Abstract

Fatigue is one of the most critical problems for steel bridges as well as for any steel structures that needs to be considered during design and operation. Fatigue cracking is developed at certain steel bridge details due to a direct result of the loads (load-induced fatigue) or a deformation that is not accounted for during design (distortion-induced fatigue). The details that are prone to load-induced fatigue can be identified using the detail categories presented in the American Association of State Highway Officials (AASHTO) Load and Resistance Factor Design (LRFD) Bridge Design Specifications Table 6.6.1.2.3-1 [1]. However, the secondary and/or distortion-induced stresses that are not typically used in design are the most common reasons for fatigue cracking developed in bridges.

An acoustic emission (AE) monitoring system with strain gages is one of the most effective technologies for fatigue event detection (i.e., crack initiation or crack growth monitoring). AE has been successfully implemented in the field and evaluated for continuous monitoring of fatigue-sensitive details. At this time, AE is the only technology that is capable of real-time monitoring of fatigue events and providing data for damage location detection. In addition to the AE sensors, strain gauges are required to evaluate the stress state to calculate remaining fatigue life, and to support AE data analysis by developing a load matrix.

AE technology can be implemented for global, semi-global, or local monitoring. Global monitoring is to identify potential source locations for planning or asset management purposes. Semi-global monitoring is implemented to identify individual source locations to assess, evaluate, and rank. The ranking is based on the source characteristics and number of emissions. The ranking system is used for planning detailed investigations through local monitoring. The local monitoring is implemented to identify the source location and to characterize the AE events. The sensor array for local monitoring is designed based on (a) the classification of the detail to be monitored, (b) prior experience with similar details, (c) inspection and maintenance records, (d) an attenuation survey, and (e) finite element analysis or a combination thereof.

Even though AE provides many capabilities with regards to fatigue monitoring, many implementation challenges are exist. The majority of the challenges are associated with noise elimination, AE signal analysis, and interpretation of the results. This article describes AE implementation for monitoring a fatigue sensitive detail (local monitoring) and use of data analysis techniques such as cluster analysis and non-linear mapping (NLM) to identify the relationship of each cluster to the characteristics of crack opening signals, background noise, and structural resonance. Thus, eliminating a majority of challenges listed in literature with regards to noise elimination, AE signal analysis, and interpretation of the results.
The bridge (S16 of 11015) that carries I-94 EB over Puettz Road, located in Stevensville, Michigan was selected for monitoring system implementation and performance evaluation. The bridge consists of category C fatigue-sensitive partial depth diaphragm details and category E fatigue-sensitive welded cover plate detail [2]. Span 3 of the bridge with staggered diaphragms and a 54.5° skew was selected for monitoring system installation. A 3D finite element (FE) model of the bridge was developed, and a submodeling concept was implemented to calculate hot spot stresses using the quadratic extrapolation equation recommended by the International Institute of Welding [3]. The permanent stresses developed at the weld toe were calculated using deck dead load as a construction load. The fatigue truck given in AASHTO LRFD [1] is a notional truck. Hence, Michigan legal load configurations were used to evaluate the stress state at the weld toe, representing more realistic loads on the bridge. The web gap detail that undergoes the highest stress range at a greater frequency was selected for instrumentation. Then, four AE sensors were mounted in a rectangular array encompassing the weld at the web gap.

The data collected from the bridge was examined directly to identify any significant similar AE activity formations using non-linear mapping (NLM) and clustering analysis available in ICEPak™ [4]. NLM presents multi-dimensional data in a 2-D space and preserves the inter-data distance and directional information. If the data in the multi-dimensional space are very close to one another, the corresponding NLM should also render their closeness to one another but not their orientation. ICEPak™ has the ability to perform NLM in time, power, phase, cepstral, and auto-correlation domains. The data set used for NLM and clustering analysis included AE signals that were above the set threshold of 45dB. NLM was performed using one feature domain at a time to visually detect significant naturally forming concentrations. Out of the 5 domains, the spectral power domain produced three significant concentrations as shown in Figure 1a. Clustering was performed using the same spectral power domain features, and produced three significant concentrations as presented in Figure 1b. The clusters are aligned with the visual presentation of the NLM result.

