Strategy for Small-Lot Manufacturing

In-process monitoring and control

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During the Cold War, the nuclear weapons complex produced thousands of components each year to support the stockpile. The manufacturing process stream—a unique combination of equipment, people, "qualified" processes, and plant idiosyncrasies—had high production capacity but not always high yields. Figure 1(a) shows the elements that define a qualified manufacturing process: Inputs are controlled, all procedures are followed, and the end product is found to be satisfactory through statistical sampling involving inspection and destructive testing. Products made by use of qualified processes were then "certified" as capable of entering the active stockpile, if they met military characteristics (demanding in-service requirements) and stockpile-to-target requirements (that is, they would operate as expected from the time they were taken out of the stockpile to the time they would reach their target) when tested. However, the manufacturing process was treated as a series of black boxes whose internal process dynamics were poorly understood and not monitored. Nevertheless, this method of process qualification and product certification served the nation well for four decades.

Challenges Faced by Los Alamos Manufacturing Processes

- Overall mission scope has shifted after the demise of the Soviet Union.
- Manufacturing operations suffered a long period of inactivity.
- Tremendous upheaval was felt in transferring operations to new sites.
- More than 90 percent of the key personnel have changed.
- Many remaining process experts are retiring.
- Significant changes in equipment, processes, and process flow have been implemented.
- Plant features and layout have been significantly changed.
- Prior continuous operations were fragmented.
- Quality requirements are the same as in the past.

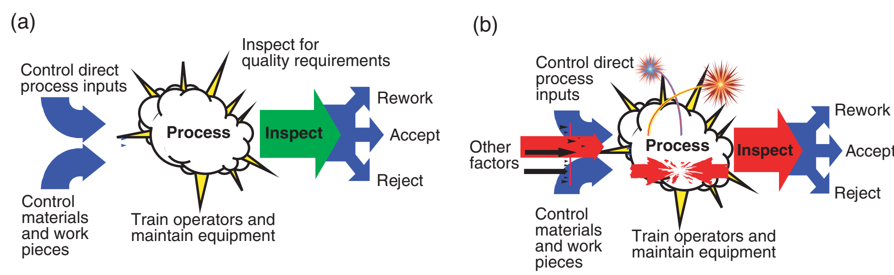

Figure 1. A Qualified Process and What Can Go Wrong
(a) Elements of a qualified process are shown. (b) Qualified processes can be adversely affected (red areas) by hidden factors such as human error caused by insufficient process knowledge; inadequate procedures or incomplete documentation; material variations resulting from changes in processing history, minor element-composition differences, and changes in surface condition and oxidation state; dimensional deviations or residual stresses in work pieces; equipment and tooling degradation; inadequate maintenance or calibration; tooling wear and fixture distress; and marginally stable parameters of process qualification.

The current Los Alamos approach to pit manufacturing follows this old paradigm. It tries to recreate as closely as possible the original manufacturing stream used at Rocky Flats but on a smaller scale because the production volume is much lower. Here, we explain why this approach is problematic for small production volumes and outline, through a real example, a modern approach to quality manufacturing by process monitoring and control in real time.

The Problem: Small-Lot Manufacturing

Figure 1(b) outlines problems that can arise when one tries to develop qualified processes with lots that are down, say, from thousands per year to tens per year. Key interaction terms and intermittent or sporadic process dynamics may be missed entirely. The resultant processes, which are supposedly qualified, could manifest spurious process dynamics in seemingly unpredictable patterns over time. Such processes may therefore be incapable of holding the product in a state of statistical process control in the absence of further process understanding. Manufacturing at Los Alamos has already reached this position.

