International Review of Business and Economics

Volume 9 | Issue 1 Article 3

2-14-2024

Selecting a Measurement System: Using Measurement System Potential Approval Criteria

Karl D. Majeske
Oakland University, majeske2@oakland.edu

Selecting a Measurement System: Using Measurement System Potential Approval Criteria

Abstract

This paper presents the results of a manufacturer's quest to identify a measuring strategy during process development. Standard Measurement Systems Analysis (MSA) criteria provide a common framework to evaluate a gauge's ability to produce data that fairly represents the quality characteristics that describe a part's fitness for use. Here, MSA criteria, as well as hypothesis tests of precision and bias, are used to compare to two alternative measurement systems. Ultimately, to compare the two systems, measures of MSA criteria are developed that reflect the potential the criteria could reach by eliminating operator-to-operator gauge error.

Keywords

Measurement System Analysis (MSA), Comparing Measurement Systems, Process Capability, Gauge Study

Selecting a Measurement System:
Using Measurement System Potential Approval Criteria

Karl D. Majeske
School of Business Administration
Oakland University
Rochester, MI 48309-4493
Phone: 248-370-4976
E-mail: majeske2@oakland.edu

Abstract

This paper presents the results of a manufacturer's quest to identify a measuring strategy during process development. Standard Measurement Systems Analysis (MSA) criteria provide a common framework to evaluate a gauge's ability to produce data that fairly represents the quality characteristics that describe a part's fitness for use. Here, MSA criteria, as well as hypothesis tests of precision and bias, are used to compare to two alternative measurement systems. Ultimately, to compare the two systems, measures of MSA criteria are developed that reflect the potential the criteria could reach by eliminating operator-to-operator gauge error.

Keywords: Measurement Systems Analysis (MSA), Comparing Measurement Systems, Process Capability, Gauge Study

1. Introduction

Quality characteristics represent a component's features that determine its fitness for use such as length, thickness or relative position in 3-dimentional space. As part of process development, a manufacturer selects a gauge or measurement system to measure a product in terms of its quality characteristics. Manufacturers use the data generated by the gauge to, among other things, make decisions about the quality of a product or the process used to produce it. Historically, measuring devices were simple and inexpensive such as hand-held calipers or dedicated fixtures with dial indicators. Over time, measure systems have become more technologically sophisticated (and expensive).

Coordinate Measuring Machines (CMMs) are considered contact measurement devices and use computer-controlled probes to identify the location of a product feature in 3-dimensional space. Using two or more locations one can determine the value of quality characteristics such as length, angle, radius, etc. Vision systems are an example of non-contact measuring devices. These systems use cameras to generate a digital image of a part and then computer software extracts values for the quality characteristics from the image. Manufacturers have transitioned to these two types of high-tech measurement systems for a variety of reasons, with the underlying assumption that they produce "better" data than traditional gauges.

Manufacturers measure parts for a variety of reasons. During process development manufacturers will evaluate a production process by measuring parts and calculating process capability. Manufacturers using control charts measure parts on a regular basis and use the data to determine if the process needs adjustment. Manufacturers measure parts and evaluate them relative to new specifications when implementing design changes. When resolving build issues with a mating part, a supplier may measure parts and send the descriptive data, to their customer which they will use to make build decisions. In all of these scenarios, the conclusions drawn depend on the integrity or validity of the data. Because of this, it is common to perform a measurement system analysis (MSA) on the gauges used to measure the quality characteristics.

The remainder of this paper presents a comprehensive comparison of two measurement systems under consideration during process development.

