

Statistical Study of Supply Chain Developmental Training
on Original Equipment Manufacturer's Defect Rates

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Doctor of Philosophy
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DEDICATION

I have dedicated my life's work trying to make a positive difference in the industries I have served over a span of forty-five years. Whether as a member of an engineering staff or a management team at a manufacturing facility, as a teacher, or as a consultant for the University of Tennessee Center for Industrial Services (UT CIS), my belief has always been unwavering and simple: a person **can** make a difference.

Making a difference can mean a lot of things: taking time to dig deep into real world problems; spending a few extra moments to ensure someone was understood; allocating extra time to a report for clarity's sake or thoroughness; adding something "extra" as value for a customer; taking a moment to double check a calculation; or just reaching out to someone when it is needed. With perseverance and dedication to a cause, any person can make a difference.

For that reason, this dedication goes to my wife Lydia and my two sons, Graeme and Logan. Their having started this journey over a period spanning a decade, they were there when I was unable to see journey's end. They were there when my job and student work load seemed as though it would overwhelm me. They were there with congratulations when I succeeded and encouragement when I failed.

They were urging me to finish what I started. I owe my spouse more than words can say. She put up with my sleep deprivation (full time job and part-time student), the extra work she did when I was studying, my grumpiness, my impatience, my inattention to the world around me, my sicknesses, and even my old age. She made this journey with me in a

different way, but it was also her journey, nonetheless. She remarked, “This is just as much my doctorate as it is yours!” I couldn’t agree with her more.

Lydia, I thank you for your devotion and belief in my aspirations to fulfill a life-long dream and you have my undying love and gratitude for taking this decade long walk with me. My only regret is I did not start it earlier in life. To my best friend in the world and life-mate – the light at the end of the tunnel grows brighter by the minute.

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ABSTRACT

Learning is an amalgam of a student's desire to understand, the willingness of an instructor to educate, the subject taught, its quality, and the delivery environment. Most importantly, a learning goal, both actionable and investment worthy, must exist for effective learning to take place. The ability to learn and then implement new concepts and ideas is ***the*** significant difference separating our species from other life on this planet. It has led to diverse discoveries such as disease vaccines, nuclear energy, the automobile, electronics, and rocket planes to name just a few.

Science advances in small steps and big leaps. Inventions increase daily to improve the quality of life for this planet's population. At the center of all these ideas are researchers looking to tease out the next piece of information for our world's knowledge base. This body of knowledge (BOK) grows at an ever-expanding rate, doubling every few years. This doubling period is shrinking rapidly as more knowledge is accumulated.

In the manufacturing world of products, this BOK is brought to bear on products that, hopefully, stand above their competition. If a product is excellent, consumers and producers are satisfied. The consumer gets the best quality for the price while the producer gets the best price for the quality offered. If product quality and price are right, there is someone willing to buy it.

However, what happens when the opposite is experienced and the product, at its asking price, is of poor quality? Buyers are less willing to spend and quick to mention the lack of quality or defects found. Defects can impact the maker's selling price and

translate into extensive efforts to make the customer whole through warranty. The producer also risks the loss of their customer (brand loyalty) if the product is deficient in quality.

Within this dissertation, training methods, useful practices, experiences, and the body of training knowledge will be presented in defense of developmental training and will conclude with a case study exploration into the connections between supply chain developmental training and defect reductions at an Original Equipment Manufacturer (OEM) using multiple statistical techniques.

PREFACE

This dissertation was written for partial completion of graduation requirements for the Industrial Engineering PhD Program (Engineering Management) at The University of Tennessee Space Institute. Within this dissertation, “Statistical Study of Supply Chain Developmental Training on Original Equipment Manufacturer’s Defect Rates,” is an exploration of the effects of supplier development training on defect reduction. The primary question being explored is does supplier development training change or impact, in a positive way, defect reductions in a supply chain?

Most trainers would postulate training creates a unique and lasting difference when it comes to individual or organizational improvements. But what about a larger supply chain with multiple companies and development training’s impact on the larger chain? Intuitively, we would agree that effective training at a site level should produce tangible improvements and, as the individual organizations improve, the results should eventually spill over into the larger supply chain.

However, is this simple line of thinking always true? How do we know? How do we prove it to others? Alternatively, do we just accept it as, “YES.....training most definitely has a positive impact!” Has this become such a “cut-in-stone” premise no one is willing to argue to the contrary? These are questions being asked more and more by senior managers as they look for proof as a condition for doing expensive supplier developmental training. While there is a wealth of information on benefits in the workplace and individual or group benefits, there is limited to no research data on supply chain developmental effects.

This dissertation provides perspectives on the above questions and the reader with some answers as to why employee training is so important to the companies they work for and the larger supply chain in general. While this researcher remains decidedly “pro-training,” these lines of questions initially struck me as difficult to answer. However, the researcher began to think about his own training, education, and work experiences.

Eight years of grammar school, four in high school, five in undergraduate school, ten years in graduate school, plus forty-five years of on-the-job training and experience brought me to this moment in time. Every piece of learning and experience, stacked and built one upon the other, played a role in what is written here to answer a simple question. Remove any piece, and this engineer and this dissertation would be the lesser for it.

Accordingly, it would seem logical that most, if not all, learners go through a similar process with their training and education, each according to their individual gifts. The learning process plays and will always play a significant role in who we are, who we become, and what we are capable of in terms of societal or industrial contributions. If there were no capacity for human learning, society would still be in the stone-age. Civilization and inventions that enhance the human quality of life at home and in our workplaces are all results of hundreds, if not thousands, of years of learning and progress.

Central to this dissertation will be a review of lessons taught through the “learning process” extracted from years of training and written experiences of educators, their recorded information obtained through research on the subject, and a detailed look at the researcher’s Case Study to explore whether supply chain training positively impacts defect reductions.

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CHAPTER 1. INTRODUCTION

A Manufacturer's Connection to its Supply Chain

Major manufacturing sites go by many names (manufacturer, producer, or maker), but their most common moniker is OEM or Original Equipment Manufacturer. As with all major manufacturers, supplier selection is extremely important. The suppliers to these facilities are normally vetted (audited by the OEM) before being offered any opportunity to bid on making parts for their assembly plants. Quality being equal, the lowest bidder usually wins the prize.

Successful bidders become recipients of substantial contracts to make parts and material as part of a much larger supply chain that consists of hundreds or even thousands of suppliers. Provision of quality parts, on time, and at cost allows the supplier to develop a long-standing positive relationship with their customer (the OEM). Failures in quality lead to trouble for the supplier and their customer business relationship.

These supply chains typically have multiple levels (or Tiers) with the closest supplier in terms of direct contact with the OEM being a Tier 1. Other Tier "N" suppliers where $N = 2, 3, 4, \dots$, supply the suppliers, on up the chain, that, ends with a Tier 1 supplying the final part or component to the assembly plant. The OEM can even decide to purchase and own suppliers, especially if a part is a critical component. This collection of supplied parts and material end their journey at the OEM's assembly plant where they are methodically pieced together to make products sold in the commercial and private business sectors.

Assembly plants can trace most of their roots back to the days of Henry Ford and the Model A at the turn of the 20th Century. Product quality, on the other hand, is traceable to ancient times where apprenticeships were common, and the worker was obligated for

years to a master craftsman to learn a skill or trade. In the 21st Century, a product and its quality continue to be just as inseparable from each other as they were in ancient times, the days of Henry Ford, and today. In an age where multiple options are now available for most products, discerning customers are always looking for the best product available for the lowest price.

Like the OEM, suppliers continually look to improve their products and quality. This effort is a competition of the fittest suppliers for the customers they serve. As an example, consider, for a moment, the automotive industry. The complexity of vehicles made today are beginning to take on unimaginable characteristics. Cars in the world today provide features that enhance ride, drive-ability, safety, passenger comfort, and style.

It may be surprising to know automobiles are comprised of as many as 30,000 or more individual parts ^[1] and components. Supplier part complexity is also increasing with each passing year. Nowadays, an automobile would be described as a “quantum leap” in technology if it were compared to Ford’s Model-A design. Regardless of the year in which the product is made, the OEM depends on suppliers to create a quality product that, in many ways, define the personas of the people that buy them. From cars, to clothes, to airplanes, to electronics, quality must always be a central supplier focus.

Consequently, good supply chains are one of the critical determining factors of success or failure in the OEM’s production world. In the case of automobiles, who would have thought in the second decade of the 21st Century, car makers would be talking about building autonomous vehicles where today’s driver will, one day, just be a normal passenger for the trip enjoying the scenery while traveling to a destination or, sleeping

while the vehicle does the driving. Complex, driverless vehicles will one-day be a driving norm; hopefully, making transportation both safer and easier.

Up until just a few years ago we would have called this concept more fiction than fact belonging to some science-fiction movie. And yet, Google has had a self-driving car on the road for several years now. Transportation services already have driverless car routes in large cities such as Pittsburgh, San Francisco and Phoenix. ^[2] This is just the beginning. To accomplish this driverless feat on a grander scale in the future, cars must become even more reliable, free from critical defects, and devoid of failures that place people's lives in jeopardy or risk vehicle damage. This requirement is no different for any sophisticated mode of transportation or other advanced product made in today's global economy.

Science and engineering advancements continually change the world in which we live. Not unexpectedly, as technology advances and products become more highly customized, the demands on today's suppliers grow. Though the specifics are different for every supplier, the focal point always comes back to three common elements (quality, cost and delivery), and, at unprecedented levels.

Science has advanced the body of knowledge for materials, electronics, and control systems. Manufacturing processes and techniques have advanced and with a much greater sophistication compared to just ten years ago. State-of-the-art computers can now be purchased with learning algorithms that have the beginnings of rudimentary artificial intelligence that learn by doing. Advances have led to supplier products that can be rapidly produced, made uniformly, and with a quality good enough to last a decade or more

without major problems or failures. Mathematics has even created modeling algorithms that can estimate the likelihood of a product's failure.

Based on news reports, some might argue that quality has declined, giving way to a larger emphasis on cost and delivery. There are many who would disagree. As one Senior Quality Manager remarked to this researcher,

“Customers in the United States are some of the most discerning customers in the world and it takes more to please them.”

That's not expected to change soon. If a supplier delivers poor quality, delivers the wrong quantities, or over-charges for the item, the supplier is soon out of business with no customers. No OEM will carry poorly performing suppliers for great lengths of time because it places their future customer business at risk.

In this fast-paced world of manufacturing, suppliers have found many ways to be creative and innovative through technological advancement. It is a timeless and age-old game of competition in the pursuit of being the best at what they do. Get it right, and every party involved are winners. Get it wrong, and the downside can be enormously bad.

It is intuitive that products with the better-quality are ones that tend to get and keep customers over time. In the automotive world, it would be rare to see a modern-day family buy just one vehicle in a lifetime. Therefore, car makers strive to get and keep their customers loyal to their product brands. When a second or third vehicle is purchased, they want to be first-in-line, again. If a significant number of mistakes are made during the manufacture of the product, customer loyalty is impacted. It is easy to get a customer the first time out but far harder to keep them. To maintain this customer, brand loyalty requires

world-class suppliers. As in a steel chain where the chain is only as strong as its weakest link, so goes the manufacturing and assembly world. Product quality is only as good as the weakest supplier in the chain.

Supply Chain Performance Metrics

Suppliers and OEMs both have access to performance metrics used in making quality parts to meet customer needs. Perception of quality is always determined by the end customers that buy and use the products, so suppliers are very interested in measuring customer feedback. One of the most important metrics used to gauge customer satisfaction is to measure quality after the sale. Most if not all major manufacturers track their warranty cost which is a key indicator of product quality and performance.

In the world of automotive manufacturing, one of the key supplier performance metrics used is defining how well the vehicle is performing three months into service (3MIS).

David Sargent, a Vice President at J.D. Power ^[3] expressed it this way:

"J.D. Power also found that car buyers who experienced fewer problems were more brand loyal. By combining data from last year's dependability study with trade-in data, the firm [J.D. Power] determined that 56% of owners who reported no problems stayed with the same brand when they purchased their next new vehicle. For those who reported three or more problems, brand loyalty dropped to 42%."

This statistic represents a fourteen-point swing in brand loyalty and auto-makers are fighting each other for every percentage point they can get (a term called market-share). Take for example the statistics on global annualized production of automobiles in 2017. According to the International Organization of Motor Vehicle Manufacturers, that number

was 97,302,534 vehicles ^[4] comprised of 73,456,531 cars and 23,846,003 commercial vehicles (vans and trucks). A one percentage point shift (up or down) in customer loyalty for just the cars means the difference between a Tier I and its other lower level suppliers staying in business and expanding or shutting down with loss of jobs and the impact on the community where the supplier is located.

A one percentage point increase in customer loyalty can double the product demand for a Tier I supplier based on the worldwide production of cars (approaching 73.5 million annually). This one percent increase in demand translates to 735,000 automobiles. The largest assembly plant in the United States is presently only capable of making 650,000 vehicles annually at a single assembly location. It is easy to see the effect a one percent point increase has on a single supplier and the supply chain – suppliers would have to double production. Consequently, quality is a central focus for all parties and tracking vehicle reliability remains a significant metric of interest for the entire supply chain.

The Failure Process

In the part failure process, most failures follow what is known as the “Bath-tub Curve.” (Figure 1.1) is a pictorial representation of this failure process. If a part is substandard, it usually fails early in its service life. If not, the part typically has a long and useful life until such time that it wears out and fails. The automotive “3 months in service” (3-MIS) metric tracks these early failures after the car sale and reflects quality and performance.

However, 3-MIS data does not include defects found during the assembly process? These defective parts were also made and passed through the supplier’s inspection

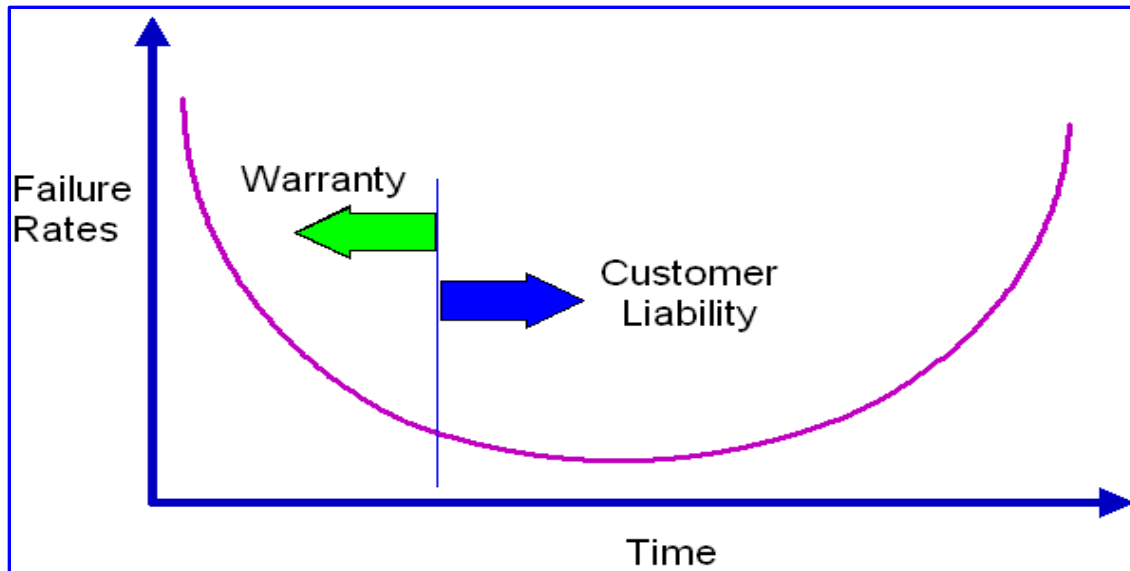


Figure 1.1 – Bath-tub Curve for Product Failure

check points in order for them to make their way to the assembly plant. These defects are parts which do not fit properly, fail to function, arrive with incorrect specifications, or are poorly designed. This metric (labeled PPM) tracks the automotive failures captured at the assembly plant before vehicle incorporation and, likewise, reflects quality and performance. Left undiscovered and incorporated into the vehicle, the OEM, at some point, will have to deal with the faulty part as a warranty issue and it becomes part of 3-MIS. The only exceptions are parts that make their way through the warranty period prior to failing. At that point, the customer now has liability for the repair cost.

Any defect type can negatively impact future brand loyalty and the worst is failure after warranty expiration (it is now the customer's money spent to repair the issue – not the OEM). Hopefully, the assembly plant discovers these flaws to avoid the down-line

warranty cost. However, unless the part has a visible flaw, does not function correctly, or does not fit, more times than not, it becomes part of the final product.

All manufacturing facilities want product failures kept at a minimum. To do this, the OEM tracks both supplier defective parts discovered at their plant and culls them from the assembly process to prevent a future warranty claim in the early part of vehicle ownership. Two defect databases (PPM & 3MIS) are normally maintained by the OEM and used to initiate parts containment (more on this later). Data of this type provide warning signals of problems and are indicators of suppliers in trouble or in need of assistance.

These poorly performing suppliers become targeted companies the OEMs must work with to improve performance through activities such as supplier development training events or supplier site containment. Make the suppliers better and the entire supply chain, the OEM, and the end-customer all benefit. If they can't be improved, the alternative is to cull the supplier from the chain and all that is involved with that process (finding, vetting and on-boarding a new supplier). Many times, suppliers are so dug-in with the OEM (supplying multiple parts) that it is difficult, if not impossible, to "fire" a supplier in favor of an alternate. This is especially true when new product-lines are being launched.

Supplier Quality Management Systems & Methods

The need for assured quality is one of the reasons that quality standards have become so popular. In an automotive environment, Tier 1 suppliers are normally required to register to the IATF-16949-2016 Quality Management Standard. In the case of the Tier N (N = 2, 3, 4, etc.) suppliers, their standard, in most cases, can be a simpler version – ISO-9001-2015. New and existing Tier 1 suppliers are audited by the OEM's quality team and

rated against the OEM's quality management system expectations. Most if not all OEM auditors will exclude a supplier from the chain when a quality management system is found missing and / or inadequate. The logic underpinning validation of the quality system is simple - assure they (the OEM) get parts and material of high quality, on time, every time, and, at an agreed cost.

Assembly plants simply can ill-afford to waste time on poor suppliers and defects. There is a simple reason behind this need. Defects in an OEM assembly plant spell bad news. The clock is ticking. Defects shut the line down (stopping production) while an effort to determine the cause is made. If not a line problem, many times, the source is traced back to a supplier. Shutdowns cost millions of dollars in lost revenue every hour. On an automotive production line for example, it's not uncommon to see a vehicle come off the line every minute.

So, loss of one hour's production at this rate translates to \$1,800,000 in revenue for a vehicle retailing for \$30,000 (a common sales price). This revenue is not recoverable assuming the vehicles not made could all be sold. Many times, the lost revenue is "charged back" to the supplier who pays for the assembly plant down-time (\$30,000 a minute). It is easy to understand why quality at the OEM level is so important. Some suppliers have gone "bankrupt" dealing with this issue.

In terms of product or part's quality, we know, full well, nothing lasts forever. However, we also know it should not fail before it rolls off the assembly line or before the customer gets it home. Consumers want high quality at the lowest cost possible, whereas the producer wants product sold at its highest price for the given quality. These goals are at

odds with each other. Somewhere in this continuum lies the quality sweet spot (quality and cost). But, just how good is “good enough?” From a review of past disasters in this industry, many might agree that it needs to improve.

Manufacturing’s storied past is littered with multiple and sometimes disastrous failure examples. These incidents resulted in loss of life, large monetary expenditures to correct the problem, liability suits, and needless wasted time. Most damaging to the OEMs financially, we see loss of reputation, loss of brand loyalty, and more importantly, loss of the customer’s trust. Once lost, the customer rarely, if ever, comes back. All the customer wants is an assurance their hard-earned cash is spent on a product that is safe, reliable, easy to use, and aesthetically pleasing. Add to all this the fact that OEMs are compelled to “*make it right with the customer*” or risk losing the customer altogether and you have the fundamental concept behind warranty.

Looking again at the automobile vehicle example, (Figure 1.2) reflects recent warranty history over five years (2012 to 2016) as reported by Automotive Weekly. ^[5] The graph in 2016 which was 92.1 million vehicles ^[6], warranty cost would average between \$412.60 and \$521.20 per vehicle in the cost of poor quality. OEMs and suppliers would be relieved if this could be lowered. Cars would also be cheaper.

While the above is an automotive example, many OEMs and assembly plant locations experience similar trends. Despite a supplier’s best efforts at getting a part right, supply-side failures are common. Someone fails to correctly communicate at the right time, somebody misses a warning signal or trend suggesting an impending problem, a key manager or leader pushes the wrong agenda or takes a risk they should have avoided,

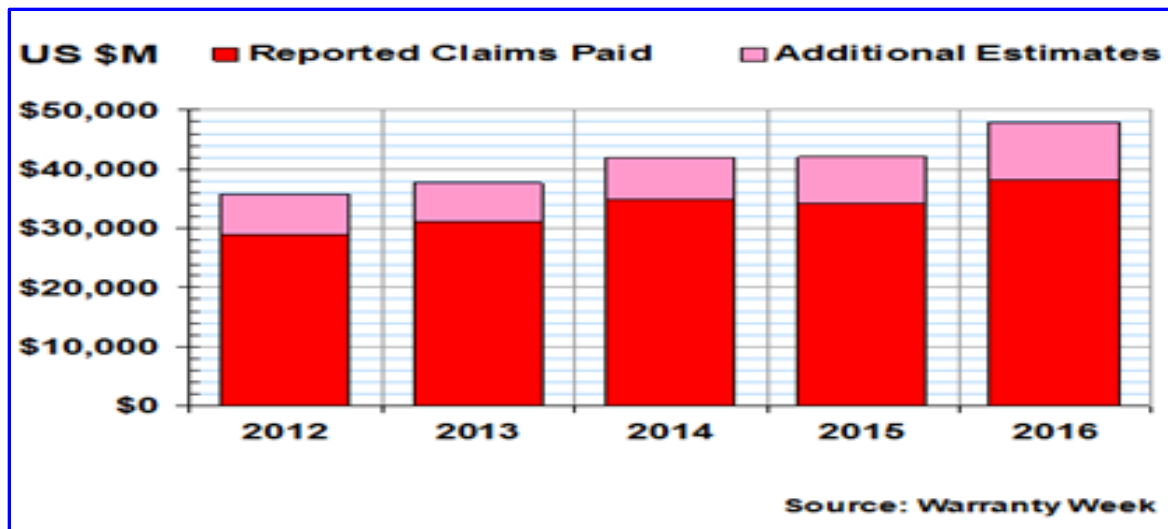


Figure 1.2 – Total Worldwide Automaker Warranty Claims Paid per Year

and the unthinkable happens. Worse yet, someone becomes so obsessed with supplier issues like profit, cost, time, or schedule, that quality does lose focus, and disaster strikes. One innocent mistake and the worst imaginable occurs.

Everyone has heard of Murphy's law named after an engineer by the name of Edward Murphy in the heady days of space exploration at Edward's Air Force Base in California. His basic law was, "If anything can happen, it will!" As a corollary to Murphy's law, failure usually happens at the most inopportune location, in the worst possible way, causing the most chaos, and, at the worst possible moment in time.^[7]

For example, consider (Figure 1.2) again. When car manufacturing is at its peak, warranty cost is also at its peak. The lowest numbers in this graph were during the period 2012 and due to the "Great Recession" where car demand was down with better performing suppliers having more time to get it right. Fewer automobiles were sold with a greater

emphasis on supply chain quality. Now that the industry is peaking again, we see the corresponding rise in warranty costs. As to Quality, producers can easily check to see if a supplier has the necessary elements in place to address quality (in other words, do they have a quality management system). However, it is more difficult to determine, longer term, if a supplier can effectively implement and improve their system to deliver quality.

Supplier contracts all specify the supplier deliver on their quality promise. Saying “yes” to these contractual promises can sometimes be more than the supplier bargained for. If suppliers were effective in delivering quality, there would be no defects and every product would be just as good as every other product. However, this is not real-world reality. Sadly, not all suppliers are created equal.

A supplier’s true performance can be masked and hidden from the OEM’s view. Suppliers can substitute multiple inspections (200 or 300% inspections – that is, inspect parts 2, 3 or more times) as a way of demonstrating capability. Deming was very direct in the third of his 14 points [\[8\]](#) about quality saying quality cannot be inspected into product – it must be built in and constitutes the only reasonable way to make parts meeting customer expectations.

As an example, by most industrial standards, companies agree visual inspections are only considered 80% effective at finding defects in a manufactured part. (Table 1.1) illustrates the futility of visual inspections. Carrying this to the extreme, a simple set of calculations suggest that 6-sigma level product defect rates in the 2 to 3 ppm level would need seven to eight inspections to achieve acceptable product quality. Each successive inspection catches only 80% of the remaining product defects not discovered from the

Table 1.1 – Six-Sigma Defect Rate through Inspections (80% effective)

Inspection	Good (ppm)	Cumulative (ppm)	Suspect (ppm)
<u>Prior to Inspect</u>	---	---	1,000,000
Inspect # 1	800,000	800,000	200,000
Inspect # 2	160,000	960,000	40,000
Inspect # 3	32,000	992,000	8,000
Inspect # 4	6,400	998,400	1,600
Inspect # 5	1,280	999,680	320
Inspect # 6	256	999,936	64
Inspect # 7	52	999,988	12
Inspect # 8	10	999,998	2

Basis: Inspect 1,000,000 parts for defects

prior inspection. Using inspection processes like the above, both the supplier and the producer pay the price in labor and warranty cost because the supplier did not choose to prevent defects. Multiple inspection processes lead to more warranty and recall as shown in (Figure 1.2) above. The bottom line is a decidedly higher cost for finished goods. Clearly, this kind of inspection practice is a waste of resources, something the customer would never be willing to pay for, and an impossible task for suppliers. Deming was right about inspection – quality is not inspected into product – it is built in. Inspection does not change the outcome; it only catches some percentage of the mistakes. Deming’s friend, Harold Dodge said, “*Quality is either there or it is not after the product is made.*”

Producer’s Last Resort – Supplier Site Containment

Manufacturers have always had a fallback position to advance their agenda for higher-quality parts, but it is reactive by its very nature. Built into contracts, the OEM has a right to place the supplier on what is termed “Supplier Site Containment” (SSC). This action

requires product inspections by an external party on the supplier's premises, and it must be completed prior to parts delivery to the OEM plant. "SSC" is expensive and time consuming. Getting back into the good graces of the OEM (buyer of parts) can require months of effort. It can also foster adversarial relationships between the assembly plant and supplier and is not a relationship desired by either side.

Additionally, after exiting SSC, suppliers can return to containment at a future date either with the same or a different defect. The reason is the supplier's methods were never good to start with and never changed because SSC was used to cull the defects and never corrected the problem's cause. Consequently, SSC becomes a reactive process mandated by the customer and not welcomed by the supplier. Unless the lessons learned from SSC are incorporated into the manufacturing system (making the process better, improving inspection, and creating a better predictive model), the supplier will, often times, experience a future repeat failure.

Within most, if not all suppliers, there is a level of product inspection that is part of any company's quality assurance program. While these companies readily admit inspections are not value-added (that is, they do nothing to generate product- or part-value), most companies have no answer as to how to dispense with them. Workers that conduct inspections are highly trained in what to watch for; and, many of them are very experienced and capable employees. However, they are human, and mistakes can be made that were never intentional.

