lead to deterioration of roads help infrastructure managers to refine their construction and maintenance specifications.

Load: Cracking and rutting caused by pavement bending under traffic loads are two of the most prominent forms of distresses. Tire pressure produced by vehicles in the radius of loaded area induces tensile stress on the pavement, lateral shear in the surface and vertical stress at the subgrade which gradually deteriorate the pavement [7].

Material Properties: Severity of distresses and the pace of their formation is heavily influenced by material properties of the pavement. Strength and bearing capacity, gradation, modules of elasticity and resilience of the materials used in construction determine pavements endurance under load and climate fluctuations. [8].

Construction Quality: Freitas et al. [9] shows that construction quality influences the two significant factors in initiation of top-down cracking: voids and aggregate gradations caused. Construction quality also determines the initial pavement condition which has an impact on the pace that pavement failures occur.

Environmental Conditions: Climate oscillations, precipitation and freeze/thaw cycles are the primary causes of some dominant distresses such as longitudinal and transversal cracks [10].

- **Temperature:** Temperature fluctuations are followed by tensile and compressive stress in pavement which initiates thermal cracking. Smith et al [11] shows a correlation between pavement deterioration and temperature where surge in temperature facilitates rutting and cracking in the pavement.
- **Precipitation:** Studies on pavement performance evaluations show that other than formation of longitudinal and alligator cracks, roughness of the road also worsens with a boost in precipitation.
- **Freeze/thaw cycles:** In cold regions, water penetrated into the pavement layers freezes in the winter. Thaw of these ice particles during spring causes deformation in pavement layers and triggers fatigue cracking [12].

1.2 TYPES OF DETERIORATION MODELS

Depending on how aging of the pavement is simulated, road deterioration models can be categorized into deterministic and probabilistic models.
Deterministic models are data driven mathematical functions typically trained with large amounts of datasets measured over a long period of time. Using these mathematical functions, these models predict future road conditions as a single value.
Probabilistic models, on the other hand, provide a range of possible outcomes with the probability of their occurrences. These models are also referred to as Markov prediction models. Although considerable effort has been devoted to improve the quality of the probabilistic modeling of pavement deterioration, the applicability of their transition matrix is limited to only several widely spaced categories typically classified by traffic volume, pavement structure and climate regions

[13]. Additionally, the fact that these models are used discrete in time led us into adapting deterministic approach in this paper.

1.3 PAVEMENT PERFORMANCE MEASURES

Pavement performance can be obtained by observing or predicting the serviceability of a pavement from its initial service time to the desired evaluation time. Typically pavement condition is evaluated according to four evaluation measurements: roughness, surface distress, structural capacity, and skid resistance. Indices have been developed to measure pavement performance in terms of one or multiple of these aspects. For example, the International Roughness Index (IRI) is used to characterize the ride quality of a pavement, whereas the Structural Number (SN) is employed to quantify the structural capacity. These four can be combined and presented by an overall condition index, such as the Pavement Condition Index (PCI), which entails information on more than one of the above evaluation measurements [14]. Discussions here are focused on using the IRI as the performance measurement of pavement sections.
Typically obtained from longitudinal road profiles, ASTM defines IRI as “a quantitative estimate of a pavement property defined as roughness using longitudinal profile measures.”[15] IRI is widely used for evaluating and managing highways since the early 1980s.

1.4 DETERIORATION MODEL DUE TO NATURAL CONDITIONS

The Long-Term Pavement Performance (LTPP) program was established to collect pavement performance data and investigates pavement related details which are critical to pavement performance since the late 1980s. Over 2,500 test sections on highways throughout North America are monitored by LTPP. Following seven modules are measured: Inventory, Maintenance, Monitoring (Deflection, Distress, and Profile), Rehabilitation, Materials Testing, Traffic, and Climatic. Now that LTPP database contains more than two decades of data, valuable insights can be extracted from studying it.
Using provided data from LTPP, Jackson et. al. [12] preformed a multivariate regression analysis to predict pavement deterioration in terms of serviceability. They considered the following factors in the analysis:

- Pavement types (rigid, flexible).
- Climate (Precipitation, Cooling Index, Freezing Index, and thawing index).
- Stresses and strains calculated from layer material properties.
- Performance data (IRI).
- Soils and material properties.
- Traffic data.

