On Condition Monitoring of a Corroding Steel Truss Bridge – A Case Study

U. SARAVANAN and KAIBALYA LENKA

ABSTRACT

A railway steel truss bridge connecting the mainland India with Rameswaram had corrosion issues. This bridge was continuously monitored from August 2020 through December 2022 to ensure the serviceability of the bridge. This paper summarizes the technical learning from the monitoring. The truss bridge was heavily instrumented – 84 out of 92 members were instrumented with linear electrical strain gauges, 20 of the 52 nodes had biaxial accelerometers, and 10 resistance-based temperature sensors. For each train pass, the collected data was analyzed to estimate the axle loads of the train, cross-sectional areas of the members, and certain other parameters from the acceleration time history. While the observed strains could be matched excellently with the strains estimated by simple truss analysis in 70 members, the computed accelerations were the order of magnitude lower for all the acceleration measurements. The displacement profile obtained by double integrating the acceleration with appropriate filtering, as suggested in the literature, did not agree with the predicted displacement even qualitatively. As one would expect, even though there was a steady deterioration of the structure, the commonly used dynamic response parameters – the natural frequency and mode shapes – did not reflect the change statistically. The extreme strains in most of the members showed a steady increase or decrease in values. But the truss being statically determinate, the strains could not capture the loss in the area of members due to corrosion at locations other than where they were located. However, certain frequency and time domain parameters of the acceleration were able to capture the steady deterioration of the truss bridge. Thus, in the case of statically determinate truss bridges, data-driven approaches seem to perform better than physics-based approaches in determining the changes occurring in the bridge.

INTRODUCTION

Railway bridges are the expensive and key elements of the railway infrastructure system. These structures are susceptible to various risks, such as natural disasters, weath-

---

Umakanthan Saravanan, Professor, Email: saran@iitm.ac.in; Kaibalya Lenka, PhD Student, Email: kaibalya45@gmail.com. Structural Engineering Laboratory, Civil Engineering Department,Indian Insti- tute of Technology Madras, Chennai, India.

ering, and corrosion which could result in the reduction of their design life or different levels of anomaly. These anomalies would range from global level changes such as bearing seizure and member stiffness loss to localized anomalies such as connection deterioration. Deterioration of these bridges over time leads to concerns regarding their safety and serviceability. In a study of 729 bridges that failed during 1977-2017 in India, 138 were steel bridges [1]. [2] studied the various types of bridge failures in the US and their causes. Based on this study, steel bridges were found to be most prone to failure. The data showed that about 40% of the failed bridges were truss bridges. The safety and maintenance of these truss bridges must be accorded paramount importance, and therefore, an effective condition monitoring strategy must be developed to quantify their present condition so that repair or strengthening or rehabilitation, or rebuilding can be done.

Condition monitoring assists and informs operators about the fitness of a bridge for its safe operation [3]. Condition monitoring provides information about the structural condition of the bridge using various sensors [4]. Using these sensors, kinematic responses such as displacements, strains, and/or accelerations at different locations of the bridge under normal operating conditions are estimated which are further used to determine different parameters such as boundary conditions, material and geometrical properties, system connectivity, which helps in the estimation of stiffness of the structure. The time-dependent risk in the operation of the bridge can be estimated if the time-dependent material strength is also available.

The main objective of this paper is to discuss the technical learning from the field implementation of a condition monitoring system on a century-old railway truss bridge. The instrumentation scheme and the challenges faced are also discussed.

BRIDGE DETAILS AND THE NECESSITY FOR ITS CONDITION MONITORING

Pamban bridge (Figure 1a) is a steel railway truss bridge that connects the town of Rameswaram on Pamban Island to mainland India. The Pamban railway bridge was opened for traffic in 1914. It was India's first sea bridge and was the longest sea bridge in India until the opening of the Bandra-Worli sea link in 2010. The rail bridge is, for the most part, has conventional I girders resting on concrete piers but has a double-leaf bascule section midway, which can be raised to let ships and barges pass through. This bascule-type section was designed by a German engineer named Scherzer, which is essentially counterbalanced, and the opening/closing operation is achieved by pivoting about a horizontal axis. The Scherzer superstructure, in particular, rolls over the track girder. There are two leaves (the one closer to the Pamban station is referred to as the Pamban side truss, and the other closer to the Mandapam station is referred to as the Mandapam side truss) comprising the total Scherzer superstructure. The center lock (Figure 1b) is of rigid jaw and tongue type and provides the means for shear transfer between two leaves without moment transfer.