As mentioned before, many of these processes are again dependent on checks that are not 100% reliable (see Table 1.1 on visual inspections). Within most companies, once a

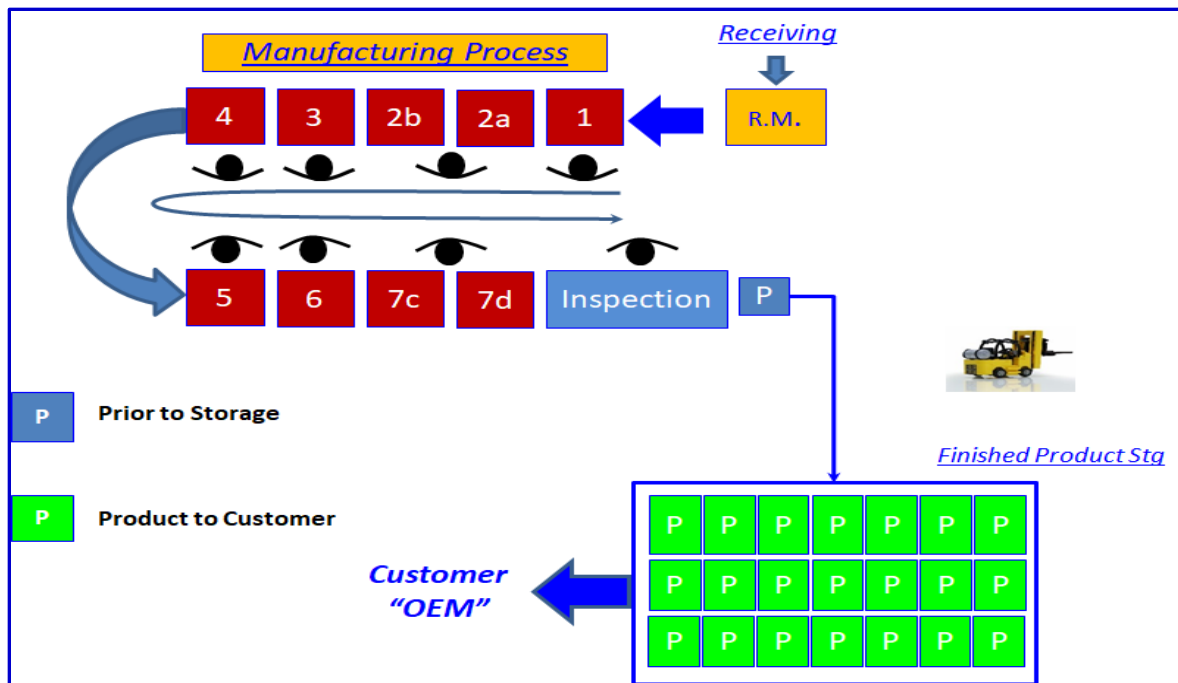


Figure 1.3 – Normal Manufacturing Process [9]

product passes the final quality control check, it is assumed “customer-ready.” (Figure 1.3) shows a multi-step manufacturing work-cell using raw materials with a quality check at the end of parts assembly. The finished product from the line is then packaged, warehoused, and shipped based on an OEM delivery schedule. This arrangement is typical for most if not all suppliers in the modern production world. Suppliers assume that since their product passed a final inspection and was packed, it is “good-to-go.” Any defects from that point forward have a very high probability (close to 100%) of not being caught until they arrive at the OEM’s assembly plant. If not identified and caught there at the assembly plant level, it will be incorporated into the final product.

Mentioned earlier, defects found at the assembly plant are tracked and reported to the supplier immediately for corrective action and at the end of the month as part of their monthly scorecard assessment showing the results of the supplier’s parts quality. To the

detriment of the OEM assembly plant, defects incorporated into the vehicle show up as part of 3MIS assuming the product fails prior to the owner's warranty expiration. Some automotive recalls also occur after warranty expiration if the National Transportation Safety Board decides it is a bad or poor design but fairly infrequent compared to the number of vehicles produced annually. This defect information comes from the product distributor and is also reported on supplier report cards on a monthly basis.

The OEM quality department can mandate Supplier Site Containment (SSC) as part of their rights under their supplier contract using either of these defect histories as justification. Infrequently, the supplier may be able to use its own internal staff for SSC but, more times than not, the containment activity utilizes an expensive, independent third party approved by the OEM. In either case, the supply-chain process has failed to meet customer expectations. This added external party inspection corrects the defect problem by culling the bad product from the good and allows only good materials to flow to the OEM assembly plant. This reactive process does not necessarily correct the supplier problem, although, admittedly, it should do so. Corrective action at this point becomes the responsibility of the supplier.

Practically speaking, this constitutes a 200% inspection with the second inspection being more rigorous than the supplier's final check. (Figure 1.4) shows the difference in SSC. Comparing (Figure 1.4) to a normal manufacturing cell shown in (Figure 1.3), we see the added step labeled SSC inset in the upper right corner of the figure. SSC's goal should be defect discovery and correction. However, assessing root cause and implementing change is not always a supplier focus. Due to the cost, the focus, many times, is to do

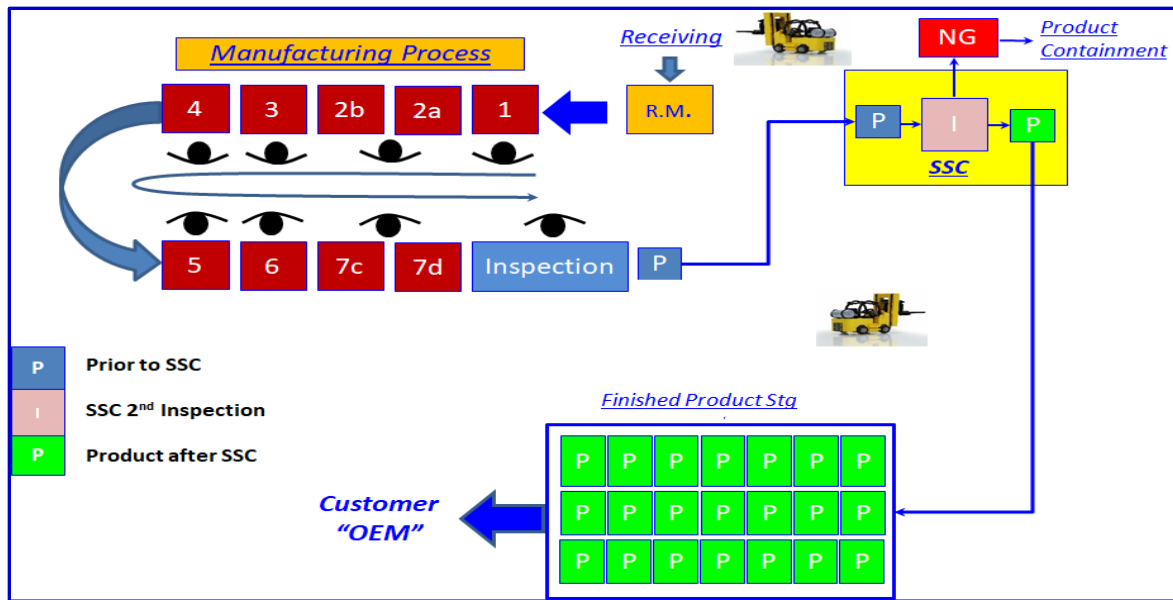


Figure 1.4 – Manufacturing Process with SSC [9]

whatever is necessary to exit mandated SSC as quickly as possible. When SSC is considered, the supplier has actually failed on three fronts and must fix three causes for a permanent corrective action. The failures are in three distinct areas:

1. Manufacturing Process Failure – The Process made a defective part.
2. Inspection Process Failure – Quality Control failed to catch it (escaped).
3. PFMEA Process Failure – Never Predicted in order to prevent it.

Not only did the supplier have a process that, for some reason, made a bad part, the supplier inspections allowed the product to pass through quality control without capture and escaped the plant with the normal product run. To make matters worse, the supplier failed to rank the risk of this failure high enough to warrant error proofing that would have prevented the failure. In some cases, a failure mode is never included as part of the risk assessment, while, in others, the risk has been correctly assessed but it lacked an adequate control plan robust enough to prevent recurrence (insufficient action taken).

In the end, these three failure modes collude together to cause the defect to leave the facility. All three causes must be corrected for “SSC” to be effective in stopping future shipments of defective parts to the OEM. Typically, it takes one to three months, to correct supplier discrepancies before being allowed to stop “SSC.” Additional failures during the SSC period normally resets the clock to zero, meaning the supplier must restart the preventive and corrective actions over again.

It is common for suppliers on “SSC” to experience five to seven figure expenses to satisfy the OEM the problem was permanently corrected. This researcher is aware of suppliers that have been in containment for over a year. “SSC” can quickly turn a supplier operating at a loss into bankruptcy, a marginally profitable company into one running at a loss, or, a highly profitable company into one that is marginally profitable. Suppliers experiencing “SSC” have an overriding monetary incentive to exit the requirement as soon as possible.

However, when SSC is done correctly, the causes behind the defects are iteratively improved, and the supplier becomes capable of delivering a higher quality part. After successful achievement of lower defect rates, the supplier can then be approved for release from the containment activity and return to its regular manufacturing activity with a more robust process. This proactive approach will always deliver higher quality parts for the assembly plant and without ever returning to mandated SSC because the supplier’s processes are now much improved.

Albert Einstein was once said to have defined insanity as:

“Doing the same thing over and over again expecting different results.” ^[10]

Einstein was also quoted as saying,

“The problems that exist in the world today cannot be solved by the same level of thinking that created them.” [10]

As SSC has been assembly plant’s fallback position for years, it is still the most common action taken by the OEM. However, it is clear that better alternatives are necessary.

There are two types of action (alternatives) available in supplier intervention:

1. Direct Intervention - OEM is directly involved with the supplier.
2. Indirect Intervention - OEM mandates a solution to the supplier.

An example of a direct intervention includes supplier development training while indirect intervention includes activities such as mandated supplier site containment using an independent third party. Both are useful but highly dependent on the time frame the OEM wishes to employ to create change and the type of change desired. If the assembly plant wants a quick-fix, then indirect methods are better. For longer term permanent fixes with improved long-term supplier relationships, direct methods are better. This is discussed in greater detail in Chapter 2 – Literature Search.

Summary

Included within this chapter, the reader should realize the importance of the supply chain to an OEM and why quality is and will remain such an important issue to manufacturers. The high cost of warranty in many manufactured products remains one of the biggest opportunities in cost reduction for every company involved in making a product. The reader should also be aware of the importance a quality management system makes in the creation of value in product manufacture and the poor substitute inspection provides for assuring product quality. The reader should also be aware that immediate action, while

necessary, in stopping product failures is not a long-term solution to supply chain defect corrections.

Quality standards mandate permanent corrective measures and assembly plant quality departments have limited resources they can use to address supply chain defects. Proactive measures become increasingly important as we move into the 21st Century where suppliers must accept a larger role in defect detection, correction and prevention. If the trend continues that technology and products become more and more sophisticated, then suppliers must accept and shoulder a bigger share of the defect prevention burden. This need will require OEM (assembly plant) quality teams to be viewed by suppliers as an improvement resource rather than an adversary. Supply chains are only as strong as the weakest supplier. Intervention starts with the Tier I supplier and moves down the chain, creating a more robust supplier at each tier with objectives to lower costs, lower defects, and improve product quality and reliability. Direct supplier / customer intervention is the answer to defect reduction even though, most suppliers know indirect methods are unavoidable when a defect initially occurs.

The methods currently used by poorly performing suppliers must change to be more proactive. In Chapter 3, the readers will see how prevention, correction, and “SSC” have been changed from a “reactive” process to a “proactive” process through supplier developmental training. The proactive answer to the problem lies in discovering and learning from supplier mistakes made in actual manufacturing, inspection and prediction processes. The better the suppliers are at discovery and permanent correction, the more robust their processes and products will be. Improved supplier capabilities should result in improved supplier quality, reduced OEM cost, and happier customers.

CHAPTER 2. LITERATURE SEARCH

Overview

The purpose of this chapter is to include and discuss relevant research on training. Some parts of this chapter are responses to questions asked in written exams preceding the preparation of this document. Still, others are borrowed from past documents this researcher wrote but never published [\[11\]](#) or taken from his capstone project [\[12\]](#) for his Master of Science degree. Most of the discoveries are from literature that was read or reviewed for purposes of learning more about the educational process and its impact on quality. All sections discussed are relevant to defects and quality failures with several questions focused on discussions in the opening preface of this manuscript.

In the enumerable hours spent reading and reviewing journals, books, dissertations, capstones, and web-articles written about the effects of training, this researcher came away with three immutable facts about training and developing organizational capacity:

- 1) “Competency” rarely (if ever) is created in workers with no training.
- 2) An important key to “world-class” operations is “continuous learning.”
- 3) More work is needed in studying long-range statistical results of training.

The Need for Competency

It matters not what a company or organization produces. It can be making a part for an automotive assembly plant or providing a service. Whether a company ascribes to the ISO-9001-2015 or the IATF-16949-2016 quality standard, personnel “competency” is most certainly one of the keys to business success. These international standards and the standards before them have existed for over half a century and continue to be revised as the quality body of knowledge grows.

Competency is discussed, stated, and / or directly implied in most of the journals and books studied on training impacts. Simply stated, training is critical to job performance and there is no substitute for it. At some point, readers should transition from the word “training” and migrate toward the word “learning” if competency is the end-goal. A company can train all it wants but if the training is not effective, the result is the same as if no training were done at all. The ISO-9001-2015 standard [\[13\]](#) speaks clearly to this need with four fundamental statements about competency and learning. Paraphrased, the standard says the following:

- 1) The organization (meaning management) decides what job skills are needed.
- 2) The organization will assure these job skill capabilities are provided and will evaluate the effectiveness of the employee learning outcomes.
- 3) The organization will ensure each employee is “competent” based on either training, education or experience to execute those required job skills.
- 4) Finally, they will maintain documented training evidence for each employee.

The more recent IATF-16949-2016 standard [\[14\]](#) provides some supplemental additions to the ISO-9001-2015 standard by saying the following:

- 1) The organization ascribing to the automotive standard will document their training methods starting with quality awareness training and continuing with the necessary skill sets effectively taught (learned) to those who directly interface with customer quality and requirements.
- 2) The organization will train each time when something new or modified occurs on the job. The training will be based on the employee’s level of education and the complexity of the task being performed.
- 3) The employee will be informed of the consequences of their failure in job performance which extends beyond management-imposed sanctions of a disciplinary nature. Examples might be “increased cost or liability.”

When management looks at new employees, temps, or employee job duty changes, it benefits the company or organization to teach these individuals what they need to know expediently. That's both a logical and financially sound practice – time is a resource that once lost is never recovered. In the real world, the addition of staff or an existing employee assuming new duties seems to always occur when there is the least time to learn and get the employee ready for the new task or job position.

This is one of the reasons why so much “On-the-Job Training” is encountered in the workplace day-to-day. At the very least, while being taught, the employee is performing some level of useful work while they learn. One of the underlying themes found in much of the materials this researcher read was the need to make training a “learning event” or a “teaching moment in time” between the student and instructor. Without it, the training benefit is lost and difficult, if not impossible, to recover.

To assure competent employees in the workplace, there must be a commitment on the part of management to assure training activities are properly undertaken to achieve the outcomes desired by the company. And, it never stops. After any training event is completed, there is always an opportunity to learn and improve more. This training concept in the automotive industry is certainly central to any supplier as it works to outperform its competition. It is an unending struggle to achieve quality, speed and cost, and, at the same time, do it better than the others.

A book titled, “*The 10 Commandments of Leadership*” ^[15] explains this struggle very simply while talking about “The Real Enemy.” The following is a common question and a consistent response given during interviews with multiple companies:

“ It’s a question we’ve asked business leaders hundreds of times over the past several years:

“What’s the biggest threat your organization faces?”

By far, the most consistent response we’ve received:

Competition!

And while there is validity to that answer, there’s an even greater threat that you as a leader, must address – and it does not come from the outside. It’s internal. And it goes by many names such as “Business as Usual,” “The Way We Do Things,” and “Same Ol’ Same Ol.” Its most common moniker: THE STATUS QUO. Its implication – sameness.”

It is also a common response this researcher has heard to quality audit questions. For example, “Well, that is the way we’ve always done it!” or, “If it’s not broke, don’t fix it!” A deeper analysis of the above is if “The STATUS QUO” is the real enemy, then “STATUS CHANGE” is your real friend or ally. Said another way, organizations must change. If one digs to the bottom of change management, one always finds “ employee learning” playing an important and crucial role in change – the implementation of new concepts and ideas. If an OEM wants better quality and lower product defects, then supplier training and change must be foundational to the effort. One cannot make a change improving a process or activity without having understanding and a vision of what needs to change.

World-Class Outcomes from Continuous Learning

This researcher is convinced learning plays a pivotal role in any organization’s goal of becoming “world–class”. While there are several important parameters involved in an organization becoming the envy of its competition, for example, leadership, technology, corporate vision, workable strategies, and teamwork to name just a few, there is no

substitute for employee training, learning, and know how. An organization can buy or deploy the very best of all the above but without well-trained employees committed to execution of the company's strategy, it will fail. Regardless of whether the need is for an individual, group, or groups within a facility, employees need training when they are impacted by work requiring an improvement to a condition or when they must take department action to create an altered reality (stated another way – workplace or organizational change).

Workplace change is mostly resisted until workers understand the need (the why) relative to how it affects them. Workers can backslide to an older way of doing things if the change is not monitored sufficiently until it becomes a part of their new culture. In the real world, employees are creatures of habit and change is unwelcome unless the “why” is reinforced until it becomes a new habit.

Training involves some level of change preparation, an intimate knowledge of the new process, along with new expectations and requirements. It is a given, that training and learning must precede change but be late enough in the change cycle such that the learning is not forgotten or lost. It must be planned as part of a larger organizational strategy that involves both management and the worker.

If there is a plan for organizational change, then there must also be a corresponding schedule running parallel and ahead of the implementation. It is the experience of this researcher in leading real-world operational startups (over 20 of them) that the more the operating team knows entering the start-up, the easier the start-up becomes. Training needs are defined by department managerial and supervisory staff working in

collaboration with their training development managers. The who, what, where, how, and when in addition to the “why” must be defined and this information integrated into a master plan and executed. Without the right learning outcomes tailored to each employee within the organization, an opportunity for failure exists. If a company wants to be “world-class,” it should be prepared to embark on a continuous learning cycle for every employee.

This philosophy does not come without risk. The company could lose the capabilities of their best and brightest employees by being hired away by their competition. However, it is this researcher’s belief that employees stay with jobs they are passionate about. A job that provides them with a living wage, freedom to do their work without fear of making mistakes, that allows them to grow and learn for advancement purposes, increased benefits, and other intangibles helping them achieve their goals in life is usually something most employees stick around for.

More Statistical Studies needed to Show Training Results

One of the more interesting findings in the literature search was an apparent lack of studies done in testing and validating results of training and learning outcomes such as those related to supply chain development. This was a bit surprising in the sense that proof of training results should carry a high level of interest within any major corporation, and, senior management. There were reams of information about the needs to assure learning was effective with such things as pre- and post-tests as described in the Kirkpatrick Model. This model also pointed to the need for assessment of learning outcomes (Level IV) by comparing them to some level of performance relative to process or product deliverables. However, the researcher found little relevant information on supply chains at Level IV. If this has been done on some holistic basis, it is not readily

available or easily accessed in the research published by the manufacturing sector or students working in these sectors.

The Kirkpatrick model states the student's perspective of the class (Level I or II) is an important part of being able to accurately assess learning outcomes. The training always begs a question, "How does the company know the training was an improvement in the employ's capabilities?" Examples of improvement should be increased levels of throughput, faster times in completing tasks, or a reduction in bad parts (defects).

What was found during the literature review were multiple statistical studies where a researcher sent a survey form to groups involved with employee training asking a series of questions about the training and then statistically analyzing the results. Invariably, the statistical outcomes all were pointedly in favor of training, leading to the conclusion it is a key component for workplace quality outcomes. The Kirkpatrick model at level four places a great deal of emphasis on the need to measure learning outcomes. The ISO and IATF standards both require this performance assessment as part of employee competency.

The biggest question faced by all trainers and teachers is how one can be sure the message stuck. How do we assure it becomes so engrained in the employee that they follow the change from that point forward and never back-slide to an older way of doing things out of convenience? Yes, one can observe the employee to make sure it is done correctly, and one can document the observations. A more telling result is knowing the training received is followed when the employee is not observed, or, said another way, what does the employee do when no one is looking? The only way to know this is to take a measurement of a process output not involving employee observations and correlating

the results to the training and education each employee received. Only then can one know if the training is followed when no one is looking – a permanent culture change.

Voice of the Customer & Voice of the Process

There are always two voices in any operational system speaking to management – one is the voice of the process while the other is the voice of the customer. The voice of the process is usually managed through statistical efforts to measure specific process performance and efficiency metrics and, in turn, uses results from this voice to adjust the resources consumed, managed or directed for the purpose of quality optimization (some would call this fact-based decision making - a Phillip Crosby Principle of Quality).

Similar, but different, is the voice of the customer. While this voice may or may not include statistical studies, it is, nonetheless, an important voice that must also be listened to because customers (the final recipients of a product) always have the final say in the marketplace. (Figure 2.1 and 2.2) ^[16] below shows how these voices work in collaboration to achieve a product meeting the customer's expectation and how they can be modified through direct supplier intervention. The end customer is not in this picture. (Figure 2.1) was originally developed by the "Big Three" in U.S. automotive manufacturing (Ford, GM, and Chrysler). This model has existed since the first publications of the AIAG (Automobile Industry Action Group) standards on Statistical Process Control, PFMEA and 8-D. It was heavily modified in (Figure 2.2), to reflect the model the researcher is using to validate supplier training development's connection to supplier defects. In (Figure 2.2), the end customers are represented in a short chain (the assembly plant to the final customer). As can be seen from the figure, both voices weigh very heavily on how resources (inputs to

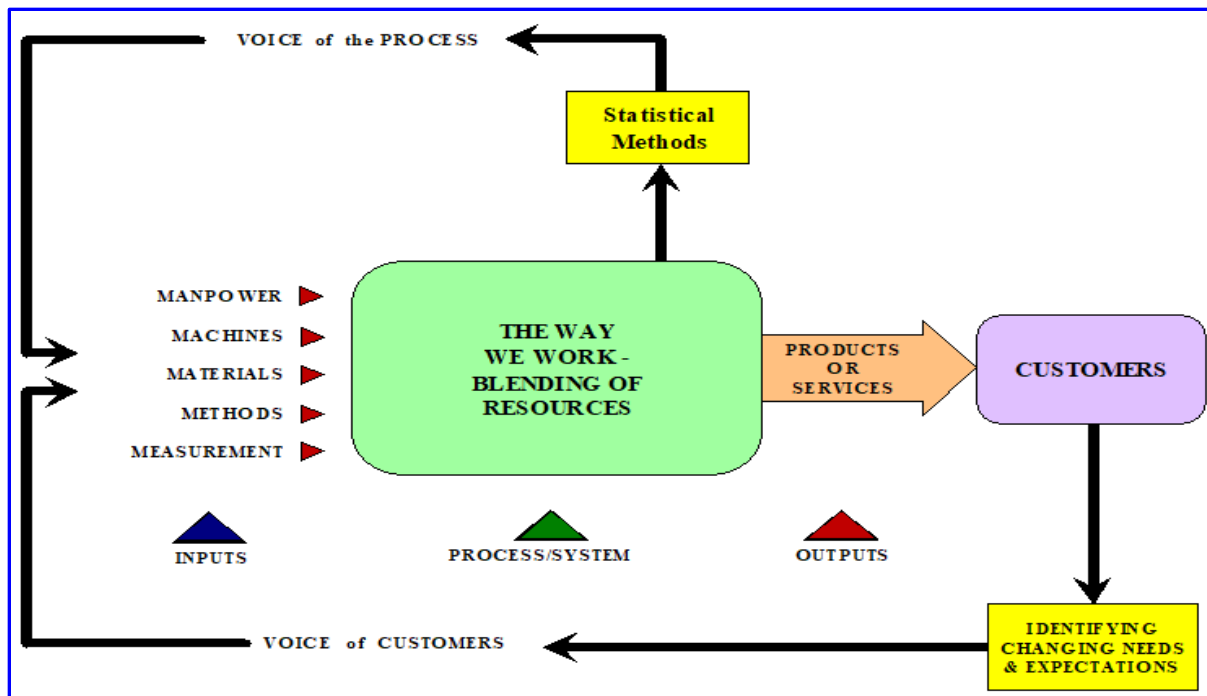


Figure 2.1 – Voice of the Process & Voice of the Customer

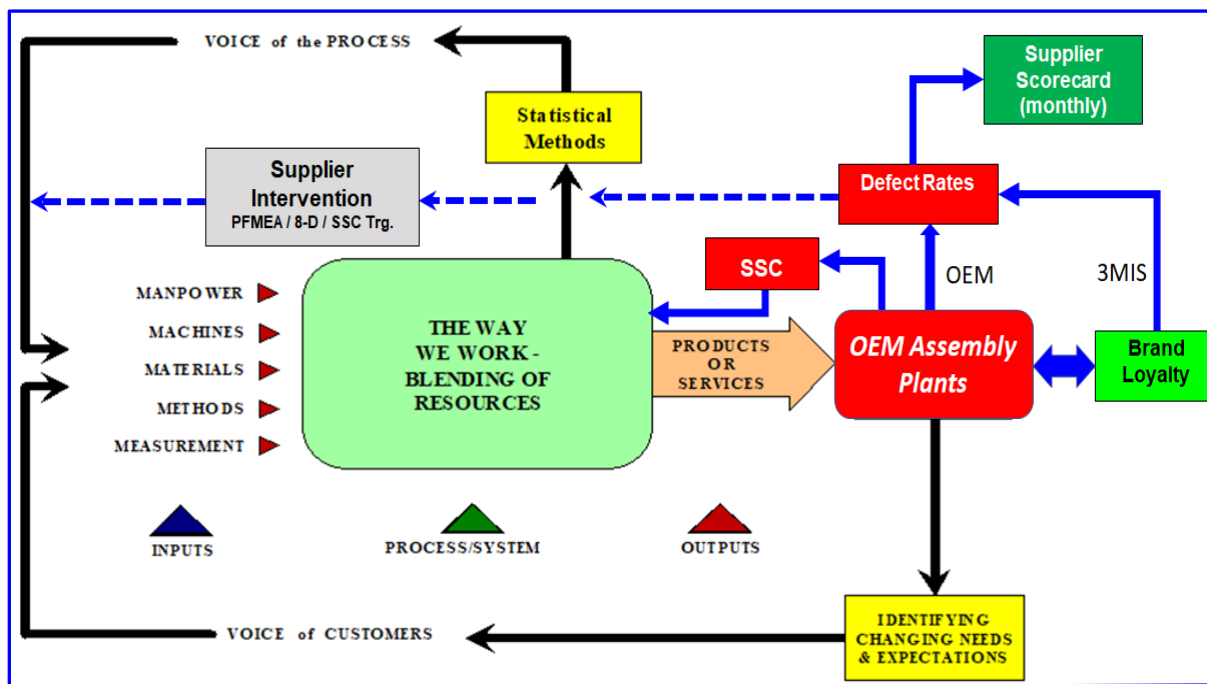


Figure 2.2 – VOP & VOC – A Different Approach

processes) are managed to effect and control customer quality. These two feedback loops are important to a manufacturer (OEM) or a supplier for it affects long-term outcomes (that is, permanent defect correction). In the case of the first figure, the customer is the OEM assembly plant – the buyer of supplier goods or services. It can also be seen why statistical analysis is not necessarily done attempting to tie downstream customer results to supplier development training. Specifically, it is difficult to do, takes a great deal of time, and is a step removed from the supply chain. The OEM gets the feedback from the end customer.

For a company that is reactionary to problems, these two voices have little bearing on customer quality. The reactionary company's basic premise is, "If there is a problem with the part (assembly plant or vehicle buyer), our customer (the OEM) will let us know and we will deal with it!" The classical tool to correct this is normally the SSC (Supplier Site Containment) process discussed earlier that did not always result in acceptable OEM Tier 1 quality afterwards. Reduction in defect rates at assembly (PPM) or at the buying customer (3MIS) must be taken seriously by the OEM and the supplier to create change.

For any suppliers that were listening, the feedback voices should change the nature of their processes and systems. If direct supplier intervention training is added (supplier development), one additional way has been provided to create further positive impacts on the process inputs at the supplier level that does rely on the old ways. This is especially true with supplier that lack the necessary knowledge to improve. The supplier now has been taught to effectively use improvement tools and their "Voices (Process and Customer)" for permanent improvements to processes, inspections and prediction.

However, connecting training results to supply chain defect rates is something rarely, if ever, done by OEM assembly plants. Defect rates are watched for specific suppliers and reported on scorecards and the suppliers are asked to make efforts to improve. This is about as far as the steps go for the OEM as their quality teams work harder and harder at defect reduction. Without accounting for the Net Present Value (NPV) of money, the global warranty costs seem to be getting worse, not better (see Figure 1.2 for details).

This researcher found no evidence of published research on supply chains. There are several factors this researcher believes are an influence to publish their results:

- 1) One reason behind this is a push to address individual suppliers. If the OEM can change the worst individual suppliers, the longer-range result should improve. But that requires a lot of individual one-on-one interventions with each and every poorly performing supplier remembering the OEM has limited resources.
- 2) It is difficult to connect supply chain defect rates in a meaningful way to supplier developmental training. Multiple databases are required, some of which are inadequately formatted (designed for other purposes) and some of which the assembly plant does not own or have access to when developmental training is outsourced to third parties (a fairly common practice).
- 3) There is also the factor of “time.” This type of analysis crosses several years of time. The data collection itself was as much as 80 to 90% of the effort. It also takes time for suppliers to implement what they learned (a year or more), and it takes time to analyze and study results (the actual Case Study research spanned 17 months just to do the investigation of the results).
- 4) The actual down-stream defect results (PPM and 3MIS data) has information of a proprietary and sensitive nature. This makes sharing information difficult to prevent disclosures to competitors.

