THE DEVELOPMENT OF AN IN-PROCESS MONITORING SOLUTION FOR INERTIA FRICTION WELDING: AN INVESTIGATION INTO FEATURE DESCRIPTORS

*D.A. Hartman, V.R. Davé, and M.J. Cola†

ABSTRACT

The development of a novel sensing method coupled with a pattern recognition system is presented as a non-destructive evaluation (NDE) technique for inertia friction welding. The complex nature of solid-state welding processes, and, in particular, inertia friction welding, prevents a system from incorporating a simple model (e.g., upset) to separate acceptable from unacceptable welds when subtle process variations occur. This work presents the application of an array of non-contact, acoustic emission sensors for determining bond integrity. The sensor data is explored through a variety of feature descriptors (RMS, energy, attack and decay, and power spectrum) and, in some cases, fused with the machine data (speed, pressure, and upset) in an attempt to develop a robust, in-situ NDE technique. The results are presented for bar-to-bar inertia friction welding of copper to stainless steel which exhibits only marginal weldability and, therefore, is ideally suited for validating the capabilities of this new sensing technique.

INTRODUCTION

Although friction welding is a relatively robust process, highly performance-critical or man-rated joints require additional scrutiny. Examples of such critical friction welds abound in aerospace applications, e.g., shafts, discs, hubs, fan and helicopter blades, and rotors. In such environments, the total number of parts made is generally low. Therefore, destructive evaluation is a very costly proposition, not to mention that commercially available post-process, non-destructive evaluation (NDE) techniques are not able to detect all of the fault conditions of possible concern. Hence, an in-process approach is invaluable in precision, small lot manufacturing of mission- or performance-critical hardware.

For large lot manufacturing environments, the total number of parts can reach upward of tens to hundreds per hour. Environments such as these perform routine destructive evaluation (commonly referred to as "book-ending") to ensure that the process is performing under control. Unfortunately, this method of inspection is not always indicative of the integrity of bonds made before (or after) the part that is currently under scrutiny. Furthermore, once a flaw is detected by destructive evaluation all parts produced previously must be rejected (or reworked) regardless of quality. This method of quality inspection reduces productivity and increases

*This work was conducted at Los Alamos National Laboratory, which is operated by the University of California for the United States Department of Energy under Contract Number W-7405-ENG-36.

†D.A. Hartman is a technical staff member in the Manufacturing and Process Science and Technology Group in the Nuclear Materials Technology Division of Los Alamos National Laboratory, V.R. Davé is the Group Leader for the Manufacturing and Process Science and Technology Group in the Nuclear Materials Technology Division of Los Alamos National Laboratory, and M.J. Cola is a Deputy Group Leader for the Weapons Component Technology Group in the Nuclear Materials Technology Division of Los Alamos National Laboratory, P.O. Box 1663, Mail Stop E506, Los Alamos, New Mexico 87545. E-mail: hartman@lanl.gov, vivek@lanl.gov, cola@lanl.gov.

waste and cost while never guaranteeing that each and every bond is adequate. An in-process approach can alleviate this burden by providing a consistent, thorough, and real-time response to part quality and, thereby, leaving only suspect parts for further post-process investigation by traditional destructive or non-destructive methods.

This paper presents the development of an in-process monitoring solution for inertia friction welding (IFRW). An Experimental Setup Section briefly describes the experimental approach. A Process Description Section presents the in-process data that was collected. An overview of the four feature descriptors that were used to explore the process data is presented in the Feature Analysis Section. A Results and Discussion Section highlights the relevant results of this work. Finally, a Conclusions Section summarizes our findings and lists the benefits of employing an in-process monitoring solution for large- and small-scale manufacturing environments.

