

ASSESSING THE ROLE OF PAVEMENT ROUGHNESS IN ESTIMATING USE-PHASE EMISSIONS

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ABSTRACT

The objective of this paper is to investigate the factors that affect pavement roughness measured using the International Roughness Index (IRI) over time. The goal of the research is to understand how IRI can be integrated into the assessment of pavement use-phase emissions. Previous studies have shown that pavement roughness, among various other factors, directly impact rolling resistance, which in turn impacts vehicle fuel efficiency. This paper describes an analysis method to mine IRI data in the Federal Highways Long Term Pavement Performance (LTPP) database, in order to identify significant statistical trends, if any, in IRI degradation over time when classified by region, traffic loading, and base preparation. The insights from the analysis will directly apply to estimating greenhouse gas emissions of pavements during the use phase. The most important contribution of this research is to draw attention to the need for context specific analysis of pavement performance when estimating pavement life cycle emissions, particularly given the inaccuracies and wide variability in the available datasets. It is critical to use caution when analyzing the data and/or generalizing outcomes from studies involving limited datasets.

INTRODUCTION

The study of pavement vehicle interaction (PVI) has become a central focus in reducing pavement life cycle emissions. PVI is defined as the impact that pavements and vehicles have on each other through the life cycle of the pavement. Energy losses at the PVI interface due to roughness, texture, surface temperature, pavement deflection and other ambient conditions increase the rolling resistance and reduce fuel efficiency of trucks and passenger vehicles (1). A reduction in rolling resistance by controlling pavement roughness, has the potential of yielding very significant system wide energy savings and reductions in greenhouse gas (GHG) emissions. However, at this time, the details of these extensive interactions are not well understood.

The goal of this study is to estimate GHG emissions during the use-phase of the pavement life cycle, resulting from deterioration over time in pavement roughness - one of the factors affecting rolling resistance at the PVI interface. Pavement roughness is measured using the International Roughness Index (IRI) metric. The *specific objective of this paper* is to analyze the IRI data in the Long Term Pavement Performance (LTPP) database, to gain insights into the factors that have historically governed and/or influenced the change in pavement IRI over time. The analysis will identify the conditions and contexts under which different pavement designs and rehabilitation interventions have led to smoother pavements. It is expected that such insights can be used in future to provide empirical support to the estimation of use-phase GHG emissions in pavement LCA, for alternative pavement types in different contexts such as region, functional class, loading (ESAL), and pavement type, and support agency decision-making that uses metrics like IRI to prioritize pavement maintenance, preservation, and rehabilitation. An understanding of the factors impacting change in IRI within their specific networks will support construction and maintenance of smoother pavements that help agencies save long-run costs and reduce emissions.

This paper provides a description of the methods used to analyze the LTPP data to provide insights that can be used to understand changes in IRI over time for different pavement types under different contexts.

BACKGROUND

There are a large number of studies that investigate the attempt to quantify the relationship between increased rolling resistance and reduced fuel efficiency. The research on rolling resistance, most relevant to this paper is the collaborative research conducted through the Models for rolling resistance In Road Infrastructure Asset Management Systems (MIRIAM) partnerships, and the National Cooperative Highway Research Program (NCHRP) 1-45 study on the effects of pavement conditions on fuel consumption (2,3).

There is evidence from the MIRIAM research that rolling resistance is a direct function of the IRI and surface texture (using the Mean Profile Depth (MPD) metric). The increase in rolling resistance as IRI and MPD increase is also dependent on the speed of the vehicle. In addition, pavement deflection has been shown to have a small, though not negligible, impact on fuel efficiency. While the MIRIAM study presents preliminary results they emphasize the need for detailed experimental testing and model development and validation.

The NCHRP 1-45 study considers texture, roughness, grade, superelevation, speed and ambient temperature to calculate vehicle operating costs. The study tests for different pavement types and illustrate that the impact of factors such as stiffness and increased roughness on loss of fuel efficiency. The Mechanistic-Empirical Pavement Design Guide (ME-PDG) contains various relevant mechanistic models that address some of these issues (4). The most specific model considering the effect of IRI on fuel efficiency was developed in (3), and this work directly builds on their results.