Predicted performance measures were presented for each of the climatic scenarios and compared at a 95 percent confidence interval to determine statistically significant performance differences. Jackson et. al. then derived an equation for both rigid and flexible pavements. As more than 85% of the roads in the United States are flexible pavements, we focus on the flexible pavements, see equation below:

$$Ln(\Delta IRI + 1) = Age(4.5FI + 1.78CI + 1.09FTC + 2.4PRECIP + 5.39\log(ESAL)/SN \qquad (1)$$

Where:
ΔIRI: Change in International Roughness Index
Age: Pavement Age
FI: Freezing Index (Degree-days when air temperatures are below and above zero degrees Celsius)

CI: Cooling Index (Temperature relation to the relative humidity and discomfort)
FTC: Freeze-thaw Cycles
PRECIP: Precipitation
ESAL: Equivalent Single Axle Load (Conversion of traffic into single axle load)
SN: Structural Number

Using large amounts of data for a long period of time in addition to the high correlation rendered at the end indicates the achievements of this model. However, this model still does not consider an important contributor in pavement deterioration: Effect of Extreme Conditions on road pavements.
The devastation of New Orleans caused primarily by the breach of a levee during hurricane Katrina, the impact of hurricane Sandy on New York and New Jersey, a 16% immediate drop in road conditions of Denver in Colorado due to sever snow storms in 2006 are some examples that highlight the drastic effect severe events could have on pavements [16, 17]. Our purpose here is to quantify the contribution of two most prevailing events on pavement deterioration: Snow Storms and floods. These events exacerbate road conditions by causing shear failure and cracking, weakening the subgrade and widening the existing cracks, mainly due to the drastic increase in moisture content they cause in the pavement layers.

2. Deterioration Model Due To Extreme Events

Two consecutive IRI values of LTPP sections are measured one to four years apart and in irregular intervals. As no continuous data is available that entails IRI values of before and after a severe event, we had to quantify the effect of extreme events ourselves.
By applying equation (1) and project one measured IRI to the point where the next IRI is measured, the two values should be reasonably close unless:

- Extreme events such as floods and snow storms occured in that period. This causes our projected IRI values to be lower than the measure values.
- Maintenance and rehabilitation activities took place in that period. This causes our projected IRI values to be higher than the measured values.

To quantify the effect of extreme events on road deterioration, by forward-projected IRI values from one measured IRI to the point where the event has occurred. Consequently, we backward-projected next measured IRI to the point where event has occurred ; the difference between these two values is due to the extreme event that happened in that month if no other events/maintenance activities had taken place in that period. This is illustrated in Figure (1). To fit a model to these quantities, we had to first collect the data we needed.

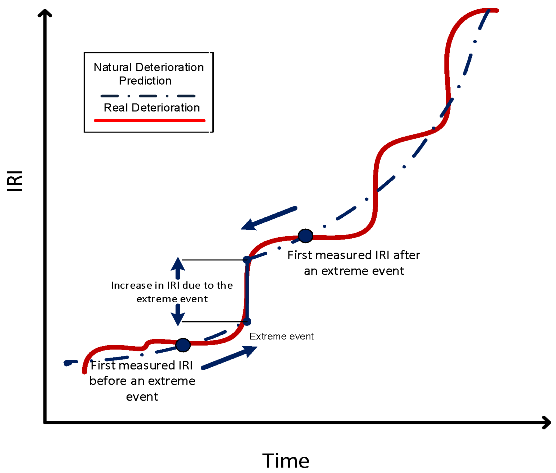

Figure 1: Quantifying the increase in IRI due to extreme events.

2.1 DATA COLLECTION

In addition to the occurrence date of extreme events and the parameters that would define their magnitude and effect, all of the variables in equation (1) had to be collected. We acquired the first from LTPP and the latter from National Oceanic and Atmospheric Administration (NOAA). Datasets were collected from January 1996 to December 2013 for the states of Florida, New Jersey, Ohio and Illinois. These states had the most comprehensive datasets available on LTPP and are more susceptible to frequent snow storms and floods.

