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Process Compensated Resonant Testing in Manufacturing Process Control

by Jim Schwarz,* Jay Saxton* and Leanne Jauriqui*

ABSTRACT

Nondestructive testing (NDT) is normally used to sort manufactured parts, that is, to classify them as acceptable (good) or unacceptable (bad). While this is a valuable function for a manufacturer, the ultimate goal should be to eliminate (or at least significantly reduce) the number of bad parts that are produced — that is, monitor the process so that when bad parts are produced, the operator is notified and the process can be fixed. We describe an approach using process compensated resonant testing as a process control tool to provide the required feedback to the operator.

Keywords: *process control, statistical process control, Mahalanobis Taguchi, process compensated resonant testing.*

INTRODUCTION

A manufacturing process is "in control" when it is producing parts at a known, acceptable error rate (Juran and Godfrey, 1999). For example, the in control nondestructive testing (NDT) reject rate might be less than 1%. This means that the process is producing greater than 99% acceptable parts — essentially operating at a three sigma level. The process is "out of control" when the reject rate increases to an unacceptable level, say 40%. From this it can be seen that an out of control process can cost the manufacturer a lot of money in scrap and lost capacity. Therefore, it is generally a sound investment to provide for process control feedback that will minimize the duration of the out of control condition.

There are two approaches to monitoring a process to determine whether it is in control. One technique focuses on process parameters, such as various reaction temperatures and temperature profiles, flow rates, pressures and material chemistry. The other approach focuses on product parameters that describe the acceptability of the part, such as the presence of a crack, porosity or oxide. This approach uses NDT to determine the part's acceptability. The NDT reject rate is then a measure of whether the process is in control.

The advantage of monitoring process parameters is that measuring instruments are readily available and a body of statistical process control methodology describes how to use the data. The disadvantage is that in many factories, the relationship between the variations in the process parameters and the product acceptability is not known, and there is little prospect of determining the relationships to a required level of precision.

The advantage of monitoring product parameters using NDT is that they are (at least nominally) related to product acceptability. However, there are two disadvantages. The first is that the NDT parameters measured (for example, the discontinuities in the magnetic field used in magnetic particle testing) are not well correlated to the function of the part. Therefore, for example, changes in magnetic particle test reject rate, may depend on exogenous variables such as the competence of the NDT operator or the calibration of the magnetic field — parameters that are not truly product variables. The second disadvantage is that NDT results are not generally available in real time, causing a substantial lag between the point at which a process problem occurs and the point at which corrective action can be initiated.

One NDT technique, process compensated resonant testing, overcomes these two disadvantages and provides an excellent tool for process control feedback.

REQUIREMENTS FOR NDT PROCESS CONTROL FEEDBACK

Effective process control feedback must be based on measurements that are:

- objective
- quantitative
- correlated to part functionality
- near real time.

Taking these one at a time, measurements must first be independent of operator attention and judgment. An NDT method that requires human attention and judgment has inherent variation that will mask the underlying process variations. Second, measurements must also provide a precise numerical result. Unless the NDT method provides a numerical output that has low variability and has a known correlation to the probability of failure, it is impossible to use statistical methods to compute the process norms and to detect the transition from in control to out of control status. Third, measurements must exhibit a known relation to probability of in service part failure. Finally, effective measurements must provide prompt feedback to operators regarding out of control processes.

These requirements can be illustrated by considering the use of a gage to measure length after a part is cut to a specified dimension — say 10 mm (0.4 in.) ±0.1 mm (4×10^{-3} in.). The gage must provide an objective, quantitative measurement of length. No manufacturer would be satisfied with an operator saying "it looks long enough to me." However, the measurement need not use a meter stick. A capacitive probe, for example, can provide an output that is indicative of part acceptability (that is, length), but only if there is a known (measured) correlation between the capacitance and length. But of course, any measurement would be useless to control the process if the results were not available for hours, days or even weeks, as is generally the case for NDT.

