



# Big Data for condition evaluation of constructed bridges



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## ABSTRACT

This paper presents Big Data analytics on the condition evaluation of highway bridges in the United States. A large dataset comprising 1,002,172 bridge decks and superstructures is constructed, based on the National Bridge Inventory (NBI), and categorized into four service zones as specified in the American Association of State Highway Transportation Officials (AASHTO) Load and Resistance Factor Design (LRFD) Bridge Design Specifications. The condition rating of the bridge members is examined statistically and probabilistically, in conjunction with the effect of traffic and environment (i.e., temperature and precipitation). The statistical characterization of the members indicates that concrete-based superstructures are predominant in Zones 1, 2, and 3 (79%, 72%, 85%, respectively), whereas steel- and timber-based superstructures account for 51% and 21% in Zone 4, respectively. The bridges in Zones 1 and 3 are subjected to significantly high traffic-induced loading relative to those in Zones 2 and 4. Thermal loading is noticeable in Zones 1 and 4. The deterioration of bridge decks rapidly develops at the bridges' early service life, and stabilizes with time owing to maintenance and repair efforts. According to a two-factor analysis of variance, adequate selection of structural types dependent upon service environments enhances the performance and longevity of constructed bridges. The likelihood of deterioration of bridges constructed in Zones 1 and 3 is higher than that of the bridges in Zones 2 and 4.

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## 1. Introduction

The emergence of an analysis approach called Big Data has opened a new era on handling complex problems using substantially large datasets, which will assist predictive analytics and efficient decision making [1]. By examining massive datasets, scientific relationships between independent and dependent variables of interest (e.g., service environment and bridge performance, respectively) can be established. Big Data analytics results in numerous advantages that are not obtainable in conventional observations with a limited number of data samples, such as the current trend of data kinetics, the interaction between constituent parameters at a global scale, and the prediction of upcoming events. Enormous datasets are generated in the bridge engineering community. Challenges associated with these huge and complex datasets include characterizing the physical significance of compiled data and extracting important and value-added information for the sake of the community. Big Data analytics on civil infrastructure has recently begun, although still conceptual and limited yet. Kobayashi and Kaito [2] discussed how the concept of Big Data could be used for infrastructure

management, in conjunction with the deterioration of constructed members, inspection, and predictive modeling. Liang et al. [3] suggested a holistic methodology to enable Big Data-based serviceability analysis for constructed bridges. The proposed hypothesis involved real-time sensing, data processing with machine learning, and performance reliability.

The National Bridge Inventory (NBI) is a compilation of bridge data acquired from all state Departments of Transportation (DOTs). With the aid of the NBI, data on a wide variety of bridge conditions are stored and updated in a timely manner. Several research projects have been conducted on the basis of the NBI. Mishalani and Madanat [4] developed a bridge deterioration model with a stochastic approach, using 1460 observations of bridges in condition states of 7 and 8. Parameters considered were traffic loading, structural types, age, highway class, environments, and wearing surface types. The proposed modeling method attempted to overcome technical limitations related to the transition probability of state-based discrete-time. Mechanical processes were found to be a primary factor degrading bridges in a condition state of 7. Bolukbasi et al. [5] performed a regression analysis with the condition ratings of 2601 bridges in Illinois. The fitted curves showed that a decrease in condition rating from 9 (*Excellent*) to 4 (*Poor*) took about 35–45 years. Kim and Yoon [6] identified critical sources influencing bridge deterioration in cold regions. A unique

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approach consisting of multiple regression and geographic information system technology was employed to evaluate the performance of 5289 bridges in North Dakota. The degradation of these bridges was affected by traffic volume, aging, and the presence of water. Concrete bridges were more durable than steel bridges in a cold-region environment. Nasrollahi and Washer [7] statistically examined the NBI data to estimate inspection intervals for constructed bridges. The data distribution of 4270 bridge superstructures in Oregon was assessed using the Anderson-Darling method, and the probability of deterioration for three superstructure types was predicted. It was found that the time-in-condition rating (TICR) for the superstructures was greater than the present 24-month inspection intervals.

This paper discusses a data-intensive study on the condition evaluation of constructed bridges in the United States, with a focus on deterioration trends and corresponding model development. Unlike the existing research projects described above, which were based on a few thousand data samples, over one million data points are gathered and analyzed to comprehensively assess the performance of bridge members. The local condition state of the individual members is consolidated to identify their global response patterns in specific geographic domains. A three-step research framework is employed: i) access to the NBI and data extraction relevant to the present work scope, ii) data processing to explore the kinetics of bridges' condition ratings, and iii) technical interpretation to elucidate the physical significance of the compiled Big Data, including the performance degradation models of in-situ bridge members. The condition of substructures is outside the interest of the current investigation, because they are generally much more durable than superstructures and decks (structural slabs supported on superstructural elements).