- 5) Individual suppliers use internal process defect statistics and customer feedback (OEM) to govern their employee developmental efforts. The supplier may have little to no access to the larger picture – that is, the whole supply chain. They also do not always implement the correct developmental training necessary to correct the problem. Additionally, the supplier defect root cause(s) can be hidden by normal process variation making it difficult to extract information from their data.
- 6) It is not uncommon for different assembly plants or home office departments to manage and keep data needed for this type of assessment (for example, data analysts manage supplier scorecards while the Supplier Quality Department manages supplier quality databases. Sales mandate the quality goals and OEM quality assurance is responsible for achieving them. This type of effort is starting to become important in manufacturing circles and the subject of organizational “data mining” and / or the analysis of “Big Data.” This type of work is still in its infancy with many companies and, for others, not even started.
- 7) Many producers have not considered how to conduct such an analysis, or, dismissed it as too difficult. Simply said, a lot of time is involved with no guarantees of meaningful information extracted from the databases.
- 8) With the voice of the process and customer not having formal methods in many supplier companies, direct involvement by the OEM produces mixed results.

The research completed in this dissertation will position others to be able to explore the training impacts on their portion of the larger supply chain and help to answer the overarching question of developmental training’s impact on supplier quality.

“Over-Training” & Negative Impacts on Suppliers

Acknowledgement is appropriate to one of my faculty committee members (Dr. James Simonton) for asking some questions that forced a look at the other side of training and consideration of issues that were not all positive. A few of them are listed below:

1. Is there such a thing as “over-training”?
2. What are the experts’ experiences with training needs?
3. Are there any key takeaways every learning organization should know about?

These are interesting questions managers wrestle with every day. Surprisingly, an article on training, “*The Disadvantages of Over-Training in the Workplace*,” [\[17\]](#) spent little time discussing training negatives. Rather, it spent most of the time talking about positives. Reading about and considering the above questions leads one to seriously ponder just how much training is enough? When do we stop? Or, do we ever stop?

Without doubt, good training is foundational to a competent and happy employee in the workplace. One of the reasons why many employees leave companies is poor training experiences. Most managers and leaders agree a capable, trained employee, working in a good environment, with enough freedom, without fear, will, more times than not, provide excellent performance results.

As a case in point, this researcher once heard the owner of PAL’S Sudden Service speak about his interaction with a group of managers concerning how his privately-owned company won the National Malcolm Baldrige Quality Award. The Baldrige Award is an award given yearly to U.S. based companies that provide excellent customer quality or service. It was named after an employee (Malcolm Baldrige) who worked for the U.S. Department of Commerce who was an avid quality supporter.

PALS is a small, fast food chain in northeast Tennessee serving hamburgers and hotdogs. PALS Sudden Service won this national award not once, but twice, in different years. Pal’s owner was speaking to a group of business managers about his business

success. These managers were considering a future application for the award. The owner had finished his presentation to his visitors and asked for questions.

One of the managers present in the audience asked him,

“So, what is the secret to your success?”

Without hesitation, Pal's owner said,

“Well, I do a lot of training for my employees. I train all my employees on every job in my stores using standard work instructions. I even train the floor employees on how to do their boss's job.”

That seemed a good answer, pointing to training as a centerpiece for success and the importance of understanding work above and below one's pay grade. Another manager in the back, not to be outdone, asked a follow-up question which was, in many ways, in opposition to this level of training. He asked the following:

“OK then, what happens if the employee is trained on all these jobs and then decides, for some reason, to leave? You've lost all your investment!”

Pal's owner said he considered the question a few moments and then answered,

“That's a good question. I will answer it with another question to you. What happens if I don't train the employee and, for some reason, that person decides to stay?”

It was a memorable answer provided in defense of training and its impact on business performance. The story hammers home the fact all companies must train. However, the question of *“Can there be too much training?”* remains. Also, what is the difference between training and learning? In any learning environment, there is the teacher and the

student. So, what is the difference between the two? One delivers and the other receives – it's that simple.

One of the best answers to this question on learning outcomes was found in a book titled *The Leader of the Future*. ^[18] The section of the book was titled, "Working Through Others." The quote tells us exactly what the difference is:

"Teachers, particularly the best teachers, understand that teaching and learning are two different and, believe it or not, empirically disconnected processes. By different processes I mean that teaching is something the instructor does, learning is something the students do. By empirically disconnected I mean that the evidence shows that there is no relationship between the quality of the instruction, as measured for instance by instructor ratings and the amount the student learns, as measured for instance by performance on standardized tests. In a similar fashion, leaders only lead successfully when others follow – leading is an activity that the leader does, but it amounts to nothing if others [the followers] aren't motivated and convinced about what they themselves need to do."

Although the book used teaching and learning as an example to connect leaders to the ones who are led, we can make a similar analogy about learners. Learners must also be motivated. The instructor can be "world-class", the venue top-tier, and the material first class; but, if the student is not motivated to accept the teaching, nothing is delivered or understood, and the teacher's voice goes unheeded.

In the case of supplier training, both student comprehension, the instruction quality and environment should all be measured as mentioned in the Kirkpatrick Model (discussed later). If there are high marks in all these categories, this is an excellent indication (evidence) both teacher and student were motivated, and the student left the session with

understanding and the instructor did his or her job teaching. This point is very important to the learning process. A student cannot implement what he or she never understood.

That said, information learned must still be implemented to be effective. The question remaining after training and education completion is, “Was it implemented on the factory floor after the student returned to the workplace?” What does the student do after the teacher is gone and management is not looking? To the researcher’s way of thinking there are at least two methods to assess effective implementation in a supply chain:

- 1) Assess (audit) the supplier and identify visible signs of implementation.
- 2) Look for signs of defect reduction in supply chain performance.

Quality Expert’s Experience with Training Needs

Quality expert Edwards Deming, a quality and training authority, had far more experience with training than most. In his 90’s, he was still teaching, and thousands attended his lectures and seminars. A statement in one of his books titled, “The New Economics for Industry, Government and Education,” ^[19] said,

“Experience by itself teaches nothing.....Without theory, experience has no meaning. Without theory, one has no questions to ask. Hence, without theory, there is no learning.”

There is a cognitive connection between theory and learning (not training) and it must include the “what and how” for a job and, the “theory” or “why” behind it. As an elementary student in school, we rarely questioned a teacher’s authority and the “why” never seemed a big or important issue – it just was because the teacher said so.

As young children, learning was less concerned with the “why” behind a basic piece of information and more about what or how. Early school years contain a lot of factual learning and memorization. As a case in point, consider how we learned the basic math skills of addition, subtraction, multiplication and division. It was through memorization. This style of teaching works for a while until the student gets older and, then, it stops. As we reach the age of reason, a student starts to ask “why” something works. Just providing the “what” is no longer enough.

At some point in all our lives, a transition occurs from accepting what we are told to suddenly possessing an inquiring-mind, wanting to know “why”. And, it stays that way for the rest of our lives. We become suspicious of anything not containing a proper explanation. Consequently, employees need not only the “what and how” but the “why” behind what they do in order to grow, develop, and be productive.

Key Takeaways every Organization should Consider

As managers, we might argue about training retention (learning), even discuss student aptitude, do research on past educational student experiences, or, explore the business culture / environment in which the student is employed and trained. All these impact learning. We can argue costs, tangible benefits, or, if the juice is worth the squeeze. We might even question when and where to stop.

Good managers, no exceptions, will not spend money when a payback is not evident or clearly understood. We would all agree; do not train if there is zero benefit seen by either the student or management. Knowledge imparted builds organizational capacity and the capability of the trained individual to accept larger roles. The knowledge transferred or

taught has some key ingredients to it. From a book titled “The Rational Manager,” ^[20] a quote describes these key ingredients:

“..... Furthermore, no matter how much effort is expended on learning, managers [or workers] cannot carry useful knowledge and increased skill from any [learning] experience unless it provides them [the learner] with the three essentials of learning – new ideas, practice in using them, and feedback on the results....”

Still another book, “The Theory and Practice of Training” ^[21] discusses training and the importance of becoming a learning organization. It’s about turning “lessons learned” by the organization and individuals into knowledge that is used for the benefit of the organization allowing it to grow and, ultimately, to become “world-class.” Written in 2009, the opening paragraph of the introduction states what all of industry knows to be true:

“As we approach the second decade of the 21st century, change remains an enduring theme. In order to survive and prosper, organizations in the private and the public sectors will need to respond in a timely and flexible way to social, technological, economic and political change. This means that an organization’s survival and growth will depend on its ability to cope with the external and the internal requirements that these changes will demand. This implies that existing and new staff will need to acquire new knowledge, skills, attitudes and perspectives on a continual basis.”

The book continued by linking the importance of training and learning to employee development. Corporate and organizational training departments must stay current with the times with new strategies and techniques in experiential learning. Advancements in training technologies are moving as fast as manufacturing technology is in most fields. The book described trainers as the “agents for change.” Chapter 1 of the book defines

what a learning organization is and gives the reader an idea of what it will take to develop people.

“ At the individual level, learning is the process whereby knowledge, skills, and attitudes are acquired through experience, reflection, study or instruction. Development refers to the general enhancement and growth of these [individuals] through conscious and unconscious learning. should help to improve and enhance an individual’s competence and potential.”

These quotes are very relevant to the strategy undertaken for the Case Study involving direct supplier intervention in this dissertation. There must be a foreseen need for supplier development, a collaboration with others to develop quality training programs to address these specific supplier needs, and a ready-made student base – supplier professionals willing to learn. The training must be well received as evidenced of pre- and post-training results and evaluations. The only unanswered question still is validation of the training results – is it (the training) making a difference and at what level?

Managing Variation in Workplace Manufacture

This short book Understanding Variation – The Key to Managing Chaos ^[22] was written for business managers unschooled in statistics and presents some fundamental perspectives on data and its conversion to information in order to run a business. In the book, the author describes the conversion of data into information as a process – a “transformation” (in his words) or the analysis of inputs (data) and the conversion of the inputs into outputs (information).

In the book the author talks about specifications being described as the “Voice of the Customer” and variation of processes or systems being called the “Voice of the Process.”

The book offers a manager a basic understanding of when to be concerned about “special cause” variation and when the process is just exhibiting normal variation as part of the process design (sometimes known as signal noise). Normal variation can even hide special cause variation if the signal noise is large enough.

Normal variation can’t be meaningfully changed through process adjustments, policy changes or asking a worker to try harder. Deming called this “tampering.” Both voices (customer and process) are important to understanding and making improvements to any system. Humorously, the author notes three ways to meet targets set before a professional and two of them are useless:

1. Work to improve the system (understand underlying causes and get better)
2. Distort the system (blame/change the system in hopes of improvement)
3. Distort the data (misrepresent performance to show false improvement)

Obviously, the latter two are not desired and working to improve the system the correct choice. The author imparts the need for understanding both voices to give the manager a starting place to create meaningful improvements relative to a manufacturing system. These are basic statistical tools that can see beyond the data and provide information on process performance. In many ways, this book validates the “Big Three” model shown in (Figure 2.1).

However, it does not discuss beyond specific company levels how to measure performance at an enterprise or supply-chain level. The book does discuss at great length the need for business metrics to monitor quality performance.

The author also notes the importance of using graphical tools such as process behavior charts (histograms, flow charts, Cause & Effect Diagrams, Pareto graphs, etc.) to gain critical insight that might otherwise be lost by simply looking at numbers. Presenting data in an enlightening and revealing way is noted by the author as one of the keys to continual improvement.

Another noted quality expert (Phillip Crosby) wrote about his eight principles of quality management. Over the years, refinement left him with only seven as two were combined. These principles are incorporated into current and past ISO standards and still are pillars upon which the quality standards are built upon. One of them is “FACT BASED DECISION MAKING” and holds true to the theme of this book on variation. Facts are important in the guidance of any effort to make a change. In the end, figuring out what to work on is just as important as being aware there is something that needs to be worked on.

The Juran Institute – Research on the Cost of Poor Quality

This article ^[23] was found on the Internet several years ago and published by the Juran Institute promoting a better understanding of the Cost of Quality. According to the author’s article (De Feo 2005) and from Dr. Juran’s 1st edition of his Quality Control Handbook, Juran refers to the cost of poor quality as the “gold in the mine.” Within the quality management domain, Juran links continual improvement to poor costs of quality and discusses the approach to continual improvement. The article speaks about realizing the financial rewards associated with addressing improvement opportunities found through improved cost of quality metrics (cost measurements). This article fits nicely with the need for process and system metrics to measure performance discussed previously.

Within the article, it said American companies were lacking in their ability to develop performance metrics involved with cost of quality (Voice of the Process). This statement implies more is needed in this area – for example, things such as connecting the training results to cost of quality and / or defect rates. The article cites a survey of American companies that revealed only about four companies in ten (40%) claim to have any sort of quality cost system in place. Phillip Crosby stated in his experience with industry, he had never found a company that got “the cost of quality right.”

The De Feo article cites other surveys that indicate while companies are aware of the importance of quality management and mathematical tools like six-sigma, far fewer of them practice the principles and techniques they offer. For a large OEM, they may have a metric they watch such as defect rates but digging into why these overall rates go up or down is a difficult, if not an impossible, task considering the size of most supply chains. There are many variables at play.

If more companies were connected to the need for supplier development, and, many are beginning to realize its importance, there would be fewer major mistakes made in the manufacturing industry. This is one of the significant driving forces behind supplier development initiatives. There is an increased emphasis on stopping a basic reactionary approach to supply chain problems and proactively doing something different (that is, changing the level of thinking that Einstein spoke of).

Further, the article speaks to another disparity in cost of poor quality – cost as a percentage of sales. Varied opinions exist on what this number is. When organizations were asked about quality costs, they admit that it does cost them something, usually

somewhere around five to seven percent of sales – a significant number in itself. Based on ten million dollars in sales, that equates to in excess of \$500,000 annually. However, the Juran Institute thinks the cost is more likely around twenty to thirty percent of sales producing a significant gap between the two numbers. So, which is correct?

Considering the size of warranty and recall (Figure 1.2) in the automotive area which is somewhere in the 48-billion-dollar range and the world automotive industry output being approximately 80 million cars in 2016, some math on warranty cost indicates the defect rate cost is somewhere in the 3% range assuming a typical car cost is \$30,000. But this excludes hidden costs – things such as liability suits, customer loyalty losses, recalls, etc. Consequently, the cost of quality must be higher than 3%.

The difference in these numbers is explained in that manufacturers do little in cost of quality aside from measuring scrap and defect rates from operations and the amount of rework involved with off-specification product, and their direct warranty costs. They may even include the cost of their quality inspections and their quality department as part of the cost. However, the Juran Institute's view of poor cost of quality is deeper than that. Very similar to an iceberg floating in the ocean – only 15% floats above the water line.

Consequently, the stuff below the water-line can be quite substantial – that is, as much as six times the visible costs. Multiplying this 3% by six and the number gets appallingly large. An actual cost of as much as 18% of sales would not be surprising at all. (Figure 2.3) [\[24\]](#) demonstrates this condition in industry very nicely. Juran referred to this cost of poor quality as the “hidden factory” and that to produce everything perfectly, the company has to eliminate the hidden factory. He talks about product that fails after the warranty



Figure 2.3 – Cost of Poor Quality – The Iceberg

expiration and the fact it is normally excluded from the cost of quality calculations because the customer foots the bill. However, it is cost, and it affects the customer's opinion of the company the purchase was made from (brand loyalty). They may or may not buy another piece of product based on that opinion. Juran was concerned less with the differences in the numbers than he was with the company's leadership failing to do anything about it – chalking it to the “cost of doing business” – maintaining the “status quo” or, “that’s the way it has always been done.” It appears Juran may have been correct in his assessment.

In a quote from his interview with Juran, De Feo ^[25] put the issue into perspective:

“By probing deeper into the cost of poor quality, a company can realize that it should allocate its resources to the prevention of a defective product, not to its

repair or rework. Empirical research supports this concept. In 1994, a study by Shank and Govindrajan showed that when companies spend a majority of their quality expenses on failure costs [Reactive], their total cost of poor quality is around twenty-five percent of sales. However, when companies spend a majority on prevention costs [Proactive], their total cost of poor quality is only around five percent of sales.”

This is a three to five-fold reduction in cost of quality and worthy of pursuit by any company with a large cost of quality. Juran promoted analysis and the presentation of cost of quality metrics, not in defect rates, rework, or scrap rates but in the language of money. Therein, lies the opportunity to get a senior manager’s attention to solve bigger and more serious problems. Juran likened it to peeling away the layers of an onion – each time one layer is removed, the cost of quality improved but there was always another layer hidden just underneath pointing to further improvement work. Thus, we have the concept of “continual improvement.” To be world-class at continual improvement requires a talented and trained workforce and this level of competence is not achieved without some serious workforce training and learning.

Questions Every Company Should Know the Answer To

The book *Developing Effective Engineering Leadership* ^[26] is filled with stories of both business mistakes and successes, results related to proper training, education and learning plus the need to create a world-class organizational learning culture. One of the clearest explanations this researcher has found on the need for training was near the end of the book. The author notes three things – the what, the how, and why behind any change as the keys to effective learning:

“ What the employee does, how they do it, and why they do it to produce a product are probably the most important questions and answers ever provided by the Company. These are the things that not only make the very culture upon which this Company will be built, but the reasons why the customer comes for the product and continues to come back over and over again. Knowing this baseline allows us to understand where we have been, and what we are doing to change the process, as we discover the need for change, hopefully for the better....”

This thinking process dove-tails nicely with the Kirkpatrick model and other articles read about training, continuous learning and the need for measuring cost of quality.

Kirkpatrick's Four-Level Model for Training & Discussion

After reading about the Kirkpatrick model [\[27\]](#), it was surprising to learn the first three steps (reaction, learning, & knowledge transfer) was a 60-year old evaluation process many trainers are actively engaged in. This methodology (Levels I, II, & III) is incorporated by our work center where this researcher is employed and used in all its training efforts. Results and examples are provided in this paper in Chapter 5. The results are reported on training oriented toward individual suppliers, and, not towards the overall supply chain performance which is the focus of this paper.

No training model is of value unless it produces results in some form that is measurable. In the article on the Kirkpatrick Model, Level IV results were discussed in that they should provide individual performance improvements and thus change company performance. However, the article was not specific on how to complete this at an enterprise level or for the supply chain. Discussion centered on sales improvement as an example, but this researcher thinks the metric of choice should be closer to the supplier. There is a reason

behind this thinking which is discussed later but centers on the variables at play in most customer sales models.

Level 1 – Trainee Reaction

Reaction is an evaluation of student response to the material delivered. This has been a normal part of every class taught by the University of Tennessee Center for Industrial Services (UT CIS). Our training evaluation form asks the trainee to answer four basic questions for reactions provided by the student relative to the training they received:

- *Question: Did the student enjoy and participate in the class?*
- *Question: Did the presenter do a good job in presenting the material?*
- *Question: Did the registration process and food meet with expectations?*
- *Question: Was presenter knowledgeable and did they keep class on-track?*

The reaction questions are based on a Likert scale (1 to 5) with “1” being worst and “5” being best. After each class, the instructor asks for a training evaluation. While some fail to submit an evaluation, the number that do submit is 95% or higher. The scores routinely average between 4.5 and 5.0 for all classes delivered. Admittedly, the evaluation is subjective, but the method is blind, so the student can be openly honest on the evaluation. The instructor and the Center use this feedback to improve what is presented, how it is presented, and for reporting on performance to our customers (for example – the OEM).

Level 2 – Trainee Learning

For the Case Study, this is also a metric measured. Trainee learning is accomplished through use of a pre-and post-test given to each student. Certification for the student in terms of the body of knowledge taught is demonstrated by a minimum score of “70” for their post-test and certificate. The pre-test is the first activity completed by the instructor

before the class is started and before any material is presented. The student is without access to any materials to gauge their current body of knowledge. At the end of the class, an open book, open note post-test is administered to measure the increase in body of knowledge. The norm has remained unchanged for all the classes offered. Starting class average is in the high 60's / low 70's with a post-class average in the mid 90's. It is not uncommon to have multiple students with post-class tests scores of 100%. The median and mode normally range from 92 to 95%.

Examples of Case Study results (Level I & Level II) are shown as part of Chapter 5 Results. The examples provided are but one of many classes with consistent results in terms of class performance. Total number of students in the class assessment in Chapter 5 was 48 students reporting on our class evaluation form dated January 12, 2016 and is typical of results over the years. The reasons these are offered is to show to the reader, that the materials, the instructor and student acceptance and learning were all excellent feedback on the training.

Level 3 – Trainee Behavior

This level is weaker in its ability to gauge trainees in terms of changed behavior but still a part of the effort, nonetheless. Obviously, efforts at changing habit or behavior (culture, if you will) cannot be fully assured by this last training action. While final exam grading is underway (usually around 20 minutes), the students are engaged in a discussion about what will change in their organization once they get back to the office.

They are asked what they will tell their supervisors and managers about key class takeaways and what they plan to do differently upon return to their plant. One of this

researcher's more memorable moments was about a statement driven home repeatedly in all the classes. When we met at his plant sometime after the class was completed, this researcher asked if he remembered materials from the classes he attended.

He saluted me (he was ex-military) and said, "Cross-functional teams, Sir!"

We all had a good laugh but one of the points driven home was the need for cross-functional teams in preparation of a PFMEA, root cause analysis (part of 8-D) and the holistic containment process the OEM wanted implemented. Most students talked about the work that was in front of them when they returned to their jobs in terms of implementing what was learned and the fact that their current systems were lacking on many fronts. Several remarked in their evaluations that they had never had the materials presented in a way that showed and demonstrated its true importance.

While there are no guarantees students ever put anything into practice, implementation should become evident over time if they did. To determine whether these companies integrated their learning into the supplier's day-to-day business efforts, a measurement must be taken. Over time, the OEM should see a return on this investment in terms of reductions in defects and, longer range, reductions in warranty cost from those drops in defect rates.

This dissertation research Case Study explored the results from two supplier databases to discover whether there was a statistical correlation in performance results (supplier defect reduction) after being trained. Longer term, the OEM's efforts could be further improved by a supplier survey at a point after the training (six to twelve months) to see if the company implemented the class information.

This assumes suppliers are truthful with themselves and with the survey. The only sure way to know with certainty, without a study connecting defects to learning, is some type of follow-up audit of the supplier's management system to determine if the learning was integrated into the company's day-to-day business culture. These two actions (survey or audit) would be improvements over the existing model and of significant benefit. It provides a way of assuring implementation because the supplier would be aware this activity will be a required "down-the-road" element encouraging an increased level of implementation.

Level 4 – Trainee / Company Results

It is simple to develop a new customer if the product is appealing and at the right price. Already stated, the difficult part is in keeping them. Loyalty is harder to keep and maintain than it is in acquiring it. Quality is at the core of this issue. Measuring this final level (results) was one the OEM had not done in terms of supplier training impacts on defect reductions. In some respects, the data collected on defects from the two databases is a measure of Level IV results but disconnected from the learning activity. If the number of defects drop and there are no correlations to the supplier development training, other initiatives could just as easily claim an improvement role. The proposed statistical study should see statistical results if there are any.

To know if the training was meaningful is a statistical model and test of the hypothesis that it is not an improvement. If the results are statistically different, it will support the decision to reject the null hypothesis and accept the alternative that the training is making a meaningful change. This is the issue this research addressed. Additionally, it provides

a repeatable mechanism any OEM or Tier N supplier can use to gauge developmental training in their future.

In the article by Kirkpatrick, he suggested measuring company sales trends to see if training was effective. One can have excellent quality and still have poor or slow sales for a variety of reasons (economy for example or pricing) and the results have nothing to do with supplier developmental training. A better metric with which to measure and compare must be an output closer to the assembly plant and, better yet, prior to the customer sale. That metric is supplier defects (discovered by the OEM prior to assembly). Sales trends are really a mixture of new and old customers and, though meaningful, the trend is over a long duration of time (a decade or more). This research project provides a meaningful result (validating the training or not) in less time. If there is no correlation, the implication will be that the OEM needs to change some facet of the training or the training process to assure learning is more vigorously implemented.

Public Utilities versus Manufacturing Sector

This dissertation titled *The Nature and Extent of Formal In-plant Skills and Technical Training in Selected Public Utility and Manufacturing Companies in the United States* ^[28]

was a statistically reviewed survey of industry and public utilities relative to the importance of training within their respective organizations. The researcher in the above document was looking for differences between utilities and manufacturing facilities gleaned from 85+ mailout surveys related to organizations with greater than 500 employees.

The researcher looked for statistically meaningful differences between training within the following areas:

- Investment in training
- Factors affecting training decisions
- Cost of training per hour per employee
- Total number of trainees and man-hours of training
- Training methods and techniques
- Location of training facilities
- Linkages to public education
- Number of instructors
- Types of government training support utilized by companies

One of the author's more interesting discussion points was a short paragraph related to resource development. In it, the author said something relevant to supplier development training:

“....Of particular importance in the concept of human resource development is the notion that employee training focuses on the job while employee education and development focus on the individual and the organization, respectively....”

While the statement may seem a bit confusing at first reading, the author connected job-specific training (for example OJT) with individual resource education relative to doing the actual work. The development training prepares individuals for the future and enhances the company's capability by “taking the employee to another level.” For example, an engineer attends on-line classes after work to get a degree in business management or engineering as future preparation for bringing added value to his / her company.

While there were reasons this statement was made due to the nature and focus of the specific research, my research Case Study did not attempt to distinguish between the two types. My research on automotive defects, by the above author's definition, would be both

individual resource, supplier development, and company capability enhancement. The students, upon returning to their manufacturing facility, should implement these new skills in the day-to-day performance of their work and improve the operational outputs of their business (see Figure 2.2 above).

Some of the author's findings were relevant to this paper's research on defect reduction:

- 1) Over 90% of responding companies stated there would be a greater emphasis and demand for skills and technical training in the next 10 years.
- 2) 80% of the responding companies reported the training instructors at their facility were responsible for other duties like production, supervision and management, safety, engineering and quality control.
- 3) Utilities and Manufacturing differed in two areas:
 - a. Increasing stability of employment was more important to the manufacturing sector than it was the utility sector.
 - b. Improvements to work environment safety was more important to the utility sector than it was the manufacturing sector.

Focusing on an Employee's Strengths to Leverage Improvement

This book, *Strengths-Based Leadership*, ^[29] focused on studying the results of over 20,000 in-depth interviews with senior leaders, involved more than 1,000,000 work teams, and 50 years of Gallop polls on the most admired leaders. Included in this study were interviews with 10,000 subordinates trying to understand why leaders were followed. One of three key finding in the introduction is relevant to this research paper:

"The most effective leaders are always investing in strengths. In the workplace, when an organization's leadership fails to focus on individual strengths, the odds of an employee being engaged are a dismal 1 in 11 [9%]. But when an organization's leadership focuses on the strength of the employees, the odds

soar to almost 3 in 4 [73%]. So, this means when leaders focus on and invest in their employee strengths, the odds of each person being engaged goes up eight-fold....”

Clearly, individual learning must be preceded by identification of employee strengths and playing to those strengths before the teaching / learning cycle is initiated. The paragraph ends stating that it not only benefits the company but the employee’s well-being and quality of life (providing reasons for the employee to stick around and continue work for the company).

As an example, it would be an unwise attempting to teach differential calculus to a student with no background in algebra or geometry due to their lack of necessary skills in advanced mathematical topics. However, it would be acceptable to teach the finer points of rocket engine design to an aeronautical engineer that has the necessary strengths to understand what is being taught.

Training Development Mistakes

Juran, in his book *Quality Planning & Analysis for Enterprise Quality*, ^[30] made a statement saying, “*extensive training*” was essential to a “*broad quality program*.” He went on to give four reasons why he thought training failures occurred based on his own experience. The following is an excerpt from his book:

- 1) “*Failure to provide training when it will be used.*”
- 2) “*Lack of participation by line managers in designing training.*”
- 3) “*Reliance on the lecture method of training.*”
- 4) “*Poor communication during training.*”

He explained that too many employers provide the training at their convenience rather than the point in time when it is needed. When the time comes for its use, the material the student learned is not fresh. The opportunity to apply learning immediately is a great way to reinforce and make permanent the training one receives. An example of this could include experiential learning during the class – TWI (training within industry) teaches this way and so does the Center for Industrial Services that taught the representatives assessed in this Case Study.

Lack of involvement of line managers in training development can leave holes or gaps in the training. Much of what people do on a manufacturing line is performance based and quality expectations are high. Training design must include line supervisor input to prevent important details being left out leading to the potential for employee failure. Already mentioned in this paper was the importance of experiential training where not only does the employee learn the skill but, where possible, gets the chance to apply it in the classroom or work setting and receive feedback on the results.