RESONANCE TESTING MEASURES PART STRUCTURAL INTEGRITY

Most NDT methods identify defective parts by scanning for indications of a discontinuity. The implicit assumption is that the presence and size of the indication correlates with the presence and severity of the internal discontinuity. The problem with this assumption is that some indications are only superficial and some

* Quasar International, 5550 Midway Park Place NE, Albuquerque, NM 87109; (505) 247-9660.

unacceptable parts show no indications. Resonant testing, on the other hand, sorts by measuring the parts' resonant frequencies, which are explicitly determined by the parts' stiffness and mass (Migliori and Sarrao, 1997). The first resonance f is determined by:

$$f = \left(\frac{1}{2\pi}\right) \cdot \left(\frac{k}{m}\right)^{\frac{1}{2}}$$

where

k = the stiffness of the part
m = its mass.

The presence of a structural discontinuity reduces the stiffness of the part and therefore reduces the part's resonant frequencies. The change in frequency is proportional to the change in stiffness and so to the severity of the discontinuity. This means that a part's resonant frequency is theoretically a predictor of its structural integrity.

Unfortunately, there is a practical obstacle to using resonances for NDT. The acceptable process variations also affect the resonant frequency, often to the extent that they mask the effect of even a fairly severe discontinuity. This is illustrated in Figure 1, which is a histogram comparing the resonant frequency for a sample of 200 good and bad master cylinder bodies.

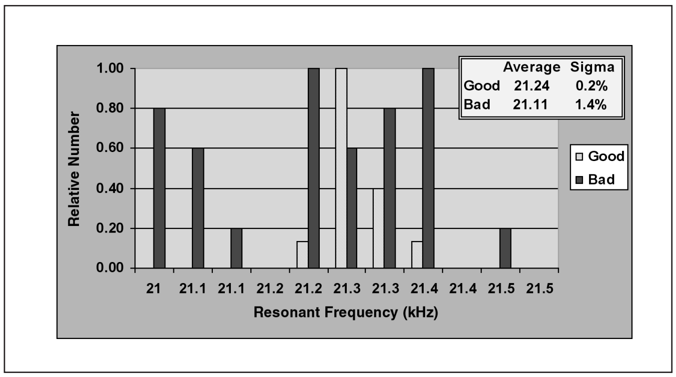

Figure 1 — Histogram of resonant frequencies for master cylinder bodies.

The bad parts include samples with oxides, porosity and cracks. The good parts' frequencies vary because the dimensions vary over time as the process changes (for example, cavities wear). The variation in the set of good parts is relatively small (sigma = 0.2% of the mean) because the process is in control. As a set, the bad parts have a lower average frequency and also have a broader distribution (sigma = 1.4%) because they represent an out of control process. The average bad part frequency is lower because of the reduced stiffness, but a few bad parts have higher frequencies because the discontinuity (a large shrink porosity, for example) reduced the part's mass. The result of this overlap in the distributions of the good versus bad frequencies is that a simple resonance measurement is not a reliable basis for sorting.

PROCESS COMPENSATED RESONANT TESTING UNMASKS DISCONTINUITIES

The solution is to compensate for the acceptable process variations. The process compensated resonant testing approach described here was developed by Quasar International. It measures several resonances for each part and uses a proprietary pattern recognition algorithm to compensate for the acceptable variations.

This compensation algorithm is based on two distributions: the Mahalanobis Taguchi system (Taguchi et al., 2001) characterizes the good parts in terms of their resonant patterns; and the bias discriminator characterizes the bad parts in terms of their resonant patterns. The algorithm predicts the frequency of a target resonance for each part. The difference between the predicted and measured frequency for a part is its predictor error. Good parts have a small error; bad parts have a larger error. The result is shown in Figure 2, which uses the same master cylinder bodies shown in Figure 1. It shows a calculated accept window based on the relatively small error computed for the good parts. Parts with errors outside the accept window are rejected.

