Condition Monitoring of Steel Truss Bridge Using Acceleration Data

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ABSTRACT

This study investigates the efficacy of utilizing data-driven techniques to continuously monitor the condition of steel truss bridges. Rather than relying on computationally intensive modeling methods, this approach utilizes parameters derived from raw acceleration time history data of on-field vibrations caused by regular traffic. Specifically, the study examines the relationship between changes in these parameters and the occurrence of damage in steel truss bridges. To conduct this research, the Pamban Bridge, which is over 100 years old, was fitted with accelerometers at various bottom node points on the bridge.

The acceleration data was then parameterized into primary, secondary, and tertiary order parameters based on amplitude, frequency, and duration. These parameters were then analyzed to determine their suitability for detecting damage. This study examines the continuous variations in each parameter over an identical duration from March to July 2021 and March to July 2022, spanning 136 days each and over 1000 train passes. The bridge underwent retrofitting during the intervening period. A linear best-fit line is found for each sensor reading for the considered duration. The slope and intercept of the linear fit are studied. It was found that the change in the intercept values indicated the changes that occurred consistently and reflected the expected trends between sensor locations.

To further validate the findings, the observations made through these parameters were compared with the retrofitting data of each member. The parameters, such as root mean square acceleration, arias intensity, characteristic intensity, and cumulative absolute velocity, were consistent and exhibited similar patterns during the observed period.

Overall, this approach to condition monitoring is highly efficient and requires only on-field vibrations caused by regular traffic to detect potential damages in steel truss bridges, making it an ideal method for continuous monitoring without operational downtime.

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INTRODUCTION

As new materials and technologies are discovered, buildings get taller, bridges get longer, and the designs of structures become more ambitious and complex. Given these developments, there is an increased requirement to provide both cost savings and ensure uniform safety. India's infrastructure boom is seeing many bridges being built. These bridges are built to have an expected design life of 50 to 60 years. However, there is a large band of uncertainty in the expected life estimation as (i) it depends on future usage assumptions, (ii) timely maintenance activities (iii) ideal construction practices. Further, ensuring the safety of the operations of these bridges requires periodic inspection. If this inspection is going to be visual, a large pool of trained manpower commensurate with the number of bridges is required. One of the better approaches to ensure safe operation with automatic and quantitative assessment of bridges is to use structural health monitoring (SHM) techniques.

In recent years, monitoring techniques that utilize the dynamical response of structures have gained considerable attention due to their robustness [1]. By deploying a well-positioned array of sensors, the structure's time signals can be collected and analyzed to estimate its physical or modal properties. Knowing the current state of a bridge is of interest for a variety of reasons. Some parameters that determine the current state of a bridge are the material and geometric properties and boundary conditions [2]. The changes in these properties over time can help determine the structure's current condition and identify potential damage locations [3]. Additionally, monitoring ambient properties such as temperature and humidity can aid in establishing correlations between the estimated properties and environmental factors, thereby distinguishing true damage from deviations caused by atmospheric phenomena. However, for these techniques to be effective, the sensors must be permanently installed on the structure, constantly recording and transmitting data to a remote server to provide reliable information on the structure's current state [4].

In the field of continuous monitoring of the dynamic response of structures, a plethora of sensors are available for use. Accelerometers, in particular, are widely utilized due to their versatile nature, high durability, and cost-effectiveness [5]. These sensors are designed to measure the acceleration response of a specific location on the structure in one, two, or three directions. Typically, accelerometers are valuable in estimating the modal properties of the structure, including its natural frequencies, damping ratios, and mode shapes [6]. However, the variability in the operational and environmental conditions of structures poses a significant challenge in deploying an on-site monitoring system that relies on mode shapes and frequencies. Moreover, in the context of truss bridges, conventional techniques like analyzing changes in modal frequencies and mode shapes are not applicable because alterations in the cross-sectional area resulting from member damage do not yield substantial reductions in modal frequencies and mode shapes [7]. Although numerous damage detection techniques have demonstrated successful results in controlled laboratory environments with scaled models or specimens, their efficacy in real operational environments remains doubtful and requires validation [8,9].

The objective of this paper is to propose an acceleration response-based method that could be useful for the continuous monitoring of railway truss bridges. The proposed method would use the data of ambient bridge vibration response recorded under opera-

Figure 1. Bascule section of the Pamban railway bridge.