Until 1980, the truss bridge was the only connecting link between the island and mainland India. The truss bridge was used for more than a century, within which it was retrofitted twice - once due to gauge conversion and the other due to cyclone-induced

(a) Pamban Bridge (b) Center lock

Figure 1. Pamban bridge and the center lock.

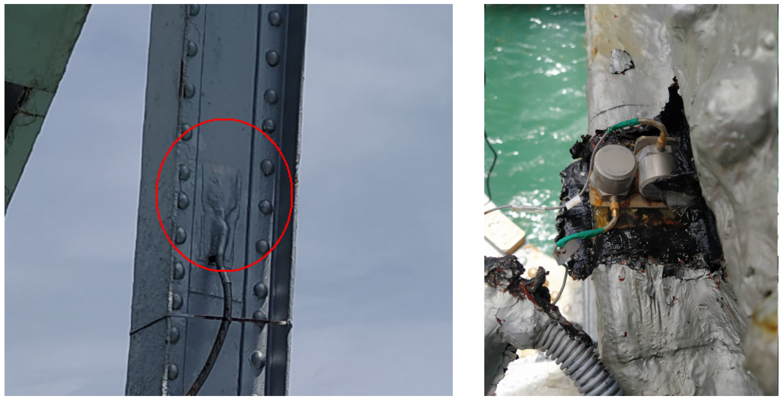
(a) Top chord (b) Diagonal member

Figure 2. Corroded section of the axial members of the Pamban truss bridge.

damage. Because of its location, which is windy and highly corrosive, arguably the second most corrosive environment on earth, the truss bridge needed routine maintenance and inspection for safety. Continuous condition monitoring of the Scherzer span of the Pamban bridge started on August 17, 2020, and was continued till December 14, 2022. The need for continuous monitoring was because of severe deterioration due to corrosion and the requirement to operationalize the bridge till the new bridge is constructed. Some of the corroded truss members are shown in Figure 2.

INSTRUMENTATION SCHEME

The truss bridge was instrumented with linear electrical strain gauges, resistance-based temperature sensors, and biaxial accelerometers (Figure 3). Totally 84 out of 92 axial members were instrumented with linear electrical strain gauges close to the mid-section and centroid of the cross-section. Figure 4 shows the numbering of the members of the truss instrumented with strain gauges. 20 out of 52 node points were



(a) Electrical strain gauge (b) Biaxial accelerometer

Figure 3. Instrumented strain gauge and accelerometer.

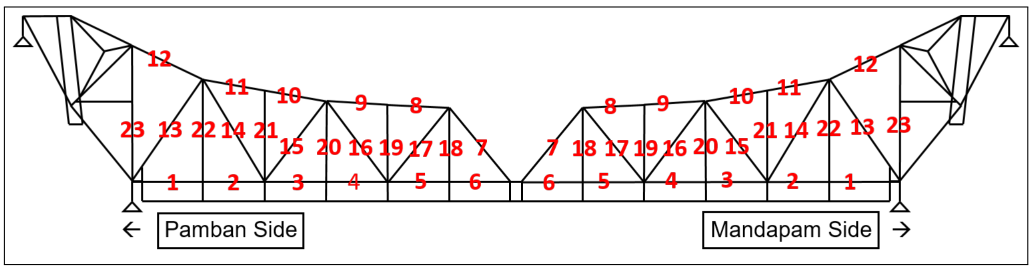


Figure 4. Position of strain gauges on the members of the north side of the truss bridge.