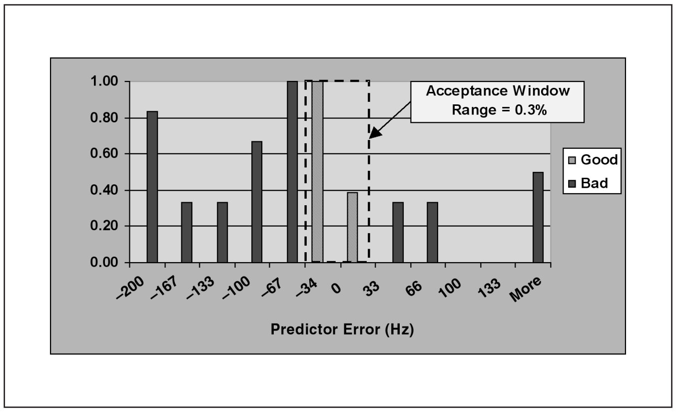

Figure 2 — Histogram of predictor error for good and bad parts.

The predictor error readily discriminates between the good and bad parts despite the overlap in the raw frequency measurements. A visual presentation of the Mahalanobis Taguchi system distribution is shown in Figure 3, which shows the measured and predicted frequencies for each of the parts in the sample. Note that the accept window is shown here as an ellipse, but is actually a multidimensional ellipsoid, since several resonances are typically used (five in this case).

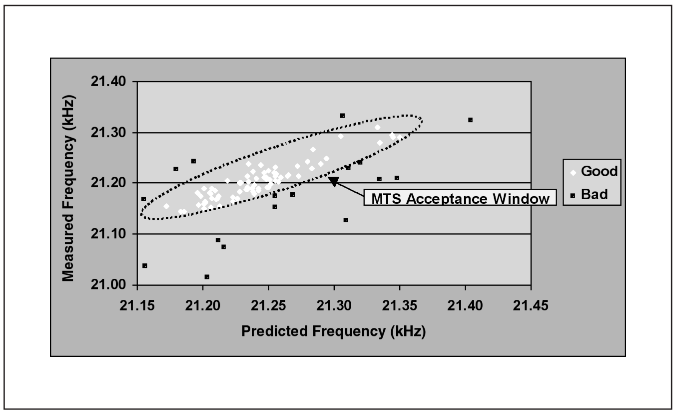

Figure 3 — Illustration of the Mahalanobis Taguchi System (MTS) acceptance pattern for two resonances.

Computing the compensation algorithm involves selecting the diagnostic and compensating resonances to be used and calculating the parameters of the Mahalanobis Taguchi system and bias distributions. This requires a sophisticated pattern recognition program to analyze a data set containing the resonant frequencies for a training set of good and bad parts. It produces a compensation pattern and presents the pattern as shown in Figure 4.

The vertical axis is the Mahalanobis Taguchi system score and the horizontal axis is the bias score. The symbols represent individual parts used to train the algorithm. Good parts are shown as filled circles and bad parts are shown as an x. Parts above the horizontal line are rejected by the Mahalanobis Taguchi system limit and parts to the right of the vertical line are rejected by the bias limit. The coordinates of each part are combined by the system into a "Qscore," which characterizes the part's structural integrity.

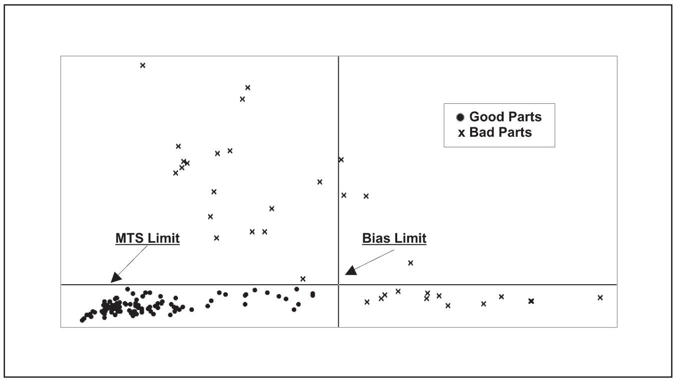

Figure 4 — Vibrational pattern recognition display showing Mahalanobis Taguchi System (MTS) and bias axes.