2. Gauge Study

The following model (see, e.g., Majeske 2008) provides the framework for evaluating the precision of a single gauge, determining if a bias exists between two gauges, and measuring the level of association between two gauges. Let V represent the variable of interest that is measured by a gauge. In the presence of measurement or gauge error (G) the data generated by the gauge (Y) doesn't exactly match V. Let μ_V, μ_Y and μ_G, and σ_V^2, σ_Y^2 and σ_G^2 signify the means and variances of V, Y and G, respectively. Assuming that gauge error and the variable of interest add to result in the data generated by the gauge gives

$$Y = V + G. \qquad (1)$$

Assuming that gauge error is independent of the variable of interest results in

$$\sigma_Y^2 = \sigma_V^2 + \sigma_G^2. \qquad (2)$$

Gauges studies are types of designed experiments used to generate data for evaluating the precision of a gauge (Burdick et al., 2005). To conduct a single operator study, have one person measure a random sample of p parts. Once each part has been measured, have the same person measure each part again in a different (random) order. Repeat the process until each part has been measured r times – the number of repeat measurements. Fit the data, i.e., the measured values, with a one-way analysis of variance (ANOVA) using part as a random factor to obtain the mean squares part (MSP) and mean squares error (MSE). Estimate the variance of the quality characteristic as

$$\hat{\sigma}_V^2 = \frac{MSP - MSE}{r} \tag{3}$$

and the variance of gauge error with

$$\hat{\sigma}_G^2 = MSE. \tag{4}$$

For a multiple operator study, have o operators each take r repeat measurements of p parts resulting in a total of orp measured values. A multiple operator study introduces two components of gauge error variance: between operator σ_O^2 and within operator σ_ϵ^2. When using a two-factor gauge study, fit the resultant data with a two-way main effects ANOVA using part and operator as random factors to find MSP, MSE and the mean squares operator (MSO). Estimate the variance of the quality characteristic as

$$\hat{\sigma}_V^2 = \frac{MSP - MSE}{or}; \tag{5}$$

the variance due to differences in operators

$$\hat{\sigma}_O^2 = \frac{MSO - MSE}{pr}; \tag{6}$$

and the within operator variance as

$$\hat{\sigma}_\in^2 = MSE. \tag{7}$$

Combine the estimated variance due to differences in operators and the within operator variance to find an estimate of gauge error variance

$$\hat{\sigma}_G^2 = \hat{\sigma}_O^2 + \hat{\sigma}_\in^2. \tag{8}$$

When fitting the data from a multiple operator gauge study, an operator-part interaction term can be added to the two-way ANOVA model – termed a three-factor gauge study. Mathematically, a portion of the MSE from the two-factor model is captured by the mean squares for the operator-part interaction (MSOP) while leaving MSP and MSO unchanged from the two-factor model. However, the three-factor model will result in different estimated variances due to the effect of the interaction term on expected mean squares. Specifically, estimate the variance of the quality characteristic as

$$\hat{\sigma}_V^2 = \frac{MSP - MSOP}{or}; \tag{9}$$

the variance due to differences in operators as

$$\hat{\sigma}_O^2 = \frac{MSO - MSOP}{pr}; \tag{10}$$

the operator-part interaction variance

$$\hat{\sigma}_{OP}^2 = \frac{MSOP - MSE}{r}; \tag{11}$$

and the within operator variance as

$$\hat{\sigma}_{\in}^2 = MSE. \tag{12}$$

In the three-factor model all variances except the variance of the quality characteristic combine to estimate gauge error

$$\hat{\sigma}_G^2 = \hat{\sigma}_O^2 + \hat{\sigma}_{OP}^2 + \hat{\sigma}_{\in}^2. \tag{13}$$

For all three gauge study designs (single-factor, two-factor and three factor) estimate the variance of the measured values with

$$\hat{\sigma}_Y^2 = \hat{\sigma}_V^2 + \hat{\sigma}_G^2. \tag{14}$$

3. Measurement Systems Analysis Evaluation Criteria

Many measurement systems analysis (MSA) criteria exist to evaluate the precision of a gauge based on the variances of Equation (2) (see, e.g., Beckert and Paim 2017). Some MSA criteria include the design specifications of the quality characteristic: the lower specification limit (LCL) and the upper specification limit (UCL). The various criteria approve gauges for different purposes such as generating data for control charts, evaluating the ability to measure a part relative to its design specification(s), and determining if a gage can distinguish between parts.

