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MISCONCEPTIONS AND MISUSES OF DATA IN INFRASTRUCTURE ASSET MANAGEMENT

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ABSTRACT: Infrastructure asset management has been around for a few decades; however, there are still many misconceptions in the domain. Some of these problematic concepts are taught in classrooms and reprinted in textbooks. This paper investigates two key bodies of misconceptions: problematic concepts borrowed from other industries such as industrial engineering or mechanical engineering and issues related to the application of data-driven solutions to infrastructure problems. First, a few well-known concepts such as bathtub curve, replacement time and asset remaining life, which are mostly borrowed from reliability engineering, are critiqued. Two examples from road infrastructure are proposed to show the limitations of the bathtub curve. The examples are based on the roads from the Long-Term Pavement Performance database and clearly indicate that their failure rate may not perfectly follow the bathtub curve, and application of this concept to different assets should be done with more caution. Second, a few common issues related to the application of data-driven solutions to infrastructure deterioration are discussed. The focused was placed on model training and particularly data representation. An example of using population stability index as a measure for assessing data representativeness was presented.

Keywords: Asset management, reliability engineering, bathtub curve, pavement deterioration modeling, machine learning

1. INTRODUCTION

Infrastructure asset management has gained traction in Canada over the past two decades. The practice of infrastructure asset management has changed significantly compared to the 2000s during which researchers were advocating for adopting asset management frameworks to manage infrastructure (Vanier, 2001) and warning about Canada's infrastructure deficit that if left unmanaged can lead to a national crisis (Mirza, 2007). Since then, much progress has been made. In Ontario, the largest Canadian province by population, since 2017 the government has introduced a regulation (*O. Reg. 588/17*) that requires municipalities to develop asset management plans for their infrastructure (Ministry of Infrastructure Ontario, 2018). Many municipalities in Canada have started to investigate ways to become more financially sustainable by balancing their operational budgets and finding more sustainable revenue sources such as increase in property tax (Slack, 2025). While the deficit still remains, and many municipalities are still struggling to manage their spending while keeping their levels of service acceptable, the least that could be said is that the awareness has certainly increased. This is also evident from the large number of universities that have introduced infrastructure asset management courses over the past two decades across Canada.

Despite this progress, there are issues that still remain in teaching and practicing infrastructure asset management. These misconceptions and mistakes are broadly coming from two sources: first, concepts borrowed from other domains that may not apply to infrastructure as well as their original domain; second, the issues related to data-driven solutions for infrastructure asset management problems. This paper investigates a few examples related to the deterioration modeling of infrastructure.

2. METHOD

This paper intends to put forward a few misconceptions taught in infrastructure asset management courses as well as some issues in the practice of asset management. The focus is on infrastructure deterioration modeling. The paper then will present the possible root causes of such errors and misconceptions using literature review and empirical data. The topics are divided into two broader categories: first, inaccurate conceptual or modeling ideas, such as bathtub curve and replacement time, taught in asset management courses; second, areas of practice related to data-driven solutions, such as data representativeness, that need improvement.

The data to demonstrate these issues was retrieved from the Long-Term Pavement Performance (LTPP) dataset (InfoPave, 2018) using SQL. The LTPP data is one of the largest pavement performance databases in the world. This database is known in the literature, and many studies have been performed using this data over the past few decades (Gong et al., 2018; Piryonesi, 2024; K. Wu, 2015; Yamany et al., 2020). The data is collected and maintained by the Federal Highway Administration (FHWA) covering roads in most states and provinces of the US and Canada. The performance indicators used in this study are International Roughness Index (IRI) and Pavement Condition Index (PCI). The LTPP does not include the latter, and it had to be calculated from the distress data in the LTPP based on the methodology proposed by the ASTM 6433-07 (Way et al., 2015). The IRI field was calculated by averaging out the right and left wheelpaths. The LTPP database includes both right and left wheelpaths. Often the right wheelpath is used as the IRI, but in this paper the average of left and right was used in order to represent the roughness of the whole pavement more realistically (K. Smith & Ram, 2016). This is because the presence of local distresses or roughness on one side of the road can skew the data of one wheelpath.