Still another book (Kouzes & Posner, 2006) ^[31] titled “A Leader’s Legacy” has another twist concerning the best way to learn. In this book, there was a quote from Peter Drucker. Tom Peters, the co-author of “In Search of Excellence,” called Drucker “the creator and inventor of modern management.” ^[32]

Kouzes and Posner’s book contained this quote from Drucker:

“People learn the most by teaching others.”

A Tried and True Method for Teaching and Learning

In the book, “Running Today’s Factory”– Lean Manufacturing Overview, ^[33] the author stated lean training in the United States had its real beginnings with Henry Ford who saw cycle time and waste elimination as important improvement elements in manufacturing. Ford talked about the ability of his plants to transform iron ore into a car in as little as 81 hours. The book contained quotes that are relevant to this research paper:

“The similarities between lean manufacturing and the early Ford system “are so impressive that Henry Ford may honestly be considered a pioneer in JIT [Just in Time] systems” [Wilson 1996: 30].”

This statement was followed by a short discussion (2 to 3 paragraphs) on an American training process invented by the U.S. Military during WWII called TWI (Training Within Industry). TWI job methods include standardized work processes, waste elimination, location of tools at points of use, using gravity-fed hoppers, and drop-delivery chutes, with the element of continual improvement (all lean principles). The relevant information in the book for this research paper were two paragraphs about the methods used to train women during WWII with the “manpower” shortage in factories making equipment and supplies for the war fighters and its ultimate transition into the Japanese culture after the war was over.

“There were 1.7 million American supervisors from more than 16,000 plants trained and certified in the TWI program. These supervisors, in turn, trained over 10 million factory workers. Almost 90% of the participating companies achieved at least a 25% improvement in production and labor efficiency. In 1945, the TWI program in the United States was deactivated by the War Manpower Commission.....”

“ In 1945 there was a different crisis in Japan. Japan’s industrial activity had been reduced to less than 1/10th of its pre-war level, and the economic base had been devastated..... As part of the assistance provided by the Occupational forces, TWI was introduced. By 1951 the Allies were relying on textiles, metals, and auto industries for supplies during the Korean War..... The following year [1952] there were over 1,000,000 certified Japanese supervisors..... In 1990, the program was still active with nineteen training organizations licensed by the Japanese Ministry of Labor.”

A quick check of the internet indicates TWI is still very much a part of Japanese manufacturing culture in 2019 and ongoing. It is closely tied to the principles of lean manufacturing and foundational to a different manufacturing approach. Most people know it today as the Toyota Production System (TPS) or some variation of it by other names. Though TPS is uniquely Japanese, it has several core principles developed following WWII which were integrated into TPS for product quality (one of which was TWI).

How do we Learn – the Stepwise Process

The book “Techonomics: The Theory of Industrial Evolution” ^[34] contained a section on the concept of learning that is applicable to anyone working to acquire a skill or improve individual or organizational capabilities. This concept is shown in (Figure 2.4) – The Cycle of Learning. Within this drawing, the levels of competency and awareness are compared on four levels of skill mastery:

- | | |
|-----------------------|---------------------------|
| 1) Ignorance of skill | 3) Proficiency with skill |
| 2) Awareness of skill | 4) Mastery of skill |

As the figure shows, mastery of a skill is the ability to perform competently on an unconscious level. It implies skill knowledge, ability to perform without having to think

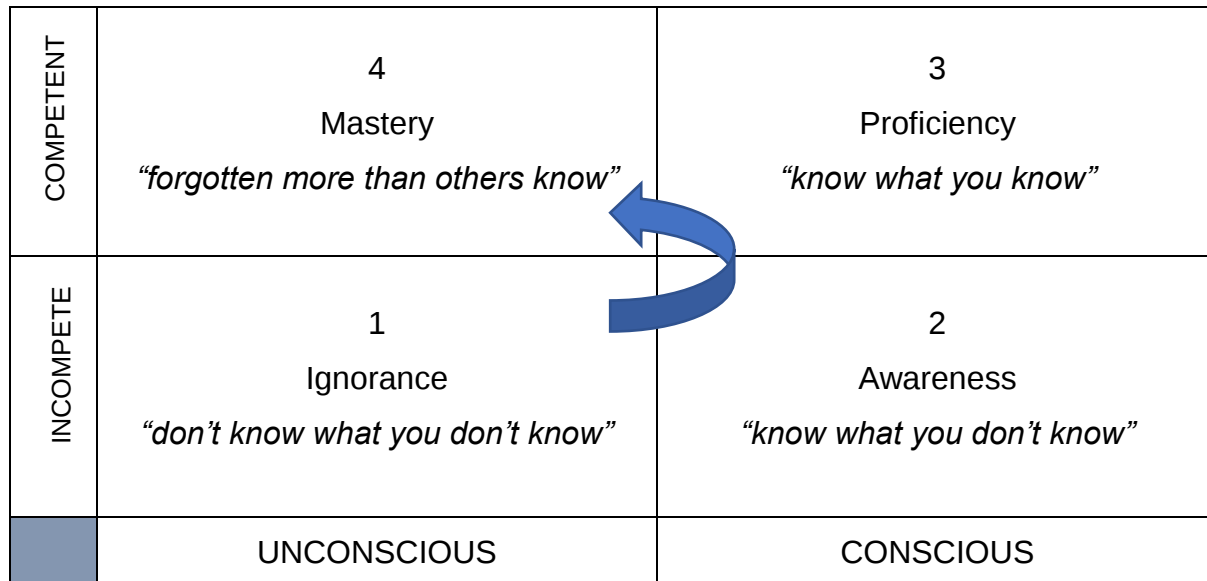


Figure 2.4 – The Cycle of Learning

about it on a conscious level and having not only the technical skill portion but also the experience to go with it. This person should be capable of teaching others.

The Importance of Avoiding Dysfunctional Systems

There are some additional takeaways from a book, *"We Don't Make Widgets" – Overcoming the Myths that Keep Government from Radically Improving.* ^[35] These concepts were statements on change and change management that should be a part of every learning experience:

- 1) Making a change does not mean you somehow made an improvement. Never confuse the two.
- 2) Mistakes lead to blame; blame leads to "cover your rear;" "cover your rear" leads to the dark side. Honest mistakes are not to be hidden but learned from.
- 3) Behind every process problem is usually a "policy" problem. Deming's stated most process problems were the fault of management:

- | | |
|--|---------------|
| a. Who selected the process to be used? | A: Management |
| b. Who decided on the process steps? | A: Management |
| c. Who approved the process design? | A: Management |
| d. Who provided the resources to be used? | A: Management |
| e. Who provided the process goals? | A: Management |
| f. Who decided timing and scheduling? | A: Management |
| g. Who trained the employees on the process? | A: Management |
| h. Who oversees and controls the process? | A: Management |

And so on.....

Many times, government processes are viewed differently than manufacturing. In reality, they are much the same (process inputs, employee work, process outputs) where quality is just as important to the outcomes. One of the more notable quotes from this book was the statement by Scholtes on the impact of bad processes:

“All of the empowered, motivated, teamed-up, self-directed, incentivized, accountable, reengineered, and reinvented people you can muster cannot compensate for a dysfunctional system.”

Scholtes provides a reasonable argument stating that processes that make up a system that is old and past its time, improperly engineered, designed, controlled, and/or managed will defeat the best intentions of man every time. While training and learning helps the people side of things, it does nothing for the process side of things in terms of functionality.

How Manufacturers can Create a “Win-Win-Win” Scenario

A research paper, *System Perspective on Warranty Problems within a Supply Chain*, ^[36] conducted by two Massachusetts Institute of Technology graduate students in 2005, obtained surveys and interviews from 100 industry professionals from a single supplier.

Their goal was to identify information leading to the root causes of automotive industry warranty failures. The survey was statistically analyzed. Survey inputs were submitted by both workers on the factory floor and members of management looking for differences in their opinions as to warranty failure causes. Surprisingly, it yielded none. Both the workers and managers agreed on answers to the questions with no statistical differences. The authors of the study placed root causes into five broad categories:

- 1) Product development related
- 2) Resource related
- 3) Supplier related
- 4) Warranty organization related
- 5) Cultural related

Under the cultural related category, a singular conclusion was stated:

“Reactive warranty fire-fighting mode dominates the entire warranty reduction process.”

This comment is quite revealing. It tells us that suppliers are not working proactively to reduce defects. It says that the automotive supply chain is in “reactive” mode and that there must be a shift in thinking to exit this mode in favor of a “proactive” culture. If reactionary methods truly dominate the warranty reduction process and the basic recourse for correction has always been supplier site containment, then the “same level of thinking that got them there” (Einstein) must change.

This survey also provided several conclusions on warranty root causes in the other categories. It is interesting to note that the recourse of most OEMs when a warranty failure occurs is to resort to the reactive protocols available to them in their supplier contracts –

namely, that of supplier corrective action and supply site containment. It is reactive in that both the producer and the supplier are working to fix the immediate problem (indirect involvement). The exploration of these findings was expanded during their interview process hoping to explore answers at a deeper level and providing new information to address some of the issues.

The researchers, after further analysis of the interviews, came away with five conclusions:

- 1) *“People need to change their mind[set] to accept a proactive warranty prevention approach.*
- 2) *Unclear accountability on warranty issues. Sales department gives warranty targets, but engineering is responsible for warranty corrective actions.*
- 3) *The purchasing department selects supplier components based on price, not quality.*
- 4) *Suppliers cannot provide adequate engineering support when product fails due to the lack of knowledge and capability.[development training needed]*
- 5) *Warranty needs to be included in the purchasing process. Warranty needs to be considered in both terms of cost and case numbers.”*

One of the fundamental themes underlying these conclusions is the need for supply chain development. If suppliers can raise the level of quality for the parts and components, they manufacture through supplier development training, the OEM, supplier, and end customer all benefit. This becomes a “win-win-win” for all the stakeholders involved. It was interesting to find one of the causes listed was the lack of knowledge and capability on the part of the supplier – a relevant finding for purposes of supplier development training. Either the supplier has to get the knowledge to improve its capabilities thru an internal or external provider or the OEM’s quality organization has to provide the training.

Warranty in European Automotive Sectors

The report, Global Automotive Warranty Survey Report, ^[37] was a review of the global automotive industry completed by a European automotive consultant agency with multiple sponsoring companies. Their objective was identification of barriers preventing reductions in automotive warranty cost. The target audience was leaders of the manufacturing sector and Tier N supplier warranty oversight groups.

The effort identified a need for supplier development as one of the issues but did not dwell on how to accomplish the effort nor did they explain how to identify results if the output of a development effort was successful – the goal of this researcher's Case Study. The report also identified the need for better problem-solving efforts which is also one of the training activities in this dissertation Case Study (8-Disciplines of Problem Solving). This survey was still another statistical analysis, Q & A approach, for the global automotive sector like so many of the others.

Continuous Learning and its Importance

A book, The Theory and Practice of Training, ^[38] discussed the benefits of training and becoming a learning organization. The words from the book explain it nicely:

“Turning now specifically to training, there are numerous potential benefits to be gained by individuals and by organizations from well-planned and effectively conducted training programs. Individual trainees can benefit in a number of ways. In relation to their current positions, trainees may gain greater intrinsic and extrinsic job satisfaction. Intrinsic job satisfaction may come from performing a task well and from being able to exercise a new repertoire of skills. Extrinsic job satisfaction may be derived from extra earning accrued through improved job performance and the enhancement of career and promotion prospects both

within and outside the organization to which they belong. Benefits for the organization include improved employee work performance and productivity; shorter learning time which could lead to less costly training and employees being 'online' more quickly; decrease in wastage; fewer accidents; less absenteeism; lower turnover and greater customer and client satisfaction.

Amongst the many developments that have been introduced to organizations, that of becoming a learning organization has taken on a high profile. It has also led to confusion about what it actually is and some skepticism as to whether it can exist at all. Although it is difficult to define precisely, the description offered by Pedler, Boydell, and Burgoyne [1991] encompasses the key sentiments: 'an organization which facilitates the learning of its members and continually transforms itself.' Learning by the organization and by individuals within it is seen as critical to its survival and development....."

Based on this description, the narrative implies organizations that survive the longest or manage to have better business performances have, as one of their key cultural elements, a business rooted in employee and organizational development and learning. The authors of this book see it as "critical to survival and development." An organization cannot grow without the necessary skilled personnel and proper resource utilization that comes from the wise application of "lessons learned." As with any manufacturer, supplier development can be viewed as a critical component of the defect or warranty reduction process.

Drivers for Organizational Learning & Performance

In this article, Global Journal of Management and Business Research, ^[39] another statistical survey was conducted using employees (both male and female) in Pakistan. Of

the 95 surveys they sent out, 79 were accepted and analyzed as part of the study. The model studied four drivers in organizational performance:

- 1) Training design
- 2) On-the-Job Training
- 3) Delivery Style
- 4) Training & Development

The statistical study concluded all four drivers had a significant impact on organizational performance. Once again, the connection between learning and performance is made.

Plant Improvement as a Result of Training

This publication, *U.S. Manufacturing Skills Gap, Technical Education Effectiveness*, ^[40] was a master's thesis by a Western Kentucky University graduate student who completed a statistical study on targeted educational training. The focus of the research was on whether employee training had an impact on the Mean Time to Repair (MTTR) for plant machinery. The study excluded scheduled or planned maintenance activities but included unplanned equipment outages. The method of analysis was the matched-pair t-statistic.

A group of workers doing a repair but having received no training before the repair work was started was baselined with a grading process. The workers then received training prior to repair work and graded a second time using the same grading process. This was later compared against their earlier baseline performance. In summary, the workers performed better in the machine MTTR scoring 26.1 points higher on the repair work after training than they did with no training as validated by a two-tailed, single-sample paired t-test with a 95% confidence level.

The grading system used larger scores to indicate better performance. The researcher in this study graded on a variety of issues during the repair process including trouble shooting, fault diagnostics, machine repair, and time taken to return the machine to full production. The differences in the no-training and training scenarios fell within a confidence interval of 10.3 to 41.9 points higher for workers who received training before the repair work was started. The difference was impressive. On a scale of 0 to 100 (evaluation scores), the no training scores averaged 40 and the scores with training performance before the maintenance work at 66.1. The result was a 65.3% performance improvement.

One of the limitations the researcher pointed out was the small sample size. There was concern whether the results could be extrapolated to larger groups. Additionally, one of the findings the researcher noted was whether prior maintenance experience had an impact on results. Their conclusion was it did not. This conclusion was validated using a two-tailed, two sample, t-test difference in means (matched pair difference).

Excluded from the study were efforts to evaluate the employee's attitude toward the training. That was left to a future study with the thinking it would be useful to know so allocation of training dollars could be directed toward the correct individuals (that is, individuals interested in learning as opposed to those who were not). Not all individuals in this small group were cut out to be maintenance technicians as their scores indicated. Two of the nine individuals failed to improve their scores – one remained at their before score of 30 while the other stayed at 40 (no change for either worker). The training served no purpose for these two; nothing was learned or added to their capabilities prior to the repair work.

Training and Impact on Aviation Flight Crews

The following article, Crew Resource Management (CRM), ^[41] was about improving team work in high reliability industries. This effort was initiated in the aviation industry and motivated by some of the more serious flight crew errors that resulted in loss of life and destruction of property. Two examples were noted in the article. The most infamous one was in the Canary Islands where two 747s (KLM – Dutch and an American Pan Am airliner in 1977) crashed in a head-on run-way collision with one plane attempting take-off in a fog. The accident resulted in the largest single loss of life incident in aviation history with 583 vacationers dying and loss of both planes. The second was an aircraft engine fire where the pilot and copilot shut down a still functioning engine instead of the one that was on fire resulting in a crash, loss of life, and loss of the plane. Interestingly, after an analysis completed by NASA-Ames, it was concluded 73% of accidents involved some type of flight crew error. A change in crew-behavior was needed – especially in areas such as accident prevention and emergency management.

One of the positive outcomes attributed to CRM was an incident involving a DC-10 where an explosion of one of engines disabled all three redundant hydraulic systems aboard the aircraft. The flight crew managed to land the plane with the help of a DC-10 training captain who was a passenger on the flight. They used reverse thrust on the remaining engines to navigate and created a landing that resulted in 184 of the 296 people on board surviving an otherwise total loss of life incident.

The flight crew attributed CRM to the success of their efforts on the ill-fated plane. CRM is now finding its way into aviation maintenance, air traffic control, merchant navy, the

nuclear power industry, medicine and, more recently, the off-shore oil and gas industry. This type of crew learning involving high reliability industries is becoming policy and practice for industries that can ill afford human error and mistakes that lead to loss of life, equipment and environmental damage, or other catastrophic results.

New Methods - Virtual Training Systems

VISTRA (Virtual Simulation and Training of Assembly and Service Processes in Digital Factories) ^[42] was a project funded in Europe to investigate whether individual gaming experience (people that played video games, past or present) experienced better training outcomes as a result of their gaming experience. This was a statistical study that tracked the learning experience, time to complete, and the number of errors made during the virtual assembly process. There were five different scenarios patterned after processes that existed in a German automotive manufacturing environment.

The results of the statistical experiment showed a learning curve for non-gamers taking them longer (averaging an additional 75 seconds) than the gamers to complete their training scenarios. Interestingly, the number of mistakes recorded during the exercise was identical for both groups indicating non-gamers were just as effective in this area as the gamers. They also found one scenario of the five that produced 50% of all the mistakes made in the exercise.

Their conclusions were that virtual training has a place in manufacturing plant learning and that even senior workers that have little to no gaming experience can adapt to virtual learning. Their initial experiences with this type of training with none-gamers was that the worker would experience a longer training cycle until they get accustomed to the virtual

training system (VTS). Because of these trials and participant feedback, it was learned that additional improvements to the system would be needed to make VTS a viable training methodology in the automotive industry. This researcher would not be surprised to see virtual learning being used in many learning environments. It is common knowledge the U.S. Navy is working on virtual learning to train submarine crews.

Indirect and Direct Supplier Development

This article ^[43] talks about many of the same things this researcher pointed out in the introduction and in the background chapter (Chapter 3) concerning the need for technological competencies and manufacturing capabilities within a supply chain. The article's objective was to provide insights relative to the effect direct and indirect supplier development has on supplier product quality, supplier capabilities, and performance.

The article begins with a discussion of the three choices available to a buying firm when faced with a poorly performing supplier:

- 1) They can switch to a different supplier.
- 2) They can vertically integrate their business and bring the supplier activity in-house.
- 3) They can assist the deficient supplier through a supplier intervention.

These choices led to a discussion of the two types of intervention (direct and indirect). Indirect supplier development involves actions such as assessing the supplier, communication of evaluation results, and setting performance goals which the supplier is then challenged to meet. It can also involve the use of competing suppliers in a competition favoring the supplier that provides the best product and / or service. This method was termed in the article as an "influencing strategy" to get better results from the

offending supplier. According to the article, influencers (change from a distance) can include:

- 1) Information exchange
- 2) Recommendations
- 3) Requests
- 4) Promises
- 5) Threats
- 6) Legal

On the other hand, direct supplier development or intervention is more of a hands-on type of approach that includes:

- 1) Consultation with the supplier
- 2) Education and training programs for the supplier
- 3) Temporary personnel transfer to the supplier site during containment or corrective action activities
- 4) Invitation of supplier personnel to their site to observe the problem

The article was a statistical study that looked at indirect, direct, or a combination of direct and indirect involvement with the mal-performing supplier across a broad range of manufacturing and service industries. The study was completed with a survey using heads of purchasing, heads of supply chain management and logistics, supplier development, procurement and quality managers as the study subjects.

There were several conclusions drawn from the statistical research.

- 1) The average magnitude of supplier product and delivery performance was higher than the magnitude of improvement in the supplier's capabilities.
- 2) The two types of supplier development (indirect and direct) have distinct effects on the improvement of product and delivery performance and supplier capabilities.

- 3) The results suggest indirect positive effects on supplier product and delivery performance as well as supplier capabilities are associated with goal setting theory and the earlier mentioned influencing strategies.
- 4) Both methods created supplier change with direct involvement being a paradigm shift in actions to improve performance and delivery.
- 5) Direct involvement of the buyer in the supplier problem allows the supplier to upgrade internal capabilities to develop, make and deliver superior products.
- 6) However, contrary to expectations, direct supplier involvement did not result in upgrades to the supplier's product and delivery performance. Their conclusion: *This was thought by the researchers to be time related in terms of implementation. This being a lagging indicator and not delivery of instantaneous results.*
- 7) Both direct and indirect supplier development activities at the same time produce a negative impact on supplier product and delivery performance. Conclusion: *It was thought that both types of intervention create supplier ambiguity and their performance deteriorates rather than improves.* Buyers should be aware of both methods and use them accordingly in their attempts to improve supplier performance but never both at the same time.
- 8) If the buyer wants immediate improvement, they should avoid direct supplier involvement and use indirect methods. If the buyer is more interested in the supplier's capabilities and long-term change, direct methods provide better results.

There was some concern on the part of the researchers that the small sample size limited the power of the statistical tests. This was also a study in German speaking countries and may not be translatable to North America or Asia. The conclusions of their study were that both direct and indirect supplier development activities have positive effects on supplier quality and delivery performance if used separately. It was interesting to note in finding #6 related to the importance "time to implement" had on direct supplier intervention. It is something that must be accounted for in the defect data. In this

researcher's Case Study, twelve months was allocated for implementation time before and after the supplier development training was completed.

Reference Books for Statistical Studies of Research Data

Finally, multiple statistical books were used for information on Student-t matched-pair comparisons, Sign and Wilcoxon Rank-Sign tests that were part of the research analysis. Method is discussed in depth in Chapter 4, but the first four books listed below were foundational in terms of methods used. Included in this research Case Study was a Design of Experiment (DOE) study along with simulated data generation to study several groupings with a small sample size. The fifth book was my source of information for the DOE. The following is a list of those reference materials used in this research Case Study:

- a) Elementary Statistics, 2nd Edition^[44]
- b) Applied Statistics and Probability for Engineers^[45]
- c) Statistics for Business and Economics^[46]
- d) Probability and Statistics for Engineers & Scientists^[47]
- e) Principles of Experimental Design and Analysis^[48]

The mathematical work for the research was completed in some cases by hand using Microsoft Excel as a calculation worksheet with equations that can be found in the above statistics books. For efforts on the larger samples, data simulations and DOE (Design of Experiment), a software package available to the researcher was used (Sigma XL) which is a Microsoft Excel compatible statistical package for calculations which included Student-t, Wilcoxon Rank-Sign, and Sign test. Results of the Case Study can be found in Chapter 5.

Summary

This researcher found a wealth of information on training, learning, and improving an organization's ability to deliver customer product and service. In my searches, there were innumerable articles and books written on the importance of this subject (human resource development) along with statistical studies to back up their claims of organizational improvement.

While this wealth of statistical information exists on training benefits, virtually all of the statistical studies were done via surveys. The article on MTTR performance improvement noted in the literature search was the only article (thesis) found looking quantitatively at a connection between training and maintenance performance results. The master's thesis demonstrates a connection between their research and this dissertation Case Study. However, its scope is limited to maintenance repairs in a single plant staying inside the confines of their manufacturing facility (this is, intra-plant) and the sample size was less than ten.

The study focused on plant maintenance technicians which, just as easily, could have been a Tier N supplier to an OEM. The research is dissimilar to mine in that it looked internally at MTTR whereas my research crosses inter-plant boundaries looking at the supply chain's defect rates (Tier 1 level) with a much larger sample size and scope (multiple training combinations for 148 manufacturing facilities). The focal points are different with supplier defects versus MTTR but a cognitive connection between these two is clearly seen.

The MTTR thesis was a unique study connecting training to performance demonstrating with statistical proof that training done in the right way can advance performance, capacity, and knowledge of a human resource. The sense of increased human resource capability should extend beyond the interplant boundary and all the way to the end-customer or buyer. Likewise, the research study completed for direct and indirect interventions also point to positive influences in supplier quality and delivery performance but cautions the intervention user to be smart in their choice of methods, and never mix the two types of interventions together.

The literature search points out what every trainer intuitively understands – if the company does not train, learning is problematic and may never occur. A company must train its employees on what they need to know. No training equals no learning and results in no performance improvement. This research paper extends training and learning efforts in a study of the correlation between supplier development and assembly plant defect rate reductions as defined by the OEM's internal defects rates (PPM) in addition to after the vehicle has been in service (3MIS). This research extends the impact of learning into a larger part of an OEM's supply chain and with a larger sample size. This methodology is translatable to any industrial manufacturing sectors (OEMs or Tier N suppliers) that perform development training and maintain a history of supplier defect rates. There were also multiple factoids (small bits of information) that can be pulled from the research noted in this chapter. Several of these are included as minor findings in the conclusions found in Chapter 6.

Some the more interesting research results are noteworthy of summarization. They follow with short narratives on each one:

- 1) The Kirkpatrick Model provides very useful suggestions for gauging class quality to assure first class delivery, material quality, overall participation, and environment. Immediate feedback is important to assure students continue to receive consistent training and education. Higher levels of this model point to the need for correlating performance to training.
- 2) Research on information related to direct and indirect interventions indicate a need for one or the other but not both types of intervention at the same time. The intervention is highly dependent on timing and whether the OEM buying supplier parts is interested in short- or long-term mitigation. Companies interested in longer term relationships with their suppliers can benefit from direct intervention such as supplier developmental training.
- 3) World-class organizations must realize the need for a non-ending stream of training and employee development by training their most valuable asset.
- 4) Training and continuous learning is key to maintaining a competent workforce at any organizational level. Consequently, every manufacturer (regardless of their position in the supply chain) needs a robust training and development department devoted to workforce improvement and organizational improvement.
- 5) Supplier development training (direct intervention) should be a focal point for OEMs or other manufacturers who possess a large or extensive supply chain. This, by no means, should replace indirect interventions when necessary but, long-term, healthy, relations in any chain is built on long-term direct supplier development.
- 6) Training is something the instructor does and learning is something the student does – they are not the same. Both must be willing (teach & learn respectively).
- 7) There is no better way to learn than to “teach” others.
- 8) A focus on employee strengths is critical to the learning process. It’s as much about getting the right people in the right seats with a willingness to learn and apply their learning for the betterment of the organization.

- 9) “Status quo” is the enemy of organizations – “Change” is the real friend. Companies and their personnel cannot survive with real change within the organization.
- 10) Most of the cost of poor quality (COPQ) remains hidden to the observer. This hidden cost can be as much as five to seven times the visible costs.
- 11) Timing on training is everything. Not too early such that it's forgotten and not too late after the employee needs it. This is not to be completed at the convenience of management but just-in-time for the employee to learn and apply it.
- 12) More longer range studies are needed for development training on supply chains. This researcher found little evidence that it has been done even at a minimal scale. The reason behind this is most likely the data is proprietary and closely guarded against discovery by others. This researcher was only allowed access to encrypted data such that actual values and suppliers are only known to the OEM.

CHAPTER 3. RESEARCH BACKGROUND

Overview

In the Case Study, the OEM assembly plants understood both the reality of the situation and a pressing need of longer-term intervention with the poorly performing suppliers and wanted to proactively change their methodology where parts with suspected defects are eliminated or, certainly as a last resort, always caught by the supplier and never shipped. It required a paradigm shift in the supplier's way of thinking.

In this case, the OEM decided to be proactive and part of this strategy to lower defects was supplier development training (a direct intervention). If this shift towards making suppliers more proactive occurs, there should be less potential for defects being made, less mistakes by quality control, and improved predictive methods for parts that left the supplier and then incorporated into vehicles. Fewer quality issues would then occur at the assembly plants. Both the supplier and the OEM win in this scenario and, best of all, the warranty cost drops and the customers win as well. Quality engineers can then devote their time to automobile continual improvement activities getting out of this reactive mode because the suppliers have now shouldered the defect reduction requirement as part of their day-to-day work activities.

Discussed in this chapter, the strategy the manufacturer decided to use was a series of supplier development training programs. The goal was to teach the supplier the OEM's way of building higher quality into supplied parts as Deming and Dodge had pointed out. These approaches are discussed in the following sections on specific training actions. Supplier development training involves using simple strategies that address high operational risk or significant process failure modes, coordinate continual improvement action and problem solving, and create error proofing mentalities that eliminate and/or

reduce process risk. In this way, a supplier addresses the problems before they can occur creating a more robust environment in which to work and make parts.