The Precision to Tolerance Ratio (P/T) scales the width of the error distribution by the design tolerance. Two variations of P/T exist that differ in how they capture the width of the error distribution. The first version (Montgomery 2020)

$$\frac{P}{T} = \frac{5.15\sigma_G}{USL - LSL} \tag{15}$$

uses 5.15 standard deviations which would represent the width of 99% of the distribution. The other version (AIAG 2010)

$$\frac{P}{T} = \frac{6\sigma_G}{USL - LSL} \tag{16}$$

uses 6 standard deviations to characterize distribution width consistent with six-sigma methodology. P/T assesses if a measurement system possesses sufficient precision to measure a quality characteristic relative to its design specification. Measurement system approval values for P/T are somewhat subjective with values below 0.1 generally considered good (Montgomery 2020), values above 0.3 considered unacceptable (Barrentine 1991) and values between 0.1 and 0.3 debatable (AIAG 2010).

Percent repeatability and reproducibility (%R&R) is a scaled gauge error - with two versions that use different scaling factors - and doesn't take design specifications into account. One measure (AIAG 2010)

$$\%R\&RA = \sqrt{\frac{\sigma_G^2}{\sigma_V^2}} = \frac{\sigma_G}{\sigma_V} \qquad (17)$$

quantifies gauge error relative to variation in the quality characteristic. The other measure (Montgomery 2020)

$$\%R\&RM = \sqrt{\frac{\sigma_G^2}{\sigma_Y^2}} = \frac{\sigma_G}{\sigma_Y} \qquad (18)$$

views gage error as a proportion of the variability in the measured values or the data generated by the gauge. %R&R is used to determine if a gauge has adequate precision to differentiate between parts (Majeske and Gearhart 2006). Gauges with a $\%R\&R \leq 0.30$ are considered to have the necessary level of precision.

The signal to noise ratio (SNR)

$$SNR = 2\frac{\sigma_V^2}{\sigma_G^2} = \sqrt{2}\left(\frac{\sigma_V}{\sigma_G}\right), \qquad (19)$$

a.k.a. the number of distinct categories (ndc), scales the variability in the quality characteristic by gauge error – the inverse of the ratio used in the %R&RA statistic. SNR is used to evaluate a gauge's ability to produce data for control charts and measurement systems with an SNR ≥ 5 should be approved (Majeske 2012A).

The correlation in repeat measurements

$$\rho = \frac{\sigma_V^2}{\sigma_V^2 + \sigma_G^2} \qquad (20)$$

has been suggested and an MSA criteria (Majeske and Andrews 2002). Manufacturers should include ρ as an MSA criteria when two parties (i.e., component production and product assembly) will be measuring a quality characteristic with different gauges. The correlation in repeat measurements - also termed the intraclass correlation coefficient (ICC) - is frequently used when evaluating measuring devices used in medical applications (see, e.g., Fletcher and Bandy 2008). Majeske and Andrews (2002) present the relationship between ρ, C_p and P/T and suggest the using an approval value for this criterion based on acceptable values for P/T and C_p.

4. Process Capability Indices

Manufacturers often use one or more process capability indices to characterize the ability of a process to produce parts that conform to design specifications. Two commonly used process capability indices are

$$C_p = \frac{USL - LSL}{6\sigma_V}, \tag{21}$$

which represents a measure of process potential and

$$C_{pk} = \min\left(\frac{\mu_V - LSL}{3\sigma_V}, \frac{USL - \mu_V}{3\sigma_V}\right) \tag{22}$$

that captures actual process performance (assuming μ_V falls within the design specifications). When the quality characteristic follows a normal distribution, the C_{pk} index directly corresponds to percent or proportion of parts that comply with their design specification, explaining how it measures actual process performance. The C_p index indicates the value the C_{pk} index would take on if the process mean were centered in the design specifications. C_p represents the maximum C_{pk} value that could be achieved given the current level of process variation, thus the process potential description. Dalalah and Hani (2016) develop the relationship between C_p and P/T and suggest a method for simultaneously evaluating a measurement system and production process.