3. RESULTS AND DISCUSSION

Two categories of issues are discussed here: first, a few concepts that are adopted from other domains and may not be a good fit for infrastructure asset management (e.g., bathtub curve); second, issues in data-driven deterioration modeling such as data representativeness and methods to assess such issues.

3.1 Conceptual Issues

Some of the concepts that are adopted from reliability engineering may not fully represent the deterioration of infrastructure. One of these concepts, repeatedly mentioned in asset management courses and textbooks, is the bathtub curve. The bathtub curve is a concept used to describe the failure rates of products or systems over time. It gets its name because its shape resembles a bathtub, shown in Figure 1, with three phases (Henley, 1980; Klutke et al., 2003):

- Infant mortality or early failure: High failure rates early in the product's life due to manufacturing defects or design issues, which decrease over time.
- Random failure: A steady, low failure rate during the product's useful life, where it operates reliably with random, infrequent failures.
- Wear out failure: Increased failure rates at the end of the product's life due to aging, wear, and tear, as components degrade over time.

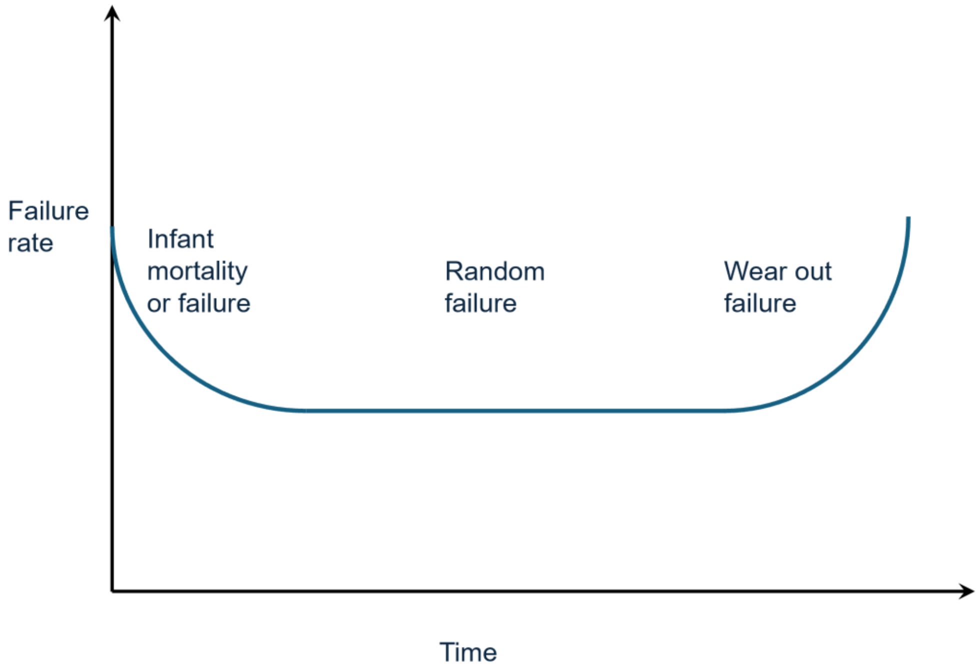

Figure 1. Illustration of a typical bathtub curve

The origins of the bathtub curve are contested. Some suggest that it was first developed in life insurance industry to represent the probability of human mortality. There is evidence of applying the bathtub curve to failure of vacuum tubes in the first half of the 20th century (A. M. Smith, 1992). However, even for electronic components the model was not fully used as it was considered that electronics only mimic the random failure phase (Gaonkar et al., 2021). The theoretical validity of the bathtub curve has been subject to discussions over the past several decades (Gaonkar et al., 2021; Klutke et al., 2003).

The theoretical limitations of this curve are not the subject of this paper, but rather this paper is concerned with teaching the curve in infrastructure management courses or discussing it in infrastructure asset management textbooks. The author discovered that this curve is taught in many infrastructure asset management courses as a basis for deterioration modeling across Canada, and it is also discussed in infrastructure management books (Coffelt & Hendrickson, 2019).

While the bathtub curve, with some limitations, can describe the deterioration of some electronics, it may not be a perfect fit for all infrastructure assets. With exception of mechanical or electrical assets or watermains (Lin & Yuan, 2019), the deterioration of most municipal infrastructure assets such as roads and buildings do not perfectly follow this curve. To demonstrate, an example based on real data of road infrastructure is presented below.