In this Case Study, the supplier developmental classes were devoted to shifting the supplier's organizational culture away from reactive and toward a proactive posture. The training programs were all collaboratively developed by UT CIS and the OEM and its Production Quality Engineers. These classes have been delivered to over two thousand supplier recipients with the expectation that supplier defects will decline in manufactured vehicles. The UT CIS has been delivering supplier development training to Tier I suppliers on behalf of the OEM since 2013. The expectation has always been that suppliers would implement what they learned and improve the quality of supplier parts and subassemblies, but this was never a given (that is, it had not been proven).

Having witnessed, first hand, the incremental and transformational changes supplier developmental training can have on companies when done correctly, the researcher's belief is it will be positive. However, it is with both equal levels of apprehension and eagerness that the solution to the original question was posed – that is, a statistical study to determine the answer. As with most chains, supplier performances, as a group, vary from the very good, to the acceptable, to the not acceptable when it comes to parts quality. Some suppliers seem to always “get it right.” They intuitively know what to do in order to effectively eliminate defects going to assembly plants. They have implemented robust continual improvement strategies for their processes and operations.

Still other suppliers, for varied reasons, fall short of effective implementation and wind up on this opposite extreme and in need of improvement. Still, others land in that middle

ground somewhere between the two extremes – not great; not terrible; but certainly, in need of improvement. The focus of the supplier developmental training has been and continues to be on these latter two groups of suppliers with the expectation that if they improve, the overall supply chain improves. When that happens, the OEM, the customer and the supplier are all winners.

The remainder of this chapter is devoted to explaining the various combinations of training that were a part of the developmental training. Note that implementation of the training and education by these suppliers is key to positive outcomes in defect reductions. New information, not implemented, will result in no improvement. Consequently, this leaves the supplier in the same condition as if they had never taken the developmental training and a waste of their time and resources.

Need for Change

In the very beginning, the OEM was of the realization something needed to be done. The producer had a limited number of engineering resources and could only do so much with each resource having multiple suppliers sometimes at great distances from the assembly plants. Effectively delivering the right developmental information would leave the supplier more capable, more knowledgeable, and better prepared to deliver on their quality expectations. This effort brought the UT CIS into the equation for creation and delivery of developmental materials for these suppliers. There are currently three supplier developmental programs in existence:

- A. Process Failure Mode Effects Analysis / Control Planning (PFMEA / CP)
- B. Eight Disciplines of Problem Solving (8-D)
- C. Proactive Containment (Supplier Site Containment – SSC)

Performance of suppliers is somewhat of an unknown at the start of every product launch, especially if it is a new launch and / or a new supplier. Problems involving a new or existing supplier are, oftentimes, discovered only after the OEM is already committed to the supplier with a production plan and strategy already deployed. This makes it difficult to shift directions in midstream to another supplier without disrupting a launch. Defective parts can take months or even years to become noticeable, requiring a statistically significant number of parts to fail before it is identified as a problem.

Vehicles are made of metals, plastics, and a host of other materials – every part can and will fail after a period. It would be logical to expect lab-testing to answer many of the failure questions and it does. Parts are tested in laboratories to understand life expectancy and their failure mode(s). However, lab analysis is not always a perfect predictor of failure modes or product life. The environment in which it is used, the part's condition(s) of use, interaction with other subassemblies or components, and, even the users themselves can impact a part's life or which parts are likely to fail first. The truer test comes with parts made without defects, incorporated into the vehicle, and performance tested by the customer in the field over long periods of time. These outcomes reveal the true nature of durability and overall quality as well as create brand and customer loyalty.

This is not to say lab predictors are unimportant – in fact, quite the opposite. Even similar parts with a prior history are, many times, good indicators of future performance. In the end, this struggle to be or become a first-rate supplier is, again, a survival of the fittest and the suppliers that allocate resources wisely. The truly good ones survive because they do the work necessary to be sustainable (consistently low defect rates, on time and

at cost). The poor ones disappear because they cannot deliver; and, are replaced with other suppliers who may or may not be sustainable over time.

In the final analysis, the product (transportation vehicles) is only as good as the quality of supplier parts received. The supplier development training was initiated to strengthen the poorly performing suppliers with the idea it would elevate the overall strength and capability of the whole chain starting with suppliers needing the most help.

One of the most difficult to achieve culture shifts in any organization is changing the attitudes of people (especially leaders). People change when they see the importance of change and the positive benefits it brings to their day-to-day work effort, their financial future, and to satisfying their personal needs. Internal organizational needs are many times secondary and come only after the personal needs are met. Whether one subscribes to Abraham Maslow's five hierarchies of needs or Frederick Herzberg's two factor theory on intrinsic and extrinsic needs, personal needs and desires typically carry more clout than organizational needs. Within each effort to train personnel, there was an attempt to demonstrate how the change being requested benefits both the individual and the supplier's organization.

The Three Supplier Development Training Programs

PFMEA / Control Plan

The training developmental effort was directed toward the issues identified in a supplier analysis conducted by the OEM in collaboration with its parts engineers assigned to their supply chain. One of their most basic concerns was repeated supplier failures in problem prevention before the problem occurred. The engineers were convinced that better

anticipation (predictive methods) was necessary to push the suppliers' culture toward a more proactive environment. There were procedures in place on the OEM's Supplier Portal explaining what the Potential Failure Mode effects Analysis (PFMEA) was supposed to achieve, but, in many cases, the required assessment mandated by the OEM was little more than a required piece of paper the suppliers completed to satisfy a customer mandate to create a PFMEA and Control Plan.

The supplier paperwork requirement was satisfied but the document was never used in the manner the OEM expected. Often, the PFMEA Risk Priority Number (Severity x Occurrence x Detection) were artificially doctored to achieve a level of risk low enough to avoid a perceived need for supplier preventive action. In some cases, new process PFMEAs were created from older processes with potential failure modes missed or left out completely. Later when a failure occurred, the "lesson learned" was never added to the PFMEA nor was it translated horizontally to other similar processes. In still other situations, the authors of the document were simply not knowledgeable enough to put a good document together (for example – done by one person without cross-functional team input) with the document being only as good as the knowledge of that single individual. Clearly, these supplier documents were lacking a necessary thoroughness to make them effective in lowering defects.

The first of three training classes was developed and initiated in 2013 with an expectation of training poorly performing suppliers in the correct method to create a PFMEA and its use to improve process and product robustness (Quality Planning). The UT CIS had a database containing all the suppliers that participated in PFMEA training. The OEM had information on the defects that each supplier generated before the PFMEA training was

started and after their training was completed. This research study includes an analysis of those suppliers that attended PFMEA training in three ways over time:

1. Those receiving just the PFMEA training (no 8D or Containment).
2. Those receiving PFMEA training and 8D Problem Solving only (no Containment).
3. Those receiving PFMEA training and Containment only (no 8-D).

The study looked at combinations of training that had the potential for making a difference in assembly plant defect rates (PPM) and, longer term, with impacts at the 3-MIS level.

Failure to find any indication of significance leads to one of two conclusions:

- a. The supplier did not implement what they learned, or,
- b. The supplier training module needs to be improved to be more effective.

8-Disciplines of Problem Solving (8-D)

Training development efforts were directed next towards a second issue identified in the OEM's supplier analysis conducted by its product quality engineers. A second basic issue was with repeated failures on the part of suppliers to permanently correct the problems the OEM identified with a supplier part. The OEM engineers were convinced better corrective abilities on the part of the supplier would create a more proactive culture.

Like PFMEA, there were procedures in place to explain how the process for corrective action (8 Disciplines of Problem Solving or just 8-D) was to be implemented on the Supplier Portal. For many of the poorly performing suppliers, the 8-D effort in determining the root causes (process, inspection, and prediction) were inadequate and fell short of permanently correcting the problem or their root causes missed altogether and the problem returning at a later date.

Again, the requirement for the 8-D was satisfied but the document's prescribed actions failed to deliver on a permanent fix. The author of the 8-D document was sometimes not knowledgeable enough to pull all the pieces of the document together (again done by one person without cross-functional team input) and the result fell short of its intended purpose – that is, fix the problem correctly and permanently. Clearly, these documents were also lacking the necessary effectiveness to lower part defects.

Developmental training was initiated in 2014 with the expectation of training the poorly performing suppliers in the right method to create an 8-D and in the document's use so the supplier could improve process robustness, inspection, quality assurance, and prediction. Information on the defects these suppliers generated was also known before the 8-D training started and after the 8-D training was completed. Similar to the PFMEA developmental training, this study included an analysis of those suppliers that attended 8-D training in three different ways:

4. Those receiving 8-D training only (no PFMEA or Containment).
5. Those receiving 8-D training and PFMEA only (no Containment).
6. Those receiving 8-D training and Containment training only (no PFMEA).

The research study looked at training combinations that had the potential for making a difference in defect generation at the OEM level (PPM) and longer-term impacts to 3-MIS results. Here again, failure to find an indication of any significance leads to one of two conclusions:

- a. The supplier did not implement what they learned, or,
- b. The supplier training module needs to be improved to be more effective.

Containment Training (SSC)

The final training developmental effort in this research study was directed towards a third issue identified in the OEM supplier analysis. Another concern was failure on the part of suppliers to utilize any effective internal containment process when they suspected problems or made changes to equipment, processes, or people that could potentially result in a defective part being made. Containment was mandated by the OEM during product launches, process change, or the addition of new personnel to a production line but was rarely followed.

The engineers were convinced better proactive measures in containment would improve overall performance. This would require that the supplier set up their own “supplier site containment” process using their own internal staff and to attack defects resulting from these discoveries. Here again, the change would create a proactive culture and reduce defects generated and potentially leaving the supplier site for the OEM assembly plants (PPM). Longer term, if done correctly, it was expected to have a positive impact on the reduction of defects shown in 3-MIS.

There were few procedures in place to explain to the supplier how this process was to be implemented or when and how it should be used although the indirect process for SSC with parts failure was clearly defined. This new process was similar to SSC but completed by supplier personnel and not independent third parties. SSC could be put into effect any time and any place or places within the supplier’s manufacturing process from receiving, to manufacturing, to warehousing, or shipping if they suspected a problem in any of these locations. Process defects would then be directed to process and maintenance

engineering, quality assurance or site engineering for permanent correction depending on the nature of the issue found.

Training was developed and initiated in 2015 with the expectation of preforming poorly suppliers be trained in the correct method of creating their own internal containment process and provide a more robust process, better QA inspections, and better predictive techniques. The goal of the process was to permanently correct defects uncovered in the containment and iteratively improve the manufacturing process to make it more robust over time. Like the other two modules, information on the defects each supplier generated was also known for the supply chain before the containment training was started and after the training was completed. This study included an analysis of those suppliers that attended containment training in three ways:

7. Those receiving Containment training only (not PFMEA nor 8-D).
8. Those receiving Containment training and PFMEA only (no 8-D).
9. Those receiving Containment training and 8-D only (no PFMEA).

This study, like the other two, looked for combinations of training that had the potential for making a difference in defect generation at the PPM level and longer-term at the 3-MIS level. Failure to find any indication of significance leads to one of two conclusions:

- a. The supplier did not implement what they learned, or,
- b. The supplier training module needs to be improved to be more effective.

Training Including all Three Developed Courses

The study finally looked at one other training combination - one which should have the potential for making the biggest difference in OEM defects (PPM) and longer range at the

3-MIS level. This study included an analysis of those suppliers that attended all three training events:

10. Those receiving PFMEA, 8-D, and Containment training (A,B,&C) together.

Failure to find an indication of significance here leads to one of two conclusions:

- a. The suppliers did not implement what they learned, or,
- b. All three supplier's training modules needed improvement.

Proposed Solution

The question of training and developmental significance was posed originally by the OEM's home office directed to the quality engineering team and OEM supplier representatives without finding a satisfactory solution as to whether the training was having an impact. This question continued across a period spanning three years. It led to some serious discussions within the OEM quality team without resolution.

This led to thought on the part of this researcher as to how to effectively answer the question. What method or methods were needed to provide an answer? Were there concepts that were applicable to other producers or to other high level (Tier I or II) suppliers with extensive supply chains? As mentioned earlier, the proposal for a solution was discussed with the OEM in late 2017 and accepted some two to three weeks later. Methods and results follow in the closing chapters of this dissertation.

This research project evaluated suppliers using OEM defect data to statistically determine UT CIS developmental training supply chain impacts. The analysis' purpose was to determine whether these combinations of training classes translated into statistically meaningful reductions in supplier part defects.

Research Study

The method to analyze the impact on defects was a statistical analysis of “matched-pair” data using standard (off-the-shelf) statistical and mathematical techniques. The statistical analysis utilized a 95% confidence level to check for statistical impact between these matched-pair average results one year prior, before supplier training took place, and, one year following, after the supplier training was completed for the various combinations. Some questions that had to be assessed before a statistical study could be completed had to do with the following:

- 1) What approach would be used if the data was nonparametric?
- 2) If the data are normal, does the encryption process make a difference?
- 3) If the data are nonparametric, does the encryption process make a difference?
- 4) What is to be done with samples that are too small to produce meaningful information?

Without answers to these questions, the statistical study could be meaningless.

UT CIS Supplier Development Hypothesis

Eq'n #1: Case Study Null hypothesis: “No statistical Effect on Defects”

$$H_0 \rightarrow \mu_{TR} \leq 0 \quad \text{where;} \quad \mu_b - \mu_a = \mu_{TR}$$

Eq'n #2: Case Study Alternate hypothesis: “Statistical Effect on Defects”

$$H_a \rightarrow \mu_{TR} > 0 \quad \text{indicating a positive correlation; defect reduction}$$

μ_b represents the average PPM / 3-MIS defect level before training was started;

μ_a represents the average PPM / 3-MIS defect level after training was completed;

and,

μ_{TR} represents the difference in the two averages (a matched pair difference).

The analysis was conducted on both defect databases, at the assembly plant (PPM) and after the car was in customer service (3MIS). Three analysis were performed for each group of training to determine statistical relevance (correlation) between training and defect reductions. Specifically, the T-distribution, the Wilcoxon Rank-Sign and the Sign test were used to study the data for defect correlations. This is detailed and discussed further in Chapter 4.

CHAPTER 4. ANALYSIS, METHODS & APPROACH

Overview

The data provided by the OEM contained a supplier identity – Supplier 1, Supplier 2,, Supplier 147, Supplier 148. The identities of each supplier are known only to the OEM which prevents a level of bias from entering the research study (many of these suppliers, the researcher knew personally). Each supplier's defect data was averaged twelve months before their company received their first supplier development training producing a mean defect rate. The researcher has designated this data as " μ_b " where "b" represents supplier 1, 2, 3,, 146, 147, through 148 represents the number of suppliers in the combination sample before training. Following the training period (explained below), a similar twelve-month average defect rate was collected after the training was completed. For each supplier, that rate has been designated as " μ_a " or "mean a" for this same set of suppliers after training was completed. Two sets of data were available for each supplier. Defects discovered before OEM assembly (PPM) and defects after the vehicle was in service (3MIS).

The two defect rates are labeled for purposes of this research as PPM data and 3MIS data for convenience. PPM data represent parts per million defects discovered at the OEM assembly plant site and not incorporated into the vehicle while the 3-MIS data are parts per million defects not discovered and assembled into the vehicle. The 3MIS data is collected after the vehicle has been in service for three months or more that normally leads to a customer warranty claim and repair assuming the vehicle part failure occurred within the OEM warranty period (see Figure 1.1). Between the two sets of data, there is a training-period where suppliers receive developmental training and no defect data is averaged. The training period for the supplier development training is the first month in

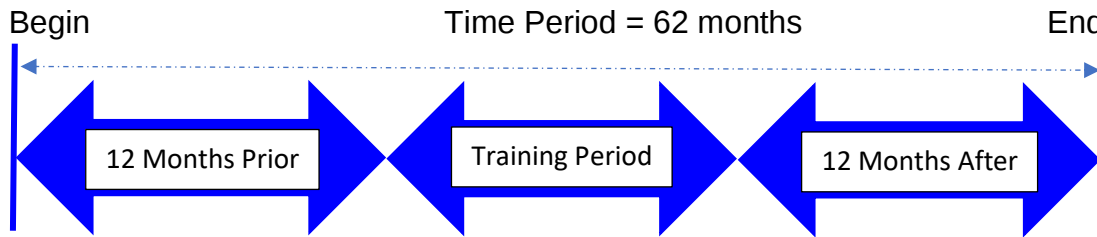


Figure 4.1 – Timeline for Research Study

which a supplier sent one or more of their technical representatives to a class including the last month in which the same supplier sent one or more representatives to a class.

The window for the research study looks like (Figure 4.1) and covers the time-span of June 2013 to August 2017 (over four years). It should be noted that the “training period” varied for each supplier and is not necessarily the same length of time.

It is the difference in these two values ($\mu_b - \mu_a$) that is of primary interest to this research and to which the researcher has designated “ μ_{TR} ” as the difference between the before and after training averages for both PPM and 3MIS. Each supplier in the Case Study now has two matched-pair differences. The research then looked at the data statistically for two results:

- 1) The mean difference of each matched pair (μ_{TR}) is “zero” or “negative.” $\mu_{TR} \leq 0$
- 2) The mean difference of each matched pair (μ_{TR}) is “positive.” $\mu_{TR} > 0$

In the original hypothesis shown in the Chapter 3, the null hypothesis is the difference between the matched pairs is equal or less than zero – that is, there is no positive correlation in the μ_{TR} difference. If this is the case, there will be no statistical evidence

indicating that the effect of the training produced meaningful results. To reject the null hypothesis in favor of the alternate, the p-value of the analysis must be less than the alpha-value chosen for the statistical test or 5%. Values less than 0.05 provide evidence the alternate hypothesis should be accepted over the null and that the training had a significant positive correlation on defect reductions.

Explained in a different way, there should be enough statistical evidence to suggest the difference is not equal to or less than zero (p-values less than 0.05 rejects the null hypothesis). Consequently, the mean or median will be greater than zero. A simple analysis of the data for positive and negative results produce a strong indication as to whether the differences in matched pairs are positive or not. This is discussed further in the Chapter 5 results section. Also, an example of this type of analysis will be shown. It should be noted the t-statistic hinges on the data being normal and that there are enough matched-pairs to approach a normal distribution to make the assessment an effective tool (≥ 30 , typically). If the data are not normal, attempts will be made to normalize it – for example, use of inversion, square root or logarithmic normalization techniques.

If a majority of the differences are negative, then the defect rate after the training will be higher than the before result and the answer to the analysis will be the training is having a reverse impact (not improving but making the situation worse) and would be an unexpected result. If there is no statistically significant difference in the number of positives and negatives, the researcher must fail to reject the null and there is insufficient evidence to conclude there is a correlated relation between supplier development training and defect reduction.

Normal or close to normal data is not guaranteed and, if not, nonparametric methods can be used to assess the OEM data. The researcher's methods of choice after having considered multiple alternatives settled on two nonparametric tools – the “Sign Test” and the “Wilcoxon Ranked-Sign test” (WRS) as candidates for analysis of nonparametric data. Of the two tests, WRS is the more robust of the two and chosen for several reasons:

- 1) The Sign test is mostly used as an initial analysis followed by WRS.
- 2) WRS is a nonparametric test that cares little about the distribution.
- 3) WRS can be used as a one sample test analyzing matched-pair data like the parametric Student-t distribution. Same applies to the Sign test.
- 4) WRS presents a way to normalize otherwise nonparametric data through a process of ranking them from smallest to largest, giving them a positive or negative value based on the difference and then allowing the data to be analyzed as a normal set of data to provide a result.
- 5) WRS excludes any matched-pair data that equals zero and addresses only the matched-pair sets that are greater or less than zero for the comparison.
- 6) WRS looks at the median which is, comparatively speaking, usually a better indicator of central tendency for data that is not normal versus mean.
- 7) WRS is robust with significant power.

Research Planning

Planning for this research and analysis included six basic steps or actions:

- a) Assess the impact that data encryption ($Y = MX + b$) has on the data, if any.
- b) Determine how data would be created and delivered to the researcher.
- c) Consider other questions posed by researcher's faculty committee and OEM.
- d) Consider the confidence level for null hypothesis rejection.
- e) Consider the power for acceptance of the alternate hypothesis.
- f) Conduct the actual research and reporting the results.

These are discussed in the following sections with detailed results provided in Chapter 5.

Data Encryption Assessment – “b” Value

A concern arose during the analysis planning process as to the effect the value “b” would have on the result. The researcher considered a small value near zero for the before and after defect averages (an example: 1 ppm). The question the researcher explored was whether adding “b” to the value of “M” times “X” would shift these small values such that the difference might be greater than zero, the result be positive, and counted as part of a positive correlation rather than negative. A simple mathematical exercise was used to show the concern was unfounded. The proof may be found in Chapter 5 – Results.

Data Encryption Assessment – “M” Value

Mentioned in the introduction was the intention of the OEM to make the actual defect rates for each supplier blind to the researcher in the same way as the supplier name by using a multiplier and the numerical add-on in the form $Y = MX + b$. The actual defect data was encrypted with a value of “M” unknown to the researcher or to competition should they read this manuscript. This choice served a singular purpose. That purpose was to prevent prying eyes (competitors) from knowing the actual defect rates. It provided for a double-blind research study in which both the supplier name and actual defect rates were unknown. From that point, the work became a simple treatment of data. All could be converted back to a specific supplier actual defect rate should the OEM desire. This approach is valid only if the numerical adjustments of the data by “M” do not impact statistical outcomes. In looking at the data, two situations were possible:

1. Normal data treatable with the Student-t distribution for paired data.
2. Data is nonparametric and treatable with Non-parametric methods.

Consequently, the researcher evaluated the impact of this transformation process for both parametric (normal data) and nonparametric (non-normal data). The encryption concern was unfounded through an analysis of hypothetical data (both parametric and nonparametric) using a “M” value of the researcher’s choosing and assessing the data as to what impact it had on the results. These results may also be found in Chapter 5.

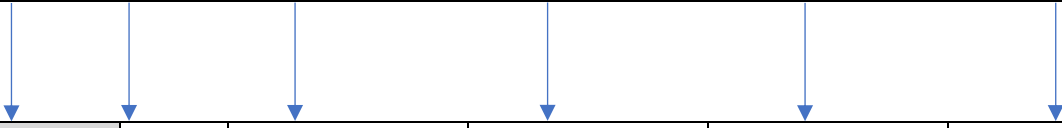
Data Creation and Delivery

Each data base on parts discovered defective at the OEM assembly plants (PPM) and parts defective after the vehicle was in service (3MIS) were listed by supplier code, company names and their monthly supplier PPM and 3MIS levels. The only difficulty was in cleaning (preparing) the UT CIS database containing the suppliers that attended the classes. There were several issues with this database having been created by multiple clerical staff over sixty-two months and the general way in which the data was compiled. The information had to be re-organized and cleaned up for the OEM staff to use the information to lookup supplier defect results and report results back to the researcher.

With the attendance data in hand from the UT CIS, the OEM provided the encrypted defect data back to the researcher within a matter of weeks and the analysis portion of the project was underway. The encrypted data was returned to the researcher in a format shown below in (Table 4.1). It was determined the data would be studied using three methods (Student-t Distribution, Sign Test, and the Wilcoxon Ranked-Sign Test).

All total 148 separate and unique suppliers became a part of this Case Study. The data labeled “Avg PPM Before” are the defects discovered at the assembly plant for each supplier taking one or a combination of these classes (12 months prior to their training

Table 4.1 – Encrypted Data from Manufacturer (Formatted)

Company Code	T Code	Avg PPM Before (adjusted)	Avg 3-MIS Before (adjusted)	Avg PPM After (adjusted)	Avg 3-MIS After (adjusted)
Supplier 1	A	94.67332485	255.4851447	13.72186785	109.612008
Supplier 2	A	7.00000000	7.00000000	9.68380725	7.00000000
Supplier 3	A	8.40859525	22.17605417	7.00000000	16.06986280
Supplier 4	A	61.33050710	39.64772814	139.02139424	7.00000000
					
Supplier 146	C	15.12285021	7.63210247	38.70620363	8.40070010
Supplier 147	C	81.80016151	297.86527315	26.29718213	243.29727755
Supplier 148	C	7.00000000	333.42130116	64.24535359	383.822334135

start) The data labeled “Avg PPM After” are the defects discovered at the assembly plant for each supplier taking one or a combination of these classes (12 months following their training completion). Similarly, the SP3MIS defect data is for the 3 months in service data (3MIS) provided by OEM distributors for their before and after results. In all four cases, “Adjusted” means the actual data was encrypted using the “ $Y = MX + b$ ” process with the values known only to the OEM. Analysis results may be found in Chapter 5.

Consideration of the “Alpha” and “Beta” Levels

There are two kinds of risk associated with any statistical evaluation of data – one is the alpha (α) risk and the other the beta (β) risk. The alpha risk was chosen early in the analysis process as 5%. Interpreted, this means that for the researcher or reader, there is a 5% risk the researcher failed to accept the null when the null hypothesis was the correct choice. This is sometimes called the producer’s risk or a Type I Error. Subtracting the Type I risk from one provides the user with a confidence level of being right. In the case with alpha = 5%, the researcher has a 95% confidence of accepting the null

hypothesis when the null is the correct choice or its rejection in favor of the alternate when the null is false. A value of 5% is a common choice in statistics. It is rare to choose an alpha value greater than 5%. The researcher wanted this alpha value low and the confidence level high.

The beta risk is sort of an opposite to alpha and is called a Type II error or consumer or buyer's risk. Beta risk is the probability that the researcher accepts the null hypothesis when in fact the null hypothesis was the wrong choice, and/or the alternate hypothesis was the correct choice. Like the alpha risk, the beta risk is also desired to be as low as possible. Subtracting the beta risk from one provides the power of the statistical study and, like the confidence level, the researcher also wanted the power as high as possible. Most statistical research considers a beta risk of 20% or lower an acceptable risk. Therefore, it is desired that power be greater than 80%, if possible. Both alpha and beta risk are shown in (Figure 4.2).

Both alpha and beta risk are managed, in most cases, by assuring there is an adequate sample size. Larger is better but there can be size limitations, based on resources – timing, personnel, money, equipment changes, etc. Usually, a sample size greater than 30 keeps the beta risk at an acceptable level. There are conditions where larger samples are more appropriate – for example – true outliers that must be included in the data.

The higher the confidence level desired, the smaller the alpha risk value must be. In cases of one-sided test and parametric data, the researcher is looking for p-values less than 5%. As the alpha value drops, the greater the degree of confidence in making the right choice on null acceptance or rejection. So, an alpha value of 1% represents a 99%

Decision or Hypothesis	Ho True	Ha True
Accept Null, Ho:	OK $CL = 1 - \alpha > 95\%$	Type II Error Buyer Risk
Fail to Accept Null, Ho:	Type I Error Producer Risk	OK $Power = [1 - \beta] > 80\%$

Type I Error: Supporting the Alternate hypothesis when the Null is true

Type II Error: Not Supporting the Alternate hypothesis when the alternate is true

Figure 4.2 – Alpha and Beta Risk for this Research Study ^[49]

confidence level. As the sample size increases the beta risk drops and the power rises. (Figure 4.3) is a graphical representation of the alpha and beta risks depicted in (Figure 4.2).

The higher the confidence level desired, the smaller the alpha risk value must be. In cases of one-sided test and parametric data, the researcher is looking for p-values less than 5%. As the alpha value drops, the greater the degree of confidence in making the right choice on null acceptance or rejection. So, an alpha value of 1% represents a 99% confidence level. As the sample size increases the beta risk drops and the power rises. (Figure 4.3) is a graphical representation of the alpha and beta risks depicted in (Figure 4.2). An explanation is appropriate for this graph to explain the alpha and beta risk present in a statistical analysis.