5. Comparing Two Measurement Systems

Many situations arise where more than one gauge exists for measuring a variable of interest and a comparison of gauges is desired. In this scenario the variables Y and G are subscripted with 1 and 2 to indicate the presence of two gauges while V doesn't require a subscript. In addition to comparing gauges based on the values of MSA criteria, differences between two gauges can be quantified using precision and bias. A method has been developed that simultaneously compares the precision and bias of two measurement systems by using the difference in the paired readings as the dependent variable and the sum of the paired readings as the independent variable in a simple regression model (Blackwood and Bradley 1991).

The bias (B) of two gauges is defined as the difference in the average readings or

$$B = \mu_{Y_1} - \mu_{Y_2} . \tag{23}$$

When the same physical items or people are measured once each with both gauges, bias can be assessed using a paired t-test. When different items are measured one time with each gauge use an independent samples t-test to evaluate bias. When using the data generated from gauge studies, the bias can be estimated with the difference between the two sample averages

$$\hat{B} = \bar{Y}_1 - \bar{Y}_2. \tag{24}$$

As a linear combination of normally distributes random variables, $\hat{B}$ also follows a normal distribution. Developing confidence intervals and hypothesis tests on B using data from a gauge study requires the mean and variance (or standard error) of the sampling distribution of $\hat{B}$. The mean,

$$\mu_{\hat{B}} = E\left[\hat{B}\right] = E[\bar{Y}_1 - \bar{Y}_2] = \mu_1 - \mu_2 = B \tag{25}$$

shows that $\hat{B}$ is an unbiased estimator of B. Taking the square root of the variance

$$\sigma_{\hat{B}}^2 = Var\left[\hat{B}\right] = Var[\bar{Y}_1 - \bar{Y}_2] = \frac{\sigma_{Y_1}^2}{n} + \frac{\sigma_{Y_2}^2}{n} = \frac{\sigma_{V_1}^2 + \sigma_{G_1}^2}{n} + \frac{\sigma_{V_2}^2 + \sigma_{G_2}^2}{n} \tag{26}$$

yields the standard deviation or standard error that could be used in hypothesis tests and confidence intervals.

The precision of a gauge is captured by σ_G^2, the gauge error variance or σ_G, the standard deviation of gauge error. The MSA criteria previously discussed provide a multitude of ways for quantifying the precision of a gauge. Majeske (2012B) proposed two-sample hypothesis tests for MSA criteria and shows that a two-sample test for P/T, either equation (15) or (16), is an F-test for the ratio of the two gauge error variances. When using two-factor gauge studies the F-test has a test statistic

$$F_0 = \frac{MSO_1 + (pr-1)MSE_1}{MSO_2 + (pr-1)MSE_2} \tag{27}$$

that follows an F distribution with numerator degrees of freedom

$$\nu_1 = \frac{[MSO_1 + (pr-1)MSE_1]^2}{\frac{MSO_1^2}{o-1} + \frac{[(pr-1)MSE_1]^2}{opr-p-o+1}}$$

and denominator degrees of freedom

$$\nu_2 = \frac{[MSO_2 + (pr-1)MSE_2]^2}{\frac{MSO_2^2}{o-1} + \frac{[(pr-1)MSE_2]^2}{opr-p-o+1}}$$

Two-sample hypothesis tests for %R&RA of Equation (17), %R&RM of Equation (18), SNR of Equation (19) and the correlation in repeat measurements of Equation (20) use normal approximations.

6. Application

A manufacturer is currently in the process development stage of a component used in the assembly of a product. The component has a variety of quality characteristics, yet QC1, with design specifications LSL = 997 and USL = 1003, determines if the component will fit into the assembly. The manufacturer has identified two approaches to measuring QC1 during production: a custom "hard gauge" built specifically to measure QC1 (Gauge 1) and a coordinate measuring machine (CMM) (Gauge 2). Gauge 1 provides measurement data in increments of 0.1 and Gauge 2 measures QC1 to the thousandth or 0.001 of a unit.