This data belongs to the asphalt pavements in the US and Canada, and it is retrieved from the LTPP database. To demonstrate the failure rate of pavements, the international roughness index (IRI) data for the following five groups of roads was retrieved. These are the roads that had a near perfect IRI value and did not go under rehabilitation for one, two, three, four or six years. Failure was defined as IRI increasing to change from Good to either of Satisfactory, Fair, Poor or Very Poor. The grid for the classification for IRI was adopted from the literature (Meegoda et al., 2014; Piryonesi & El-Diraby, 2021c) and is shown in Table 1.

Table 1. Ranges used for IRI classification

IRI classification	Range (m/km)
Good	<1
Satisfactory	1-1.263
Fair	1.263-1.8
Poor	1.8-2.352
Very Poor	>2.352

Figure 2 shows the number and percent of roads failed after each horizon. The red dotted curve shows this percentage, while the bars show the total number of roads and the frequency of failed roads after each horizon. Clearly the dotted curve is increasing monotonically with horizon or time suggesting that a larger percent of roads fail when left without maintenance. Therefore, the infant mortality or phase one of the bathtub curve shown in Figure 1 is almost missing. The longest horizon, i.e., six years, has the largest percent of roads failing (23.53%), which is about five times bigger than that percentage for one year (5.22%), which is supposed to indicate the infant mortality phenomenon. This is against what the bathtub curve suggest that the deterioration and failure rate should look like.