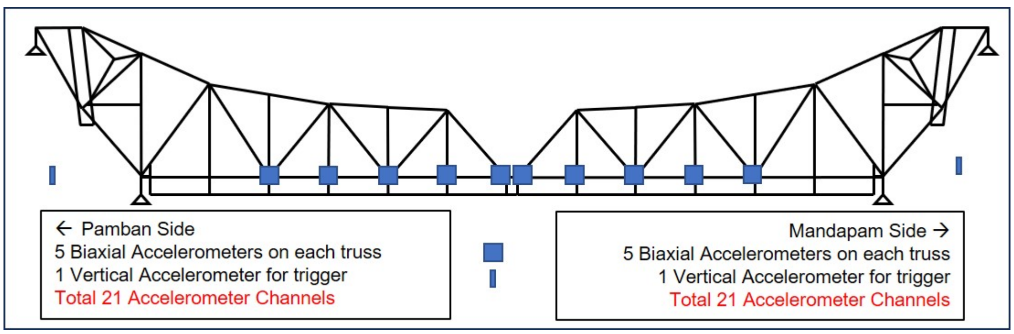


Figure 2. Position of accelerometers on the bridge.

tional conditions along the selected directions and node points of the bridge.

DETAILS OF THE BRIDGE AND INSTRUMENTATION SCHEME

The Pamban Bridge, a railway truss bridge connecting Rameswaram town on Pamban Island to mainland India, was inaugurated for traffic in February 1914. The majority of the rail bridge consists of conventional steel I girders supported on concrete piers, with the exception of a double-leaf bascule section located at the midpoint that can be elevated to allow passage for ships and barges.

The section being monitored is the double-leaf bascule section (Scherzer's span) of the Pamban Bridge, which comprises a total span length of 67.513 meters. There are four trusses in Scherzer's span, namely Pamban North, Pamban South, Mandapam North, and Mandapam South. A schematic illustration is provided in figure 1.

The bridge girder was instrumented with bi-axial accelerometers at selected node points to measure the response of the bridge during the train passage. Totally 20 accelerometers were instrumented on various bottom node points on the Mandapam leaf and Pamban leaf of the bridge in the north and the south direction as depicted in the figure 2.

PARAMETERS DERIVED FROM ACCELERATION TIME HISTORY

The motion of the bridge is inherently stochastic and non-stationary, owing to its dependence on a multitude of factors such as vehicle-bridge and rail-sleeper interactions and also environmental loads such as wind. In order to address this issue, several parameters have been proposed over the years that can represent the unique characteristics of acceleration time histories in terms of amplitude, time, and frequency [10]. These parameters, unlike the accelerogram, are stable and can be modeled mathematically. After careful examination of various established parameters, four key parameters are studied for the purpose of quantifying the characteristics of acceleration time history data. The following section outlines the method used for estimating each of these four parameters.

Root Mean Square Acceleration

The parameter that includes the effects of the amplitude and frequency content of an acceleration-time history motion is the root mean square acceleration (a_{rms}), defined as:

$$a_{rms} = \sqrt{\frac{1}{T_d}\int_0^{T_d}[a(t)]^2 dt} = \sqrt{\lambda_0}, \tag{1}$$

where T_d is the significant duration of the motion and λ_0 is the average intensity (or mean squared acceleration). Because the integral in equation (1) is not strongly influenced by large, high-frequency accelerations (which occur only over a very short period of time) and also it is influenced by the significant duration of the motion, the root mean square acceleration can be very useful for condition monitoring purposes. Its value, however, can be sensitive to the method used to define significant duration.

Arias Intensity

A parameter closely related to the root mean square acceleration is the Arias intensity, defined as:

$$I_a = \frac{\pi}{2g}\sqrt{\int_0^{\infty}[a(t)]^2 dt}. \tag{2}$$

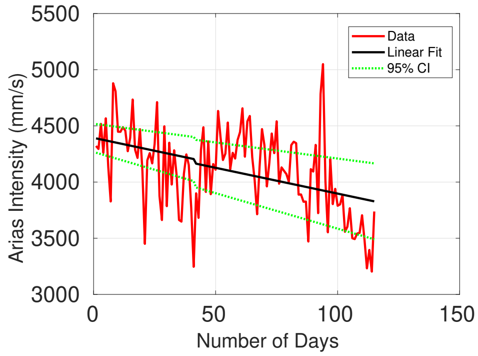
The arias intensity has units of velocity and is usually expressed in meters per second. Since it is obtained by integration over the entire duration rather than over the significant duration, its value is independent of the method used to define the significant duration.

Characteristic Intensity

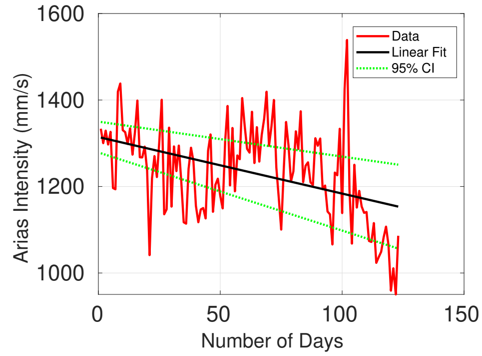
The characteristic intensity is defined as:

$$I_c = a_{rms}^{1.5} T_d^{0.5}, \tag{3}$$

is related linearly to an index of structural damage due to maximum deformations and absorbed hysteresis energy [11].