Broadly speaking, current research empirically models correlations between increases in IRI and decreases in vehicle fuel efficiency. This research effort departs from current research by shifting the focus to studying the variation in IRI over time, to identify the factors that have historically influenced deterioration in IRI.

METHOD

This section describes the modeling of the IRI data in the LTPP database. While the LTPP database is a critical resource in characterizing IRI performance across different pavement types in different regions, the data is not always complete and accurate. Therefore, a challenge of this research was to ensure that the analysis was robust and reliable. Robustness means that the models developed should not be sensitive to gaps, outliers, or noise in the dataset. Reliability means that model users should be able to trust the model output, and investigate or modify the modeling assumptions to suit their needs.

As a first step we used a subset of the IRI data previously used by other authors for validation of ME-PDG models. This allowed the focus to be on the underlying statistical methods, minimizing the impact of noise in the data. The metrics that have been used for the analysis are 1) Initial IRI of a pavement section immediately after construction, 2) IRI at the first intervention since construction, and 3) time to first intervention. As the construction number (CN) marks the occurrence of maintenance or rehabilitation, or broadly, the beginning of a performance period, it is used to track time to first intervention. IRI changes over subsequent interventions were not considered to minimize the impact of differing maintenance policies and resources available to different jurisdictions. Instead, the three metrics were used to investigate the factors that govern the change in IRI over time. The impacts of differing construction quality can have an impact on the IRI performance, but was not considered at this time.

In this section we first, describe the process for characterizing an individual pavement section, and then a description of its extension to analyze a population of sections is presented.

Data Subset Selection

For this work we have used a 221-section subset of the 2742 unique roadway sections included in the LTPP database. This subset is a combination of those used in Appendices PP (5) and EE (6) of the Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structures. Appendix PP uses data from the GPS-3 and GPS-5 experiments to calibrate the ME-PDG roughness prediction models for JPCP and CRCP. Appendix EE uses a mixture of GPS (General Purpose Studies) and SPS (Special Purpose Studies) sections to calibrate and validate the 2002 Design Guide for New Constructed Pavement Sections.

Regression Model Selection for Individual Sections

The LTPP database does not include information about initial roughness for many sections. This presents the challenge of estimating the initial IRI from the existing data. Appendix PP describes the use of a linear model to estimate (back-casting) the IRI of a section immediately following section construction. They characterized the IRI of a section as a function of age, as follows:

$$IRI_e(t) = \alpha * t + \beta \tag{1}$$

Where:

- IRI_e = estimated IRI in meters per kilometer,
- α = slope in meters per kilometer per year,
- β = y-intercept constant equal to initial roughness ($t = 0$) in meters per kilometer,
- t = pavement age in years since initial construction.

The authors validate their model by an examination of goodness-of-fit statistics and comparing back-casted initial IRI values calculated from their model with measured values from new-construction LTPP-SPS sections (5). We used this model to characterize the performance of each pavement section in terms of initial roughness, rate of change in roughness, and time to first intervention. This serves two purposes: 1) estimate the initial IRI, final IRI, the slope or change in IRI over time (measured as a function of initial and final IRI) and the time to failure for a given section, especially when there is missing data, and 2) identify sections with possibly erroneous data for exclusion from the analysis.

By design, interventions cause discontinuities in pavement roughness trends and so the model presented in Eq. 1, is valid only when it fits IRI data collected between roadway construction and pavement rehabilitation interventions as illustrated in Figure 1. These periods are assigned construction numbers in the LTPP database, starting at one and incrementing with each intervention. Each construction number requires a separate regression. The procedure for extracting data for IRI regression is adapted from LTPP User Guide suggested deflection back-calculation sequence. For a section identified by a <STATE_CODE, SHRP_ID> pair, the IRI regression procedure is:

1. Extract intervention information from ADM_EXPERIMENT_SECTION table, including CONSTRUCTION_NO, CN_ASSIGN_DATE, and CN_CHANGE_REASON.
2. Extract data for the section from MON_PROFILE_MASTER table, including PROFILE_DATE and IRI_AVERAGE columns.
3. Use the date of longitudinal profile data collection (PROFILE_DATE) to link profile data to its associated construction number (CONSTRUCTION_NO).
4. For each profile date, compute the mean value of IRI_AVERAGE from all profiling runs on that date.
5. For each construction number, regress against all associated profiles and to find y-intercept β and rate of change in IRI, α .
6. For each construction number, c_i , use the assignment date (CN_ASSIGN_DATE) for itself and the next construction number c_{i+1} to calculate the time to intervention.