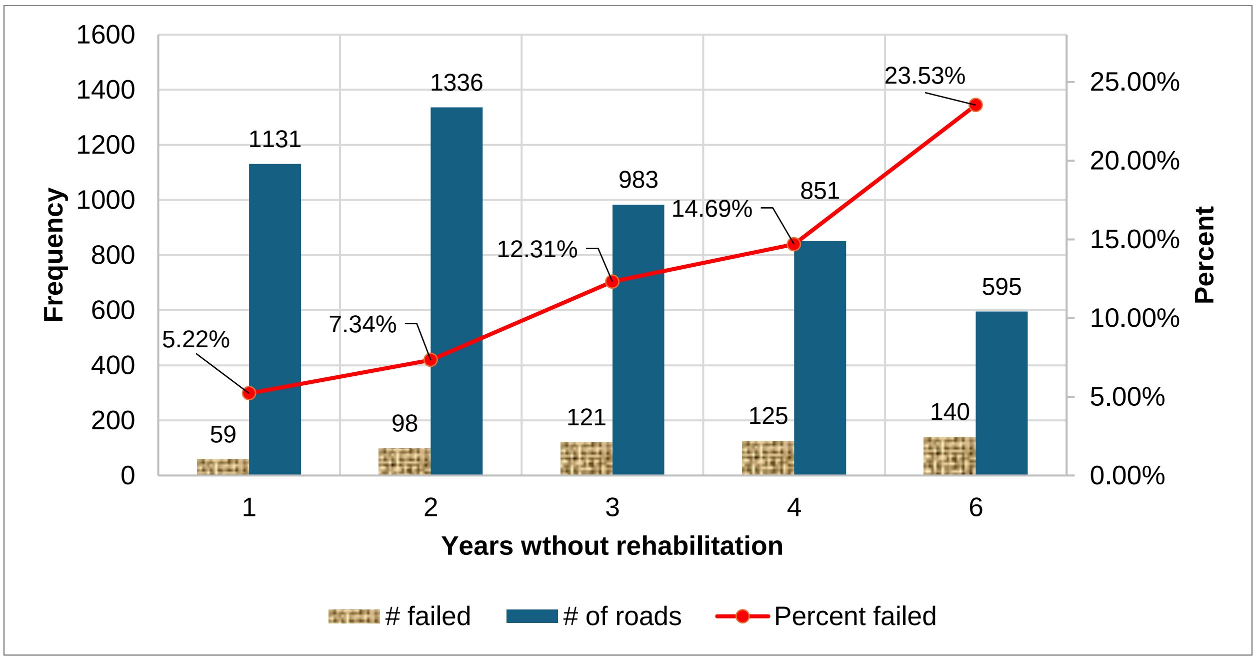

Figure 2. Example of road failure over time using IRI performance indicator

A similar analysis was performed using another pavement performance indicator, pavement condition index (PCI). The results and conclusion were similar to that of the IRI, and the failure rate did not follow a bathtub curve. For this case study, four sets of brand-new roads (PCI>95) were studied, and their PCI was reevaluated after four horizons under no maintenance. These horizons or time intervals were 2, 3, 5 and 6 years as shown in the bins of Figure 3. Here too, no large failure rate was observed in the smaller intervals, suggesting that there is no considerable infant mortality regime. The longest horizon, i.e., six years, had the largest percent of roads failing (71.28%), which is about three times that percentage for the smallest horizon, two years (27.31%). In this example, failure was defined as a road deteriorating to a PCI class other than Good. The PCI calculation and classification was performed based on the methodology proposed by El-Diraby and Piryonesi (2021b), which is inspired by the ASTM 6433-07 (Way et al., 2015).

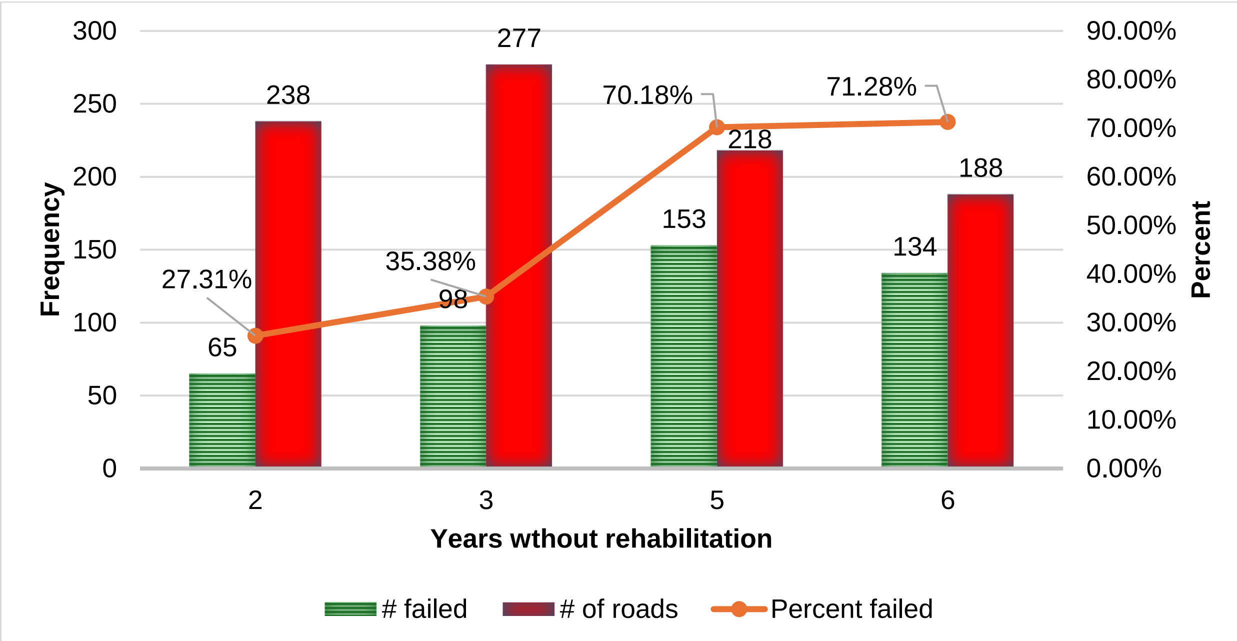

Figure 3. Example of road failure over time using PCI as performance indicator

The results of the examples discussed above are in good agreement with the literature and the sigmoidal (K. Wu, 2015) or other deterioration curves (Piryonesi & El-Diraby, 2021a) developed for assets such as roads. The models developed by previous researchers suggest that deterioration in the early stages are slow and accelerate when assets age. For example, for roads, there are no or limited reports of premature failure in roads in different regions. The only account the author could find was a study performed by Weiss et al. (2019) on premature failure of concrete pavements in Indiana, in which the authors associated this early deterioration in pavement joints to the impact of the deicing salt used in the region. This looks like an exception rather than a rule.

