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STATISTICS FOR ENGINEERS – ABET CRITERION 3b

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1. INTRODUCTION

"The average Japanese worker has a more in-depth knowledge of statistical methods than an average American engineer," explained a U.S. businessman returning from a visit to Japan, when he was asked why the Japanese were able to produce better quality products than U.S. manufacturers (Gabor 1990). That statement, made almost 30 years ago, is probably true even today as, for example, the Japanese cars are still sought by consumers who buy for quality and reliability.

Dr. Walter Shewhart, considered the father of modern statistical quality control, said (Shewhart 1939): "The long-range contribution of statistics to quality control depends not so much on getting a lot of highly trained statisticians into industry as it does in creating a statistically minded generation of physicists, chemists, engineers and others who will in any way have a hand in developing and directing the productive processes of tomorrow."

Dr. W. Edwards Deming, the quality guru who taught the Japanese how to make quality products, realized the need for training engineers (and others) in statistical methodology. He said (Deming 1986) "Industry in America needs thousands of statistically minded engineers, chemists, doctors of medicine, purchasing agent and managers." He further said "no one should be teaching statistical theory and applications, especially to beginners, unless he possesses knowledge of statistical theory through at least the master's level, supplemented by experience under a master." His emphasis was that the engineers and others should learn the statistical methods along with the theory behind them, from people who have the competence to teach that theory.

A report in the *Wall Street Journal* last year read (Chakravorty 2010): "Recent studies … suggest that nearly 60% of all corporate Six Sigma initiatives fail to yield the desired results." The report suggests that lack of adequate knowhow for performing sophisticated statistical analysis is one of the reasons for the surprisingly high rate of failure.

Dr. T.N. Goh, an international consultant, and an Academician of the International Academy for Quality, was lamenting the inadequacy of Black Belts he had come across in statistical thinking: "Black Belts using conventional Six Sigma procedures on service systems could end up with results that could not stand up to serious scrutiny of a good statistician…The tragedy is doubled if the Black Belts are not even aware of their own inadequacy or limitations and instead brandish to management or customers the outcomes of half–baked studies" (Goh 2010).

The industry leaders have spoken on many occasions of the need for training all engineers in statistics and quality, and possibly as a result, the Criterion 3b was included as one of the student outcomes in the ABET accreditation criteria. The criterion calls for "an ability to design and conduct experiments, as well as to analyze data and interpret results," (ABET 2011)

The intent of the requirement is clear to someone like this author who is an industrial engineer with training in statistics. It calls for educating engineering majors in concepts of probability and statistics to the level where they will be able to prepare statistically designed experiments, gather data from such experiments, analyze them using appropriate techniques, draw engineering conclusions, and make changes to processes so as to solve problems that will improve the quality of a process and its output. The science of design of experiments (DOE) is an advanced topic in statistics, which requires a basic understanding of probability, random variables, probability distributions, confidence intervals and hypothesis testing, in order to be able to understand and use designed experiments in practical situations. The science has developed into a mature discipline and is well documented in many books (e.g. Montgomery 2009).

However, as an ABET program evaluator for the last 15 years, this author has seen many instances where engineering programs, excepting IE programs, try to show that they meet the Criterion 3b without incorporating any classes in statistics in their curriculums. See for example the excerpts taken from rubrics created by two engineering programs in their self-study documents, in the Table 1a and 1b. Note that neither of the programs make any mention about education in statistics.

Table 1a: Excerpt from a rubric created to evaluate student accomplishment against Criterion 3b

	Outcome		Performance criterion	Level of achievement
3b	XXXX graduates will have an ability to design and conduct experiments related to operations, marketing, management and finance, as well as to analyze and interpret data	b.1	Design an operation system and analyze and interpret data relative to de designed system.	
		b.2	Analyze operational and financial data of organizations in case studies and organizational profiles	
		b.3	Conduct research related to publicly traded firms and apply financial tools to evaluate the firm as a possible investment choice.	
		b.4	Analyze organizational structure and understand origin of organizational culture and mechanisms of communication within organization.	

