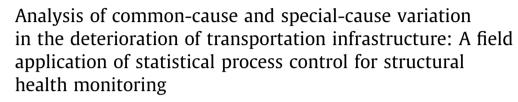
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ANSPORTATION RESEARCH

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ABSTRACT

We present a statistical process control framework to support structural health monitoring of transportation infrastructure. We contribute an integrated, generally-applicable (to various types of structural response data) statistical approach that links the literatures on statistical performance modeling and on structural health monitoring. The framework consists of two parts: The first, estimation of statistical models to explain, predict, and control for common-cause variation in the data, i.e., changes, including serial dependence, that can be attributed to usual operating conditions. The ensuing standardized innovation series are analyzed in the second part of the framework, which consists of using Shewhart and Memory Control Charts to detect special-cause or unusual events.

We apply the framework to analyze strain and displacement data from the monitoring system on the Hurley Bridge (Wisconsin Structure B-26-7). Data were collected from April 1, 2010 to June 29, 2011. Our analysis reveals that, after controlling for seasonal effects, linear trends are significant components of the response measurements. Persistent displacement may be an indication of deterioration of the bridge supports. Trends in the strain data may indicate changes in the material properties, i.e., fatigue, sensor calibration, or traffic loading. The results also show that autocorrelation and conditional heteroscedasticity are significant sources of common-cause variation. Use of the control charts detected 43 possible special-cause events, with approximately 50% displaying persisting effects, and 25% lasting longer than one week. Analysis of traffic data shows that unusually heavy loading is a possible cause of the longest special-cause event, which lasted 11 days.

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1. Introduction

Structural health monitoring (SHM) is the process of collecting and analyzing data related to the condition/properties of (subsets of elements that comprise complex) structures, such as bridges. Such data are used for a variety of purposes; however, the fundamental objective of SHM involves assessment and prediction of structural integrity, i.e., load-bearing capacity, to ensure safe and reliable operations. The most-widely used approach to achieve this objective consists of comparing

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measurements¹ to the predictions of a model of (immediate) structural responses to specific loading conditions. Deviations between the measurements and predictions, particularly those exceeding certain thresholds, are taken as indications of damage,² e.g., loads on members are too high to be supported safely. As acknowledged in the SHM literature, a fundamental limitation of this approach is that, in general, structural models (of deterioration) do not explain, and therefore cannot be used to predict, (long-term) variations in response measurements, e.g., strain, exhibited by complex structures, even when they are undamaged and operating under ordinary conditions (Sohn et al., 2002). This lack of explanatory and predictive capability hinders damage detection because it is difficult to separate damage from other sources of variation, and explains the prevalence of SHM methods to analyze structural properties that are insensitive to operational variation, including minor damage, i.e., vibration-based methods.

The objective in SHM overlaps with the literature on transportation infrastructure/asset management. The latter having a broader focus, ideally encompassing a structure's life-cycle and supply-chain, where the objective is to support a plethora of decisions, e.g., maintenance and rehabilitation, and where, in addition to safety and reliability, metrics include functional performance, i.e., ride quality, economic and environmental consequences, as well as other criteria. Statistical deterioration models have been developed to support this objective, i.e., to predict (the effect of management strategies on long-term) deterioration, and indirectly the aforementioned criteria. While, in principle, such models can be used to explain and predict measurement variations under ordinary conditions, and thereby adapted to support SHM; with few exceptions, statistical deterioration models are cross-sectional, meaning that they describe differences between facilities. This, in turn, limits their applicability to SHM, and motivates the need for methodologies capable of facility-specific (as opposed to population-level) inferences and longitudinal forecasts.

In this paper, we introduce a generally-applicable (to different types of data) statistical framework that links the two parallel streams of literature described above. The objective is to support efficient monitoring and management of transportation infrastructure. The proposed framework builds on the notion in Statistical Process Control (SPC) (cf. Shewhart, 1931; Deming, 1975) that changes in the output of a stochastic process consist of three components: **common-cause variation**, which refers to changes that can be explained, and importantly, predicted by *usual*, often observed, and recurrent operational conditions; **special-cause variation**, which refers to changes attributed to *extraordinary* events; and inherent **random variation** discussed in subsequent paragraphs. In the case of a stochastic process consisting of measurements collected from an infrastructure facility, operational conditions are those associated with traffic, weather, etc. Extraordinary events could be exogenous and even observable, such as extreme or infrequent/unique traffic or weather events, or endogenous and sometimes latent, such as the advent of certain types of damage.

Perhaps stemming from development and implementation in controlled environments, e.g., manufacturing settings where it is possible and desirable to eliminate sources of systematic variation, the focus in traditional SPC is on first, achieving, and subsequently, detecting deviations from a *state of statistical control* (SSC). In a SSC, variability is random; that is, measurements or statistics derived from a quality characteristic are assumed to be stationary, independent and identically distributed (*iid*). This variability is understood to represent the cumulative effect of many small, unavoidable causes, which explains why the Central Limit Theorem is often invoked to justify the assumption that the measurements follow a Normal Distribution (Montgomery, 2009). Occasionally, other sources of variability, i.e., special causes, alter the process of interest. In manufacturing settings, sources can include improperly adjusted or controlled machines, operator errors, or defective raw materials. Variation produced by special causes is systematic and generally large relative to random variation (Montgomery, 2009). Detection of special-cause events, therefore, consists of detecting departures from a SSC. In manufacturing settings, it is desirable, though not always possible, to identify the sources of special-cause events, i.e., *assignable causes*, in order to take corrective action.

In SHM and other settings, interventions to eliminate or correct sources of systematic variation may be (physically/politically) impossible or undesirable, meaning that such variability may be present throughout the data, i.e., it constitutes common-cause variation. The effect of temperature on response measurements, e.g., strain, is a relevant example in the SHM context. As explained by Alwan and Roberts (1988), in such situations, the SPC focus is narrowed (from reaching a SSC) to the detection of special-cause events. To achieve this objective they propose the following two-part framework, which we adapt to support SHM:

1. Formulation and estimation of statistical models to explain and predict common-cause variation. These models allow for inferences based on the measurements, as well as for forecasting their progression under usual operating conditions. It is this analysis, therefore, that allows decision-makers/agencies to be proactive in terms of planning interventions. Importantly, these models are also used to control for, i.e., remove, common-cause variation from the data. The resulting *stan-dardized innovations*, i.e., prediction errors, constitute the fundamental input to the second part of the framework, consisting of:

¹ Measurements can be replaced with surrogates, i.e., damage-sensitive features, obtained by processing the data.

² Wenzel (2009) defines damage as changes to material or geometric properties of a structure, including changes to the boundary conditions and connectivity. Damage affects current or future performance of such systems, i.e., load-bearing capacity. Herein, deterioration refers to the damage initiation and progression process.

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