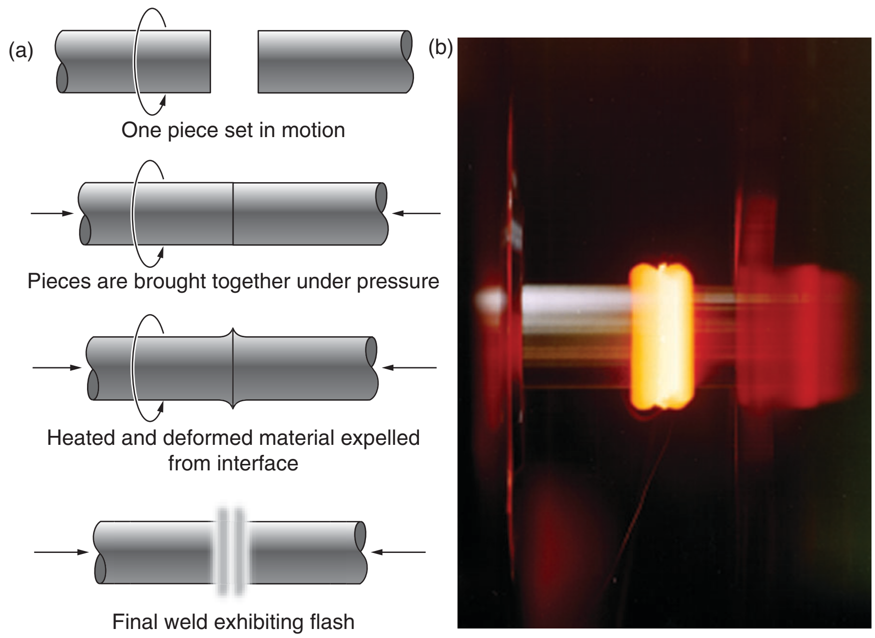

Figure 3. Steps in Inertia Welding
(a) The steps of the welding process are listed, and a photo of the final welding step is shown in (b).

The Solution: In-Process Monitoring and Control

In the new approach, we shift our frame of reference from an outside view, in which the operations are items on a work instruction sheet, to an inside view, in which physical processes are interrogated and controlled as they happen. In-process data

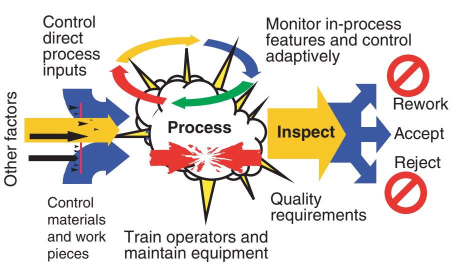

Figure 2. In-Process Monitoring and Control

are interpreted through pattern recognition and classification algorithms that are trained not only to identify processing faults but also to classify the root causes of those faults. The shift is somewhat analogous to going from alchemy to chemistry, from a black art to a predictive science based on underlying physical principles.

Various steps are required to create in-process assurance of part quality. First, we identify critical in-process physical behaviors determining part quality and the means to measure them. We then find out how those behaviors are correlated to specific attributes that constitute quality. Typically, in-process raw data cannot be directly correlated to specific faults in part quality or process integrity. We must therefore employ data reduction methods to find those key signatures that might identify the presence of specific faults. We then use those signatures to develop learning algorithms that not only identify the faults but also classify their causes. We train the algorithms during process development by intentionally creating fault conditions. We then establish an operating window, or range of values of allowed in-process behavior. Finally, we deploy an in-process control system based on this operating window. The results of this methodology can be spectacular: In the F-22 Advanced Tactical Fighter Program, there are engine components that have never been inspected after having been manufactured and are flying as built. The elements of in-process quality assurance shown in Figure 2 can be compared with those of traditional process qualification shown in Figure 1(b).

Practical Example: A Welding Problem

Inertia welding, or the solid-state friction welding of two parts, is a process used on certain defense and aerospace components (see Figure 3). Several defects (hidden factors) are of concern in inertia welding: insufficient or excessive speed or pressure resulting in inadequate joint strength, angular offset in grips or at bond plane resulting in variations in residual stress, and machining defects, handling damage, or contamination at the bond plane.