Table 1b: Excerpt from a rubric created to evaluate student accomplishment against Criterion 3b

	Outcome		Performance criterion	Level of achievement
3b	XXXX graduates will have an ability to conduct experiments, as well as to analyze and interpret data related to manufacturing processes, materials evaluation, and manufacturing systems.	b.1	Observe good laboratory safety procedures	
		b.2	Formulates an experimental plan of data gathering	
		b.3	Carefully documents data collected	
		b.4	Develops and implements logical experimental procedures	
		b.5	Selects appropriate equipment and instruments to perform the experiment	
		b.6	Is able to operated instrumentation and process equipment	

The engineering educators who prepared these rubrics seem to miss the real point - the need for training engineers in statistics to be able to plan good experiments, analyze data and interpret results. The result is, nearly 85% of graduates from a typical college of engineering are not trained in statistics, and a more alarming fact is that nearly 85% of the U.S. engineers who design, produce and deliver products today (according to our informal survey) have had no training in statistical methods needed for designing and producing quality products.

2. WHY DO ENGINEERS NEED EDUCATION IN STATISTICS?

Study of statistics creates in an engineer the ability for statistical thinking which helps in seeing order in the world, which would otherwise seem random, haphazard, or chaotic. The engineer will see that there are underlying patterns in the random phenomena, which can be captured in models such as normal, Weibull, gamma, etc., provided to us by mathematicians. Such modeling helps in revealing relationships among variables, which in turn enables prediction of their behavior in the future. When an engineer with such an ability views processes that produce products, he/she is able to see signals among noise, extract meaningful relationships among variables that are clouded by variability, and gain a deeper knowledge about processes. This empirical knowledge gained about processes when combined with the physical, chemical and other technological relationships the engineer already possess leads to a deeper understanding of the causes and effects in processes. Such knowledge helps in identifying solution to problems that would otherwise cause defective products and waste. The following case studies illustrate this contention.

A series of case studies are described below to illustrate how statistical thinking enables an engineer to frame a problem in the models of statistics and then find solutions. In each case, the reader will note that without this ability for statistical thinking by the engineer the problem would have continued to be misunderstood and produce waste and cause customer complaint. Also to be noted, in each case there is a planned experiment, data collection, analysis, recommended solution and its implementation. All these cases are drawn from manufacturing since manufacturing environment offers the most challenges in this regard. All these cases were part of an article the author wrote for the *IE* magazine of the Institute of Industrial Engineers (Krishnamoorthi, 2011).

2.1 Case 1: The chemical engineers' quandary.

A customer's specification for a chemical product stated: No more than half percent of the packages should contain more than half percent of ash.

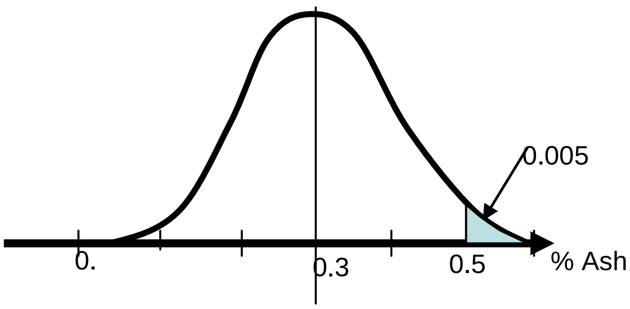


Figure 1: Using normal distribution to model percent ash in packages.

The chemical engineers in charge of production did not know how to interpret the specification; they just made the product as well as they could and delivered it to the customer *hoping* that it would be accepted. Often packages were rejected by customers, returned to the plant and burned in incinerators.

It was a revelation to the engineers when they were shown how the normal distribution model could be used to interpret the specification (see Fig. 1) and how they could verify the acceptability of their product even as it was being produced. They had to take small samples of 4 packages from the process periodically and create $\overline{X}$ and R charts for ash content. Estimating the process average as $\overline{\overline{X}}$, the center line of the $\overline{X}$ -chart, and the process standard deviation as $\overline{R}/d_2$ where $\overline{R}$ is the center line of the R-chart, the proportion of packages having more than 0.5% ash could be estimated on normal assumption, and compared with the specified limit. Thus the engineers would know the quality of their product even before shipping it to the customer, and could adjust it to the level the customer expects.

2.2 Case 2: Tolerance of a sum is not equal to sum of the tolerances of the parts

In a shipping dock, skids were assembled with each skid stacked with 36 bags of a chemical. Before loading the skids on to trucks, the trucker was checking the skid-weights as a quick way of checking the bag-weights. The bags had a tolerance of $\pm$ 0.5 lb and so the trucker had been given a tolerance of $\pm$ 18 lb for the skid-weight. There were frequent customer complaints of bags being under-weight. The engineer in charge was at a loss as to why the bag weights would be low when skid weights were correct.