This example has a few limitations though that should be considered. First, despite the author's effort to find roads that resemble brand new assets, it is difficult to find a large enough network of such roads. The author ensured that the roads selected for this example were almost intact (initial PCI or IRI were good), had no distress and did not go through minor maintenance such as crack sealing. The latter was done by utilizing CONSTRUCTION_NO, a counter in the LTPP data tracking number of maintenance actions. However, it is quite difficult to find a completely newly built set of roads (with an age of zero) to perform this experiment because roads in a network are not typically constructed or put into service in the same calendar year. Roads get rehabilitated and rebuilt. While this makes their absolute age less significant, it is not completely irrelevant to deterioration pattern (Piryonesi & El-Diraby, 2018). Furthermore, this study did not distinguish between network-level and asset level analysis.

Other concepts such as replacement time and asset remaining life, which are borrowed from reliability engineering or equipment management, are often used in infrastructure asset management as well. However, the application of such concepts to public infrastructure, especially to those like roads that all parts are almost integrated, may not be quite valid. Researchers, teachers and practitioners in asset management should revisit the suitability of adopting these concepts and the degree to which they can be applied to infrastructure assets.

3.2 Data Analysis Issues

Another area that this paper investigates is problems arising when applying statistical or machine learning models to infrastructure deterioration modelling. This part of the paper focuses on the issue of data representativeness. Consultants and some municipalities often develop models using a data set and use that model for a long time without assessing the suitability of their development data or recalibrating the model. If the population distribution of the data shifts significantly, the development data cannot represent the current state of the assets and thus predict the behaviour of the current population. This shift can be observed in values or data distribution across different dimensions. When such significant shifts are observed, model recalibration is needed. There are metrics to measure this shift between the development data and the current data. A commonly used measure is the Population Stability Index (PSI) (D. Wu & Olson, 2010; Yurdakul, 2018). The theoretical foundation of the PSI is derived from the Kullback–Leibler (KL) divergence, which measures the difference between two probability distributions (Kullback & Leibler, 1951).

An example of pavement performance is presented below. The example is based on PCI prediction across two timeframes: the development data that spans from 1989 to 1995 and the most recent cohort from 2011 to 2013 and comparing the development data with data of 1996 to 1998 (which is closer to the time of model development). The question is if the development data still represents the data in those more recent cohorts. The PSI analysis examines the PCI factors. PCI class is a five-category variable ranging from Good to Very Poor as explained above.

The relative frequency of roads belonging to each PCI class are shown in Tables 2 and 3 and Figure 4. Table 2 includes the PSI calculation for each PCI bin comparing the development data with cohorts of 1996 to 1998. Limited studies are available about the statistical properties of the PSI. Utilizing existing industry rules of thumb, one can use the following decision matrix for PSI values:

- PSI < 0.10 ➔ little shift
- 0.10<PSI<.25 ➔ moderate shift
- PSI>0.25 ➔ significant shift

If we take 0.1 as the threshold for PSI, clearly in most classes have no or limited population shifts in years 1996-98 compared to the development cohorts. The total PSI for all classes is 0.16, which falls into the moderate region. Table 3 presents the same calculations for data of roads in 2011 to 2013. Here a change in population distribution is observed in the Fair PCI band.

Table 2. PSI calculation for PCI classes, comparing the population of development and 1996-98 data

PCI class / Frequency	Development data (1989-1995)	Current data (1996-1998)	PSI or KL
Good	0.40	0.57	0.06
Satisfactory	0.19	0.17	0.00
Fair	0.30	0.15	0.09
Poor	0.07	0.09	0.00
Very Poor	0.03	0.02	0.01
Sum	1	1	0.16

Table 3. PSI calculation for PCI classes, comparing the population of development and 2011-13 data

PCI class / Frequency	Development data (1989-1995)	Current data (2011-2013)	PSI or KL
Good	0.40	0.46	0.01

Satisfactory	0.19	0.17	0.00
Fair	0.30	0.11	0.18
Poor	0.07	0.17	0.09
Very Poor	0.03	0.09	0.05
Sum	1	1	0.33

This change in population explained by Tables 2 and 3 is clearly visible Figure 4 as well, with many roads migrating to Poor and Very Poor classes, while some rehabilitated and reverted back to Good. This resulted in a smaller percent of roads in Fair and Satisfactory classes. The total PSI is larger than 0.25, which is a clear indication of a population shift. This substantially large PSI means that the development data is no longer representative of the current data, and the model must be recalibrated. This is intuitive that the data in years closer to the development period were more similar to the development data. However, the factor of time is not the only factor. Often time data distribution change because of other factors such as change in demand or maintenance policy.