EXPERIMENTAL SETUP

The focus in this preliminary investigation was to search for and identify features within the acoustic energy and/or machine data that are indicative of bond quality. Bar-to-bar inertia friction welding of 1-inch diameter, oxygen-free, high-conductivity copper bar to 0.5-inch diameter, annealed Type 304L stainless steel was used in this proof-of-concept study. This material combination exhibits only marginal weldability and, therefore, was ideally suited for validating the capabilities of this new sensing technique. All welding was conducted using a MTI Model 90B inertia friction welding system. The welding parameter selection was based upon work by Bell, et al. (Ref. 1) but altered slightly to accommodate differences in available inertial mass.

Prior to welding, all copper specimens were machined and stored for five weeks at ambient temperature and pressure. In order to remove surface oxidation that might have developed during storage, selected copper specimens were machined immediately before welding while bathed in isopropyl alcohol. Others were welded as is. In all cases, the stainless steel was rotated during the weld cycle while the copper remained fixed.

A non-contact array of microphones surrounds the weld joint and collects the rapid release of energy (i.e., sound pressure) due to the mechanical, thermal, and metallurgical phenomenon occurring during the weld cycle. The acoustic transducers used in this research are off-the-shelf electret condenser microphones that were sampled at 40 kHz per channel. The welding system provided process data (speed, pressure, and upset) that was sampled at 100 Hz per channel.

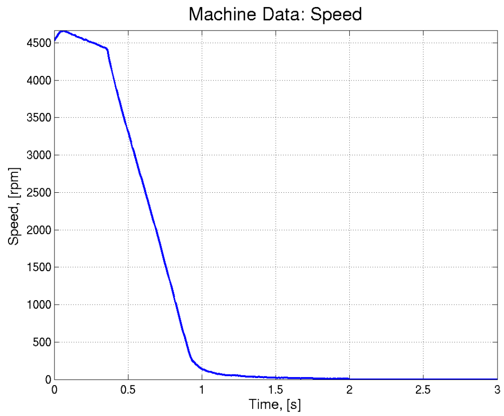
A semi-quantitative evaluation of each joint was performed using unguided bend testing. As-welded, full-size specimens were tested. Image analysis techniques were used to determine the percent of bonded area after fracturing each specimen. A presentation of the experimental setup and the sensor can be found in Ref. 2.

PROCESS DESCRIPTION

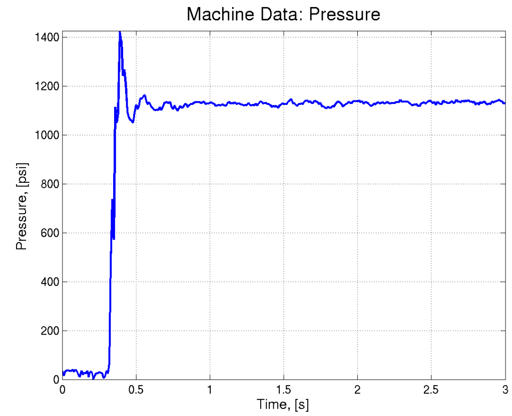
The process description for this work was captured with machine process data (speed, pressure, and upset) and acoustic energy[1]. Representative plots for speed, pressure, upset, and acoustic energy are illustrated in

[1]A curious feature within all of the Cu-SS acoustic signatures is the presence of a second burst of acoustic energy soon after the initial weld burst. This burst also coincides with a sharp drop in the speed to zero. One plausible explanation for this phenomenon

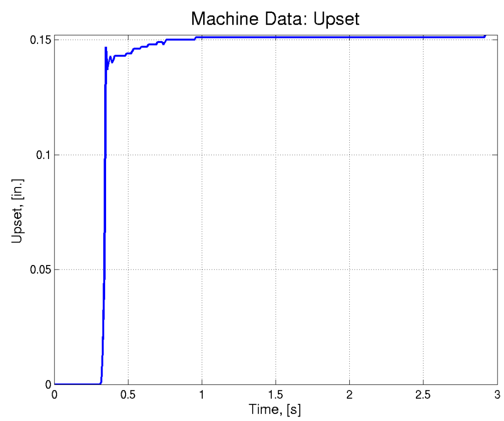
Figure 1. This data represents the process inputs for an in-process monitoring system, while the process output (i.e., quality metric) is bond integrity.