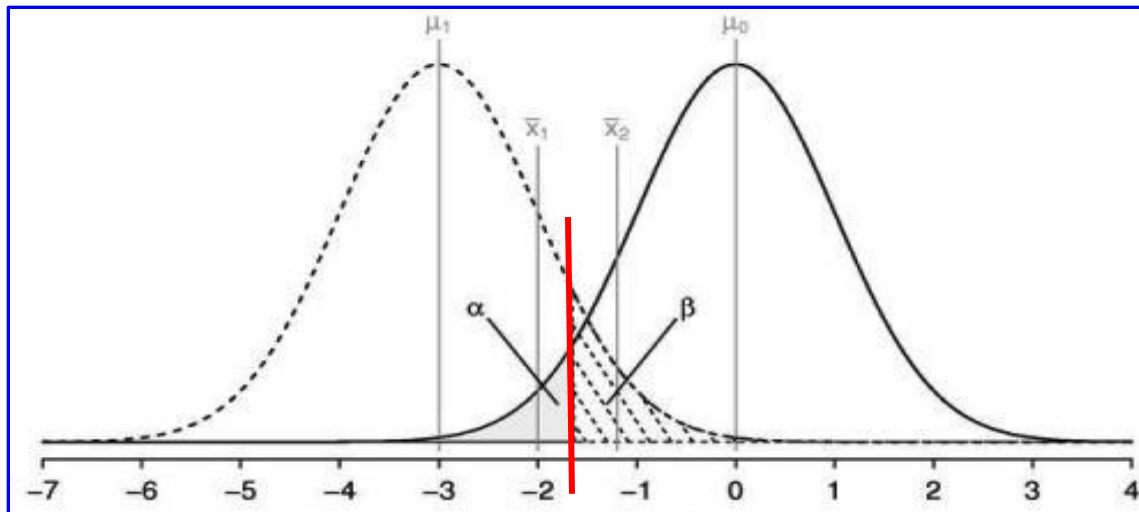


Figure 4.3 – Graphical Representation of Alpha & Beta Risks [49]

The normal expectation is that the sample collected has a mean of μ_0 and for the Type I Error to be avoided, the mean of a sample ($\bar{X}_1$) must lie beyond or to the left of the one-tailed significance level boundary line – marked in red. If the sample is like $\bar{X}_2$ (to the right of the boundary) then the null cannot be rejected (must be accepted). Thus, rejecting the null (or said a different way – supporting the alternate) when the null is true would be a Type I Error. The opposite is true of the β risk. Assuming the actual sample is μ_1 , the value of $\bar{X}_2$ must lie outside or to the right of the boundary value set for μ_0 for the Type II Error to be avoided. If the sample is like $\bar{X}_2$ and the alternate is true, the null is rejected (cannot be accepted) in favor of the alternate. Thus, rejecting the alternate (or said a different way – supporting the null) when the alternate is true would be a Type II Error.

Power was also calculated and graphed in (Figure 4.4) for a t-statistic. The blue line (upper line) is the graph for a 1-sided t-statistic with the same alpha level of 5%. The red

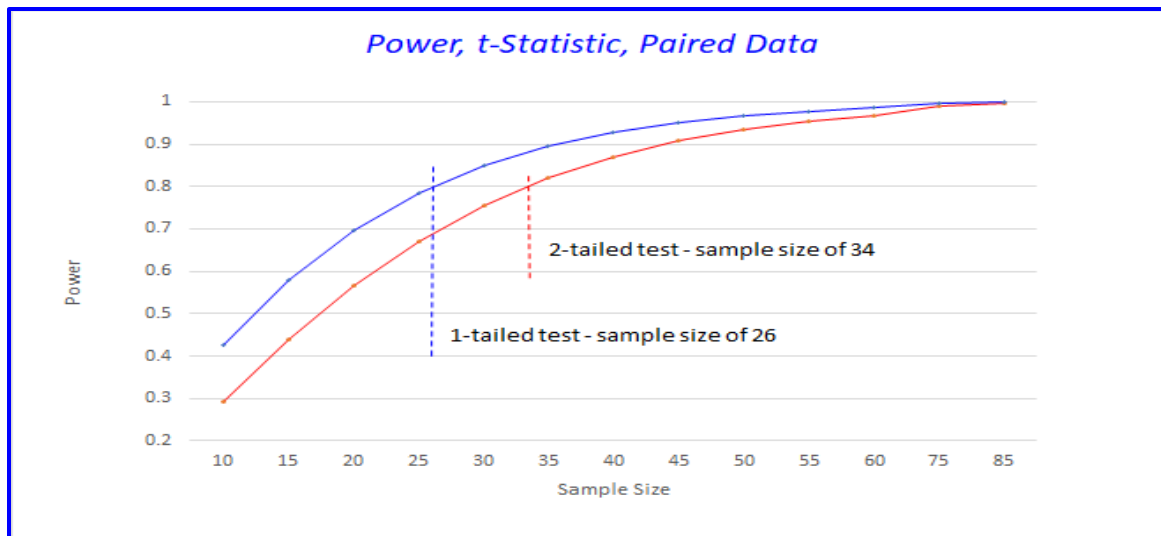


Figure 4.4 – Power for T-Statistic with Different Sample Sizes ^[50]

line (lower line) is the graph for a 2-sided t-statistic with alpha level of 5%. Effect size is the relationship between the two variables on a numerical scale – usually 0.3, 0.5, or 1.0. A weak effect size could be 0.3 or less, a medium effect 0.5 and a strong effect size 1.0 or greater. The value chosen in this case was 0.5 due to the relationship between the matched pairs being unknown. There is a relationship between the two values (before and after) so it is not low. But since the effect is not truly known, the value of 1.0 was not chosen either. The effect size does have an impact on the power just as sample size does. With unknown effect size, it is common to select this mid-point like 0.5 as the value for the power calculation.

As can be seen from (Figure 4.4), the power grows more rapidly for the one-sided than the two-sided test. A sample size minimum in the range of 26 to 34 is an appropriate sample size for the t-statistic power to be greater than 80%. If the effect size were raised to 0.8, the sample size decreases to as low as 14 data points to achieve a power greater

than 80%. These results fall in line with the general rule of thumb on sampling protocols for statistical analysis, that is, a sample size equal than or greater than 30.

The following comparison was found in a brief study published on the internet. The title of the article was "How to choose between t-test or non-parametric test e.g. Wilcoxon in small samples." ^[51] Within this short article was a comment about the power of the two tests compared to each other:

"Wilcoxon tests have about 95% of the power of a t-test if the data really are normal, and are often far more powerful if the data is not, so just use a Wilcoxon" is sometimes heard, but if the 95% only applies to large n, this is flawed reasoning for smaller samples."

While power is highly dependent on sample size and this is the case with the actual research data, this left the researcher with a level of discomfort if the sample size is small – that is much less than 30. If the data is nonparametric, many researchers have stated the Wilcoxon Rank-Sign test has significantly lower power.

While power is not difficult to calculate for the t-statistic matched-pair data, it is much more difficult for the Wilcoxon Rank-Sign test. Unfortunately, about the only way to estimate the power for the Wilcoxon Rank-Sign test is through statistical modeling programs such as Monte-Carlo simulations where a simulation test is run multiple times and the number of successful results divided by scenario test runs provides a ratio which is the test power value.

This researcher looked for studies that had been completed where the t-statistic and the Wilcoxon Rank-Sign test had been compared and found the following information in a

Table 4.2 – Relative Frequencies of Null Hypothesis Acceptance (Power)

<i>Sample Size</i>	<i>t-statistic Test</i>	<i>Sign Test</i>	<i>Wilcoxon RS Test</i>
5	0.9560	0.8900	0.9020
10	0.9760	0.8600	0.8980
15	0.9820	0.8500	0.8840
20	0.9660	0.7980	0.8020
30	0.9860	0.6640	0.7780
40	0.9540	0.5100	0.6040
<i>Average</i>	0.9720	0.7620	0.8113

journal of mathematics. The normal distribution results are shown in (Table 4.2) [\[52\]](#) below.

What they discovered in their research was that for small samples the relative power of the t-statistic, sign test and Wilcoxon Rank-Sign tests, compare favorably for normal distributions but as the sample size grows, there is some divergence in the power of each test. Within this study, the researchers compared the t-statistic, sign test, and Wilcoxon Rank-Sign test using 500 Monte Carlo simulation runs at a 5% significance level. The researchers compared their data generated for normal, gamma, exponential and uniform distributions but only normal is shown here. Distribution comparisons were averaged for each study and their conclusions recorded. There is less difference as the size becomes smaller, but a smaller sample size increases the likelihood of a Type I Error.

The option is to either increase the sample size or adjust the alpha. One weakness in this data was a short-sightedness on the part of the researchers in stopping at just 40. However, they were, admittedly, looking at small sample sizes. The research would have been more interesting had they inserted a sample size of 100 or more and tested the

results just for the sake of comparison. Of note are the drops in power for Sign and Wilcoxon Rank-Sign tests. Literature says to increase power, one must increase the sample size. It would be interesting to see these values at 100 or more.

This becomes somewhat of a balancing act between alpha and beta values in assuring the confidence of statistical results reported. Within this study the researchers also looked at the alpha values from the same Monte-Carlo runs for a normal distribution and is shown in (Table 4-3). ^[52] As for making a Type I Error, the researchers reported there is relatively little difference between the three methods. The averages rounded to two decimal places are identical (all were ~ 0.04).

In conclusion, the effort to analyze the research data is highly dependent upon whether the data are normal or can be normalized. If so, the t-test will be used for statistical significance. If normal data does not exist and normalization attempts fail, the Sign and Wilcoxon Rank-Sign tests will provide the analysis for significance. As it turns out, this researcher was able to use all three in the analysis to produce some meaningful results.

The researchers in this paper went on to conclude the following:

“....Meanwhile, the t-test is the most suitable test when the underlying distribution is normal and when the sample size is large for any distributions as reported in Tables 1 – 8 [only two of the eight are shown here]. However, the two nonparametric tests [sign test and Wilcoxon Rank-Sign] are indeed alternative tests to t-test when the assumption of normality is not met.” ^[52]

Discussion of T-Distribution with Matched-Pair Method

The Student-t distribution is a statistical distribution that approaches a normal distribution with sample sizes larger than 30. Within the alternatives for the Student-t distribution is a

Table 4.3 – Relative Frequencies of Null Hypothesis Rejection (Alpha)

<i>Sample Size</i>	<i>t-statistic Test</i>	<i>Sign Test</i>	<i>Wilcoxon RS Test</i>
5	0.0400	0.0280	0.0480
10	0.0440	0.0320	0.0480
15	0.0440	0.0460	0.0460
20	0.0435	0.0420	0.0400
30	0.0380	0.0360	0.0360
40	0.0340	0.0380	0.0340
<i>Average</i>	0.0406	0.0370	0.0420

method for matched-pair data. If the data are normal, these matched-pair (before average – after average) can be used in a statistical test for significance. The process evaluates the data to determine if the mean of the data is less than or equal to zero (null hypothesis). If there is statistical evidence there are sufficient results greater than zero, then the calculated statistic must be greater than the critical t-statistic.

It is the intent of the researcher to use this distribution strategy to analyze whether there is enough evidence to show a difference between the matched pairs for each supplier taking specific training combinations. If there is a statistically large number of positive results where the t-statistic is greater than critical, there is statistical evidence that the training programs are having an impact and that the suppliers are implementing what they learned during the training sessions. An example of this t-Statistic is shown in (Figure 4.5) using data for suppliers taking all three classes. In this statistical calculation, the three values of “zero” were excluded from the degrees of freedom for the calculation of the observed and critical statistic.

Company Code	Count	T Codes	Avg PPM Before (Adjusted)	Red'n, No Change, or Gain	Avg PPM After (Adjusted)	d-bar (before minus after) for PPM	SIGN (+1/-1)
Supplier73	1	ABC	13.17653487	Red'n	9.91883746	3.3	1
Supplier74	2	ABC	19.48219729	Red'n	17.13027929	2.4	1
Supplier75	3	ABC	28.22272218	Red'n	13.12124059	15.1	1
Supplier76	4	ABC	9.19618337	Gain	15.62107840	-6.4	-1
Supplier77	5	ABC	59.10072807	Red'n	28.76870212	30.3	1
Supplier78	6	ABC	76.88236496	Red'n	23.80149726	53.1	1
Supplier79	7	ABC	111.42038352	Red'n	9.94182454	101.5	1
Supplier80	8	ABC	103.46754740	Red'n	11.54065577	91.9	1
Supplier81	9	ABC	19.51435499	Red'n	11.54065577	8.0	1
Supplier82	10	ABC	9.56556651	Red'n	8.52624555	1.0	1
Supplier84	11	ABC	7.00000000	Gain	11.75737393	-4.8	-1
Supplier85	12	ABC	637.25216989	Red'n	174.14145448	463.1	1
Supplier86	13	ABC	12.71707514	Gain	35.43861088	-22.7	-1
Supplier87	14	ABC	19.43891179	Red'n	17.98971933	1.4	1
Supplier88	15	ABC	19.43891179	Red'n	17.98971933	1.4	1
Supplier89	16	ABC	19.28113267	Red'n	14.55168723	4.7	1
Supplier90	17	ABC	453.45631706	Red'n	29.72914601	423.7	1
Supplier91	18	ABC	47.57909490	Red'n	32.87759896	14.7	1
Supplier92	19	ABC	18.40807698	Gain	47.21539737	-28.8	-1
Supplier93	20	ABC	7.00000000	Gain	22.21930432	-15.2	-1
Supplier94	21	ABC	9.81759461	Red'n	12.26074507	-2.4	-1
Supplier95	22	ABC	106.58168220	Gain	18.88912748	87.7	1
Supplier96	23	ABC	164.48031496	Red'n	106.76784789	57.7	1
Supplier97	24	ABC	7.00000000	Gain	72.05622717	-65.1	-1
Supplier98	25	ABC	38.73647335	Gain	46.58823722	-7.9	-1
Supplier101	26	ABC	12.85702660	Red'n	7.79048283	5.1	1
Supplier83	27	ABC	7.00000000	No Chg	7.00000000	0.0	0
Supplier99	28	ABC	7.00000000	No Chg	7.00000000	0.0	0
Supplier100	29	ABC	7.00000000	No Chg	7.00000000	0.0	0
			70.8	average	28.9	41.8	
			139.6	Std dev	35.4	117.0	
			19.4	Median	17.1	2.4	
			Avg before		Avg after	difference	
Redn by Supplier Gain by Supplier Suppliers Avg Red'n Avg Red'n 18 8 26 = n 41.8 ppm 59.1% before to after							

OneTailed Student - t Test for Significance; PFMEA / CP & 8-D Problem Solve only

using Ho = 0, assume	Ho: d-bar ≤ 0	α = 5%
	Ha: d-bar > 0	d.f. = 25
	d-bar = 41.8	for one-sided t-test
	U _d = 0.0	C. L. = 95%
	Sd = 117.0	
	n = 25	d.f. t _{critical}
	1.787 Test Statistic	
	Reject Ho	for d.f. = 25 1.708

Figure 4.5 – Example of Student-t Distribution applied to Matched-Pair Data

Discussion of Wilcoxon Rank-Sign Matched-Pair Method

Mentioned earlier, after some extensive reviews of various analysis possibilities, the researcher settled on using the nonparametric Wilcoxon Rank-Sign Test as one of the tests for significance. There were multiple reasons for this choice (see abstract) but most importantly:

1. In the event there are ties (and there are several of these within the data), the result of the before and after difference (μ_{TR}) is zero, the test ignores (or excludes) zero value results and compares only matched pair negatives against matched pair positives for significance.
2. The test is simple to do (much like the Student-t distribution) and provides a meaningful statistical analysis for the data.
3. The test is a non-parametric test and it matters not what the distribution is. It will work on both normal and non-normal data.

It should be noted that in the Wilcoxon Rank Sign test, medians are compared to see if they are less than or equal to zero (the null). The alternate hypothesis looks at the median and whether it is greater than zero. In normal data, the mean and the median are equal. In the case of non-parametric data, it is not a requirement the mean and median equal each other. In fact, they are almost never equal.

Recalling from the previous section that the matched pair data will be either positive, negative, or zero, the Wilcoxon Rank-Sign test ignores the zero values and statistically compares positive differences against the negative ones. The mechanism whereby this calculation (Wilcoxon Rank-Sign) is made is shown on (Table 4.6) where the number of positive results is statistically compared to the number of negative results with any zero results excluded. Recall from a prior discussion that positive differences indicate the after-

Count	Sign (+1/-1) for SP3MIS Data	Absolute Value	Delta	Rank	Rank / Sign	Rank Sum (+)	Rank Sum (-)
1	1	146	146	28	28	28	0
2	1	6	6	9	9	9	0
3	1	33	33	18	18	18	0
4	1	242	242	33	33	33	0
5	1	20	20	15	15	15	0
6	1	123	123	24	24	24	0
7	1	29	29	17	17	17	0
8	1	24	24	16	16	16	0
9	1	1	1	3	3	3	0
10	1	0	0	2	2	2	0
11	-1	137	-137	27	-27	0	27
12	1	129	129	25	25	25	0
13	1	72	72	20	20	20	0
14	1	6	6	10	10	10	0
15	-1	64	-64	19	-19	0	19
16	1	186	186	30	30	30	0
17	-1	20	-20	14	-14	0	14
18	1	403	403	35	35	35	0
19	1	0	0	1	1	1	0
20	-1	4	-4	8	-8	0	8
21	1	187	187	31	31	31	0
22	1	1	1	4	4	4	0
23	-1	1	-1	5	-5	0	5
24	1	110	110	22	22	22	0
25	1	163	163	29	29	29	0
26	1	206	206	32	32	32	0
27	1	11	11	12	12	12	0
28	-1	76	-76	21	-21	0	21
29	1	111	111	23	23	23	0
30	-1	2	-2	6	-6	0	6
31	1	2	2	7	7	7	0
32	1	133	133	26	26	26	0
33	-1	387	-387	34	-34	0	34
34	1	17	17	13	13	13	0
35	-1	483	-483	36	-36	0	36
36	1	10	10	11	11	11	0
						496	170
						Sum (+)	Sum (-)
Nonparametric Wilcoxon Test for SP3MIS Data (A Only)							
1 Sample Wilcoxon Test (Rank/Sign Test) - Test on Delta (before - after) data							
	Ho: Median $\leq$ 0						
	Ha: Median $>$ 0						
	Wstat =	326.0000					
	std. dev. =	127.302789					
	U w =	0.50					
			probability =				
	Z =	2.5530	0.0053				
Reject Ho; Sufficient Statistical Evidence AT 95% CL to Indicate PFMEA/Control Plan Training had an effect on SP3MIS Reductions.							

Figure 4.6 – Manual Method for Wilcoxon Rank-Sign Test

training defect rate is lower than the rate before the training. If the results are opposite after training (that is, negative), this indicates after training average results are higher than before supplier training. Should the study show more negatives, then there will be no statistical correlation of note between defects and training and a high probability the supplier failed to implement any of the training received in the training sessions. Incidentally, the result of the Wilcoxon Rank-Sign test provides a normal distribution of the rankings as can be seen in (Figure 4.7).

If the results show an indication of statistically more positives than negatives, then we have a meaningful study correlation and it being implemented at the supplier level. In the case of the examples (both the Student-t and Wilcoxon Rank-Sign), it can be seen there were three (3) zero results excluded in the Student-t and two zero results in the Wilcoxon Rank-Sign.

Discussion of Sign Test for Matched-Pair Data

While the sign test can supply statistical evidence of correlation in this research study, book literature states the sign test is usually a quick test to see if there is a relationship. Like the Wilcoxon Rank Sign test, the sign test will also accept matched-pair data. The test uses the binomial distribution to calculate their probability. If the number of positives signs statistically outweigh the number of negatives, then the p-value must be less than the alpha value selected – for the research Case Study, 0.05.

As a check of the Wilcoxon Rank-Sign test, the nonparametric Sign Test will also be run and reported as part of the results. This test, like the Wilcoxon Rank-Sign, can be used on parametric as well as nonparametric data. In the set of calculations using a 5%

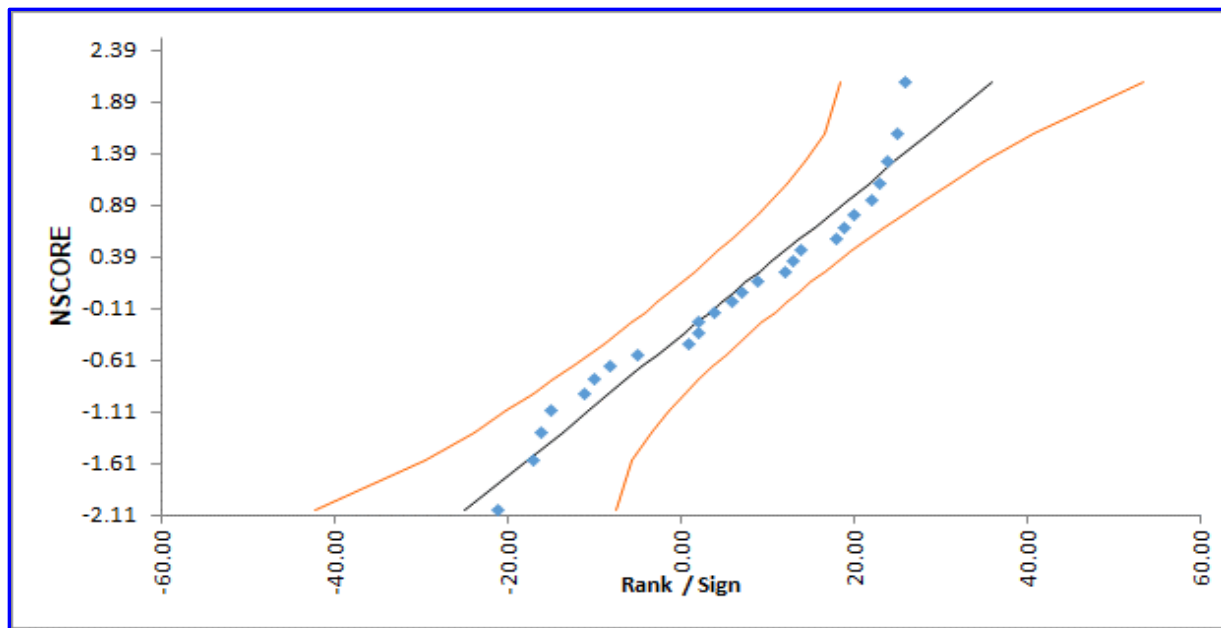


Figure 4.7 – Normality Plot of ABC Rank-Sign Data

confidence level, a sample with only eight data points could only have one negative value in order to claim rejection of the null hypothesis in favor of the alternate (that is, mean greater than zero).

Of note in this process is the fact that the Sign test adds the probability of each negative values in a cumulative way to get the actual probability (discrete probability calculations). An example of this binomial calculation is shown below in (Table 4.4). Equation #3 shows the results of the probability calculation of there being 2 or less negatives in a data set of eight. The assumption is there is an equally likely number of positive and negatives for acceptance of the null. Equation #4 is the binomial calculation method where n represents negative values. The value of 0.1445 is greater than 0.05 so the null cannot be rejected, and six positives are not statistically sufficient to claim a significant positive correlation for

Table 4.4 – Binomial Prediction Example

Binomial Prediction for a Sample with 8 Data Points								
0	1	2	3	4	5	6	7	8
P (x=0)	P (x≤1)	P (x≤2)	P (x≤3)	P (x≤4)	P (x≤5)	P (x≤6)	P (x≤7)	P (x≤8)
0.39%	3.13%	10.40%	21.88%	27.34%	21.88%	10.40%	3.13%	0.39%
0.39%	3.52%	14.45%	36.33%	63.67%	85.55%	96.48%	99.61%	100.00%

[Eq'n #3: Binomial Prediction Example for Sign Test](#)

$$P(x \leq 2) = P(x \leq 0) + P(x \leq 1) + P(x \leq 2) = 0.39 + 3.13 + 10.94 = 14.45\%$$

[Eq'n #4: Binomial Distribution Equation](#)

$$P(X \leq n) = \sum_{i=0}^n x C_n (0.5)^n (0.5)^{x-n} \text{ where: } x \text{ is the sample size; and, } n \text{ is the negative result}$$

such a small sample. That value could have only one negative or less to reject the null.

The probability is calculated using the binomial distribution equation (see Equation #4):

Normalization for Research Analysis

Should the results be nonparametric, normalization of data will be attempted for the Student-t distribution as needed. The three normalization techniques most used in statistics are the logarithmic, square root and inversion techniques. If these attempts prove unsatisfactory, the Sign and Wilcoxon Rank-Sign test will be used for data statistical correlation. Evidence of these three analyses will be compared to their appropriate critical values and logged as results found in Chapter 5.

Faculty Committee Considerations

Some of the data combinations had a small sample size (one was 6 entries). This brought into question their ability to provide meaningful statistical results. This was discussed with my faculty committee chair (Dr. Andrew Yu) as to alternatives in determining if the data could be modified in some way to extract useful information from the OEM data file that was provided. As a result, the research conducted on the data included data simulations to increase sample precision and give the data some semblance of normality before applying the tests noted above (Student-t distribution assumes parametric data as a given). The Sign and Wilcoxon Rank-Sign tests will work on parametric data as well as nonparametric data, so all three tests were eventually used in the analysis. Data simulation is addressed in more detail below.

Also, a question raised by the OEM as well as one of my faculty advisors was whether there were combinations of training more effective than others. Data simulation was also used to see if some combinations of training were somehow better than others. Finally, the faculty chair requested I consider a DOE (Design of Experiment) on the original data to extract more information from the databases pulling further information, if possible, from the data analysis. The approach to these data simulations and DOE are discussed in this chapter and the research results may be found in Chapter 5.

Data Simulation

Since four of the seven combinations in the data set had insufficient sample sizes, it was suggested that the researcher try data simulations to expand the information and determine whether meaningful information could be found. The researcher had available the average and standard deviation for each data grouping. This information is provided

in (Table 4.5 and 4.6). An equation found in Microsoft Excel to create a random number run in excel was used to generate the normal data simulation:

Eq'n #5: Simulation Generator for Normalized Data

$$= \text{NORMINV}(\text{Rand}(0,1), \bar{X}, \text{Std. Dev.})$$

The method for creating a simulated data base was simple. All that was needed was a random number generator, the mean, and standard deviation for each grouping of original data. Results were produced by using Microsoft Excel's ability to generate a normal set of data by choosing a random number between zero and one to represent a data point percentile. For example, 0.250 would represent the 25th percentile of normal data (left to right) and the value chosen for that percentile would reflect the parts per million difference (positive or negative) for that percentile based on mean and standard deviation.

This generator was then used to create as many data points as needed for the simulation. One of the concerns the researcher had as a result of the study of the actual data was its sensitivity relative to sample size. Starting with a small sample of fifteen, the data was observed in terms of its p-value output versus the sample size (that is, was it the same each time). The researcher noted a tendency of the data to produce different statistical results that gave positive and, at other times, negative results. Results can be found in Chapter 5 and was expanded for clarity compared to an earlier version of this dissertation.

The normalized data provided results finally stopped varying giving repeatable p-values for each test even when a data run was recalculated. As this was a simulation of 500 data

Table 4.5 – Mean & Standard Deviation for each Data Combination – PPM

OEM PLANT	PPM	PPM	PPM	PPM	PPM	PPM	PPM
Code	ABC	BC	AC	AB	C	B	A
Mean	41.82	3.11	57.25	35.97	15.96	200.63	20.46
Std. Deviation	117.00	371.16	147.67	109.87	67.72	860.67	123.66

Table 4.6 – Mean & Standard Deviation for each Data Combination – 3MIS

3 Months in Service	3MIS	3MIS	3MIS	3MIS	3MIS	3MIS	3MIS
Code	ABC	BC	AC	AB	C	B	A
Mean	-26.13	-16.78	62.96	244.65	-10.19	133.37	30.71
Std. Deviation	330.40	124.13	245.40	998.54	97.42	674.78	148.58

points and was easy to generate with little calculation time, the researcher settled on this amount for each grouping using its actual data means and standard deviations. Results may also be found in Chapter 5 for the simulation runs.

Effective Class Combinations

One of the questions asked during the preliminary development work with the OEM and by my faculty chairman was are there certain class combinations that deliver better results than others? This was answered with another data simulation run in which an attempt to compare the combination of classes with each other to see if there were any significant ones that stood out. The method of choice was to use a larger 1,000 data-point simulation run to get even higher precision and to use the One-Way ANOVA and Welch F-statistic tests to determine differences in the combinations.

Both methods are F-statistic tests and use mean sum of squares to test combinations against a critical F-statistic value based of degrees of freedom. Significance would indicate that at least one or more of the groupings (combinations) is different. The One-Way ANOVA then compares each combination with the other to determine which one(s) are statistically different. The software provides a box plot of the confidence intervals for the means.

The other option (Welch F-statistic test) assumes unequal variances within the data from the beginning of the test. This package, like the One-Way ANOVA test also compares the combinations with each other and provides a box-plot graph of the confidence intervals. Both statistical packages were available in the Sigma XL software and were used on the simulation run. Report on the results of these two analyses may be found in Chapter 5.

Design of Experiment (DOE) on Original Data

One additional effort was undertaken at the suggestion of the researcher's faculty chair consisting of a design of experiment (DOE) conducted on the original data to determine if other useful information could be discovered. The researcher chose a 2^3 full factorial design using the three classes (A, B, and C) as generators for the interactions (AB, AC, BC & ABC) with six replicates of the data pulled at random from the original data base.