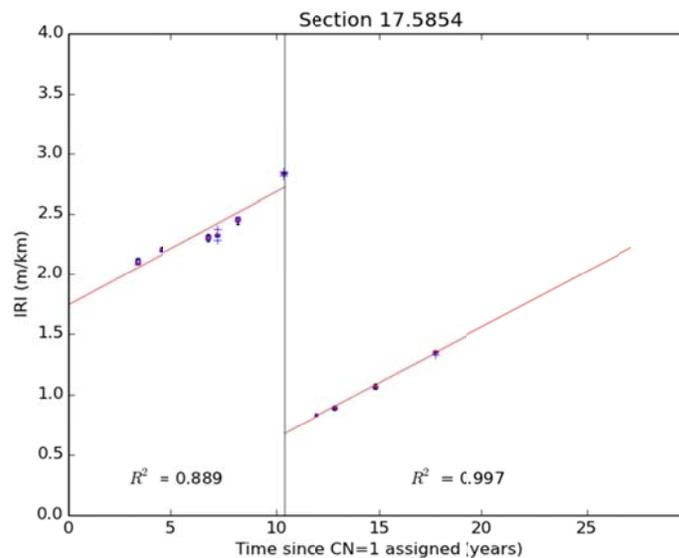


Figure 1: A representative section from the LTPP database with fitted IRI trendline overlaid on whisker plot of section data.

Note the discontinuity caused by the construction event shortly after the $t = 10$ year mark.

A section must have been profiled on at least two occasions during each construction number in order to establish an IRI trend for that period.

Data Filtering and Cleaning

For some sections, IRI data and construction numbers is missing, and for others there is reason to believe that the data leads to untrustworthy regression results. For example, when construction numbers are not associated with any corresponding section profile date, it is impossible to extrapolate a trend. Besides insufficient data, other reasons that can lead to untrustworthy regressions are: infeasible trends, and poor goodness-of-fit measures. In each of these cases, any metric calculated from the data has low reliability. Insufficient data and infeasible behavior trends are often closely linked, wherein a section has a construction number with data from two consecutive profile dates describing extremely rapid increases or decreases in IRI in ways that are unlikely to occur in reality.

For example, Figure 2(i) shows the results of running our algorithm on Section 4-1016 in the LTPP database. During construction number 3 we see that the first profile event describes a significantly rougher surface than subsequent events, even though there were no reported interventions between these two dates. The resulting regression is skewed by this outlier and indicates slowly decreasing roughness even though a clear increasing trend is visible in the most recent six profiles. Other sections may have construction numbers with only two profiles describing rapid increases or decreases in roughness.

Hence, the following method is used to exclude pavement sections from the data analysis.

- First, we look only at construction number one for each section to estimate trends in IRI deterioration till the first intervention. This also reduces the chance of injecting uncertainty associated with Intervention schedules differing across jurisdictions due to differences in budgets and policies.
- Second, we exclude any construction numbers with two or fewer profile dates.
- Third, we exclude any construction numbers whose regressions show poor goodness-of-fit, i.e. they have root-mean-square error (RMSE) less than 0.2 m/km.

Figure 2(ii) is a histogram illustrating the distribution of RMSE values for the set of section data that meets the first two criteria in the above list. We chose a cutoff of 0.2 m/km RMSE based on visual inspection of individual section regressions. Regressions falling under this value generally appeared to describe feasible pavement behaviors. Disadvantages of the RMSE technique include sensitivity to scale – sections with higher IRI values will on average have regressions with correspondingly higher RMSE values. Based on our inspection of actual quality-of-fit compared to RMSE values, this effect has not resulted in unwarranted rejection of high-IRI sections.