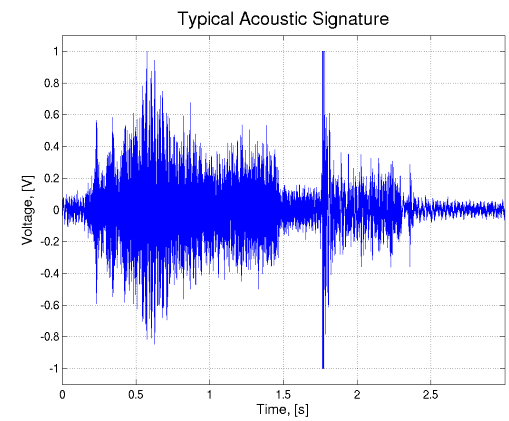
(a)



(b)



(c)



(d)

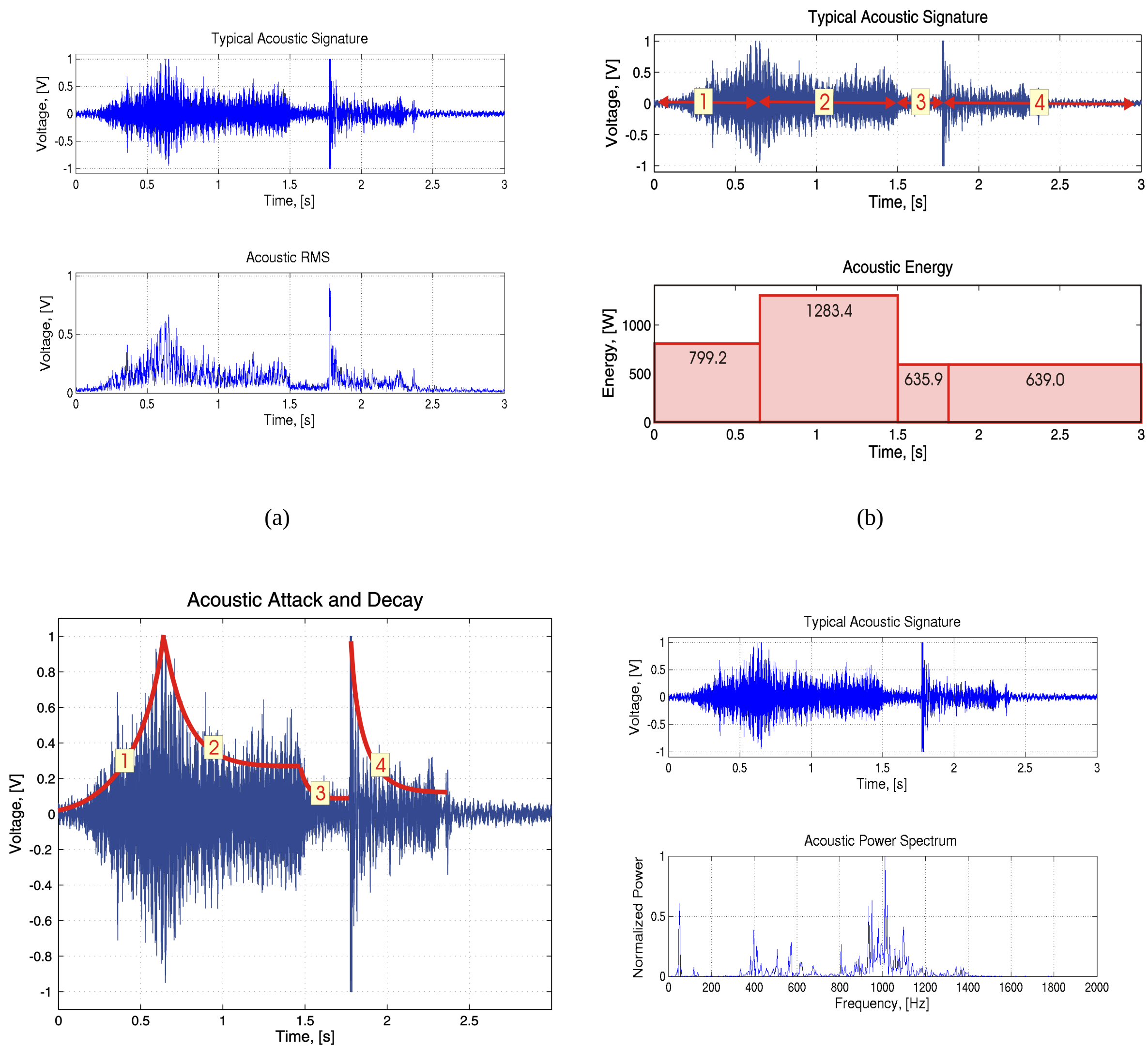
Figure 1: Representative plots for machine data and acoustic energy.