To evaluate the two gauges, the manufacturer performs gauge studies with p = 20 parts, o = 2 operators and r = 3 repeat measurements on both gauges, using the same parts and operators. This approach blocks on the part and operator factors to remove any additional variability associated with them. This results in 60 data points for each study (see Table 1). The manufacturer fit a two-factor with interaction ANOVA model to the Gauge 1 and Gauge 2 data and found the interaction term was not statistically significant at $\alpha = 0.05$ for either study. The manufacturer then fit a two-factor main effects model to the Gauge 1 and Gauge 2 data and used equations (5) -> (8) to estimate the variance of the quality characteristic, gauge error and measured values (see Table 2). These variances will be used to evaluate and compare the two gauges based on precision, bias, MSA criteria and measures of process capability.

First, the manufacturer evaluated precision and bias. The data from Gauge 1 had an average of 1000.86 and the data from Gauge 2 had an average of 1001.48. This results in an estimated bias of 0.62 with a 95% confidence interval of 0.49 to 0.74. Gauge 1 had an estimated gauge error variance of 0.0340 with Gauge 2 at 0.0074. Using the hypothesis test previously presented to compare these variances, Equation (25) yields a test statistic of 4.624 with 2.4 numerator and 27.2 denominator degrees of freedom for a p-value of 0.0188. In summary, at $\alpha = 0.05$, the two gauges have significant difference precision and a significant bias.

Next, the manufacturer calcualted the 5 MSA criteria of Equations (16) -> (20) for both gauges (see Table 3). Gauge 2 has a P/T value of 0.09 which satisfies the manufacturer's P/T criteria of less than 0.1 while Gauge 1 has a value of 0.18 which falls in the "debatable" region. Gauge 2 passes the 0.3 or 30% criteria for both %R&RA and %R&RM while Gauge 1 was deemed inadequate with %R&RM of 36.0% and %R&RA of 38.6%. Similarly, Gauge 2 passes the SNR criteria of ≥ 5 while Gauge 1, with a value of 3.67, does not. To evaluate the gauges using ρ requires an approval value for the criterion. The manufacturer uses P/T of 0.1 and a C_p of 2.0, respectively, to approve a measurement system and production process. This results in a correlation in repeat measures criterion of 0.962 which Gauge 2 satisfies and Gauge 1 does not. Overall, the MSA criteria provide consistent results: Gauge 2 passes all 5 and Gauge 1 fails them all.

The manufacturer also used the results of the gauge study to evaluate process capability (see Table 3). Data from both gauges produce C_p values of greater the 2.0 with little difference in the gauges (2.09 for Gauge 1 and 2.20 for Gauge 2). These values suggest the process has the potential to produce an acceptable proportion of parts within the design specifications. However, neither gauge produces C_{pk} values greater than 2.0 - 1.49 for Gauge 1 and 1.11 for Gauge 2 - meaning that the process, in it's current configuration, does not meet it's quality objective. Interestingly, the gauge that performs the best on the MSA criteria (Gauge 2) produces data that results in the lower C_{pk} value. This is mainly driven by the difference in the two overall average readings for the gauge studies, captured by the bias noted above.

To investigate the source of the bias, the manufacturer identified a standard part by doing a very thorough detailed layout which determined the "true" value of QC1. Measuring the standard part multiple times with each gauge, the manufacturer determined that the CMM was producing data that exceeded the actual value of QC1 by approximately 0.7 - which corresponded to the value of the bias. Modifying how the CMM program established a datum on the part, the manufacturer was able to correct the bias issue.

Ultimately, the manufacturer needed to identify a strategy for measuring QC1. Gauge 1 is portable, relatively small, and used by the production worker at the point of manufacturer. Using Gauge 1, a production worker can measure parts immediately after manufacture, which would allow the production worker to measure parts for control charts and get immediate feedback. Measuring QC1 using Gauge 2 requires transporting parts to the inspection area where the CMM resides. Once there, one of the operators will measure the parts when the CMM becomes available. Using gauge 2 would require either keeping control charts in the inspection area and communicating the results back to the production operator or keeping the control charts in the production area and having to return the data after the measurements were complete. Either scenario creates a communication step to the control chart process. The manufacturer preferred Gauge 1 but could not justify the decision based on the results of the gauge studies.