CORRELATION OF SCORE TO STRUCTURAL INTEGRITY

The real test of the utility of any NDT method is whether it correlates to the functional acceptability of the part being tested (Papadakis, 2003). Depending on the use of the part, its acceptability is determined by its durability under either a static load or a fatigue cycle. Figures 5 and 6 show examples of experimental correlations between score and load for both cases (Nath et al., 2004).

Figure 5 shows the correlation between the score and break force for a powder metal exhaust flange. The correlation is nearly perfect. This is possible because, in this case, the discontinuities in the flanges were artificially introduced and their size and location were controlled in such a way that the discontinuities would qualify as defects in an actual product.

Figure 6 shows the correlation between the score and fatigue cycles for a cast steering knuckle. The correlation is still excellent, but not perfect because this experiment used normal production parts in which the location and size of the defects varied.

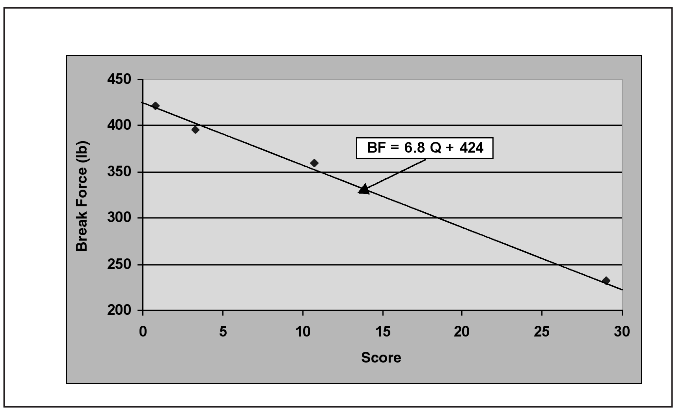

Figure 5 — Score correlation to break force.

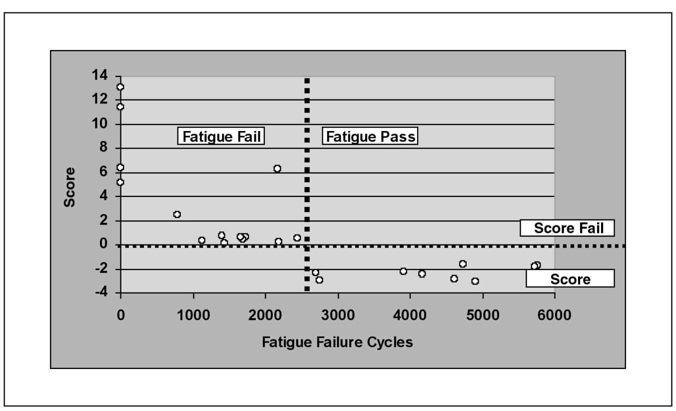

Figure 6 — Score correlation to fatigue failure cycles.

PROCESS COMPENSATED RESONANT TESTING APPLICATIONS TO PROCESS CONTROL FEEDBACK

Example 1

Two examples will illustrate the application of process compensated resonant testing feedback to real world manufacturing operations. Note that these examples are synthesized from several different applications; they don't precisely describe any specific process or application.

The first example is illustrated in Figure 7. It is a casting operation for automobile wheels (Prucha and Nath, 2003). The plant has eight cells, each containing two casters plus cooling tanks and rough machining capability. Each cell is staffed by an operator. Each caster has a throughput of 20 wheels per hour. When the process is in control, the reject rate is 2%. When the process is out of control, the reject rate is 65%. The overall mean reject rate is 15%. Currently, NDT is performed 4 h after a given wheel is cast, after several additional processing steps have been performed.