Future work will include exploring the use of robust regression methods to reduce the impact of outliers on performance parameter estimation. The entire LTPP dataset is an order of magnitude larger than our test set, and it would be advantageous to have systemic approaches for identifying and rejecting outlier data points or missing information. The focus of our analysis is determining aggregate performance trends as opposed to the cause of specific behaviors exhibited by specific sections, and therefore robust approaches to outlier rejection will increase the utility of our methods.

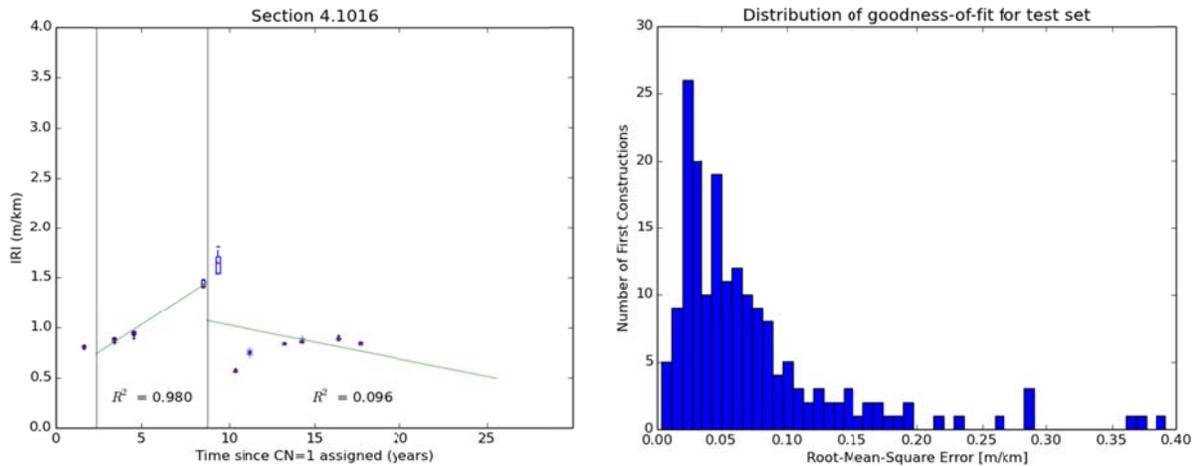


Figure 2(i): Lack of data during construction number=1 and untrustworthy regression results during construction number = 3. (ii) Linear regressions are not reliable in all cases.

Metric Development

The next step is to develop a set of metrics to allow comparison of different pavement populations. We develop a representative value for each regression parameter for a population of sections by averaging the regression results for each section. We calculate:

- α_{avg} = mean slope of IRI_e in meters per kilometer per year,
- β_{avg} = mean initial IRI_e in meters per kilometer, and
- $T_{FI,avg}$ = mean pavement age at first intervention.
- $R_{FI,avg}$ = mean pavement roughness at first intervention.

We use these parameters to benchmark and compare different populations of pavements. Each parameter allows us to investigate a different facet of pavement performance, and together they allow us to identify and hypothesis-test pavement performance categories.

α_{avg} : The mean slope of IRI_e describes the average rate at which roughness changed for a population of sections. This value is important for understanding long-term pavement performance in terms of GHG emissions, because rougher pavement surfaces result in higher vehicle emissions and initially smooth pavements with a high $\bar{\alpha}$ may become rougher than initially rough pavements with a low α_{avg} .

β_{avg} : The mean initial IRI_e describes the average starting roughness of a population of sections. This value is important because it represents the expected baseline performance of a pavement, and in general sets a lower limit on a roadway's performance due to degradation over time.

$T_{FI,avg}$: Mean pavement age at first intervention describes how long a pavement is put to use before maintenance occurs. This value helps us understand the actual longevity of pavements, taking into account real-world roadway maintenance decision-making processes.