7. Adjusted Measure System Analysis Criteria

Statistical measures and criteria have been developed that account for bias or a (potentially) controllable factor. In regression analysis, the statistic Adjusted R-Squared provides an unbiased (relative to R-squared) estimate of the variance explained. Majeske et. al. (2010) provide two variations of the statistic R^2 that correct for measurement error. In process capability, the statistic C_p measures potential process capability that could be achieved by adjusting the process mean to the center of the design specifications. Majeske and Hammett (2007) suggest a method for estimating C_p that corrects for batch-to-batch mean shifts and represents the potential C_p value that could be achieved by having a stable mean.

To provide a new set of metrics to evaluate gauges, define gauge error potential $\sigma_{G_P}^2$ as the value that would be achieved by eliminating differences between operators (the variance captured by σ_O^2 and in some cases σ_{OP}^2). In application, due to estimation methods, this will also result in different values for the variances of the quality characteristic $\sigma_{V_P}^2$ and data generated by the gauge $\sigma_{Y_P}^2$. Using these three potential variances, define new MSA criteria - potential measures - that correspond to the precision to tolerance ratio

$$\frac{P}{T}_P = \frac{5.15\sigma_{G_P}}{USL-LSL} \tag{28}$$

or

$$\frac{P}{T}_P = \frac{6\sigma_{G_P}}{USL-LSL}, \tag{29}$$

the two repeatability and reproducibility measures

$$\%R\&RA_P = \sqrt{\frac{\sigma_{G_P}^2}{\sigma_{V_P}^2}} = \frac{\sigma_{G_P}}{\sigma_{V_P}} \tag{30}$$

and

$$\%R\&RM_P = \sqrt{\frac{\sigma_{G_P}^2}{\sigma_{Y_P}^2}} = \frac{\sigma_{G_P}}{\sigma_{Y_P}}, \tag{31}$$

the signal to noise ratio

$$SNR_P = 2\frac{\sigma_{V_P}^2}{\sigma_{G_P}^2} = \sqrt{2}\left(\frac{\sigma_{V_P}}{\sigma_{G_P}}\right) \tag{32}$$

and correlation in repeat measurements

$$\rho_P = \frac{\sigma_{V_P}^2}{\sigma_{V_P}^2 + \sigma_{G_P}^2}. \tag{33}$$

To estimate the criteria, assume that the manufacturer has used a multiple operator gauge study. Fit a three-factor model (or two-factor model if the interaction is not significant) to the data and estimate the potential variance of the quality characteristic with

$$\hat{\sigma}_{V_P}^2 = \frac{MSP - MSE}{or}; \tag{34}$$

the potential gage error as

$$\hat{\sigma}_{G_P} = MSE; \tag{35}$$

and then combine quality characteristic and gauge error to estimate variance of measured values

$$\hat{\sigma}_{Y_P}^2 = \hat{\sigma}_{V_P}^2 + \hat{\sigma}_{G_P}^2. \tag{36}$$

To continue their comparison of the two gauges, the manufacturer then calculated the potential variance estimates of equations (34) -> (36) for each gauge and used them to estimate the potential MSA measures of equations (29) -> (33) which appear in Table 4. Using the measures of potential, the assessment of Gauge 2 does not change – it satisfies all 5 criteria. However, the perception of Gauge 1 changes. Using these new measures of MSA potential, Gauge 1 satisfies the two %R&R and the SNR criteria suggesting that, if operator variance is eliminated, the gauge can differentiate between parts and produce data for control charts. Using the potential MSA values, Gauge 1's P/T_P value of 0.11 doesn't meet the 0.1 threshold and the ρ_P of 0.96 falls short of the 0.97 cutoff.

The part described by QC1 is a high-volume part that will be made on multiple machines. Once in production, a single operator will run each machine and the operator will keep their own control chart for QC1. For purposes of each control chart, QC1 will be measured by a single gauge operator which eliminates between operator variance. Therefore, the manufacturer relied on the measures of MSA potential and approved Gauge 1 for control charts. When measuring parts for other purposes the manufacturer will use Gauge 2 (the CMM).