LTPP Data Collection: Most of the parameters were given in an annual format (e.g. FTC, FI, etc.) in the LTPP database. To isolate effect of an extreme event from natural deterioration, we transformed all datasets to a monthly format. This process involved interpolations and further calculations for some of the parameters, each had to be dealt with individually according to their meaning. The LTPP database lacked data in some places, some considerations and calculations had to be made, such as calculating cooling indices based on daily temperature, assigning missing SN values based on a study of pavement type and structural number of sections in that region and calculating missing ESAL values from available daily traffic and axle loads/numbers of vehicles.

NOAA Data Collection: NOAA is a scientific agency focused on the conditions of the oceans and the atmosphere [18]. This database contained information on Snow Storms and Floods, their date of occurrence, duration and accumulated depth of water or snow.

Using data from these four states, most of the time more than one event occurred between two consecutive measured IRIs. We considered the points where the extra increase in IRI was due to only one event to calculate the parameters of the model more realistically. Figure (2) shows an example of how data points were reduced for each state and we ended up with less than 50 points for each individual event.

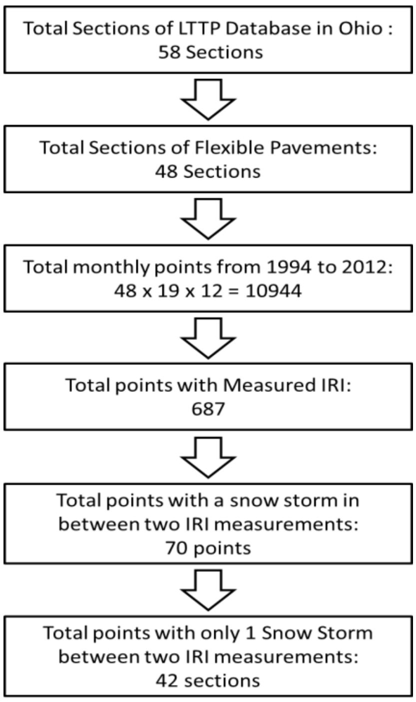

Figure 2: Ohio Data Collection for Snow Storms

2.2 IMPLEMENTATION

Other than magnitude of the extreme event in terms of depth and duration, traffic (ESAL) and IRI values at time the event occurred were considered as predictors of deterioration. While each of these parameters provides worthy knowledge about this deterioration process, none alone can furnish sufficient information that will entail all needed to calculate the effect of Snow Storms. Our purpose here is to predict an increase in IRI from the right combination of all these parameters.
Data fusion algorithms have been developed to deal with these challenges. Pattern recognition, artificial intelligence and regression are some common fusion techniques. Deciding what algorithm to use depends heavily on the application and what is expected from the fusion system. Here, we are looking for an algorithm that is adept at variable selection as we might conclude that not all of these parameters are necessary to predict IRI scores. Looking at the high correlations between our variable and predictors in Table (2), regression would be worthwhile to consider. Another reason for considering regression is our limited number of data points, regression could deal better with them than some machine learning techniques such as Neural Networks [19].

Table 2: Correlation of Predictors with percentage increase in IRI due to the extreme event

Predictor	Correlation with %ΔIRI for Snow Storms	Correlation with %ΔIRI for Floods
Initial IRI	0.721	0.317
ESAL	0.163	0.033
Event Depth	0.046	0.089
Event Duration	0.015	0.383

Regression is a statistical tool for exploring relationships between variables that are related in a nondeterministic manner. Our proposed model here is Stepwise Regression. Stepwise regression enters and removes variables one at a time to see whether it improves the model. Usually, this takes the form of a sequence of F-tests, but other techniques such as t-tests, adjusted R-square, Bayesian information criterion, or false discovery rate are also possible [20].

3. RESULTS

Snow Storms: Stepwise regression was applied using all the four parameters shown in Table (2) in addition to four combinations of them. From the 42 available sections, 29 were entered into the fusion model along with all the potential predictors and response variables calculated for these streets to train the model. These sections were handpicked for training as they entail a diverse range of our predictors and response variable in order to fine-tune the fusion model's boundaries. The fusion model used is shown in Figure (3).
In the final model, only four parameters were sufficient to predict IRI values, and the presence of any other parameter with the existence of these four was trivial, if not harmful, to the correlation rendered by the model. The final equation derived through the fusion model is:

$$\%\Delta IRI = 5.09 - 2.5 NIRI + 1.7 NDepth - 1.74 NDuration + 0.706 ESAL * Duration \quad (2)$$