Here, we describe our in-process approach for detection of bond plane contamination in inertia welds made between copper and stainless steel. Contamination is the most difficult problem to diagnose because thermomechanical material flow during the weld expels the original interfacial material. Nevertheless, as shown in Figure 4, even minor amounts of contamination can have dramatic effects on the bond. The three very different weld qualities shown were produced with identical process parameters (knob settings on the welding machine). Thus, the only means to detect conditional or unacceptable welds without destructive testing is an in-process sensing approach. Other forms of nondestructive evaluation have proved to be inconclusive.

To detect bond-plane contamination, we collect acoustic and vibrational signals emitted during the welding process—see Figure 5(a). Because those signals are not useful in their raw form, we have applied various data-reduction procedures to extract key features, as illustrated in Figures 5(b) to 5(e). First shown is the so-called attack and decay descriptor, an analytical tool typically used in speech recognition, describing attack phases, or regions of increasing sound intensity, and decay phases, or regions of decreasing sound intensity. Next is the root-mean-square (rms) intensity of the acoustic signal. Third is the total acoustic energy for different portions of the signal, or simply the total accumulated acoustic counts for given portions of the signal. Finally, the frequency content of the signal is shown. It is obtained from the Fourier transform of the time-domain data. The resulting acoustic power spectrum showing the relative signal intensities at various frequencies will, when linearly superimposed, reconstitute the time-based signal.

In the next phase of in-process data analysis, we want to use the key features to make inferences about weld quality. We need an analytical method that assigns a unique set of in-process "signatures" to a good weld and at the

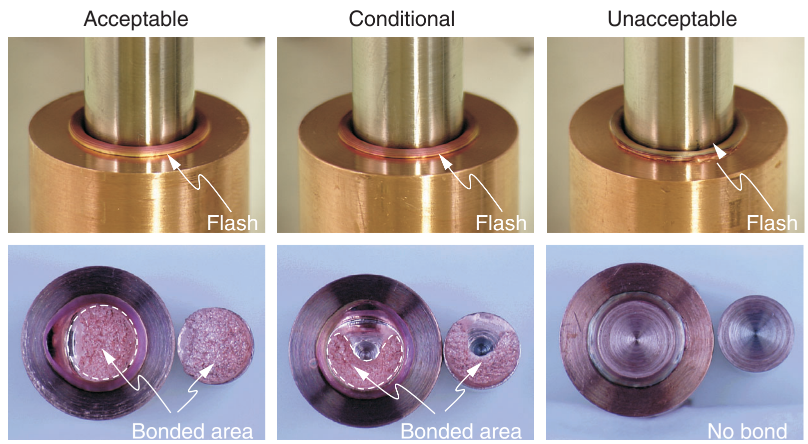

Figure 4. Acceptable, Conditional, and Unacceptable Welds
An acceptable bond (90% to 100% of the area is bonded) requires that surfaces be machined, cleaned, and immediately welded. A conditional bond (50% to 90% of the area is bonded) results if trace amounts of contamination accumulate on the surfaces, and an unacceptable weld (less than 50% of the area is bonded) results if the surfaces are not well cleaned and therefore residual organic contaminants are left at the interface.