$R_{FI,avg}$: Mean pavement roughness at first intervention describes the degree to which a pavement was allowed to degrade before the decision was made to rehabilitate it. This value identifies differences in

maintenance thresholds for different pavements, and allows us to discuss ideal roughness-based maintenance planning as a function of long-term performance trends.

ANALYSIS

We used the discussed method to compare the performance of different subsets, cross-classifying on dimensions expected to correlate with different long-term pavement performance trends. These dimensions include: region, KESAL (traffic loading in thousands of equivalent single-axle loads), and pavement subgrade type (treated or untreated). For each dimension, we examine the performance of Asphalt Concrete (AC), Jointed Plain Concrete Pavement (JPCP), and Continuously Reinforced Concrete Pavement (CRCP) separately.

The LTPP program is organized geographically into four administrative regions: North Atlantic (NA), North Central (NC), Western (WR), and Southern (SR). This cross-classification was performed as a first-order approach to examining interactions between geographical region, pavement type, and roughness.

Traffic load is a major factor in pavement degradation. Hence, we cross-classify sections by traffic load in thousands of single-axle equivalent loads per year to see if there is any discernible correlation between loading, pavement type, and roughness over time.

The third cross-classification involves categories based on whether the sections were constructed on a treated or untreated subgrade. Treated subgrade types in the database include bituminous treated bases, non-bituminous treated bases, and a catchall treated subgrade type. Untreated subgrade types include granular bases, unbound bases, and a catchall untreated subgrade type.

Results

Our first set of classifications suggests our metrics are useful for making comparisons between pavement types in decision-making situations. In this section we first present the results of applying our algorithm to each of the cross-classification dimensions, and provide a brief discussion of their possible utility. Each finding was evaluated by testing the null hypothesis that there is no difference in the mean value of a given parameter between two pavement populations, and the level of significance was set at $p \leq 0.05$. We report p -values for each of these tests where possible. We follow with a discussion of the limitations of our findings.

Region

- AC sections in Western (WR) and North Atlantic (NA) states saw maintenance occur sooner than in the Southern (SR) regions of the country, with $P = 0.03$ and $P=0.02$ respectively.
- The initial roughness of AC sections is lower ($p < 0.001$) but increases faster ($p < 0.001$) than for CRCP sections (Figure 3).

Traffic Load

To evaluate the effects of traffic loading we grouped the sections into quartiles based on their mean yearly ESAL loading, with the first quartile representing the lowest loading scenarios and the fourth quartile representing the highest loading scenarios.

- AC is used more in low-traffic scenarios, with only four AC sections found in the fourth (e.g. highest loading) ESAL quartile. CRCP and JPCP are used more in high-traffic scenarios. (No hypothesis test performed.)

- There is no evidence in our dataset that pavement performance over time is sensitive to loading within pavement groups. However, there is evidence to suggest that JPCP may undergo earlier maintenance in the second ($p = 0.035$) and third ($p = 0.049$) loading quartiles respectively.
- AC undergoes repair earlier than JPCP in the first loading quartile ($p = 0.005$) and earlier than both CRCP ($p = 0.006$) and JPCP ($p = 0.034$) in the second loading quartile.
- The roughness of CRCP sections increases at a slower rate in the third and fourth loading quartiles than both AC ($p = 0.009$, $p < 0.001$) and JPCP ($p = 0.012$, $p = 0.009$).

Subgrade Treatment

- AC has better initial performance with an untreated base ($p = 0.018$).
- CRCP is not sensitive to base type – both treated and untreated bases perform equally.
- The roughness of JPCP sections increases more quickly with an untreated base ($p = 0.046$) (Figure 4).

In summary, there is evidence of performance and use-case differences between AC and CRCP pavements. There is evidence of tradeoffs between initial roughness (favoring AC) and the rate of change of roughness over time (favoring CRCP). We have also found that AC pavements in the test set see lower amounts of traffic compared to CRCP and JPCP sections.

Limitations

The utility of these results is limited in a number of ways. These limits stem from the statistical properties of the distributions of our regression parameters, the small size of the dataset, and the sensitivity of the algorithm to outliers in section-level data. Distributions are not normal across any of our regression parameters. This can be seen in parameter distribution plots (Figure 2(ii)), and inferred from plotting section data in aggregate. Figure 5 illustrates the distribution of performance parameters for a population. Averaging the parameters behind individual section trend lines results in a single representative trend for a population. However, there is significant population variance in each parameter, for example time to first rehabilitation has a range from five years to over twenty-five years.