The researcher, in looking at the original data decided to ignore values with a difference of zero and exclude them from the design – only positive and negative values were included as part of the DOE. Reasoning behind this was a reverse logic in the sense of what would the results be if the data points were all zeroes? If that were so, the sum of

Table 4.7 – Generator for 2³ Factorial Design

Factorial Effect for OEM & 3-MIS Data								
Treatment	I	A	B	AB	C	AC	BC	ABC
I	–	–	+	–	–	+	+	–
a	+	+	–	–	–	–	+	+
b	+	–	+	–	–	+	–	+
ab	+	+	+	+	–	–	–	–
c	+	–	–	+	+	–	–	+
ac	+	+	–	–	+	+	–	–
bc	+	–	+	–	+	–	+	–
abc	+	+	+	+	+	+	+	+

squares used in the F-statistic would be meaningless. (Table 4.7) shows the generators for the interaction effects (AB, AC, BC, & ABC). In order to exclude zero difference values, the maximum number of replicates possible was six, related to group AC (PPM) where there were only eight data entries with two zero values resulting in six positive / negative values. Therefore, six replicates were chosen for both the PPM and 3MIS data. For the specific combination of AC, 100% of the non-zero data was used for combination AC. One issue arose in the selection of candidate sample data for the identity (I).

For the identity replicates for A, B, and C, a means of getting the data was needed. This was not anticipated during the original design for data extraction and encryption from the company databases. All suppliers in the databases have been exposed to one or more classes. Without information for the identity group, a full factorial design would not be possible to execute. Logically thinking through the methodology, there seems to be a solution to generate the needed data. These three classes should pull from data where suppliers did not take a class but should also be poorly performing suppliers.

Suppliers that took classes and did not implement what was taught can be likened to the suppliers that failed to show reductions in defect rates from either database (PPM or 3MIS data) and therefore have negative results on their defect rates. This would be the same as not taking a class. This makes a lot of intuitive sense as many suppliers that attended these classes were poorly performing suppliers anyway – meaning they were generating negative values on the matched-pair differences over time.

The original data was resorted from smallest to largest and zero and positive values excluded. Using a random number generator for datapoint selection, six values were extracted for the identity in each group and the results analyzed using the F-Statistic algorithm for correlation effect by comparing mean sum of squares divided by the mean square error to generate the observed F-statistic “Fo” and comparing it against the critical statistic which is 4.08 for each grouping for $F_{1,40}$ degrees of freedom. Results of the effort are discussed in greater detail and found in Chapter 5.

Zero Difference on Several Data Points

As part of this chapter, there is a final discussion point that impacts the outcome of this research. Several data points from the original data sets for PPM and 3MIS when the before and after averages were obtained provided a value of zero in the difference. Specifically, 35 of the 148 data points for PPM (23.7%) and 13 of the 148 data points for 3MIS (8.9%) provide zero values. These numbers were all low and all identical.

Each had a value of 7.000000 and remained unchanged before and after training was completed – that is, the before and the after results were the same. This condition implies that if nonparametric methods are used for the data analysis, a significant percentage

(16.2%) of all the initial raw data (48 of 296 match-pairs of data) will be culled from the analysis process due to the nature of the analysis method. The Wilcoxon Rank-Sign and Sign tests both have to ignore zero differences for matched-pair data.

Assuming manufacturers attending class implemented what they learned, this information needs to be accounted for. In these forty-eight cases, the supplier is doing a great job both before and after training. There is zero change in their condition. There is even a possibility the training may have prevented a negative result. As a consequence, the data needs to be accounted for in some way. These zero values are included as part of a preliminary mathematical analysis on percentage improvement for each data grouping but is not a part of the statistical study. Each zero value was accounted for as part of a percentage improvement and compared to suppliers that showed a decline in performance. This analysis is included as a separate set of tables, graphs, and the results may also be found in Chapter 5.

CHAPTER 5. CASE STUDY RESULTS

Overview

Despite the easy methods that were used, the work was far more difficult to statistically translate into meaningful information than originally thought. From the very beginning of the analytical work when OEM data was received by the researcher, normality was far from a given. Within several of the combination differences, there were multiple outliers (both positive and negative results) with their relative distance as much as 50 to 300 hundred times some of the more normal or usual values common to the data. One would normally question these outliers, but they were real and a consequence of two factors:

- 1) They are, in part, a reflection of the multiplier effect of “M” used in encrypting the data making them larger than they actually are.
- 2) They reflect actual supplier performance.

Some suppliers in the database did not perform as expected – the OEM’s past history predicted there would be data outliers – this is common in suppliers struggling with product quality so large defect changes are not surprising (as much as 1 to 3% of the larger supplier base). The options are to cull them from the research or keep them. This researcher chose to keep them as part of the data. Data simulations helped lessen the effects for these outliers so they could be managed.

Normality plots, histograms and statistical information confirmed what was already visible in the data. The researcher looked at each data combination and the data were decidedly nonparametric (that is, not normal). Histograms showed the data typically skewed to the right in most cases but not all. It should be mentioned in the overall analysis of the training classes coded “B,” “C,” and “BC” are the shorter running classes of the three with PFMEA / CP launched in 2013, 8D / PS in 2014 and Containment in the year that followed (2015).

Consequently, fewer individuals have taken some of these classes (Containment for example) versus the older classes involving PFMEA & 8-D (A & B respectively). This impacted sample sizes for several combinations.

One of the needs in this research was to assure data encryption would not, in some way, negatively impact the research results. There are many examples in statistics of using algorithms to normalize data, for example inversion, square root, or logarithm. The data is squeezed to a smaller range with a different mean and standard deviation. This changes the data, but it is easy to recover the original data point by reversing the process. These methods are analogous to using a multiplier to change data (in our case, the multiplier for data encryption labeled M).

Variation and thus standard deviation are larger as a consequence, and the mean is shifted on the x-axis by whatever the original mean times the multiplier was. Research was conducted to identify whether this multiplier and add-on of the form $Y = MX + b$ would change the data preventing its recovery back to the original data maintained by the OEM's headquarters. Whether results of the data were normal or nonparametric, there was no difficulty in re-acquiring the original data.

These findings were demonstrated for a normal distribution and also for a distribution that was nonparametric. In each case, the data was recoverable back to the original values before encryption. The conclusion of the study was that linear data encryption, while it changes the values of the mean and standard deviation or variation, does not change the relative distances between each data point in the set. Consequently, the researcher is

satisfied that the application of the encryption technique does not impact the statistical study results. Details of the assessment are found within this chapter.

Statistical analysis was completed on the data. Knowing the data was non-parametric, the Student-t test was performed on the data anyway to see what results could be seen.

The combinations, initially looked at in the original data, were as follows:

- 1) Suppliers taking only the PFMEA / Control Plan class – Coded A
- 2) Suppliers taking only the 8-D / Problem Solving class – Coded B
- 3) Suppliers taking only the Containment class – Coded C
- 4) Suppliers taking the PFMEA / CP & 8D / PS classes – Coded AB
- 5) Suppliers taking the PFMEA / CP & Containment classes – Coded AC
- 6) Suppliers taking the 8D / PS & Containment classes – Coded BC
- 7) Suppliers taking all three of the classes for their site – Coded ABC

As predicted, the data was decidedly nonparametric as demonstrated by histogram and Anderson-Darling (A-D) tests. An example of this type of information on normality plots can be seen in the Appendix – see (Figures AF-5.1 and AF-5.2). The first is the histogram for PPM and the second for 3MIS. Statistical data can also be found there as well for these two histograms (see AF-5.22 and -5.23).

There were samples that only had nine and fewer data points which were incapable, in terms of test power and confidence level, of obtaining meaningful information. A sample greater than 25 to 30 would have been better but this was all the data existing for these combinations with the smallest being 6 and the largest being 17 (AC, BC, B, & C). The smallest sample for the remainder of the combinations was 25 with the largest being 36 (A, B, & ABC).

The data was looked at in a variety of ways attempting to extract useful information. As the data was decidedly nonparametric, a decision was made to go ahead and run the Sign and the Wilcoxon Rank-Sign tests as part of the study for the nonparametric data even if the data for the groupings could be normalized for the t-distribution. As it turned out, data normalization attempts produced a mixed result – most of the larger samples could not be completely normalized with a few of the data points falling outside the normality plot confidence limits. The results were much improved, but the data was still slightly nonparametric but acceptable.

The plots for normalization of all the data can be found in the appendix for combinations coded A, B, C, AB, AC, BC, and ABC – see normality plots Figures AF-5.3 through AF-5.16 for each normalization. Normalization for these plots was a logarithmic reduction. Since the normalization results were much improved, the t-distribution outputs were calculated for these combinations and displayed as part of the results in this chapter. The larger group sizes using the nonparametric tests produced results and also corroborated what earlier analysis tended to show.

Despite the difficulties encountered in data normalization and based on the results of the nonparametric statistical trials, the results indicate there is a positive correlation between suppliers receiving training and reduced defect rates both at the assembly plant (PPM) and after the car was sold (3MIS). There also appears to be a correlation between certain training combinations that are more meaningful than others.

Already mentioned, the combinations coded B, C, AC, and BC were too small to produce a meaningful result (all non-positive correlations) even though the sample size for B

(3MIS) was larger at 17. These four groups were tested, and results documented for the initial data file and for simulated and DOE activities. In fact, all four of these groupings yielded a null finding in the initial data analysis – that is, no correlation between a class or classes and reduction in defects for either PPM or 3MIS data. This was expected.

Within the study, a data simulation was run to look at these four combinations to see whether any meaningful information could be extracted from the simulation run. The run was for 500 data points with the hope of normalizing the data with a sufficient sample size in order to extract information. The Student-t distribution, the Sign and Wilcoxon Rank-Sign test were all applied to the simulated data after enlarging the sample. Three of the four combinations (B, C, AC, and BC) of the smaller sample combinations produced some usable information; actually, all of them did though one was a negative correlation. However, most of the combinations showed positive correlations through data simulation.

With little to no data for four of these combinations, there was no way to compare the seven combinations for best combination due to lack of size in these four (B, C, AC, and BC). Also, none of the sample sizes for these training combinations were the same which would have been good for comparison purposes. A decision was made to use data simulation to also determine whether some training combinations were better than others. A desire to make any differences stand out resulted in an enlargement of the sample size from 500 to 1,000 using the same means and standard deviations for the various combinations as in the prior simulation run. The analysis for differences was completed using two F-Statistic related analysis methods – the Welch ANOVA (Analysis of Variance) and the One-Way ANOVA to see if any of the combinations produced better results than others. All tests run on each combination also provided an Anderson-Darling normality

result and indicated the sample size produced normalized data to allow the above two tests to be conducted.

The Welch ANOVA provided numeric and graphical representations of each combination that was identical to the One-Way ANOVA. The Welch test provided both an analysis of means as well as an analysis of medians for the simulation while the One-Way ANOVA provided a similar analysis but excluded the median. These are shown graphically in the results section of this chapter. The results showed two combinations each for the PPM and the 3MIS data that gave better results - for PPM data – combinations B & AC; and for 3MIS – combinations B & AB.

One combination common to both the PPM and 3 MIS data was the class encoded as B (8-D / Problem Solving) and appeared to be the largest difference for all combinations. The other notable result was the two-class combination (AC & AB) with a common course in both (A = PFMEA / Control Plan). Again, of note to the reader is the fact that classes “A” and “B” are the two longest running classes of the three. This would suggest two classes (A & B) have had more effect on defect reduction for the supply chain. Additionally, both these are oriented toward process risk reduction, control and permanent problem correction.

On the one hand, class “A” (PFMEA/CP) is 100% risk-management oriented and designed to reduce and control or eliminate defects through “error proofing” or “Poka-Yokes” applied to a process. Done correctly over time, the use of this tool can systematically eliminate workplace defects. Likewise, class “B” (8-D / Problem Solving) is 50 – 65% risk-management oriented in the sense that of the eight disciplines in 8-D, there

are at least five devoted to risk reduction and elimination. These being root cause analysis, permanent countermeasures, countermeasure validation, prevention activities, and follow-up to prevention activities. Intuitively, we would expect these two classes to produce bigger impacts and this was confirmed using the above two tests. Additionally, both the Welch and One-way ANOVA produced comparable results for each class of defects (PPM & 3MIS) so there was no disagreement between the two tests.

Comparison of the actual data to simulated data runs for correlation of defects to training produced comparable results for the combinations A, AB, and ABC (the remaining three combinations) with one exception. The course combination ABC (all three classes) for the 3MIS data were negative on their p-value for all three tests. Remembering that the original data tests were performed on normalization of data, the Student-t test indicated no significance. However, the Sign and Wilcoxon Rank-Sign test both gave borderline results with p-values of 0.0610 and 0.0714 respectively but, still, a negative correlation – greater than 0.05. In the simulated data, all three tests showed a negative correlation with definitive p-values above 0.05 and not borderline.

Summarized, all larger sample sizes agree in both simulated and actual sample data test. Of the remaining small sample combinations (B, C, AC, & BC) all gave negative correlations in the original data but several positive correlations in simulated data – (both PPM & 3MIS data for “B”), (PPM data for “C”), (both PPM & 3MIS for “AC”). The remainder (“C” for 3MIS and “BC” for PPM & 3MIS) gave negative correlations. It appears differences behind these results were that the simulation increased the data precision and information available for the analysis. This narrowed the confidence interval allowing

the researcher to infer some positive correlations for several of these combinations rather than a conclusion of no correlation.

One additional study, a DOE (Design of Experiment), was completed on the original data to find additional meaningful information. The DOE was a full factorial, two level, 6 replicate study of the original data with the information selected from the original database utilizing a random number generator for each data point in the six replicants. The results were analyzed using the F-statistic for meaningful correlations and found that Class A (PFMEA / CP) showed a significant correlation for both PPM and 3MIS Data. More detail is included in the results section of this chapter.

Finally, as was mentioned earlier in Chapter 2, some Case Study results are offered on Kirkpatrick Model metrics used to monitor trainer, trainee and class environment during the training delivery. The reasoning behind offering these results was to serve as evidence that negative correlations are not a result of inappropriate or inadequate materials being delivered, nor was the instructor or the environment inadequate for message delivery. For any message to be delivered, there must be willing students, knowledgeable instructors, and an acceptable environment. In all cases, student feedback was measured and produced consistent marks in terms of class evaluation.

This abstract has included a high-level overview of each research effort completed in this study. They are summarized below and discussed in detail in the remainder of this chapter.

- 1) Study of the impact of encryption on the statistical study of data (M & b).
- 2) A high level mathematical / graphical / trending look at the original data.
- 3) A study of simulation runs and their impact on the data simulation.

- 4) Statistical analysis and results of simulation study for the four small samples.
- 5) Statistical analysis and results of simulation study of all seven combinations.
- 6) Statistical analysis and results of the original data.
- 7) A comparison of large sample combinations against 500 data point simulation.
- 8) A DOE study of the original data.
- 9) Level I & II results from the Kirkpatrick Model training results.

Analysis Results for Study of “b” on Statistical Outcomes

When the decision was made by the OEM to encrypt the data, it was agreed the value “M” and “b” would be positive numbers. A quick test of the encoding format shows the “b” value does not change the result. In fact, the addition of “b” for matched-pair data served no purpose in the encryption process. The following explanation and Equation #5 show why:

Let D1 = difference in the matched-pair data for supplier “1” in the database
 Let Y_b = encrypted average of 12-month average before training for supplier 1
 Let Y_a = encrypted average of 12-month average after training for supplier 1
 Let X_b = actual 12-month average before training (supplier actual rate), supplier 1
 Let X_a = actual 12-month average after training (supplier actual rate), supplier 1
 Let M = the encryption value greater than “0” and known only by the Manufacturer
 Let b = the add-on value chosen by the producer and known only by the producer

Accordingly, the difference in the matched-pair data would be:

Eq’n #6: Proof of Drop-out of “Add-on” from Encryption

$$D_1 = Y_b - Y_a = (MX_b + b) - (MX_a + b) = MX_b + b - MX_a - b = M(X_b - X_a) = M\mu_{TR}$$

The value of “b” for the encryption process was never needed and superfluous to the encryption effort. In matched-pair data, the value of “b” disappears from Equation #5 by being added as part

of the training defect rate before and, then, subtracted as part of the after-training value yielding a result impacted only by “M.” If the value of D_1 is negative, the difference in the actual data (μ_{TR}) for defects is negative and the multiplier “M” only makes the value smaller. A negative value means larger defects rates are occurring after the training. The reverse is true if the difference is positive making the average before the training larger. This result (adding b) would apply whether the data were parametric or nonparametric and of no consequence to the Case Study results.

If the difference is “0,” then the before and after training values are identical (unchanged). There were several of these found in the data. The impact on the Student-t distribution is that the value would count as part of the null hypothesis in the calculations where the mean $\leq$ zero. If the Wilcoxon Sign-Rank test is used, these values are culled from the analysis process so only the positive results are compared to the negatives for an actionable statistical result. In the case of the sign test, the binomial calculation includes the zero values recalling the work shown in (Table 4.6).

Encryption Process, Impact of “M” on Normal Data

As we learned from the analysis of “b” in the data encryption process, we are left with the simple algorithm which is a linear positive-constant times the original data. In statistical circles, this practice is known by a different name called “Data-Scaling.” This practice is used in biology and in other business sectors where the data scale does not fit statistical comparison needs.

Examples could include a data set for flatness of a part which is measured in $\pm 1/1,000$ of an inch and the engineer multiplies the entire data base by 1,000 to get the data in whole numbers rather than working in fractions. Another example would be two engineers taking temperature data on two different process batches and one reports their results in

Centigrade while the other reports results on a Fahrenheit scale. Compared, they would produce dramatically different results. However, if the Centigrade values are multiplied by 1.8 and the value 32 added to them, both are now on the same scale and statistically comparable. As a final example, suppose both temperatures were recorded in Centigrade scale and the researcher wanted them in Fahrenheit, you would convert both to degrees Fahrenheit and then do the analysis.

According to an article researched on this subject, if the transformation (re-scaling or encryption in this paper's case) does not alter the ranks of the data (that is relative positions to each other), the results are known as monotonic transformations. The re-scaling in the case of the OEM research on encryption impact was to apply the multiplier to the whole of the data base thus creating re-scaled values. According to the article:

“Transforming a variable re-scales it. A transformation can be any mathematical operation applied to data. A de-transformation reverses or inverts that process. Although an infinite variety of transformations are possible, the most important transformations are applied to all values. Those that do not alter the ranks of the data are known as monotonic transformations. The transformation is linear if plotting the transformed data against the untransformed data produces a straight line. Linear transformations are mainly used to ease data handling or display...”

[\[53\]](#)

In the cases of both the normal data and the nonparametric encryption studies, both data bases are “monotonic transformations.” These can be seen in (Figure 5.1 and 5.2) for the normal and nonparametric data sets, respectively. For purposes of the OEM research, the reason behind the transformation was not data handling or display but that of “data

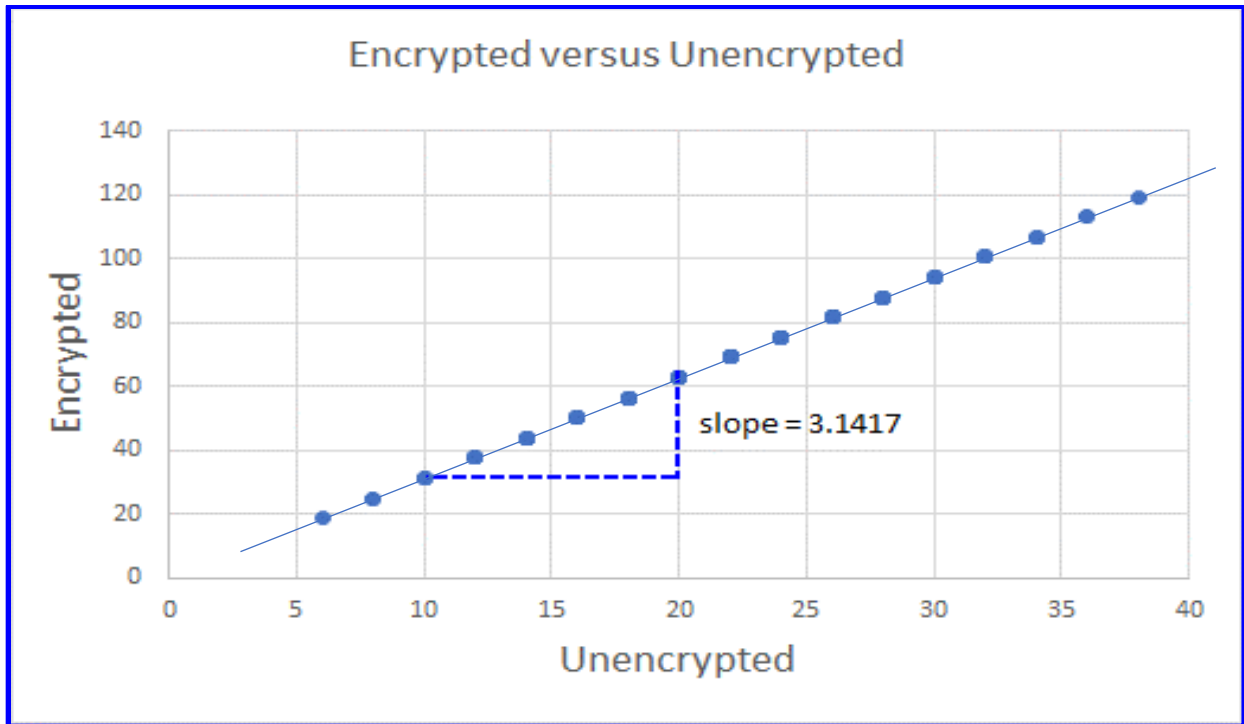


Figure 5.1 – Monotonic Graph, Encrypted & Unencrypted, Parametric

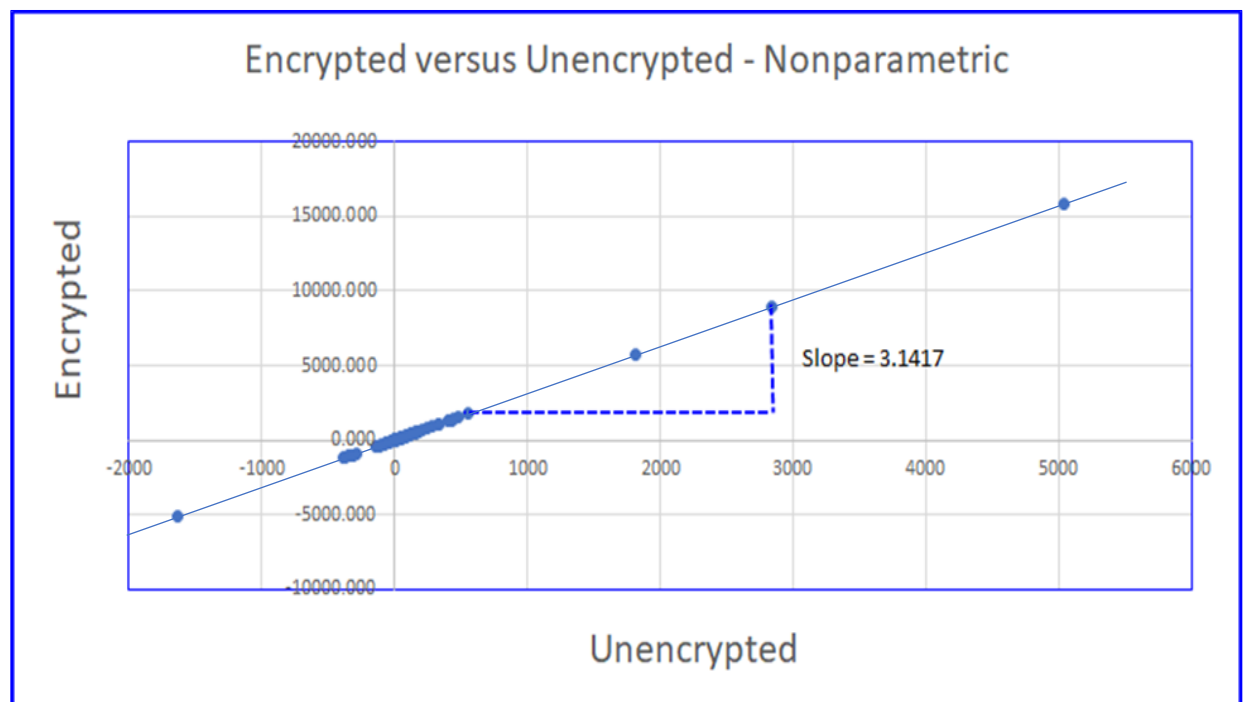


Figure 5.2 – Monotonic Graph, Encrypted & Unencrypted, Non-parametric

security.” The article speaks to the need to de-transform data back to its original state after analysis is completed for obvious reasons (back to real data; not encrypted).

As the value of “M” does not affect the rank of each converted data point relative to others in the data set and the relative distances between each data point was unaltered by the value of M (monotonic graph slope), they also do not affect the statistical outcomes of the study results. If encrypted outcomes are statistically significant, they can be converted back to unencrypted values.

Mathematically, for both the Student-t and the normal distribution upon the Wilcoxon Rank-Sign (WRS) test is derived, the value of “M” drops from the calculation for the observed t-statistic and for z-scores on the WRS tests. The governing equation for the t-statistic (observed or calculated) is as follows:

Eq'n #7: Governing Equation for Calculated t-Statistic

$$t_o = (n)^{1/2} (X_i - \mu) / S; \quad \text{where:}$$

t_o = observed test statistic

n = number of data points

D_i = value of the data point; and, $\bar{X}$ is the average of all D_i matched-pair data

μ = zero, null hypothesis; mean is ≤ 0

S = standard deviation of the sample

Proof of the drop-out can be seen with a following example. Albeit a smaller sample, it will work for any sample size. Suppose a small sample “R” is created of size ten (10).

Within the sample “R” we place the following numbers such that $R = \{4, 3, 6, 4, 3, 5, 4, 5,$

4, 6} and we now want to calculate the t-statistic to determine if the average of the data is greater than zero. Simple observation of the data set shows this to be true (all values are greater than zero). If the t-statistic is applied to this set of data, we obtain the following results shown in (Table 5.1). Also shown in the table is the scaling product as a function of “M = 2.00.”

This simple calculation shows a calculated statistic that is sufficiently greater than the critical statistic for nine degrees of freedom and a 5% alpha level (t-Table, $t_c = 1.833$). Since the value of $t_o > t_c$, we can conclude that the average, $\bar{X}$, is greater than zero. Exploring further, we can check for a similar result of the scaled value of D_i and to establish a pattern for this scaling process as proof of the drop-out for the value of M. (Table 5.2) shows the results of the scaled original data set which is shown in the last column of the table.

A pattern appears in the data for the scaling factor. In the case of (Table 5.2), each value of D_i is a multiple of the value of M. In the case of our example, it is a multiple of 2.00. It is easy to see two times the original mean of 4.4 yields the new mean (8.8) in our scaled example. Further, we can see that the new standard deviation is a product of 2.00 and the original standard deviation (that is, 2 times 1.075 yields 2.150). Finally, if the variance of the original data (10.4) is multiplied by two-squared (2^2), the result of the scaled variance is produced (41.6).

The pattern for M becomes visible in (Table 5.2). The final column in (Table 5.2) removes the value of M from the original data and represents it algebraically as $M=2.00$. The last

Table 5.1 – Student-t statistic for Small Sample Test – Original Data

M = 2.00 n = 10 $\mu = 0$	D_i	$D_i - \bar{X}$	$(D_i - \bar{X})^2$	$(R_i)(M)$
	3	-1.4	1.96	6
	3	-1.4	1.96	6
	4	-0.4	0.16	8
	4	-0.4	0.16	8
	4	-0.4	0.16	8
	4	-0.4	0.16	8
	5	0.6	0.36	10
	5	0.6	0.36	10
	6	1.6	2.56	12
	6	1.6	2.56	12
$\Sigma =$	44	Variance =	10.40	$\Sigma = 88$
$\bar{X} =$	4.4	Std. Dev. =	1.075	$\bar{X} = 8.8$
$t_0 = (n)^{1/2} (\bar{X} - \mu) / S = (10)^{1/2} (4.4 - 0) / 1.075$			$t_0 =$	12.944

Table 5.2 – Student-t statistic for Small Sample Test – Scaled Data

M = 2.00 n = 10 $\mu = 0$	D_i	$D_i - \bar{X}$	$(X_i - \bar{X})^2$	$(R_i)(M)$
	6	-2.8	7.84	3 M
	6	-2.8	7.84	3 M
	8	-0.8	0.64	4 M
	8	-0.8	0.64	4 M
	8	-0.8	0.64	4 M
	8	-0.8	0.64	4 M
	10	1.2	1.44	5 M
	10	1.2	1.44	5 M
	12	3.2	10.24	6 M
	12	3.2	10.24	6 M
$\Sigma =$	88	Variance =	41.6	44 M
$\bar{X} =$	8.8	Std. Dev. =	2.150	4.4 M
$t_0 = (n)^{1/2} (\bar{X} - \mu) / S = (10)^{1/2} (8.8 - 0) / 2.150$			$t_0 =$	12.944

of the three tables (Table 5.3) shows conclusively what transpires with the value of M when it is algebraically and mathematically tracked separately throughout the calculation used to determine the observed t-statistic.