The individual data clusters were exported and labeled as [cl1], [cl2], and [cl3]. Then, each cluster was used to train a three-class classifier. Four statistical classifiers (i.e., linear discriminant, K-nearest neighbor, empirical Bayesian, and minimum distance classifiers) and a neural network classifier were tested. The design of the classifiers included optimizing the feature sets. The design procedure included separating available data into two groups; one was used to train the classifiers and the other to test the performance of the classifiers. The
Linear discriminant classification results are shown in Figure 2. As an example, [c11] had a total of 7,915 data points. This set was separated into two groups of 3,957 and 3,958 data points for training and testing, respectively. When the linear discriminant three-class classifier was trained with 3,957 data points, the data was classified into three classes with rejections. As shown in Figure 2, classes 1, 2, and 3 contain 3777, 2, and 0 data points with 178 rejections. The classification rate is 95.45%. In other words, 95.45% of the data in [c11] falls into class 1 (i.e., 3,777/3,957 × 100). A similar process was employed for [c2] and [c3] data sets, and yielded classification rates of 94.99% and 95.95%, respectively. When all three data sets were considered, the linear discriminant three-class classifier yielded a weighted average classification rate of 95.43% for training (Figure 2). Overall, all the classification methods yielded very high classification rates for training as well as for testing.

<table>
<thead>
<tr>
<th>Linear Discriminant Classification Results</th>
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<tr>
<td>Class</td>
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<td>c11.cxf</td>
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<td>c12.cxf</td>
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<td>c13.cxf</td>
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<td>Training:</td>
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| Class  | 1     | 2     | 3     | Reject | Total | Percent |
| c11.cxf | 3822  | 2      | 0   | 134   | 3958 | 96.66% |
| c12.cxf | 2     | 995    | 4   | 57    | 1058 | 94.05% |
| c13.cxf | 0     | 7      | 714 | 20    | 742  | 96.56% |
| Testing: | 96.05% |

Figure 2. Linear discriminant classification results

Generally, AE signals generated through a properly conducted pencil lead brake (PLB) contains characteristics similar to that of an AE signal emanated from a fatigue event (crack initiation or opening). Hence, a set of PLB data was tested against this three-class classifier with a rejection option. The rejection option is triggered when an incoming signal cannot be classified with an acceptable level of confidence. The PLB data file contained 100 data points. The PLB data fell into class 1 and 2 but not class 3, with a lot of rejections. Nine data points were classified as class 1 and 8 as class 2. None was classified as class 3. There were 83 rejections. Then a waveform visualization and real time classification capabilities were used to identify the type of waveforms in the three classifications (i.e., in class 1, 2, and 3) along with the rejected ones. The PRISM™ program was used to analyze the waveform characteristics of signals in each class and the rejected group, and yielded the following observations:

- The waveforms classified as class 1 usually have very fast rise times, relatively quiet pre-trigger portion, and a broad spectral content spanning from 100 to 400 kHz.
- The waveforms classified as class 2 usually have very fast rise times; however, the pre-trigger portion may show some small structure, and the main pocket contains multiple ringing peaks. The spectral content mainly centers around 150 kHz with very little or nothing above 250 kHz, and nothing below 100 kHz.
- The waveforms classified as class 3 usually have a slower rise time, and the spectral content is mainly located below 100 kHz and centered around 50 to 75 kHz. Moreover, there is absolutely nothing above 200 kHz.
- The waveforms classified as “rejected” are mostly associated with over-saturated clipped waveforms, and some have slow changing, somewhat smooth, waveform centered around 50 kHz.

The observations of sample data analysis show that both class 1 and class 2 waveforms are more structured with a faster rise time at the beginning of the waveform. Thus, they are likely associated with the AE signals from the crack opening. Class 3 waveforms are more slowly
rising, and their spectral content is more in line with common background transient noise. The rejected waveforms are more likely due to saturation and clipping of the signal, and the non-saturated ones, centered around 50 kHz are more likely results from structural resonance. Since class 1 and 2 waveform characteristics closely represented AE signals from the crack opening, the source location plots were analyzed. During the inspection of this specific bridge there were no active sources documented within the zone of interest. Therefore, further analysis was not performed. When AE sources are located within the zone of interest, the following steps can be followed to validate the presence of potential cracking or crack opening events:

- Check the waveforms to evaluate the resemblance of signals to the crack opening signals.
- Observe the source location plots for the formation of data clusters and the cluster growth direction.
- Correlate AE events with the strain data from the strain gage that is mounted to develop the load matrix. If AE events occur during increase in strain, there is a potential for the presence of a crack opening event.
- If the observations of the above steps require additional investigations, make a field visit and perform NDE to confirm the observations.
- If NDE fails to identify cracking, adjust signal thresholds and gains to calibrate the monitoring system for the specific detail.

Specific conclusions and recommendations derived from the monitoring and analysis are the following:

- Even though a large number of AE data sets were recorded during monitoring, data analysis and interpretation process followed during this study confirmed the nonexistence of the fatigue cracks at the monitored detail.
- With a large volume of data generated from operating traffic, tools for identifying and separating fracture events from traffic and ambient noise with a high recognition rate are provided; and the associated theoretical basis is presented.
- The signal types belonging to each class can be identified by inspecting the waveform features. Therefore, the data analysis capabilities presented during this study provides a sound basis for the use of AE for monitoring the performance of fatigue-sensitive details and elements or sections with retrofits.

References