(a) X-direction



(b) Y-direction

Figure 3. Temporal variation of the Arias intensity (March-July 2022) in the (a) X-direction and (b) Y-direction.

Cumulative Absolute Velocity

The cumulative absolute velocity (CAV) is simply the area under the absolute accelerogram:

$$CAV = \int_0^{T_d} |a(t)| dt. \tag{4}$$

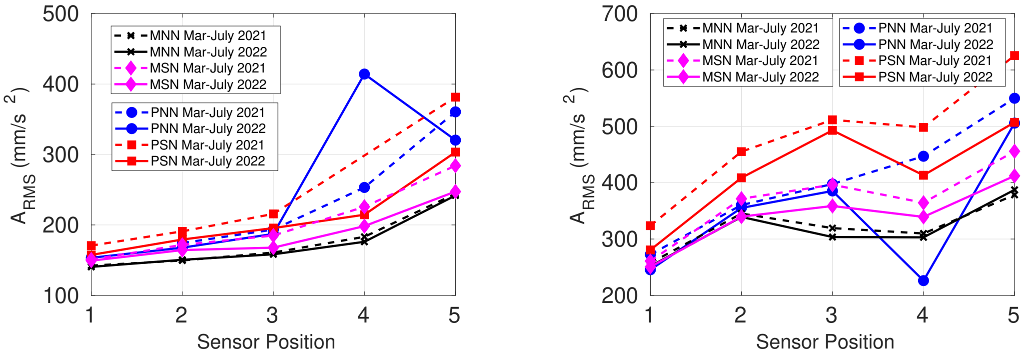
RESULTS AND DISCUSSIONS

In this study, bi-axial accelerometers have been installed at specific bottom node points on the bascule section of the Pamban bridge to obtain temporal variations in each parameter for every node point. The study aims to investigate the continuous changes in each parameter over an identical duration between March and July of 2021 and 2022, spanning a total of 136 days for each observation period. These periods encompassed more than 1000 train passes, providing a robust data set for analysis. Meanwhile, the bridge underwent retrofitting during the intervening period.

For each train pass, the above parameters are computed. Then, for each day, the mean value of the parameter for that day is computed, and the plots similar to that depicted in figure 3 are constructed for the observed period. A linear degree best-fit line and 95% confidence intervals are produced from the plots of each parameter (as shown in the plots with a solid line representing a linear fit and a dotted line portraying the confidence interval line).

If the product of the slope of the 95% confidence interval lines is negative, it indicates that there is no trend in the observed parameter. All four parameters studied here exhibited a trend indicating steady deterioration occurring due to corrosion. The steady deterioration is due to the geographic location of the bridge, which exposes it to one of the most (arguably the second) corrosive environments on the earth.

However, the value of the slope as a function of the location of the sensor did not reveal any trend. Also, the value of the slope before and after retrofitting did not show any statistically significant difference or pattern, as the cause for the rate of deterioration did not change. Hence, an alternative parameter that would reflect the changes consistently



(a) X-direction (b) Y-direction

Figure 4. Intercept plots of the root mean square acceleration (A_{RMS}) in the (a) X-direction and (b) Y-direction for the bridge's four trusses.

is sought. Towards this, the intercept values of the linear fit are explored.

For the two analysis periods, the intercept values are plotted from a linear best-fit line obtained from continuous measurement of each parameter at different sensor positions as depicted in figures 4 through 7. The accelerometer located at sensor position 4 of the Pamban truss on the south leaf in the x direction was damaged during the observation period of March to July 2021 and hence was not included in any inference made in this paper.

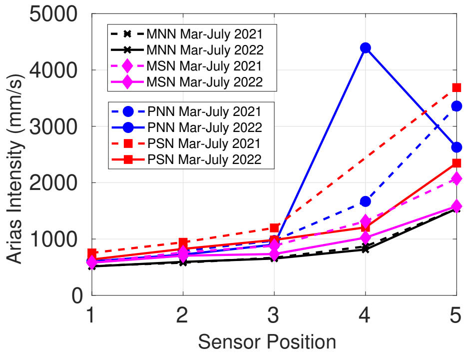
The plots shown in the study illustrate the comparison study for the bridge's four half-trusses (Pamban North, Pamban South, Mandapam North, and Mandapam South), with a dotted line representing the intercept values obtained during the observation period from March to July 2021 and a solid line portraying the intercept values obtained during the observation period from March to July 2022. In these plots, the y-direction represents the direction of the action of gravity, and the x-direction denotes the direction of the train movement.