The method used to compute the tolerance for the skid-weight from the tolerance of bag-weight is incorrect. The formula called the Root Sum of Squares (RSS) Rule should be used to calculate the tolerance for the skid-weight. The tolerance for skid-weight should be $\pm$3 ($T_{skid} = \sqrt{36 \times 0.5^2} = \pm\, 3$) – not $\pm$18 lb. The RSS formula is based on the laws of statistics used for calculating the variance of a sum from the variance of components.

2.3 Case 3: Resolving a raging debate.

A brand of testing machine that is currently used to test the strength of cores (made of sand with bonding material) in a foundry is no longer available to buy because the supplier went out of business. The existing machines cannot be serviced, either. A new brand has to be purchased. However, all the specifications for core strength in the foundry have been created using the old tester. A group of technicians are arguing that all the specifications (a few hundreds of them) should be reset using the new tester. Another group is arguing that new specs are not necessary; they are mainly concerned about the enormous time and expense needed in redoing the specs. A satisfactory resolution is needed; otherwise, next time any scrap is produced anywhere in the plant, someone will point fingers at the lack of revised specs for sand strengths as the reason for the defectives.

The question to be answered: Are the populations of readings generated by the two testers, for the same sand, identical? The question was answered using hypothesis testing comparing the means and variances of the two populations. Samples were collected from both testers for several sand types (see Table 3 for an excerpt) and hypotheses were tested as stated below for each sand type.

$$\mathrm{H}_0: \mu_1 = \mu_2, H_1: \mu_1 \neq \mu_2 \;\; , \;\; H_0: \sigma_1^2 = \sigma_2^2, H_1: \sigma_1^2 \neq \sigma_2^2$$

The testers were found to give “equal” results. Everyone agreed that there was no need for revising the specs.

Table 3: Comparing strength readings generated by two testers

Sand batch	Trial	D tester			TA tester		
		Specimen 1	Specimen 2	Specimen 3	Specimen 1	Specimen 2	Specimen 3
1	1	340	360	375	359	351	345
	2	350	335	345	348	329	348
2	1	225	210	250	254	255	247
	2	255	245	230	244	253	202
3	1	220	250	245	243	251	235
	2	240	225	230	241	251	204

2.4 Case 4: How tall is too tall?

The president of a company that produces paper cubes, an advertising specialty, believes that the workers are making cubes too tall compared to what is called for in the spec. The cube height depends on the height of a "lift" of sheets of paper the workers pick from the paper stack using eye-judgment. The height varies from lift to lift for the same worker, varies from worker to worker, and over time. The humidity in the air is another serious variable confusing the judgment of the workers because the paper bulks and contracts with changes in humidity. The workers are erring on the safe side by making the cubes too tall. The president wants to know how much money the company is losing in the excess paper given away, and if that loss would justify installation of an expensive sheet-counting machine recommended by a consultant with promise to deliver the "same" height for every lift.

The current height of the cubes is a random variable and has a distribution. The ideal height is also a random variable with a distribution because every cube cannot be made with exactly the same height (unless forced to be so by a sheet-counting machine). We assume normal distribution for both, and parameters of the two populations have to be estimated. The "difference" between the distributions is the overage that can be avoided (see Fig. 2). This difference is then converted into dollar amount. The reader will recognize, estimating the variability in the ideal distribution and computing proportion too tall needs a bit of sophisticated statistical thinking.

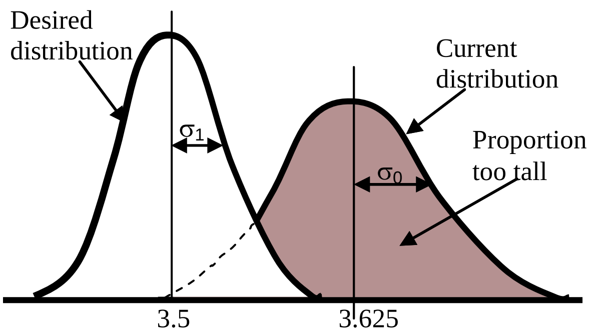


Fig. 2: The distribution of difference between actual and ideal height of paper cubes.

Incidentally, this study resulted in discovery of the sources of variability in the cube height, which led to implementation of production rules that reduced variability and reduced the paper give away - all without the expensive sheet- counting machine.