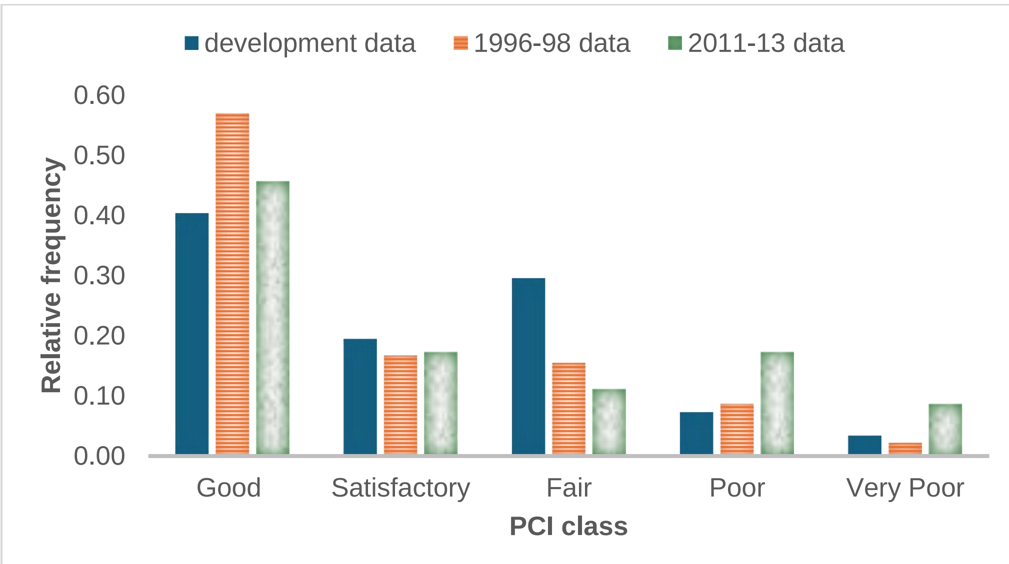

Figure 4. Comparing percent of roads in each PCI class for development data and recent data

4. CONCLUSIONS

This paper highlights the common misconceptions and misuses of data in infrastructure asset management, emphasizing the need for a more informed and rigorous approach to data-driven decision-making. The paper had two main modules: one that demonstrated how the idea of a bathtub curve deterioration model cannot realistically represent infrastructure asset deterioration and second an example of a road data set that showed some population distribution shift over time. While the examples in section 3.1 do not fully invalidate the applicability of the bathtub curve to explaining pavement performance deterioration (due to the limitations discussed in the same section), the morale of the first component is that not every concept borrowed from other domains can be directly applied to infrastructure assets. Each type of asset may have its own deterioration regime. Lesson learned from the data representativeness example is that a model developed by a certain data set should be evaluated and recalibrated on a regular basis to ensure that its predictions remain accurate enough. This requires more model and data governance in the infrastructure asset management practice, something that is currently almost missing in many municipalities.

While data is a powerful tool for optimizing asset performance and extending infrastructure longevity, its improper use can lead to misleading conclusions and ineffective management strategies. Issues such as selection bias, data overfitting, and misinterpretation of statistical relationships often compromise the reliability of asset management decisions.

To address these challenges, infrastructure managers must adopt a critical perspective on data, ensuring that statistical methods are applied correctly and that findings are interpreted within the appropriate context. The integration of robust data and model governance processes, domain expertise, and transparent methodologies can help mitigate errors and improve decision-making processes. By fostering a culture of data literacy and continuous learning, infrastructure asset management can move beyond flawed assumptions and toward a more evidence-based and sustainable future.

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