8. Conclusion

As measuring technology evolves, manufacturers have more options when developing gauges to measure products. Each technology has its own strength and works better in certain situations. Vision systems lend themselves to 100% inspection better than either CMMs or hard gauges. CMMs and vision systems have flexibility to measure new or modified parts with changes to software routines. Hard gauges can be located in production areas easily accessible to production operators.

The various MSA criteria are intended to assess a gauge's ability to produce data used for different purposes. They may also serve as decision criteria when selecting a specific measurement system. In this case, using standard techniques lead a manufacturer to identify a CMM as the measurement system when this may not have been the ideal solution for them. Using the CMM would separate the measuring of the parts for control charts from the production of the parts. It would also create a lag between when parts were produced and when they were measured and the resultant data plotted on a control chart. It was the downside of using the

CMM to generate data for control charts that lead the manufacturer to further investigate the hard gauge option.

Using standard techniques has many benefits; however, one must take the nuances of their situation into account when using them. In this case, understanding how a multi-operator study impacted the MSA criteria led to the development of new criteria that provided a better fit to the situation. In a sense, the measures of MSA potential used in this application ignore operator-to-operator differences as a source of measurement error. For this reason, one should not blindly follow this approach without fully understanding the statistical implications.

References

Automotive Industries Action Group (2010). *Measurement Systems Analysis 4th ed*. Southfield MI: Automobile Industries Action Group.

Barrantine, L.B. (1991). *Concepts for R&R studies*. Milwaukee Wisconsin: ASQC Press.

Beckert, S.F., Paim, W.S. (2017). Critical analysis of the acceptance criteria used in measurement systems evaluation. *International Journal of Metrology and Quality Engineering*, 8(23).

Blackwood, L.G., Bradley, E.L. (1991). An omnibus test for comparing two measuring devices. *Journal of Quality Technology*, 23(1):12-16.

Burdick, R.K., Borror, C.M., Montgomery, D.C. (2005). *Design and Analysis of Gauge R&R Studies: Making Decisions with Confidence Intervals in Random and mixed ANOVA models*. SIAM: Philadelphia, Pennsylvania.

Dalalah, D., Hani, D.B 2016. A precision-to-tolerance ratio model for the assessment of measurements uncertainty. *Precision Engineering*, 44:143-151.

Fletcher J.P., Bandy W.D. 2008. Intrarater reliability of CROM measurement of cervical spine active range of motion in persons with and without neck pain. *Journal of Orthopaedic & Sports Physical Therapy*, 38:640-645.

Majeske, K.D. (2008). Approval criteria for multivariate measurement systems. *Journal of Quality Technology*, 40(2):140-153.

Majeske, K.D. (2012A). Approving vision-based measurement systems in the presence of within-part variation. *Quality Engineering*, 24(1):49-59.

Majeske, K.D. (2012B). Two-sample tests for comparing coordinated measurement systems. *Quality Engineering*, 24(4):500-513.

Majeske K.D., Andrews, R. W. (2002). Evaluating measurement systems and manufacturing processes using three quality measures, *Quality Engineering*, 15(2):243-251.

Majeske K.D., Gearhart, C. (2006). Approving measurement systems when using derived values. *Quality Engineering*, 18:523-532.

Majeske K.D., Hammett P.C. (2007). Quantifying the variance contribution of special cause mean shifts in reconfigurable batch manufacturing processes. *International Journal of Production Research*, 15(12):2799-2817.

Majeske K.D., Lynch-Caris T., Brelin-Fornari J. (2010). Quantifying R^2 bias in the presence of measurement error. *Journal of Applied Statistics*, 34(4):667-677.

Montgomery, D. C. (2020). *Introduction to Statistical Quality Control, 8th ed.* New York: John Wiley & Sons.