2.5 Case 5: Blood all over the place

A huge consignment of castings, cylinder heads for automotive engines, was returned to a foundry by the machine shop because of blisters found when the castings were machined. The returned castings were stacked all over the floor in the plant and the night-shift inspector described the scene as "blood all over the place," reflecting the seriousness of the problem. The customer's machining and assembly operations needed the castings badly; the foundry could lose the customer if the problem was not resolved right away.

Table 4: Factors and levels for the experiment to eliminate blisters in castings

Factors	**Levels**	
	Low	**High**
A: Sand for port-cores	Silica	Lake
B: Drying oven temp.	350°F	400°F
C: Flow-off vents	Yes	No

The foundry engineers did not know exactly what caused this defect although they knew that a few changes to the foundry processes had been made recently to achieve some savings. It was decided to run a designed experiment on the most plausible set of factors with two levels for each. The engineers agreed to run a 2^3 factorial experiment with factors and levels as shown in Table 4. Preparations were made, the experiment was conducted and results were obtained all within 48 hours. When the castings were poured, cooled, cut, and inspected, the percentages of defective castings at each treatment combination were as shown in Figure 3. The results showed that there was a treatment combination that had zero blisters. A trial production run with these "optimal" parameters for the process confirmed the findings from the experiment, and the process specs were changed. The problem was resolved.

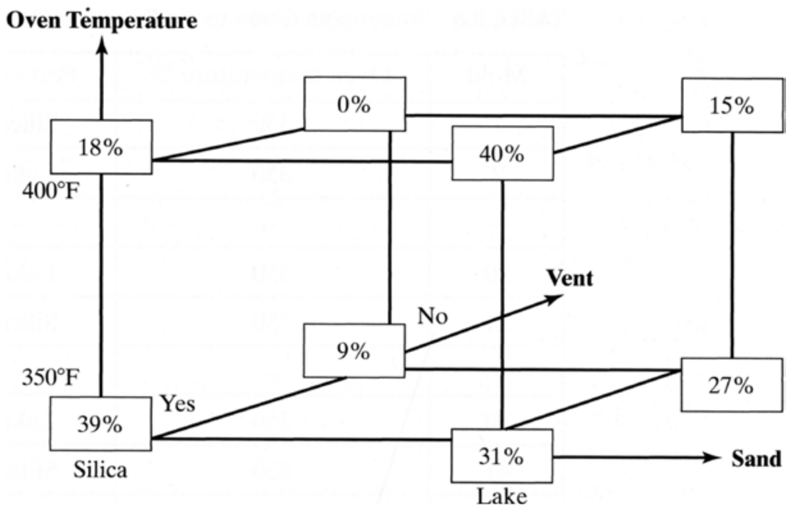


Fig. 3: Results from a designed experiment to eliminate blisters in castings.

2.6 Case 6: Dry-ability of an oven vs. humidity

Whenever it rained outside, a foundry experienced an increased amount of scrap inside. The foundry wanted to know how the rain outside the buildings affected the processes inside, and if there was a way to proof the foundry processes from the outside rain.

It was suspected that the rain (atmospheric humidity) was affecting the drying ability of the oven that was used to dry the molds after they were dipped in a wash. Data were collected on the factors such as temperature of hot air used for drying, conveyor speed of the oven, and atmospheric humidity, corresponding to a measure called dry-ability index of the oven that reflected how well the oven was drying the cores.

Regression analysis was used to find how much impact each of the factors had on the dry-ability (see Fig. 4). The results confirmed that the dry-ability decreased when the humidity increased, but it increased when hot air temperature increased or when the conveyor speed decreased. Using this knowledge, when the humidity increased on a rainy day and dry-ability dropped, the other factors were appropriately adjusted to get the dry-ability back at the desired level. For example, when the dry-ability dropped on a day (these readings were taken twice a day on a regular basis) due to increase in humidity, the foreman would call for increasing the hot-air temperature to restore the dry-ability. If increasing the hot-air temperature alone did not restore dry-ability, the foreman would authorize reducing conveyor speed. Increasing the hot-air temperature made the workplace a bit more hot and reducing the conveyor speed reduced production output; yet the workers and foremen understood the relationship between dry-ability and casting quality and were willing to make the sacrifices.

When the dry-ability was thus maintained at a consistent level, the casting scrap declined. The foundry process was made robust against an uncontrollable variable, the outside rain, which, along with the resultant casting scrap, had been accepted earlier as a given, fact of life.

Regression Analysis: Dryblty versus R-Humidity, Air-Temperature, Conv. Spd.