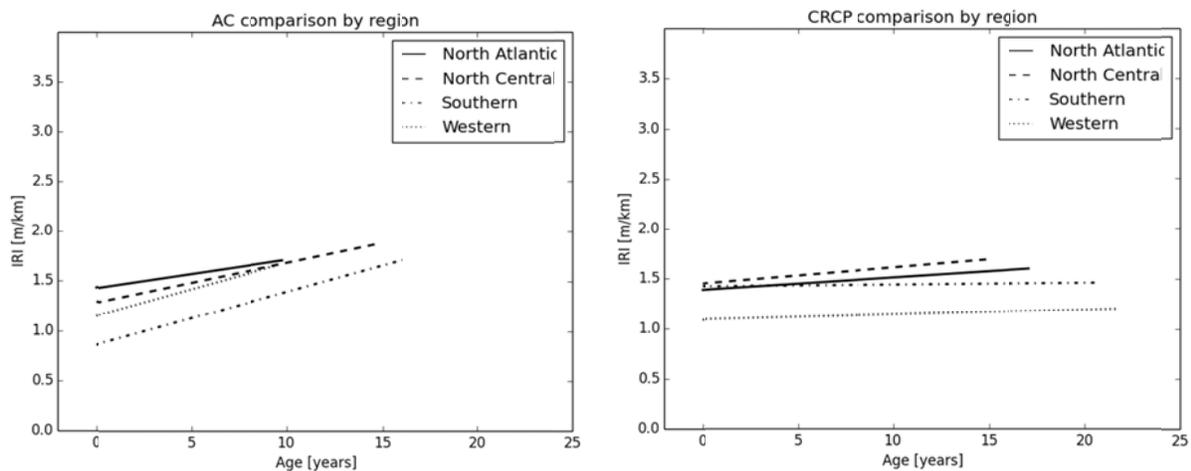


Figure 3: Performance profiles for AC and CRCP are different.

Therefore, researchers must exercise caution when developing hypothesis-testing techniques as tests that assume underlying distributions may provide unreliable results. Strategies for mitigating this issue

include structural and methodological approaches. Structural approaches involve searching for well-behaved subsets using more advanced context-based cross-classification techniques, such as stronger controls for climactic region, road surface composition, functional classification, and other section metadata available in the LTPP database. Methodological approaches involve developing hypothesis-testing techniques that are robust to non-normal distributions. These may involve more context sensitive formulations or the presentation of richer graphical information to decision makers. The former will be preferable for the implementation of machine-learning systems (including those for identifying structural relationships as previously discussed), while the latter will be preferable for presenting and interpreting findings.

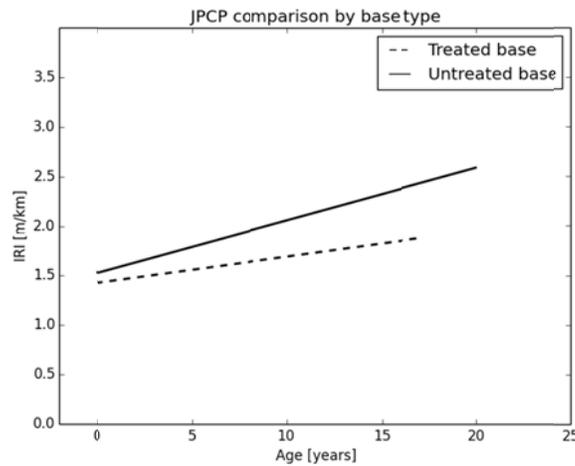


Figure 4: There is evidence to suggest JPCP benefits from the use of a treated subgrade.

The sensitivity of the regression techniques used to outlier's means that we are forced to dispose of otherwise useful data. The next phase of this research will involve examining the use of robust regression algorithms for outlier identification. Increasing the amount of useful data will improve our results by allowing cross-classification on more variables without reaching unrepresentative bin sizes.