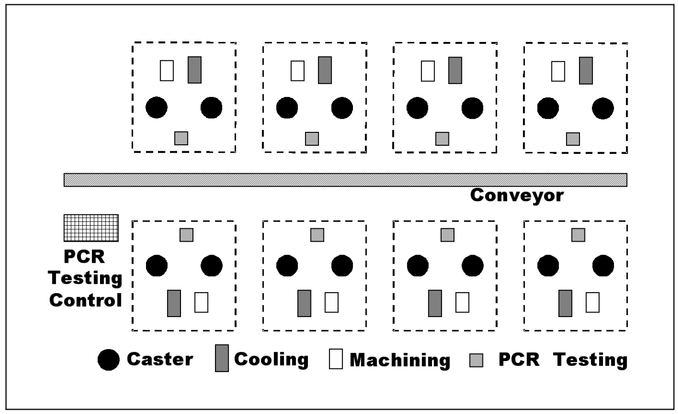

Figure 7 — Plan view of example wheel casting operation with process compensated resonant (PCR) testing.

The average caster cycle is calculated to be as follows. The caster is in control for 13 h at which time it goes out of control, which lasts for 4 h until the operator receives feedback from NDT and makes the appropriate adjustment to regain control. Therefore, 52 defective wheels (65% of 4 h production) are produced in each 17 h caster cycle. This average cycle is repeated for each of the 16 casters. Of course, the 13 h in control cycle is only an average. Individual casters can lose control in a few hours or remain in control for several shifts.

Designing the process compensated resonant testing feedback system begins by measuring the statistical distribution of the good and bad parts. Figure 8 shows a histogram of the scores of a training

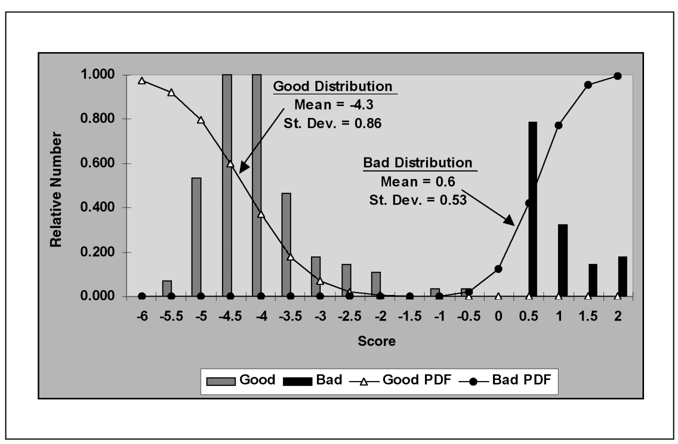

Figure 8 — Distributions for wheel training sample scores (PDF = probability distribution function).

set of good and bad parts and a cumulative probability distribution function for each.

The test sample is fairly large (approximately 300 good parts and 150 bad parts) because it includes samples from all of the casters and all of the molds (although not all permutations), each sampled from several different time periods. The figure shows the mean and standard deviation for both distributions. As would be expected, the distribution for the good parts is proportionally tighter (good sigma is 20% of the mean, bad sigma is 90% of the mean).

The next step is to select the alarm limits that will indicate that the process is out of control and trigger the feedback. The alarm limit for the good part distribution is set at the statistical mean +3 sigma. A part that has a score that exceeds the alarm limit for the good part distribution has less than 1% probability of being good. The alarm limit for the bad part distribution is set at the mean, which means that a part whose score exceeds the alarm limit for the bad part distribution has a greater than 50% probability of being bad.

The third step is to compute the feedback sensitivity — that is, to determine how many parts will be produced before the operator can be informed that the process is out of control. Table 1 summarizes this sensitivity (in terms of the probability that the alarm limit will be exceeded) of the two alarms for the in control and out of control states.