Where:

%ΔIRI: Percentage increase in IRI due to the snow storm
NIRI: Normalized IRI of the section before the snow storm
NDepth: Normalized Depth of the snow storm
NDuration: Normalized Duration of the snow storm
ESAL: Equivalent Single Axle Load (derived from traffic)

Floods: Similar to what was discussed above, eight parameters were entered into a stepwise regression model for 28 sections affected by a single flood, the remaining 7 sections were used for testing. The final equation derived through the fusion model is:

$$\%\Delta IRI = 10.7 - 1.66NIRI + 7.30NDepth - 2.10NDuration + 14.3Depth * IRI \tag{3}$$

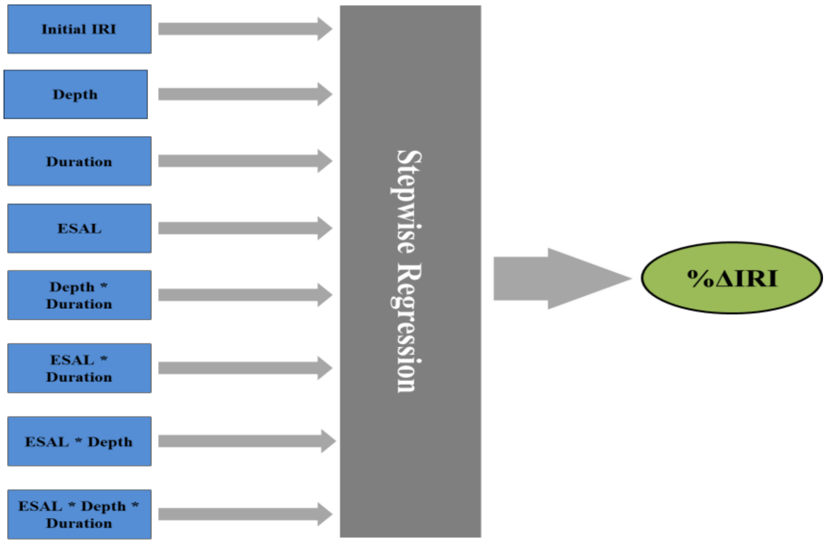

Figure 3: Illustration of fusion model for Snow Storms.

3.1 Testing The Models

IRI values of the remaining sections were predicted with the models developed above. Results were promising, rendering correlations of more than 90% for both events as shown in Figure (4).

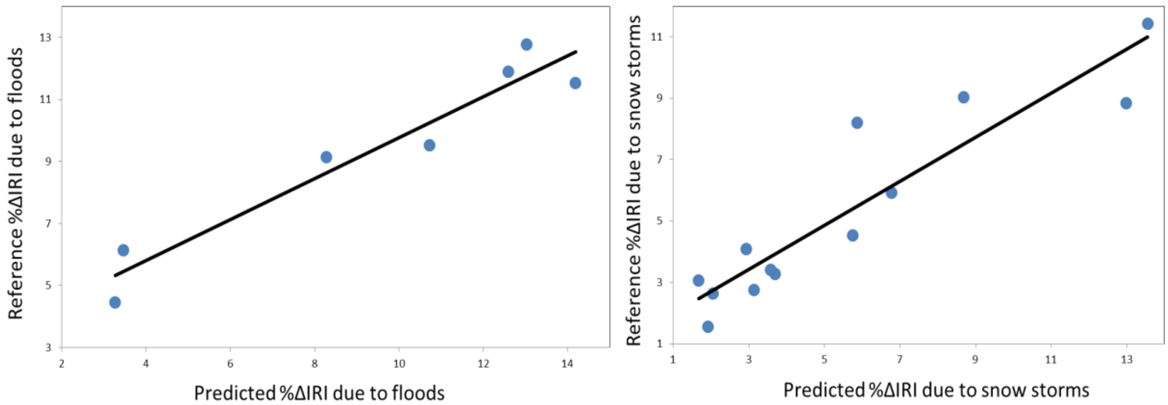

Figure 4: Test Results for Floods (Left) and Snow Storms (Right).