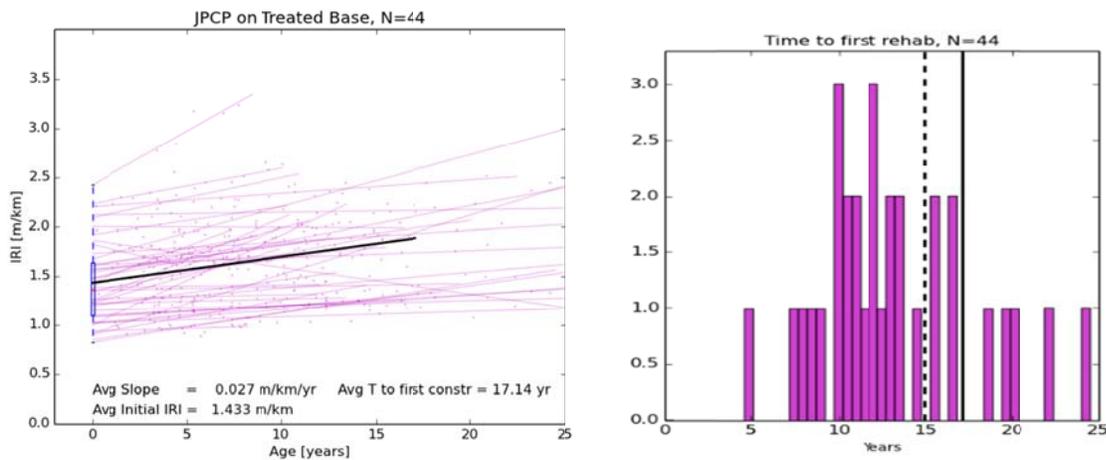


Figure 5: The data behind the creation of a single trend line. In the right-hand histogram, the dotted vertical line represents the median value and the solid line represents the mean value.

APPLICATION TO PAVEMENT LCA: USE-PHASE LCA

The motivation of this study was to understand how pavement roughness influences use phase GHG emissions resulting from PVI. The method discussed allows us to estimate the use-phase impact due to roughness for different classes of pavements relative to a baseline, using the following steps:

1. Establish baseline roughness $IRI_{baseline}$
2. Estimate pavement roughness at time t using previously described metric:

$$IRI_e(t) = \alpha_{avg} * t + \beta_{avg}$$

3. Estimate fuel consumption change ($\Delta FC_{relative}(t)$) for a section relative to baseline due to increase in pavement roughness based on a 2 m/km increase in IRI resulting in a 2% increase in fuel consumption (3):

$$\Delta FC_{relative}(t) = (IRI_e(t) - IRI_{baseline}) \left(\frac{0.02}{2 \frac{m}{km}} \right) \quad (2)$$

Decision makers can use this calculation to aid in their decision-making processes by accounting for expected loading patterns and rehabilitation practices. By defining a function:

$$L_e(t) = \text{expected pavement loading rate at time } t, \text{ in ESAL per time period} \quad (3)$$

and, integrating over time to find total expected relative fuel consumption due to roughness:

$$FC_{lifetime} = \int_{t=0}^{t=T_{FI}} FC_{relative}(t) * L_e(t) dt \quad (4)$$

This approach allows for a benchmark based approach to estimating change in fuel consumption over a period of time t , for a particular pavement type, without bringing in an explicit comparison between pavement types.

Based on this study, there is evidence to suggest that there are significant differences between the IRI performances of pavements. However, due to the limitations of the analysis, the most reliable result is the notion that the pavements can be classified into two types: Pavement type A: Has a lower initial and final IRI, with a relatively faster time-rate change in IRI; and Pavement type B: Has a higher initial and final IRI, but with a relatively slower time-rate change in IRI. Under different classifications of climatic conditions, traffic loading and base preparation; these types could represent either of the two pavement types. Figure 6(i), illustrates the two scenarios.