Table 1 Probability that the alarm limit will be exceeded in a sample of three parts for Example 1

	Good Part Alarm	Bad Part Alarm	Combined	Alarms Per Three Parts
In control	7%	2%	9%	0 to 1
Out of control	60%	40%	76%	2 to 3

The last column of Table 1 applies these probabilities to compute the number of alarms that would be expected in a sample of three parts. When the process is in control, the sample will normally have zero alarms, but about 10% of the time it will have one alarm. When the process is out of control, the number of alarms will be either two or three. Therefore, the loss of control can be fed back to the operator within three parts. That reduces the expected number of bad parts that would be produced during the out of control event from 52 to 3.

Justification of the application requires an economic analysis. Figure 7 shows that the process compensated resonant testing feedback system involves placing a test station at each cell, all multiplexed to a central process compensated resonant testing control, which contains the control computers and transceivers. After the operator completes rough machining on a wheel, it is placed on the test station, where it is automatically tested, which requires about 15 s. Then the operator loads the wheel onto the conveyor. It is important to recognize that in this application no parts are actually rejected by the process compensated resonant testing system. The part flow is unchanged and the process compensated resonant testing system only collects data for feedback.

The casting line produces 1.6 million wheels per year (20 h per day, 5 days per week, 50 weeks per year). 15% of these wheels are rejected by NDT, so the net production is 1.36 million wheels. The wheels sell for $30 each, so the revenue stream is $40.8 million. Installing process compensated resonant testing feedback reduces the number of rejected wheels and increases the total output. The reject rate is reduced to 1%, which increases the net output to 1.58 million wheels, with a revenue stream of $47.5 million. The resulting annual economic benefit of installing the process compensated resonant testing feedback system is $6.7 million. The cost of the system is less than $1 million, making the payback almost immediate.

Example 2

The second example is conceptually simpler. It is a forging operation with a single forge producing 1000 wheel hubs per hour. The in control reject rate is 0.3% and the out of control reject rate is 80%. The hubs are sent to an NDT testing lab and the feedback period is three days, which means that up to 60 000 parts can be produced before the operator knows that the process is out of control. The annual average reject rate is 2%.

The same three steps discussed in the first example are used to compute alarm probability levels as shown in Table 2.

Table 2 Probability that the alarm limit will be exceeded in a sample of three parts for Example 2

	Good Part Alarm	Bad Part Alarm	Combined	Alarms Per Three Parts
In control	5%	1%	6%	0 to 1
Out of control	73%	48%	86%	2 to 3

Again, the last column applies these probabilities to compute the number of alarms that would be expected in a sample of three parts. When the process is in control, the sample will normally have zero alarms, but about 6% of the time it will have one alarm. When the process is out of control, the number of alarms will be either two or three. This means that the loss of control will be fed back to the operator within three parts. That reduces the expected number of bad parts that would be produced during the out of control event from 48 000 to 3. Given the disparity in numbers, this is essentially instantaneous feedback.

The forging line produces 5 million hubs per year. Two percent of these hubs are rejected by NDT, making the net production 4 875 000 hubs. The hubs sell for $3 each, so the revenue stream is $14.6 million. Installing a process compensated resonant testing feedback system reduces the number of rejected hubs and increases the total output. The reject rate is reduced to 0.02%, which increases the net output to 4 990 000 wheels, with a revenue stream of $15 million. Therefore, the annual economic benefit of installing process compensated resonant testing feedback is $400,000. The cost of the process compensated resonant testing system is about the same as the benefit, making the payback is approximately one year.

CONCLUSION

We have described an approach to using process compensated resonant testing to provide functional process control feedback to the operator of a manufacturing process. Process compensated resonant testing can be installed in line in the process and provide essentially real time feedback when the process moves out of control. Assuming that the operator has the tools to restore the process to control, this approach can provide substantial economic benefit to the manufacturer. The economic benefit increases directly with the value of the part and the annual reject rate. For processes that have relatively valuable parts and high reject rates, using process compensated resonant testing feedback can provide enormous benefits and the economic payback can be measured in weeks.

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