The regression equation is
Dry-ability = 0.487 − 0.00119 RH + 0.000874 Hot-air − 0.260 conv spd

Predictor	Coef	SE Coef	T	P
Constant	0.4867	0.1585	3.07	0.005
Humidity	−0.0011853	0.0005206	−2.28	0.031
Air Temp	0.0008740	0.0004090	2.14	0.042
conv spd	−0.25963	0.04280	−6.06	0.000

S = 0.04482 R-Sq = 65.5% R-Sq(adj) = 61.5%

Fig. 4: Results from regression among variables in a foundry process.

3. HOW MUCH OF STATISTICAL KNOWLEDGE IS NEEDED?

First of all, it should be recognized that in each of the above cases, an engineer who knew the process well and who had the ability for statistical thinking was needed to find satisfactory solutions. In at least one case there was no time to bring in a statistician and educate him or her on the process details before performing the experiment. This goes to prove the point that Drs. Shewhart and Deming made that the problem solvers need not be all statisticians, but they must be engineers, chemists, and scientists who know their processes well and at the same time have the ability for statistical thinking.

Such ability for statistical thinking, in this author's view, comes from an understanding of the fundamentals of probability, the laws of statistics, and the theoretical basis of the statistical methods employed in quality engineering. Several authors have written on what a quality analyst should know in order to possess the needed stat-ability. The article by Roger W. Hoerl (Hoerl, 2001) provides an overview of such recommendations and suggests a lesson plan. The knowledge base needed for an analyst/engineer can be summarized as follows.

There is variability in every population. This variability can be quantified, and modeled using probability distributions. There are several distributions proposed by mathematicians to model various types of variability. Normal, Binomial, Poisson, Exponential, Weibull, etc., are the names attached to these different models. Quality engineers (all engineers may have to don the quality-engineer's hat one time or other) should know the appropriate application for these distributions and the mathematics to make predictions with them. They should know how to monitor and control the variability in process variables and product characteristics using control charts. They should know the methods to find the relationship among process variables and product characteristics, such as regression analysis and designed experiments (DOE). Methods to determine the variability in measurements generated by instruments are another important set of tools. They should learn these methods with an understanding of the theoretical basis behind them. For example, when an analyst learns about $\bar{X}$-chart, he or she should learn how the formulas for the limits are derived, why small sample sizes and 3-sigma limits are used, what is meant by the power of the control chart, and how the performance of a control chart is evaluated using OC curve and ARL. It is possible to teach all of this in one course; the author has a course plan.

Some believe that it is not necessary for an engineer to understand the theory behind statistical methods in order to use them. They will use the analogy that "there is no need to learn how a car is designed in order to be able to drive it." However, when the methods are learned without understanding their theoretical background, only half knowledge is gained. Yes, there are places where that partial knowledge can be adequate. But, that partial knowledge does not cultivate the deeper statistical thinking needed when facing larger, more complex problems.

4. CONCLUSION

Statistical thinking provides the empirical complement to the engineering knowledge of processes, which leads to fuller insight into problems and then to their resolution. A certain knowledge base is needed to achieve the ability to think statistically. Lesson plans are available to grow this knowledge base. They are not at the master's level in statistics, not even at the bachelor's level statistics; they are at a level that would complement the engineering or science knowledge an engineer would already possess. There will always be the need to consult a master statistician on issues where the engineer recognizes the need for help.

The author has a course plan that he has used successfully to provide this knowledge base, especially to non-IE majors – in a one-semester course. He would be glad to share the course plan with interested engineering educators. He has also created an objective test to further define/test this knowledge base. The test has 25-30 questions and can be answered without use of a calculator. It can be used to determine if a student has acquired the knowledge base adequately. It can also be used – in the context of training working engineers – to verify if there are enough people in a productive organization having the requisite stat-ability and accordingly plan training strategies to create the adequate statistical know how for the organization. A short excerpt from the test is provided below.

An ongoing survey by the author indicates that less than 5% of people involved in the design and production of products in U.S. industry today have this ability. The same survey also indicates that, if at least 20 to 25% of them have this knowledge, the quality system of that organization will be much healthier. Engineers can easily acquire this knowledge because of their preparation in mathematics and can become the source of such knowledge to an entire organization where they are employed. The engineering educators can greatly facilitate this change by suitably incorporating statistics education in their engineering curriculums.