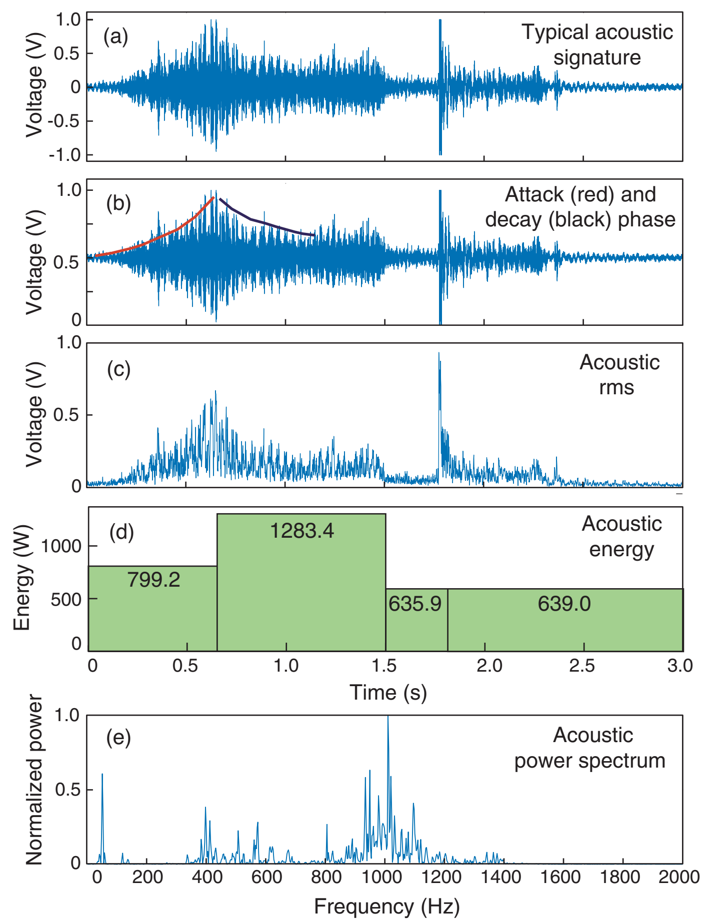

Figure 5. Typical Acoustic Signature and Reduced Signatures

Table I. Ability of Neural Network to Identify Weld Quality

Feature Used	Identification of Weld Quality (Accuracy, %)		
	A or U	A or C	A, C, or U
Attack and decay	85	63	54
Acoustic rms	74	47	50
Acoustic power spectrum	100	100	100
Acoustic energy	100	32	50
Number of Training Instances	19	18	25

A = acceptable bond, C = conditional bond, and U = unacceptable bond
or = exclusive "or" (xor)

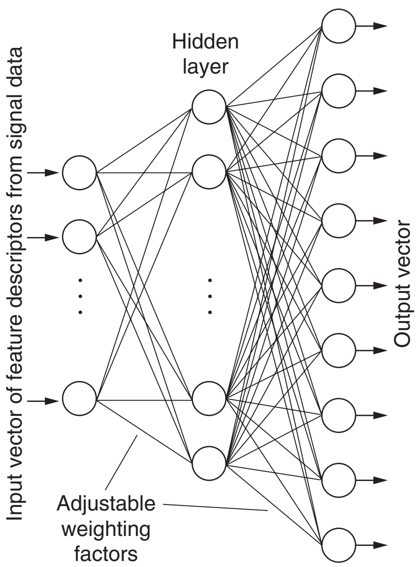

Figure 6. The Neural Network for the Welding Process

same time enables us to classify the probable root cause for a bad weld. Many statistical and nonstatistical approaches are possible. In this work, we have used an artificial-intelligence algorithm known as an artificial neural network. A neural network is a collection of heuristic computational architectures and algorithms that are biologically inspired, nonlinear, massively parallel, distributed, composed of simple computational elements, and ideal for pattern identification and classification in complex data sets. These architectures and algorithms acquire process knowledge through a learning process that uses data sets. The knowledge is stored in a neural network through interneuron connection strengths or synaptic weights.

We train our neural network (see Figure 6) using feature data representing good and bad welds, and the network stores this knowledge implicitly in its weighting factors. The network can infer the quality of the bond and thus distinguish among acceptable, conditional (or marginal), and unacceptable welds, and it performs root cause analysis of faults, deducing the cause of the faults. Both capabilities are very important for small lots that require precision welding. Table I summarizes the neural network's ability to identify the quality of the bond from the various feature descriptors in Figure 5.