Table 1: Gauge Study Raw Data

Gauge 1						
	Operator 1			Operator 2		
Part	Reading 1	Reading 2	Reading 3	Reading 1	Reading 2	Reading 3
1	1001.6	1001.7	1001.7	1001.4	1001.6	1001.5
2	1000.3	1000.4	1000.4	1000.1	1000.0	1000.2
3	1000.7	1000.7	1000.4	1000.2	1000.4	1000.5
4	1001.5	1001.4	1001.5	1001.4	1001.3	1001.3
5	1000.9	1000.9	1001.0	1000.9	1000.6	1000.6
6	1001.1	1001.3	1001.2	1001.0	1001.0	1000.9
7	1000.8	1000.5	1000.5	1000.2	1000.3	1000.4
8	1001.5	1001.6	1001.5	1001.1	1001.3	1001.2
9	1000.5	1000.7	1000.6	1000.4	1000.3	1000.3
10	1000.5	1000.4	1000.7	1000.3	1000.4	1000.3
11	1001.2	1001.3	1001.3	1001.3	1000.8	1000.8
12	1001.6	1001.4	1001.7	1001.3	1001.3	1001.5
13	1000.7	1000.8	1000.6	1000.5	1000.6	1000.5
14	1001.7	1001.8	1001.7	1001.6	1001.7	1001.4
15	1000.2	1000.4	1000.3	999.9	1000.1	1000.0
16	1000.9	1001.0	1000.9	1000.8	1000.9	1000.7
17	1001.6	1001.4	1001.3	1001.2	1001.2	1001.3
18	1000.3	1000.3	1000.4	1000.3	1000.1	1000.2
19	1000.7	1000.7	1000.8	1000.4	1000.6	1000.7
20	1000.8	1001.0	1000.9	1000.6	1001.0	1000.7
Gauge 2						
1	1002.195	1002.264	1002.185	1002.099	1002.171	1002.023
2	1000.774	1000.887	1000.706	1000.948	1000.807	1000.811
3	1001.342	1001.338	1001.328	1001.094	1001.199	1001.015
4	1002.126	1002.096	1002.039	1001.866	1002.117	1002.119
5	1001.336	1001.333	1001.502	1001.421	1001.372	1001.424
6	1001.735	1001.663	1001.588	1001.453	1001.564	1001.754
7	1001.126	1001.040	1001.246	1001.132	1001.121	1001.131
8	1002.067	1002.015	1001.897	1001.862	1001.940	1001.837
9	1001.091	1001.037	1001.185	1001.140	1001.107	1001.003
10	1000.936	1000.999	1001.011	1000.996	1000.978	1001.057
11	1001.970	1001.739	1001.739	1001.771	1001.822	1001.748
12	1002.015	1001.918	1002.153	1002.065	1002.077	1001.881
13	1001.191	1001.334	1001.198	1001.232	1001.188	1001.253
14	1002.247	1002.274	1002.242	1002.053	1002.212	1002.178
15	1000.786	1000.813	1000.862	1000.730	1000.766	1000.847
16	1001.424	1001.405	1001.458	1001.436	1001.495	1001.516
17	1001.869	1001.940	1001.790	1001.786	1001.840	1001.735
18	1000.913	1000.992	1001.091	1000.906	1000.835	1000.969
19	1001.361	1001.234	1001.277	1001.208	1001.245	1001.151
20	1001.665	1001.623	1001.499	1001.491	1001.572	1001.559

Table 2: Variance and Standard Deviation Estimates

	Variance		Standard Deviation	
Variance	Gauge 1	Gauge 2	Gauge 1	Gauge 2
Quality Characteristic	0.2290	0.2071	0.4785	0.4551
Operator	0.0218	0.0013	0.1478	0.0362
Within Operator	0.0122	0.0061	0.1104	0.0778
Gage Error	0.0340	0.0074	0.1845	0.0858
Measured Values	0.2630	0.2145	0.5128	0.4631

Table 3: Process Capability and Measurement System Analysis Criteria

	Gauge 1	Gauge 2
Cp	2.09	2.20
Cpk	1.49	1.11
P/T	0.18	0.09
%R&RM	36.0%	18.5%
%R&RA	38.6%	18.9%
SNR	3.67	7.50
Correlation	0.87	0.97

Table 4: Potential Measurement System Analysis Criteria

	Gauge 1	Gauge 2
P/T_P	0.11	0.08
$\%R\&RM_P$	22.5%	16.8%
$\%R\&RA_P$	23.1%	17.1%
SNR_P	6.13	8.27
ρ_P	0.95	0.97