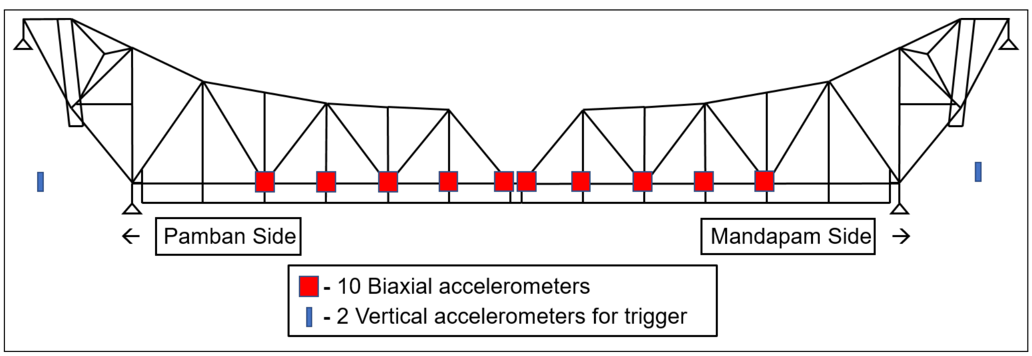
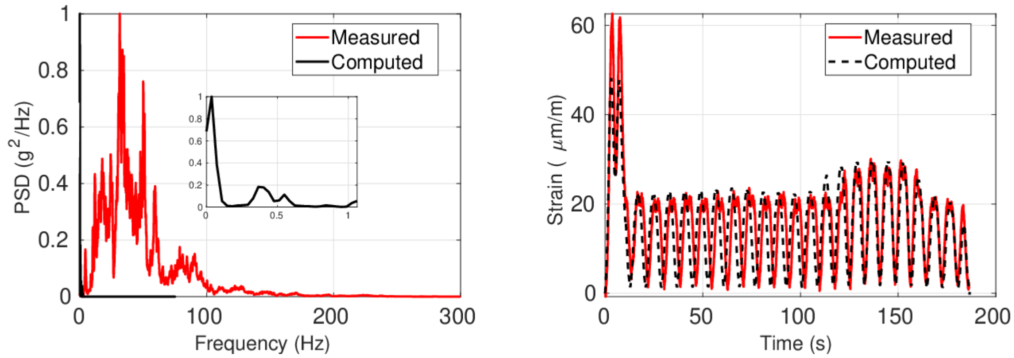


Figure 5. Position of accelerometers at the nodes of the north side of the truss bridge.

instrumented with biaxial accelerometers, as shown in Figure.5. 10 resistance-based temperature sensors were instrumented to measure the temperature variation.

DATA COLLECTION AND PROCESSING

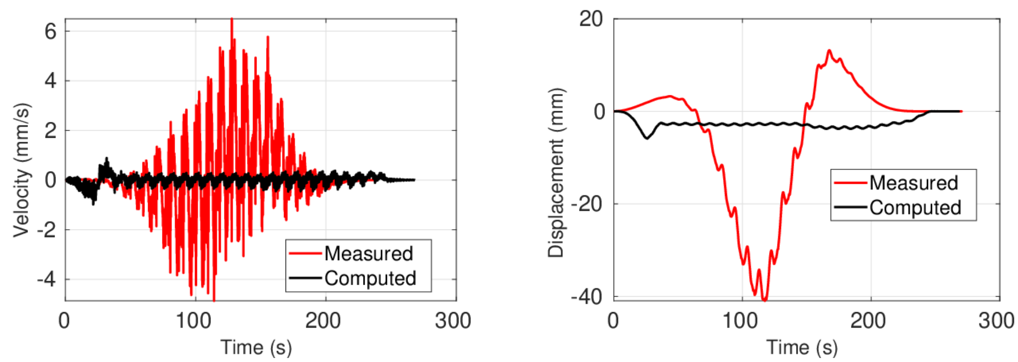
A trigger-based recording was being used for the truss bridge in which the first accelerometer instrumented on the rail-track girder just before each leaf, acted as a trigger in which acceleration readings exceeding a certain predefined limit, 0.5g, was considered as a train pass, and the readings were recorded. When a train traversed the truss bridge, the strain and acceleration responses were recorded for a period of 8 minutes.



(a) Power spectral Density in the vertical direction

(b) Strain in member 22 of the Mandapam north truss

Figure 6. Comparison of the theoretical and measured (a) acceleration frequency content, (b) strains in a member.



(a) Velocity

(b) Displacement

Figure 7. Comparison of the theoretical and field estimated (a) Velocity, (b) Displacement.

Strain and acceleration responses from the sensors were recorded at a frequency of 100 Hz and 600 Hz, respectively. Analog signals of the sensors were converted and stored as digital recordings in a binary file at the bridge site. These readings were transferred to the cloud from where the data was downloaded and analyzed every hour. The binary files were converted to ASCII file and further processed by a custom code.