## 2. Research significance

Existing evaluation methodologies using the NBI data concentrate on individual bridge components, which may not be sufficient to fully utilize the accumulated data. The fusion of independently collected local NBI data can provide global insights into the performance of spatially distributed bridges. The contemporary research approach introduced above, Big Data analytics, appears to be promising and robust to accomplish this technical demand. The present research attempts to understand the complex kinetics of performance degradation in constructed bridges, based on the Big Data-enabled interpretation of heterogeneous statistical data acquired from four different regions in the nation. Another interest is the interaction between multiple factors influencing the condition rating of bridge members. The compilation of more than one million bridge members enlarges the limited (or regionally biased) boundary of existing bridge engineering research. By analyzing Big Data associated with the performance of existing bridges, dispersed knowledge is integrated to generate practical information, which can assist technical personnel in planning, managing, and operating highway infrastructure. The inherent complexity latent in the large amounts of the NBI's condition rating data and their interaction with contributing attributes (e.g., structural types) are probabilistically characterized to examine the degradation rate of constructed bridges.

## 3. Database construction

According to the four temperature-gradient zones specified in the American Association of State Highway Transportation Officials (AASHTO) Load and Resistance Factor Design (LRFD) Bridge Design Specifications [8], two representative states per zone (except Zone 4, which has only one state) were selected (Table 1). Bridge data in

each zone were decentralized, without mutual interaction. For instance, bridges constructed in Zone 1 are not necessarily subjected to traffic and environmental loading conditions applied to those in Zone 4, and bridge deterioration in Zone 2 does not influence the operation of bridges in Zone 3. Therefore, condition ratings recorded in the NBI independently represent the characteristic response of bridges in the respective zones (i.e., *exclusive clustering* from a data analytics standpoint). Because the NBI is a standardized non-hierarchical data system, the selection bias often observed in Big Data formulation was not a concern. Data on a total of 1,002,172 bridge decks and superstructures from inspection years 2010–2014 were extracted from the NBI. Table 2 lists the types of these bridge members alongside the NBI item numbers and code designations. The performance of these members was assessed following the NBI's nine-point condition rating scale (Table 3). It is recognized that bridges rated at four or below are categorized as structurally deficient, requiring major technical action such as rehabilitation. The NBI's metadata were extracted to create separate data files, which were necessary to efficiently analyze the performance of the considered bridges with subsequent unique identifiers: year-built (NBI Item 27), average daily traffic (Item 29), superstructure types and conditions (Items 43 and 59, respectively), and deck types and conditions (Items 107 and 58, respectively). Having organized these items, all data were processed to establish kinetic patterns in bridge performance. Unlike the case of descriptive data analytics, the constructed database is classified as structured data.

## 4. Data analytics and interpretation

The details of bridge data are examined to identify construction trends, preferred structural types, and service conditions in four zones classified by the AASHTO LRFD Bridge Design Specifications. The performance of these bridge members is evaluated and statistically characterized.

### 4.1. Overview of bridge data

#### 4.1.1. Erection trend

Fig. 1 illustrates the year-built distribution of bridge data for inspection year 2014 (other inspection years exhibit similar distributions, and the full data are available in Table 1). As shown in Fig. 1(a), the number of constructed bridges in Zone 1 exponentially increased up to 1970, followed by a sudden decrease (1971–1980), then a stabilized construction pattern (1981–2000). This observation indicates that infrastructure development in Zone 1 rapidly grew and peaked in the period of 1961–1970. The states in Zone 2 began to invest resources in infrastructure earlier than others [Fig. 1(b)], evidenced by the significantly more bridges erected before 1910 relative to the bridges of Zone 1. The development of infrastructure in Zone 2 continued until 1990, then gradually decayed. The trend of bridge erection in Zone 3 was similar to that in Zone 1, as shown in Fig. 1(c), although the bridge number of the former was only 39% of the latter. The growth of bridge infrastructure in Zone 4 began after 1951 and peaked between 1981 and 1990 [Fig. 1(d)]. Overall, the bridge construction in all zones was saturated after 2011, as corroborated by the low number of newly erected bridges. The economic crisis of 2008–2010 influenced construction planning and implementation as well.

#### 4.1.2. Structure types

The structure types of the bridges discussed above are summarized in Fig. 2, based on an inspection year of 2014 for consistency. The most used superstructure system in Zone 1 [Fig. 2(a)] was concrete (54% for Types 1 and 2: Concrete/Concrete continuous, as

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