FEATURE ANALYSIS

Feature analysis involves implementing signal processing and data analysis techniques that explore and, potentially, improve upon the "raw" data. The implementation of a specific feature analysis technique is called a feature descriptor. Oftentimes, the raw data is in a format that is not conducive for direct input into a classifier and, therefore, requires manipulation in order to reduce and/or enhance the data for classification purposes.

is that as the weld material cools, its effective rheological behavior rapidly changes, and at a point the material reverts from a viscoplastic behavior to a largely elastic behavior. This change could occur over a very short time, and thereby result in a sudden "seizing" behavior. When this happens, an impulse load is effectively applied to the joint causing it to ring, and the acoustic sensor is able to discern this ringing

Ideally, the implementation of a feature descriptor makes the decision making process of the classifier trivial. The task of feature analysis is normally a domain-dependent operation. In addition to using the raw data in a normalized format, the following feature descriptors were investigated: root mean square (RMS), energy, attack and decay, and power spectrum. Each of these will be addressed separately in the following sections.



(c) (d)

Figure 2: Four feature descriptors are investigated in this work.

RMS

The root mean square value is one way of describing an AC waveform. A true RMS measurement relates the heating potential of an applied voltage. The RMS gives the effective value of an AC voltage or current signal by (1) squaring the instantaneous values, (2) calculating the mean, and then (3) taking the square root. The following equation calculates the RMS value of an instantaneous current or voltage signal, $f(t)$:

$$RMS(f(t)) = \sqrt{\left| \frac{1}{T} \int_{t}^{t+T} f(t)^2 \right|} \,, \tag{1}$$

where $T = 1/f$ and $f = fundamental\ frequency$. A pure AC signal swings about a zero voltage (or current) axis, going positive one moment and negative the next. Consequently, its average value over a complete cycle is zero. The RMS value does not average out to zero, however, and is, therefore, essentially the AC equivalent of DC voltage or current. Figure 2(a) illustrates the RMS for a representative acoustic energy waveform.

Energy

The energy of a signal, $f(t)$, is defined as

$$E(f(t)) \equiv \sum_{t=-\infty}^{\infty} \left| f(t)^2 \right| \,. \tag{2}$$

The energy of a discrete-time signal, $x(n)$, over a finite interval, $-N \leq n \leq N$, is defined as

$$E(x(n)) = \sum_{n=-N}^{N} \left| x(n)^2 \right| \,. \tag{3}$$

Figure 2(b) illustrates the energy calculation for four segments of a representative acoustic energy waveform.

Attack and Decay

The attack and decay feature descriptors are commonly applied in audio processing of voice and musical instruments (Refs. 3, 4). Attack and decay phases are described by fitting a linear or non-linear function to a set of data. Attack descriptors are used for describing regions of increasing sound intensity, while, conversely, decay descriptors are used for describing regions of decreasing sound intensity. Similar to the energy descriptor, an important consequence of using attack and decay descriptors is in their ability to richly define a signal in an extremely compressed manner.