ANALYSIS OF RESPONSES

Data measured by accelerometers include white noise, as well as colored noise due to the addition of frequencies from vehicle bridge interaction, sleeper spacing, and velocity of the train. Even though the instrumented accelerometer was designed to capture low frequencies, there was a mismatch in the frequency content between the theoretically computed and field-measured acceleration (see Figure. 6a). However, there was a good agreement in the strain time history, as can be seen from Figure 6b.

In theory, the displacement of a bridge can be calculated from the double integration of the acceleration. To avoid overestimation of displacement due to constant error in acceleration, detrending was performed before integration. A Tukey window filter was applied to suppress noise below and above specified cut-off frequencies. The filtered acceleration data was then integrated to obtain velocity data, which was filtered again before integration to obtain displacement data. However, there was a large error between the theoretically predicted and field-estimated velocity and displacement (see Figure 7).

Further, for each of the train pass and the 40 acceleration time histories, the following 14 parameters were computed: central frequency, predominant frequency with respect to the Fourier amplitude spectra, peak acceleration, peak velocity, peak displacement, spectral parameter, significant duration of acceleration time series, root mean square acceleration, cumulative absolute velocity, ratio of peak velocity and peak acceleration, arias intensity, characteristic intensity, curvature of the power spectral density, and peaks of the power spectral density.

Algorithms for determining the direction of travel of the train, train configuration (no of wagons), the velocity and acceleration, and axle loads were used, and these algorithms were calibrated using the 8 train passes on October 4, 2020, and 10 train passes on October 8, 2020. The cross-sectional areas of the members were determined from the strain measurements through a 1 step iterative technique. Using the estimated configuration of the train, axle loads, and the geometric properties of the truss, dynamic analysis was performed. The theoretically computed strain, acceleration, velocity, and displacement are then compared with the field-measured responses. The root mean square error between the theoretical estimate and the measured value was also computed and saved. The extreme values of the strain, acceleration, velocity, and displacement for each sensor were saved. The mean of the first 12 acceleration parameters over a day's train pass, a damage metric based on the comparison of the curvature of the power spectral density between the current and the one obtained on October 8, 2020, was determined, and the first 5 predominant peaks of the power spectral density were saved.

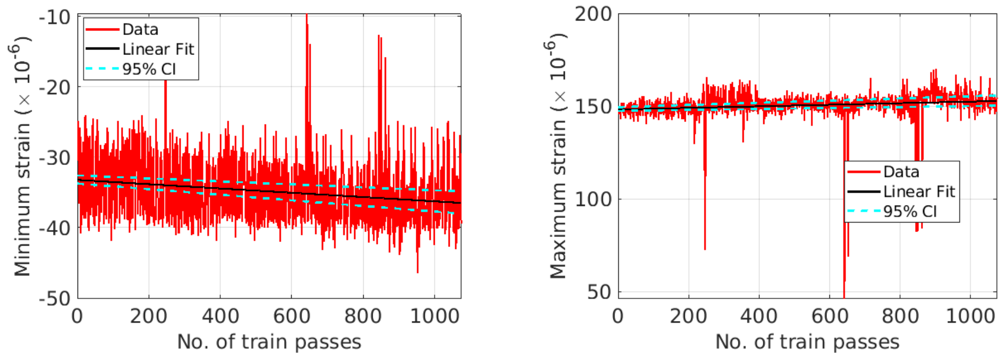
The above analysis was performed every day. Reports were generated where the predicted and measured values were compared for all the sensors, and relevant reduced data was found and archived.

The trend plots of the extreme values of the sensed data and its parametrization were generated every month. The slope of the linear trend line for the data, along with the 95 percent confidence interval, was determined and saved (see Figure 8). In cases where the confidence interval for the slope of the trend line encompasses zero, it was inferred that the variation of the parameter with time is not significant. Apart from looking at the trend plots to get a qualitative feel, quantitative analysis was done using the determined slope of the trend line, which indicates the changes occurring in the structure.