In this context, using the $FC_{lifetime}$ metric to compare the use phase emissions of pavement types A and B can be difficult, as the analysis can be conducted over two different time windows: t_1 , i.e. the life of pavement type A, or t_2 , i.e. the life of pavement type B. In the first case, pavement type B is penalized as it is not given credit for its slower degradation rate and longer life, while in the second case, pavement type A must be credited for savings in emissions due to lowered IRI after the first intervention at the end of t_1 even though it must be penalized for the emissions accrued due to the maintenance operation at first intervention. Such considerations must be accounted for when using roughness as a factor in pavement selection.

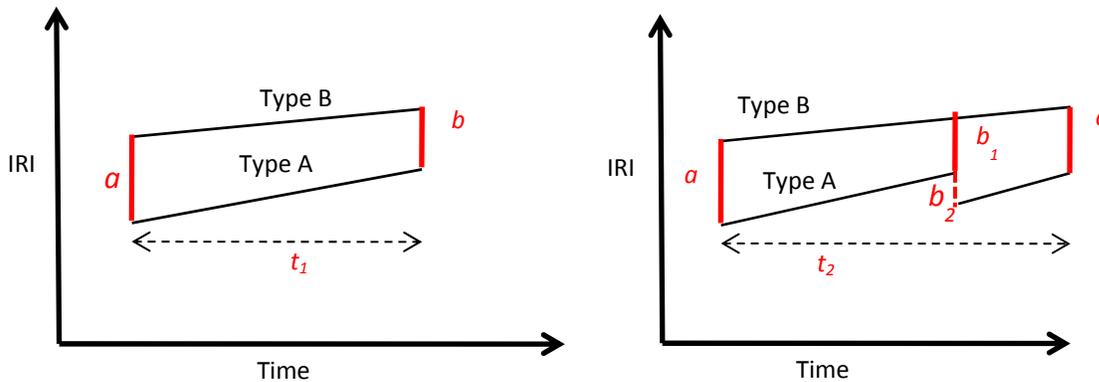


Figure 6: Alternative time windows to be considered when using IRI as a factor in pavement selection.

FUTURE WORK

It is important to recognize that this paper is a starting point towards informing pavement life cycle analysis with empirical trends in pavement performance. To that effect, this study recognizes the incompleteness in available datasets, variability due to geographical and climatic diversity, differences in maintenance strategies, and available resources at the state level. The reason for using linear methods in this study is to provide researchers with tools for using context reduction in identifying sources of variability in performance. This makes the analysis accessible and empowers decision-makers to use context specific knowledge to get a better understanding of their networks and support effective decisions.

Future work will address two primary issues: 1) ways of directly integrating lessons from pavement performance analysis into pavement use phase LCA, and 2) extending the methodology in this paper to allow decision-makers and academic researchers to make custom comparisons of publicly available national and state level data. A web-based analysis platform is being developed that will allow easy access and transparency to the datasets, while allowing stakeholders to directly identify ways in which their decisions influence PVI.

CONCLUSIONS

Reducing the roughness of pavements as measured by IRI can reduce their rolling resistance and lead to improvements in fuel efficiency, in turn reducing the use phase GHG emissions of pavement sections. An analysis of IRI data using a reliable subset of the LTPP database indicates that there are some significant differences in which the IRI of different pavement types, under different circumstances, as defined by region, traffic loading and base preparation changes over time. Due to the limitations of the available datasets it is difficult to reliably declare one pavement type to be smoother than another. However, it can be reliably stated that within specific contexts, there usually is a trade-off between the initial and final IRI of a pavement and how fast the IRI changes over time.

The most important contribution of this research, so far is to draw attention to the need for a context specific analysis of pavement performance when estimating pavement life cycle emissions. In addition, it is important to note that given the inaccuracies and wide variability in the available datasets, it is critical to use caution when analyzing the data and/or generalizing the outcomes from studies involving limited datasets. Finally, it is also important to acknowledge that there are rarely any free lunches, e.g.,

pavement types that tend to have lower average IRIs tend to have shorter times to intervention and pavement types with longer times to intervention tend to have higher IRIs. Hence, in order to build smoother and low emission pavements, decision-makers should consider network wide context specific assessments.

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