In this work, the attack and decay feature descriptors were fit to both machine and acoustic energy data using an exponential function of the form:

$$f(t) = ce^{kt} \,. \tag{4}$$

Figure 2(c) illustrates one attack and three decay descriptors for four segments of a representative acoustic energy waveform.

Power Spectrum

The power spectrum is accomplished using a discrete Fourier transform (DFT). The DFT “transforms” an ordered sequence of data samples from the time domain into the frequency domain. Spectral information about the signal can be represented explicitly. In certain problem domains, the spectral information can prove to be extremely revealing, e.g., when attempting to describe physical phenomenon that exhibit periodicity.

A moving-window DFT was performed on the AE data using the fast Fourier transform (FFT) algorithm. A step size of 250 data points was used to move through the time-domain data without overlap. A representative power spectrum is illustrated in Figure 2(d).

RESULTS AND DISCUSSION

The experimental matrix consisted of 24 welds. Although the experimental matrix was designed with only one variable in mind, i.e., surface preparation of the copper, three different quality welds were generated: *acceptable*: bonded area is approximately 100%, *conditional*: bonded area is less than 100% but greater than 5%, and *unacceptable*: bonded area is less than 5%. Table 1 summarizes the bend test results.

Weld Number	Surface Condition Before Welding	Bond Quality	Bonded Area (%)
1 - 12	Freshly Machined	Acceptable	100.0
13	Freshly Machined	Conditional	80.0
14	Freshly Machined	Conditional	70.0
15	Freshly Machined	Conditional	69.0
16	Freshly Machined	Conditional	67.0
17	Freshly Machined	Conditional	54.0
18	Freshly Machined	Conditional	48.0
19	Freshly Machined	Conditional	26.0
20 - 24	Not Machined	Unacceptable	0.0

Table 1: Bend test results.

A Probabilistic Neural Network (PNN) was used as the classifier in this work[2]. The training/testing method was motivated out of a limited size of the available data set. Commonly referred to as the single holdout method, the training/testing method holds out one data point from the n-sized data set for testing while the remaining $n-1$ data points in the data set are used for training. This procedure is repeated until all of the data points in the data set have been tested independently. Classification accuracy is calculated based on the sum of the correctly classified data points minus the sum of the incorrectly classified data points divided by n.

Table 2 tabulates some of the more noteworthy process data combinations and feature descriptors that were investigated. Tests 4 through 7 employed a data-level sensor fusion operation on the normalized machine data, while tests 11 through 14 and 21 through 23 employed feature-level sensor fusion operations on the machine data and on the acoustic energy and machine data, respectively.

Among the machine data, speed provided the most accurate classification results, which agrees well with Bell, et al.'s (Ref. 1) findings, i.e., any minor contamination at the bond plane prevents a metallurgical bond from occurring which is manifested in the speed curve. Furthermore, the decreasing accuracy between acceptable versus unacceptable and acceptable versus conditional demonstrates the extreme subtleness that bond plane contamination can have on bond quality for this particular material combination. The authors