In this example, we did not take the additional step of constructing a process window because the objective was to detect and diagnose the occurrence of a very problematic defect, namely, bond-plane contamination.

In carrying out this work, we made a conscious tradeoff between less expensive sensors coupled with sophisticated data analysis versus expensive but more capable sensors. We used an array of low-cost thin-film piezopolymer sensors and miniature acoustic-emission sensors that cost less than a dollar a piece in place of a quartz sensor costing $10,000.

On the Verge of a New Quality-Control Revolution

By emphasizing in-process dynamics and control, we can significantly increase our ability to characterize and control manufacturing processes of small precision lots. The potent combination of inexpensive and virtually limitless computational power, inexpensive sensors, and algorithms capable of dealing with large, complex data sets has set the stage for a revolution in our approach to manufacturing quality. This effort has sufficient intellectual scope to be a "grand challenge" for Los Alamos, in particular, and the weapons complex of the National Nuclear Security Administration, in general. If successfully implemented, this new approach could shift the present conformance and inspection mindset to a predictive approach that would emphasize fundamental process understanding. The new approach would bring tangible and quantifiable benefits to Los Alamos manufacturing. Here is a list of the most significant ones: process characterization based on what the part experienced and not just on knob settings on a machine tool that may be obsolete within a decade, manufacturing recipes that can be easily moved from one machine tool to another, reduced scrap and rework, automated analysis of root causes, targeted process improvements, reduced cycle time to bring new processes online for new products, and less work to qualify a new piece of equipment or process.

For the past 80 years, we have used final inspection to verify product conformance to specifications and statistics and to quantify the consistency of the process in meeting those specifications. In-process dynamics, therefore, represents the first major new concept in quality control in almost a century. Its impact may well be as far-reaching in this century as statistical process control has been in the last century. ■

Historical Timeline Leading to In-Process Dynamics Approach

B. C. to 1700s	Manufacturing is dominated by the artisan and the guild structure.
1750s to 1850s	The Industrial Revolution reaches both the Old and New Worlds.
Late 1700s	First use of interchangeable parts in manufacturing assemblies.
1880s to 1900	Thomas Edison literally electrifies America, having profound influence on industry.
Early 1900s	Both the National Bureau of Standards in the United States and the British Institute of Standards in England are founded—standards drive improved inspection methods.
1900s to 1920s	Ford establishes the production line, the manufacturing paradigm for the next 100 years.
1920s to 1930s	Alfred P. Sloan at General Motors formulates the management structure for the twentieth-century manufacturing firm.
1920s	Walter A. Shewhart invents statistics for process control.
WW II	The U.S. military-industrial complex helps win the war by using mass production methods, together with inspection to ensure conformation to specifications.
WW II	Stan Ulam, John von Neumann, Nicholas Metropolis, and others at Los Alamos form the basis for modern digital computers as well as a scientific computation.
1947	Bell Laboratories invents the transistor.
1950s to 1980s	W. Edwards Deming promulgates the modern approach to statistical process control. The Japanese eagerly adopt it and experience a manufacturing revolution.
1958	Texas Instruments invents the integrated circuit.
1974	Intel launches the 8080, the first successful commercial microprocessor.
1960s to 1990s	Development of heuristic algorithms, John Holland's genetic algorithms, Lotfi Zadeh's fuzzy logic, the Hopfield model of neural networks, and data mining and complexity sciences.
1960s to 1970s	ARPANET, the ancestor of the Internet, is developed.
1970s to 1980s	The first personal computers arrive on the market.
1980s to 1990s	Cheap computing and sensors following Moore's Law.
1990s to 2000	Six Sigma is widely implemented, representing the culmination of 80 years of statistical measurement and control of conformance to specification.
1990s to 2000	First implementations of the in-process approach (for example, military engine parts).
21st century	A new revolution in quality control is made possible by the existence of key ingredients: cheap computing and sensors, as well as advanced data processing algorithms for large and complex data sets that represent in-process behavior.

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