5. AN EXCERPT FROM THE TEST FOR STATISTICAL THINKING

1. If a fair die is tossed 12 times, what is the probability that the number 6 shows exactly 6 times?

A. $\left(\frac{1}{6}\right)^6$ B. $\left(\frac{5}{6}\right)^6$ C. $6\times\left(\frac{1}{6}\right)^6$ D. $\binom{12}{6}\left(\frac{1}{6}\right)^6\left(\frac{5}{6}\right)^6$ E. $\left(\frac{1}{6}\right)^{12}$

2. The random variable that represents the number of bad welds per fabricated cabin will have which of the following distribution:

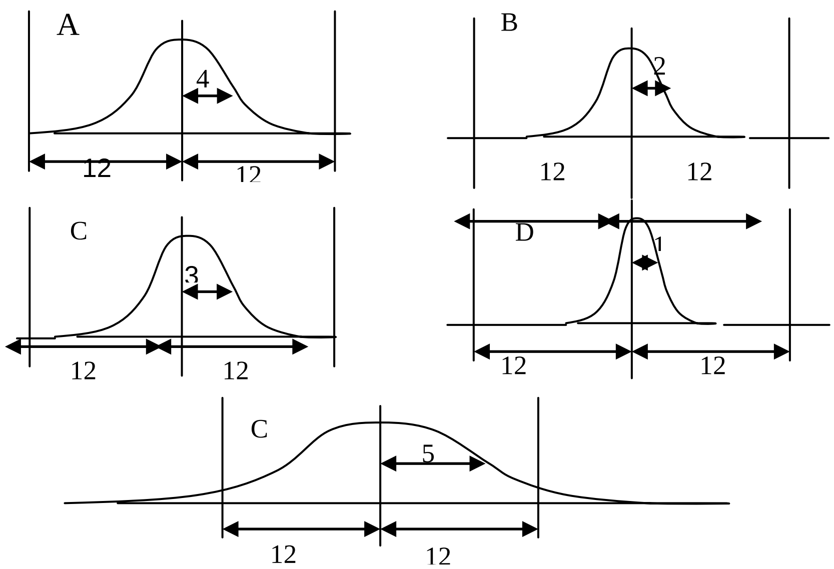
A) $p(x)=\frac{e^{-\lambda}\lambda^x}{x!}, x=0,1,2,...$ B) $p(x)=(1-p)^{x-1}p, x=1,2,.....$ C) $p(x)=\binom{n}{x}p^x(1-p)^{n-x}, x=0,1,2,...n$

D) $p(x)=\frac{\binom{D}{x}\binom{N-D}{n-x}}{\binom{N}{n}}, x=0,1,..., \max(n,D)$ E) none of the above

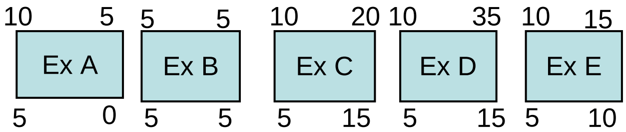
3. The 3-sigma control limits for current control of a process using $\bar{X}$ - chart, is given by $(\bar{\bar{X}}\pm A_2\bar{R})$ The factor A_2 stands for:

A. $\frac{3}{d_2\sqrt{n}}$ B. $\frac{2}{d_2\sqrt{n}}$ C. $\frac{3}{d_2 n}$ D. $\frac{3}{A\sqrt{n}}$ E. $\frac{3}{c_2\sqrt{n}}$

4. Pick out the process with 6-sigma capability



5. Identify the example(s) below where interaction exists in the 2^2 experiment.



6. The residual sum of squares used to estimate the variance of Y in regression is given by:

A. $\sum_{i=1}^{n}(y^2{}_i - \hat{y}_i{}^2)$ B. $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ C. $(\sum_{i=1}^{n}(y_i - \hat{y}_i))^2$ D. $\sum_{i=1}^{n}(y_i - \overline{y})^2$ E. $\sum_{i=1}^{n}(y_i - \overline{y})$

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Dr. Krishnamoorthi is a professor of industrial engineering at Bradley University in Peoria, IL. He holds a BE in mechanical engineering from University of Madras, India, and an MA in statistics and PhD in industrial engineering from SUNY, Buffalo. He teaches, consults and does research in the area of product and process improvement using statistical methods. He is a Fellow of the American Society for Quality and a senior member of the IIE. His book *A First Course in Quality Engineering*, 2nd edition, was published by CRC Press, in September 2011.

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