[2]For a thorough presentation of Probabilistic Neural Networks see Ref. 5

Pattern Classification Results

			Accuracy, [% correct]		
Test	Process Data	Feature Descriptor	Acceptable Unacceptable	Acceptable Conditional	Acceptable Unacceptable Conditional
1.	Speed	Normalize	82	74	63
2.	Pressure	Normalize	59	58	42
3.	Upset	Normalize	59	74	63
4.	Speed, Pressure	Normalize	76	63	54
5.	Speed, Upset	Normalize	59	68	58
6.	Pressure, Upset	Normalize	59	63	54
7.	Speed, Pressure, Upset	Normalize	59	63	54
8.	Speed	Attack and Decay	71	63	50
9.	Pressure	Attack and Decay	65	68	50
10.	Upset	Attack and Decay	47	68	50
11.	Speed, Pressure	Attack and Decay	65	68	54
12.	Speed, Upset	Attack and Decay	47	68	50
13.	Pressure, Upset	Attack and Decay	59	63	46
14.	Speed, Pressure, Upset	Attack and Decay	59	63	46
15.	Acoustic Energy	RMS	71	47	46
16.	Acoustic Energy	Energy (1 segment)	76	58	54
17.	Acoustic Energy	Energy (4 segments)	94	31	41
18.	Acoustic Energy	Attack and Decay	88	63	54
19.	Acoustic Energy	Attack and Decay, Energy	94	52	50
20.	Acoustic Energy	Power Spectrum	100	100	54
21.	Acoustic Energy, Speed	Attack and Decay	82	68	71
22.	Acoustic Energy, Pressure	Attack and Decay	71	68	63
23.	Acoustic Energy, Upset	Attack and Decay	72	68	63

Table 2: Pattern classification results for different combinations of process data and feature descriptors.

expect, however, that the classification accuracies (in all three categories) would improve with additional training patterns.

Perfect classification accuracy was found to occur only during the acoustic energy power spectrum feature descriptor (test 20). Upon further investigation, the authors found a unique characteristic ringing for both an acceptable and conditional part. This ringing occurs during the second burst of acoustic energy (i.e., when speed reaches 0 rpm)[3]. The existence of this phenomenon is readily discernible in the power spectrum. Consequently, bond integrity classification of acceptable versus unacceptable and conditional versus unacceptable[4] bonds becomes trivial – which is the ultimate goal of a feature descriptor.

The implementation of an in-process monitoring system does not, however, need to be limited to the use of a single data combination and feature descriptor. The PNN classifier's computational efficiency and

[3]This phenomenon is analogous to the mechanism employed in a resonant inspection system: the acoustic response of a part is monitored after being impacted by a hammer with a known and repeatable force.

[4]The classification results for conditional versus unacceptable is not presented in Table 2.

framework (i.e., its ability to not only provide a decision but also estimate the probability and reliability of a classification) enables it to be implemented on multiple data sets and feature descriptors. The output of each classifier (decision, probability, and reliability) can then be input into a decision-making module that employs, for example, a voting or “winner takes all” template.

Furthermore, feature descriptors and data combinations that do not yield 100% classification accuracy should not preclude their implementation in an in-process monitoring solution. In particular, an in-process monitoring solution can provide additional feedback about the process, such as, fault classification. Although the power spectrum is feature rich in indicating existence of a bad (or good) bond, it fails to reveal the reason why. In-process data can potentially yield relevant process information, in the form of fault diagnostics, when an unacceptable bond is made. For IFRW, speed, for example, is an indicator of surface contamination or joint misalignment. Consequently, the functionality of an in-process monitoring solution can provide both quality indicators and fault diagnostics.

CONCLUSIONS

A bond quality classification system was developed using a novel, non-contact, acoustic emission sensing technique. Various feature detectors were investigated to correlate the in-process data to bond integrity. The system provides a (near) real-time response with minimal hardware requirements.

The following benefits can be achieved by using an in-process monitoring solution for both small- and large-lot manufacturing environments:

- *Fast*: provides a real-time response immediately after welding is complete,
- *Inexpensive*: minimal hardware requirements are necessary,
- *Robust*: is capable of mapping complex or ill-defined multidimensional input/output systems and is tolerant of noisy data,
- *Consistent*: sensing and interpretation are performed without operator intervention and, therefore, ensures an accurate, repeatable, and reproducible system,
- *Thorough*: examination is performed for each weld, rather than randomly to ensure joint integrity,
- *Efficient*: only suspect welds are examined further using an “inspect for cause” methodology, and
- *Revealing*: in addition to providing quality feedback, an in-process monitoring system can potentially expose the cause for failure and, hence, provide fault diagnostic capabilities.

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