Conclusion

This paper has studied the effect of snow storms and floods on pavement deterioration in terms of increase in International Roughness index (IRI) values. Extracting data from the Long Term Pavement Performance (LTPP) and National Oceanic and Atmospheric Administration (NOAA) databases for four states in the span of seventeen years, the effect of a single snow storm/flood was quantified between two consecutive measured IRIs. Then, a regression-based statistical approach has been undertaken to model this behaviour with respect to magnitude of the events, traffic at time of the event and condition of the road at time the event occurred. Testing both flood and snow storm models on IRI prediction for sections that were not included in the training process rendered more than 90% correlation with the real values. Adopting this model along with a reliable natural deterioration model will result in a more realistic assessment of future costs, maintenance planning and rehabilitation activities.

REFERENCES

[1] Wang M., Birken R., Shahini Shamsabadi S., Framework and implementation of a continuous network-wide health monitoring system for roadways, SPIE Smart Structures, San Diego, CA, March 2014.
[2] Federal Highway Administration, U.S. Department of Transportation, 1999, Pavement Preservation: A Strategic Plan for the Future, FHWA-SA-99-015.
[3] Hudson, W. R., R. Haas, and R. D. Pedigo. NCHRP Report 215: Pavement Management System Development. TRB, National Research Council, Washington, D.C., 1979.
[4] Xue-zhen D., Lei X., Bo Z., Research on Intelligence Decision-Making Analysis and Optimization Design Development of Pavement Management System, Springer-Verlag Berlin Heidelberg, 2011.
[5] José J. Ortiz-García; Seósamh B. Costello; and Martin S. Snaith, Derivation of Transition Probability Matrices for Pavement Deterioration Modeling, Journal of Transportation Engineering, 2006.
[6] V. Schaefer, L. Stevens, D. White, H. Ceylan, Design Guide for Improved Quality of Roadway Subgrades and Subbases, Iowa Highway Research Board (IHRB Project TR-525), 2008
[7] Pais J., Amorim S., Minhoto M., Impact of Traffic Overload on Road Pavement Performance, Journal of Transportation Engineering ASCE 139:873-879, 2013.
[8] ARA, Inc., ERES Division, Guide for mechanistic-empirical design of new and rehabilitated pavement structures, National Cooperative Highway Research Program, Transportation Research Board, National Research Council, 2004
[9] Fraga de Freitas E., Pereira P., Picado–Santos L., Papagiannakis T., Effect of Construction Quality, Temperature, and Rutting on Initiation of Top-Down Cracking, Journal of the Transportation Research Board, No. 1929, Transportation Research Board of the National Academies, 2005.
[10] Li W., Mills L., McNeil S., The Implications of Climate Change on Pavement Performance and Design, University of Delaware University, Transportation Center (UD-UTC), 2011.
[11] Smith J. T., Tighe S. L. and Andrey J. and Mills B., Temperature and Precipitation Sensitivity Analysis on Pavement Performance, Transportation Research Circular, 2008.
[12] Jackson N., Puccinelli J., Effects of Multiple Freeze Cycles and Deep Frost Penetration, Long-Term Pavement Performance (LTPP) Data Analysis Support: National Pooled Fund Study TPF-5(013), 2006.
[13] Li N., Xie W., Haas R., Reliability-Based Processing of Markov Chains for Modeling Pavement Network Deterioration, Transporation Research Record 1524.
[14] American Society for Testing and Materials (ASTM), 2009, Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys.
[15] American Society for Testing and Materials (ASTM), 2014, Standard Practice for Computing International Roughness Index of Roads from Longitudinal Profile Measurements
[16] Gaspard K., Martinez M., Zhang Z., Wu Z., Impact of Hurricane Katrina on Roadways in the New Orleans Area, Louisiana Department of Transportation and Development, Louisiana Transportation Research Center, 2006.
[17] Kennedy W., Hager A., Severe Winter Weather Impacts On Urban Pavements, 7th International Conference on Managing Pavement Assets, Canada 2008.
[18] NOAA - National Oceanic and Atmospheric Administration, http://www.ncdc.noaa.gov/
[19] Bishop C., 2006, Pattern Recognition and Machine Learning, Springer, ISBN-10: 0-387-31073-8
[20] Tamhane A., Dorothy D., Statistics and Data Analysis : From elementry to intermediate, ISBN 0-13-744426-5.