SETTING UP OF BRIDGE ALARMS

At the bridge location, an anemometer and strain gauges were used to generate alarms when the reading in those sensors crossed the predefined threshold. There were two situations when the alarms were initiated. One was when the wind velocity crossed 55 km/hr, and the other was when the strain reading in any one strain gauge crossed 538 microstrains on the compression side or 710 microstrains on the tension side at any time.

A second set of voice and SMS message alarms were given when any incremental



(a) Minimum strain in member 5 of the Mandapam north truss

(b) Maximum strain in member 20 of the Mandapam south truss

Figure 8. Variation of (a) minimum strain in member 5 of the Mandapam north truss (b) maximum strain in member 20 of the Mandapam south truss with train passes during January 2021 to July 2021 (see Figure 4 for the member identifiers).

strain during the passage of the train crossed 538 microstrains in compression or 710 microstrains in tension.

It was observed that the electrical strain measurements drifted from zero position to certain hundreds of microstrains due to humidity variations, temperature changes, and electrical drifts. So every 2-3 hours, the sensor channels were restarted. Despite these measures, during rains and inclement weather conditions, the first and second sets of alarms did not coincide many a time. There were more alarms at the site due to the drifting of the strain readings.

CHALLENGES DURING THE CONTINUOUS MONITORING

Some of the challenges faced during the continuous condition monitoring of the truss bridge are as follows:

- The strain measurements have a high signal-to-noise ratio. However, in open-to-air and harsh environments, despite taking adequate precautions while installing, some 10 percent of the gauges had abnormal drifts. This required restarting the data acquisition job, which could not be automated for a variety of logical contradictions.

- In statically determinate structures, strain measurements provide information only about the section where it was installed. This was reinforced in the current study. Therefore, acceleration measurements were more robust to indicate damage. But accelerometers have a low signal-to-noise ratio, due to which inferring the damage requires a significant amount of signal processing.

- The predicted displacement time history did not agree with that computed from the acceleration time history by appropriate filtering and double integration. Hence, the average member stiffness could not be obtained reliably. For a member with an irregular cross-section, determining the average stiffness of the member is required to ensure the serviceability of the bridge.

CONCLUDING REMARKS

The continuous condition monitoring of the Pamban bridge, which was a unique type of bridge located in the second most corrosive environment on earth, was carried out for a period of more than 30 months. From the responses recorded using strain gauges and accelerometers, the trend line of different parameters estimated from the strain and acceleration responses was plotted and analyzed to detect any changes in the current state of the truss bridge.

It was observed that the field observed strains matched well with those computed from dynamic analysis for 70 axial members. The linear trend of the extreme value of the strain responses either increased or decreased. As the strain gauges were instrumented at the mid-section of the axial members, the actual corrosion could be captured at that particular section but not at other locations. In the case of acceleration responses, the analytically computed values were found to be of much lower magnitude than the field-measured ones. The displacement profile obtained by double integrating the acceleration with appropriate filtering, as suggested in the literature, also did not agree with the predicted displacement even qualitatively. As one would expect, even though there was a steady state deterioration of the structure, the commonly used dynamic response parameters – the natural frequency and mode shapes – did not reflect the change statistically. However, certain frequency and time domain parameters of the acceleration were able to capture the steady deterioration of the truss bridge.

Thus it is concluded from the study that the data-driven approaches seem to perform better than physics-based approaches in determining the changes occurring in a statically determinate truss bridge.

ACKNOWLEDGMENT

The authors thank Southern Railways for funding this work and allowing the utilization of the collected data for analysis.

REFERENCES

1. Garg, R. K., S. Chandra, and A. Kumar. 2022. "Analysis of bridge failures in India from 1977 to 2017," *Structure and Infrastructure Engineering*, 18(3):295–312, ISSN 17448980, doi:10.1080/15732479.2020.1832539.
2. Lee, G. C., S. B. Mohan, C. Huang, and B. N. Fard. 2013. "A study of US bridge failures (1980–2012)," Tech. rep.
3. Brownjohn, J. M. 2007. "Structural health monitoring of civil infrastructure," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 365(1851):589–622, ISSN 1364503X, doi:10.1098/rsta.2006.1925.
4. DeWolf, J. T., R. G. Lauzon, and M. P. Culmo. 2002. "Monitoring bridge performance," *Structural Health Monitoring*, 1(2):129–138, ISSN 14759217, doi:10.1106/147592102027111.