For the three parameters studied, the figures 4 through 6 show that the intercept values for all sensor positions on the bridge decrease after retrofitting. However, for cumulative absolute velocity (see figure 7), the intercept values increase after retrofitting.

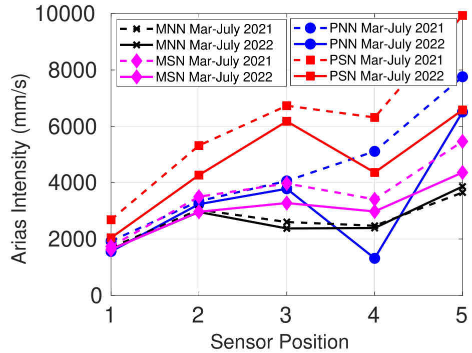
Moreover, during the observation period from March to July 2022, each sensor position follows a consistent pattern across all parameters, except for sensor position 4 of the Pamban truss on the north leaf. This deviation is evident in both the x and y directions for all parameters considered in this study. Consequently, it can be inferred that sensor position 4 of the Pamban truss on the north leaf exhibits an anomaly, likely indicating a structural fault.

CONCLUDING REMARKS

Through the application of the four parameters derived from acceleration time history, the identification of potential damage in railway truss bridges has been explored using on-field data obtained from instrumenting Scherzer's span of the Pamban bridge. The results obtained, with the data plots, reveal a discernible disparity in the bridge's response during the March to July 2022 period, as compared to the March to July 2021

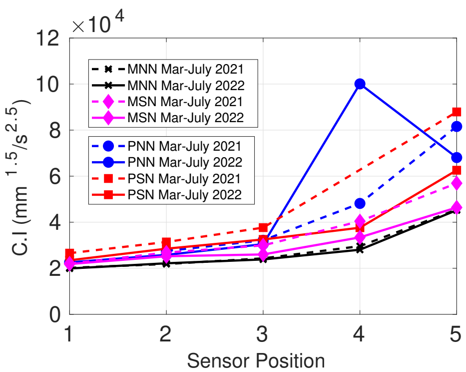


(a) X-direction

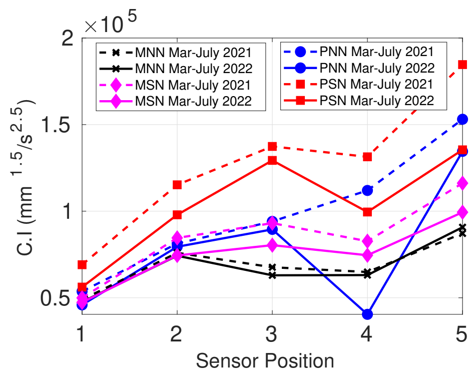


(b) Y-direction

Figure 5. Intercept plots of the arias intensity in the (a) X-direction and (b) Y-direction for the bridge's four trusses.

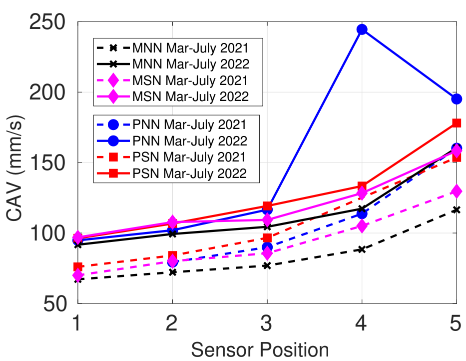


(a) X-direction

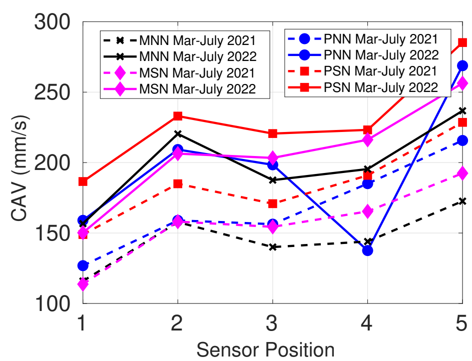


(b) Y-direction

Figure 6. Intercept plots of the characteristic intensity (C.I) in the (a) X-direction and (b) Y-direction for the bridge's four trusses.



(a) X-direction



(b) Y-direction

Figure 7. Intercept plots of the cumulative absolute velocity (CAV) in the (a) X-direction and (b) Y-direction for the bridge's four trusses.

time frame, particularly at the sensor position 4 of the Pamban truss on the north leaf. The proposed methodology is also sensitive to discern the changes due to retrofitting, as the value of the intercepts before and after retrofitting is significantly different.

Thus, the technique proposed for condition monitoring is effective in detecting any potential structural damages in railway truss bridges and is ideal for continuous monitoring without causing any disruption to operations.

ACKNOWLEDGMENT

The authors express their sincere gratitude to Southern Railways for sponsoring this project and use of the collected data for analysis.

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