As can be seen in the above equation used to arrive at the observed statistic of 12.944, the value of M is present in both the numerator and denominator, cancel each other algebraically, and drop from the calculation. This analysis provides proof that regardless of the value of M in scaling, it has no impact on the calculated statistic. Since the non-parametric data was also monotonic, the same outcome will occur for the WRS test.

A similar calculation can be repeated for the z-score used in calculating the probability for WRS. Like the t-statistic, the value of " M " is embedded in both the numerator and denominator and cancel in the same way. Consequently, the value of " M " does not impact the results of the calculated z-score. In the special case where $M = 1.00$, the encrypted and unencrypted value for either would be identical and a non-issue.

The Sign test assumes an equal number of positive and negative differences and the value of " M " plays no role in this calculation so, it too, is not impacted by the encryption process. Therefore, the expectations of any calculation done using these three statistical tests on the data should produce identical encrypted or unencrypted results. We can see in the above three tables the t-statistic is the same for all three results (12.944). Similar results are also visible in two additional studies that follow where Student-t and WRS test outcomes produced independent identical encrypted and unencrypted results using a much larger data set where the sample size was 144 data points. Though the values are different for different tests, the test itself produces an identical outcome.

Table 5.3 – Review of Statistical Pattern for Drop-out of “M”

$M = 2.00$ $n = 10$ $\mu = 0$	D_i	$D_i - \bar{X}$	$(D_i - \bar{X})^2$	
	3 M	- 1.4 M	1.96 M ²	
	3 M	- 1.4 M	1.96 M ²	
	4 M	- 0.4 M	0.16 M ²	
	4 M	- 0.4 M	0.16 M ²	
	4 M	- 0.4 M	0.16 M ²	
	4 M	- 0.4 M	0.16 M ²	
	5 M	+ 0.6 M	0.36 M ²	
	5 M	+ 0.6 M	0.36 M ²	
	6 M	+ 1.6 M	2.56 M ²	
	6 M	+ 1.6 M	2.56 M ²	
$\Sigma =$	44 M	Variance =	10.4 M ²	
$\bar{X} =$	4.4 M	Std. Dev. =	1.075 M	
$t_0 = (n)^{1/2} (\bar{X} - \mu) / S = (10)^{1/2} (4.4 \text{ M} - 0) / 1.075 \text{ M}$			$t_0 =$	12.944

This final demonstration of no impact takes a much larger known normal data set and adjusts it by a different value “M” of my choosing. The data should remain normal, the variation will again be changed because of the multiplier, but relative distance (one data point to the other) is still unchanged and the results will be identical for each test along with data demonstrating similar properties as shown in the earlier example.

Choice of this normal data came from a file, generated by the researcher and known to be statistically normal. The file consisted of 144 data points and is a close approximation to the actual OEM data file received (148 suppliers). A portion of this file is shown in a table with an adjusted (encrypted) result. The adjusted data is rounded to three decimal points for ease of manipulation. My choice of “M” was the numerical value 3.1417 (not π but close) – this was simply another arbitrary number chosen by the researcher.

The entire parametric data (normal) file used in this analysis can be found in (Table AT-5.1) in the appendix. A small portion of the encryption process is shown in (Table 5.4) below using the value of “M” selected by the researcher and ignoring the value of “b” as it is no longer applicable to the work. The actual data is shown as values of “X” and would represent the difference in defect rate averages as in the Case Study data – these are the values taken from (Table AT-5.1). Each value of “Y” is the encrypted results but using the arbitrary multiplier, “M = 3.1417.” Looking at the normal data and the encrypted data shows similar but uniquely different value sets.

The question is, “Does the change represent a difference?” If we were measuring the variance, there would be a difference. The base of the encrypted data is wider and with greater variance because of the multiplier “M.” However, as part of the Student-t analysis, the focal point was on the mean of the data and not the variance although variance and standard deviation play a role in the analytical calculations for the Student-t. (Table 5.4) values of “X” will represent data points before difference encryption and subtraction. The data was plotted to check for its normality and graphed as a histogram. Looking at (Figures AF-5.17) (unencrypted normal data) and AF-5.18 (encrypted normal data), found in the Appendix, it would be impossible to tell the difference between the two if the horizontal axis legend on each graph were removed. As can be seen in the two plots of data, both are highly normalized. The question becomes, “Does the encrypted data give a different result compared to the original data?”

By deliberate design, all values in the 144 data points were chosen to be greater than zero to provide a mean **known** to be greater than zero for each point. We would expect

Table 5.4 – Normal Data File – Generated by Researcher

<i>X = Actual Data Difference</i>	<i>Modifier</i>	<i>Y = Adjusted Data Point</i>
6	Y=MX M = 3.1417 n = 144	18.850
14		43.984
18		56.551
28		87.968
22		69.117
12		37.700
14		43.984
-		-
-		-
-		-
-		-
20		62.834
18		56.551
16		50.267
10		31.417
20		62.834
18		56.551
22		69.117
16		50.267
24		75.401
34		106.818
-		-
-		-
-		-
-		-
26		81.684
16		50.267
22		69.117
24		75.401
18		56.551
24		75.401
14		43.984
22		69.117
30		94.251
20		62.834

Note: “b” is ignored since it is included as part of the subtraction difference to obtain the value of “X” and drops from the equation.

any analysis by the Student-t distribution for matched-pair data to provide a similar result assuming the encryption process has no impact. All the encryption process does is shift the entire data set to the right by a value of 3.1417 and widen the base of the histogram (increased variance and standard deviation).

We can look at normality of the data through descriptive statistics analysis. The math and the histograms for these analyses were done using Sigma-XL. They can also be completed by-hand, but the effort would be time consuming and subject to error. Also, the size of the sample mandated the use of computer system software for the analysis and calculations.

Looking at (Figures AF-5.17 and 5.18) (Appendix), both figures show a similar histogram profile. (Figure AF-5.23) for (Figure AF-5.17) and (Figure AF-5.24) for (Figure 5.18) also provide identical results with a p-value (0.1355) indicating both are normal data. As expected, the statistics provided a different mean, standard deviation, and average square error but the data in both cases (encrypted or not) is still normal. Applying the one-sample t-test to both the normal and the encrypted data, we get the following results shown in (Table 5.5) below. The differences are translatable if the value of “M” is known. Information about the data can easily be converted from unencrypted to encrypted values and reversed if needed. Note that the counts are the same. The mean in the unencrypted data can easily be converted to the mean in the encrypted data, remembering the value of “b” does not factor into the conversion (it dropped out during the difference calculation). The standard deviation for the unencrypted data (22) can be converted to the encrypted data also by simply multiplying by 3.1417. The t-statistic for both is greater than 40 (identical in both instances, 40.198) providing excellent evidence that both distributions

Table 5.5 – Comparison Data for Normal and Encrypted Data

1-Sample t-Test – Unencrypted & Encrypted Data		
Test Information		
Ho: Mean (MU) = 0		
Ha: Mean (MU) > 0		
Results	Unencrypted	Encrypted
Count (N)	144	144
Mean	22	69.117
Std. Deviation	6.568	20.663
SE Mean	0.547297	1.719
T (calculated)	40.198	40.198
p-value (1 sided)	0.0000	0.0000
LC (1-sided, 95%)	23.298	73.197

$$Y = (3.1417) (22) = 69.117$$

are not equal to zero and the encryption does not change the t-statistic result. We also know from the fact the data was chosen with positive values for all points in the sample there is 100% confidence that the mean will be greater than zero for both the unencrypted normal data (23.30) and the encrypted data (73.20) – rounded to 2 decimal places (there are small rounding errors in the calculations). Even the encrypted value for the confidence interval can be calculated by multiplying by 3.1417 times the unencrypted data to obtain the results in the confidence interval values:

$$Y_e = (23.30) (3.1417) = 73.20$$

One can reverse the encrypted data points back to their original normal value by dividing the result by “M = 3.1417”.

$$Y_u = (73.20) / (3.1417) = 23.30$$

The conclusion drawn from this exercise is that encryption changes made on the OEM defect data will have no impact on the statistical analysis process if the data are normally distributed. If the encryption multiplier is known, the data can be manipulated back and forth between the encrypted and unencrypted data without loss of statistical confidence in the result.

Encryption Process, Impact of “M” on Nonparametric Data

This same question relative to nonparametric data was also assessed – that is, what if the data are not normal? Will nonparametric analysis hold for either case (encrypted or not)? Continuing with the same line of thinking as the normal data, a new data set using 144 modified data points that were not normally distributed was created. The nonparametric data had significant outliers in the data (similar to our Case Study data set) making it nonparametric – highly skewed. Additionally, included within this set are multiple negative values that, interpreted for this research, implies the difference in the after result is greater than the before result, thus a negative value. The nonparametric data set can be found in (Table AT-5.2) of the appendix.

While it may be possible to normalize this data, it is not a requirement for this research activity. It must be nonparametric for both unencrypted and encrypted data. Like the normal data impact study, the histogram plots were made for both the nonencrypted data (Figure AF-5.25) and the encrypted data (Figure AF-5.26). Using the same value for “M” as was done to the normal data and recalling “b” drops out during the subtraction difference process the encryption was completed and compared similarly as for the normal data. These two figures (AF-5.25 and 5.26) may be found in the Appendix as well.

As expected, the normality plots were decidedly nonparametric with obvious outliers in the data compared with the earlier results for the normal data. Like the earlier example, the nonencrypted data was also plotted as histograms with statistics along with the encrypted data and statistics for comparison. Just as with the normal data, the same results can be obtained using the $Y = MX$ adjustments to get the other data. Again, the counts were the same. The mean in the unencrypted data (94.84) can be easily converted to the mean in the encrypted data (297.96):

$$Y = (3.1417) (94.84) = 297.96$$

Note that the Anderson Darling test for both sets of data (Figures AT-5.25 and AT-5.26) produced identical test results indicating nonparametric data; that is, the p-value is less than 0.05 (actual = 0.0000) and indicated data is not normal using the hypothesis test (H_0 : Normal data versus; H_a : Data are not Normal).

In this data set, **not all** results in the data (unencrypted or encrypted) were greater than zero. As the data is decidedly nonparametric, the Student-t distribution was not used. In this scenario, the Wilcoxon Rank-Sign (WRS) test was used to evaluate both positive and negative values for a disposition on the median. There were no zero values within the test, again by design. Using the same approach as the normal data test $\mu_b - \mu_a = \mu_{TR}$ and assigning the difference between the two means as the training result (that is, the value of each of the 144 data points times its 'M' value), the Wilcoxon Rank-Sign test was performed on unencrypted and encrypted data.

The non-parametric Wilcoxon Rank-Sign test is a pseudo-normality test in which the data is converted to a positive or negative rank ignoring all values equal to zero. The WRS test

first takes data and orders the absolute value of each data point from the smallest value to its largest. In cases where the same value appears more than once, (for example; in a situation where an identical value is recorded for two data points, say a value of 50 and 50 in rank positions of 25 and 26) the values of each are assigned a rank-value of 25.5 ($(25 + 26) / 2 = 25.5$) and then given back the sign of the original data point (whether it be positive or negative) before the ranking.

All positive values and all negative values are then tabulated and the probability of the positive value outweighing the negative value is calculated (W-statistic). If the probability is less than 0.05, the researcher abandons the null in favor of the alternate hypothesis meaning the median is greater than zero. Within the software, the median can be a one-sided test for the alternate hypothesis and chosen as greater than zero or less than zero before the test is performed.

The rearrangement of data (that is, the Rank-Sign) then becomes somewhat of a normal distribution and can be plotted as a normal distribution. Within this test, there has been some past user confusion as to what the test checks for. Remembering the data is nonparametric, the “Rank-Sign” result is normal in the sense that the researcher could calculate a rank order mean and it would plot as normal data (see Figure 4.5). However, it makes no sense to address the mean at this situation. The mean of the rank order has no special meaning other than to indicate what the average rank is. One could track backwards from the mean rank and correlate it to a value in the nonparametric data but there is an equal possibility it could be positive or negative. Therefore, this tactic has no logic. It makes more sense to look at the median and let the software tell the researcher whether there is a statistical majority of positive or negative values in the rank.

Since the data was nonparametric, outliers skew the mean result in an unwanted way and can potentially provide a false positive result. Therefore, the median (which the test calculates) is a much better approximation for central tendency. From what this researcher gathered, the confusion among test users is in trying to answer exactly what the test is looking at (mean or median). You can look at the mean of the rank as it is normalized (no logic) or look at the test median (this researcher's understanding of the test's actual intent). This explanation clarifies what the Wilcoxon Rank-Sign (WRS) test actually does.

Executing the WRS test on the unencrypted and encrypted data files produced identical results. The rank-order should be the same with a corresponding exactness in result. The only difference in this case is the relative distance between each data point (multiplied by 3.1417). (Table 5.6) below provides the results of the WRS test on both nonencrypted and encrypted data. Of note is the fact that the Wilcoxon statistic (value = 8,078) is the same for each as they should be – there is no difference in the rank order and sign for each set. Note also the one-sided test p-values are both less than 0.05 (actual = 0.0000) resulting in a decision to reject the null hypothesis in favor of the alternate.

It is easy to conclude this test will produce an analysis of nonparametric data that, in many ways, is as strong as the t-statistic for normal data. In this case, analysis using the WRS test, the researcher abandons the null hypothesis in favor of the alternate – that is, the median is greater than zero. Said another way, the result shows the difference is a decided reduction in defects (represented by the median). Consequently, encrypting the defect rates does not alter the data relative to statistical results using the Wilcoxon Rank-Sign test. The Sign test was not checked – but one would expect similar results.

Table 5.6 – WRS Test for Nonparametric Data Impact Study

1-Sample Wilcoxon Rank-Sign Test – Study of Nonparametric Data		
Test Information		
Ho: Mean (MU) = 0		
Ha: Mean (MU) > 0		
Results	Unencrypted	Encrypted
Count (N)	144	144
Count for Test	144	144
Median	20.5	64.405
Wilcoxon Statistic	8,078	8,078
p-value (1-sided)	0.0000	0.0000

Regardless of the method (t-statistic or Wilcoxon Rank-Sign), the researcher can be confident in reporting the experimental results. Based on the studies just completed using different encryption values, both normal data and nonparametric data are not impacted by the multiplier. There were study three conclusions of note:

- 1) Encryption of normal data analyzed by using the t-statistic or t-distribution is unaffected by the multiplier “M” and the researcher can conclude no negative impact on process statistical results in terms of research outcomes.
- 2) Encryption of nonparametric data analyzed by using the Wilcoxon Rank Sign test is unaffected by the multiplier “M” and the researcher can conclude there no negative impact on process results in terms of research outcomes.
- 3) The value of “b” was never needed for the encryption process for matched-pair data – a minor error on the part of this researcher. The value of “b” disappears in the subtraction process. Future analysis of this nature should eliminate the “b” element of the encryption process.

Results of High-Level Data Review

Initially, a high-level look at the data combinations was completed looking for meaningful information that would provide some level of insight into the data without a great deal of mathematical computation. The findings of this review are shown below but some description of method is needed before discussing and showing results. These findings were also statistically assessed using data simulations as a statistical means of showing relationships and a statistical analysis and DOE as well performed on the original data. In the data, one of three supplier results have occurred while looking at the matched pair differences of the 12-month average before and after the completed training:

- 1) The supplier shows a performance improvement – a reduction in defects.
- 2) The supplier shows no change or shift in defects – reduction rate is unchanged.
- 3) The supplier shows a performance decline – an actual increase in defects.

A zero value reflects no or zero change in defect rates. This can be seen in 16.2% of the data provided where the data points all show the same value of seven (7.000000) before and after the training providing a “zero” in the matched-pair difference. These values are excluded by the Sign test and by the Wilcoxon Rank-Sign tests.

The only way these data points can be zero in their difference is for these suppliers to have had a zero-defect rate both before and after training. When b is then added to zero, the result is seven exactly. This result is an indication the value of “b” is seven.

Eq'n #8: Derived earlier during analysis of “b” impact

$$D_1 = M (X_b - X_a)$$

Eq'n #9: Equation #5 rearranged

$$(X_b - X_a) = D_1 / M$$

It is a given that “M” was a positive value – agreed before generating the data the researcher received. If the before and after match-pair difference “D₁” is zero, the only way this result can be true is for “X_b – X_a” to equal zero. Therefore, the only way to get this result is for the values of both “X_b” and “X_a” defect values to be zero – otherwise, the value of “D₁” would be either a positive or negative outcome.

Consequently, no meaningful change is shown in these data points. However, to the benefit of the OEM, no increase in low defect rates (that is, results equal to zero) from these suppliers is at least one desirable state or condition. Looked at another way, these are some of the better suppliers within the supply chain and they are doing well both before training and after. These suppliers are “holding their own” while incorporating new information into their manufacturing culture.

Consequently, these zero difference values should be accounted for and included in some way along with reductions in the high-level review. In the high-level mathematical development of these numbers, they are tracked separately but combined as part of the percentage for improvement or no change. These are positive performance results much like the positive differences even though the result, in each case, is zero.

Some of the results in the matched pair differences are negative. The companies that experience gains in their defect rates over time are the suppliers that need further investigation as to why their rates are rising rather than falling. At least one explanation is they attended but failed to implement what was taught in the class – the most likely scenario. The cause behind this is unknown but can be cultural or resource related.

The results, at a high-level, provided confirmation that the supplier development training is having a positive impact on defect reductions. The results imply 7 in every 10 suppliers are on the right track while the remaining 3 in 10 are experiencing negative results. In each case, training combinations are greater than 50% with one combination approaching 80% - all good news for the OEM and UT CIS. This was a simple set of observations and with some of the smaller sample groupings having only a limited amount of data to support their claim. The numbers are reflected in (Tables 5.7 and 5.8) respectively for PPM and 3MIS data. These groups will be explored further using statistical analysis and simulations to provide additional information.

The implications of a gain in defect outcomes (negative differences) is an indictment of the supplier in terms of their failure to implement what was taught in class. The supplier's defect rates after training is higher than the average before training was started. This is counter-intuitive. Had they implemented what they were taught, improvements should be visible like the other suppliers. The OEM should explore with these suppliers what is happening at their locations and why defects have risen rather than declined.

Looking at the data further, another discovery was made related to the length of time each of the training interventions have been implemented. There is supporting evidence that the training classes with a longer history in supplier development are producing a greater impact in terms of percentage improvements for defect rates. Likewise, shorter history programs are showing the least improvement.

The data was graphed for just the groups A, B, and C with results shown for both PPM and 3MIS data. As evident from the graphs, there is supporting evidence that PFMEA

Table 5.7 – Percentage of Improvement / No Change for PPM data

Code	PPM	PPM	PPM	PPM
	Suppliers – No Change	Suppliers Increases	Supplier Reductions	No Change + Reductions
AC only, not B	25.0%	37.5%	37.5%	62.5%
BC only, not A	0.0%	33.3%	66.7%	66.7%
C only, not A&B	27.3%	36.4%	36.4%	63.6%
B only, not A&C	36.8%	42.1%	21.1%	57.9%
AB only, not C	24.2%	36.4%	39.4%	63.6%
AB, AC, or BC	20.0%	36.0%	44.0%	64.0%
A, B, or C	31.9%	30.4%	37.7%	69.6%
ABC (all)	10.3%	27.6%	62.1%	72.4%
A only, not B&C	30.8%	23.1%	46.2%	76.9%
A, B, C, AB, AC, BE, or ABC	23.6%	31.8%	44.6%	68.2%

Table 5.8 – Percentage of Improvement / No Change for 3MIS data

Code	3MIS	3MIS	3MIS	3MIS
	Suppliers – No Change	Suppliers Increases	Supplier Reductions	No Change + Reductions
AC only, not B	0.0%	37.5%	62.5%	62.5%
BC only, not A	22.2%	22.2%	55.6%	77.8%
C only, not A&B	9.1%	45.5%	45.5%	54.5%
B only, not A&C	10.5%	42.1%	47.4%	57.9%
AB only, not C	9.1%	33.3%	57.6%	66.7%
AB, AC, or BC	10.0%	32.0%	58.0%	68.0%
A, B, or C	8.7%	31.9%	59.4%	68.1%
ABC (all)	6.9%	31.0%	62.1%	69.0%
A only, not B&C	7.7%	23.1%	69.2%	76.9%
A, B, C, AB, AC, BE, or ABC	8.8%	31.8%	59.5%	68.2%

shows improvement with 8D / PS and Containment training programs having a lower improvement impact. The first (Figure 5.3) is PPM data (defects found at the OEM assembly plant) versus the defects found after the vehicle was sold (3MIS) – (Figure 5.4). Whether this is the nature of the class (what is being taught) or due to having been in existence a lesser time (“B” by one year and “C” by two years) is not known. What is known is there are fewer supplier representatives having gone through the last course (C) compared to the PFMEA and 8-D courses (A & B).

Longer term, one might infer the “shorter-history” class combinations may be capable of producing similarly effective results to PFMEA / CP but that is not currently evident in the data using this analytical technique. In both the PPM and the 3MIS data, the same trend is seen but with 8-D (group B) reversed with containment (group C) training. In the PPM case, the order is A, C, then B, whereas, in the 3MIS data, the order is A, B, then C. The researcher attempted to determine why this was reversed. Intuitively, if time is the reason, one would expect A, B, and then C in that order due to the dates the classes were launched (each a year apart). That’s not the case in both databases so a different reason was sought. It is possible the cause lies more with the suppliers that took the courses.

What was discovered in the reversal analysis was the two combinations (B and C) are both a part of the sample combinations with smaller data sets, so the data simulations would be better indicators of meaningful results. The combination of “B” (8-D / Problem Solving) had the larger mean value by an order of magnitude compared to C. The results themselves are simple supplier ratios showing improvement including a number of suppliers whose defect rates had not changed divided by the total number of suppliers in the group.

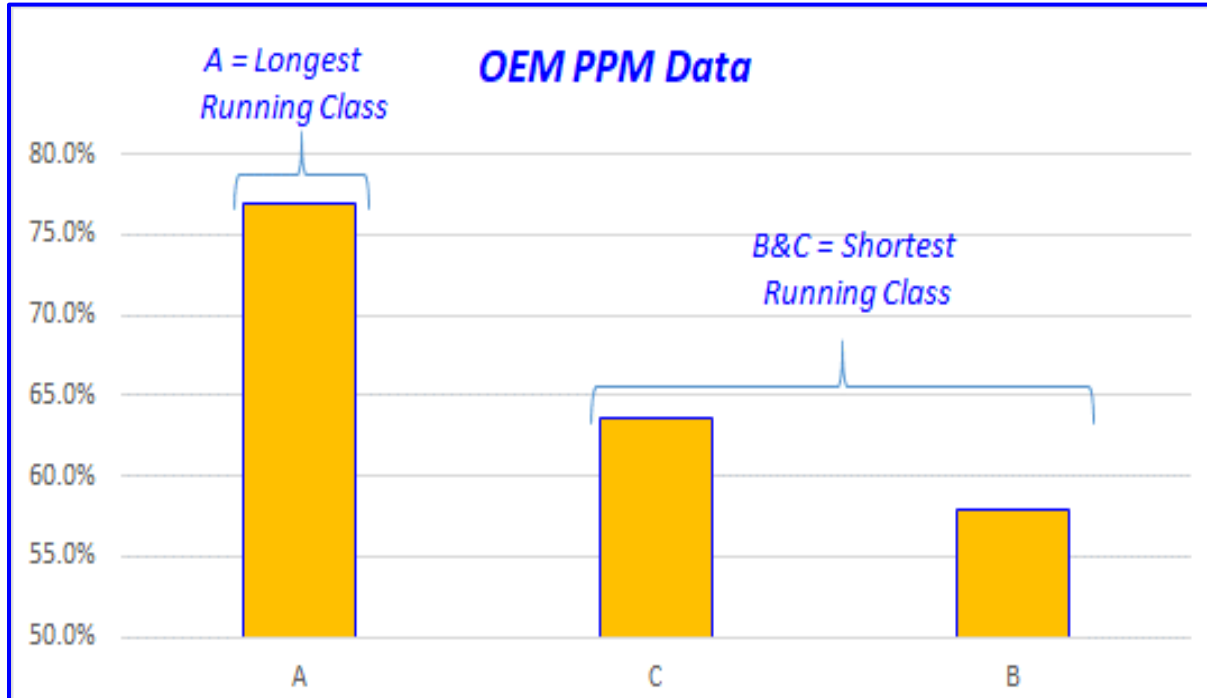


Figure 5.3 – Training Program Run Time versus % Improvement – PPM Data

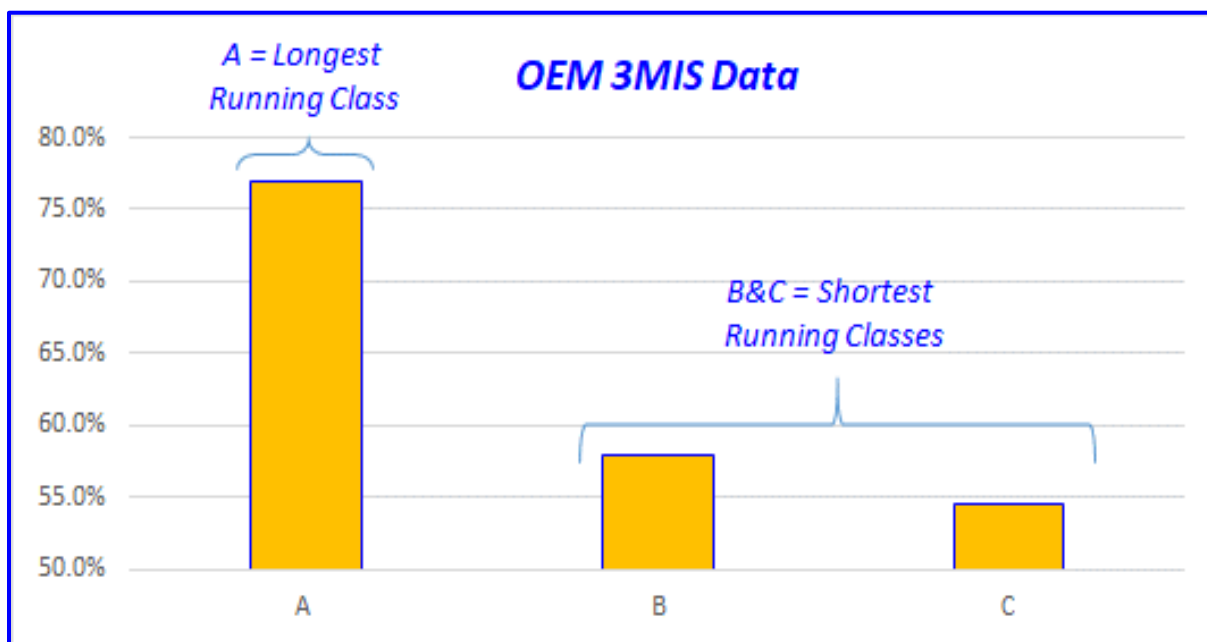


Figure 5.4 – Training Program Run Time % Improvement – 3MIS Data

In looking at the data, it was noticed in the “B” and “C” combinations there were more suppliers with unchanged defect rates for the PPM data than existed for 3MIS. This resulted in the reversal of the data values. This reversal is related to suppliers that took the classes so there may be a dual cause at work here (time and supplier).

Looking at the data for B and C separately, both are just a few percentage points different from each other, so the reversal would appear of little importance. In both cases for the PPM and the 3MIS data, combination “A” (PFMEA / Control Plan) is superior to the other two in terms of performance by a significant amount (10 to 20 percentage points). The simulation run and DOE discussed later in the chapter supports this conclusion as well. Interestingly, class “A” is by far the longest running class of the three by more than a year compared to “B” and more than two years compared to “C”.

This additional year would give suppliers a larger time window in which to implement efforts using PFMEA / CP as a predictive tool improving their error proofing activities. Consequently, this should provide more time to lower defect rates. Or, alternatively, the supplier will experience no change since the supplier was already at zero. This reversal anomaly in the data seems to be satisfactorily explained. The simulation studies are included in a separate section of their own which follow.

Data Simulation Study for Normality

The simulation generator for normality was investigated as to the cause of why some results were nonparametric. It would make sense that an equation designed to generate normal data curves should do just that. Simulations were tried at 25, 50, 75, 100, 125, 150, 250, 500, 800, 1000, 1200, 1400, 1500, 1750, 2000, and 3000 using the PPM data

(mean and standard deviation) for ABC, BC, AC, AB, C, B, and A and the Anderson-Darling normality tests run on each group to determine normality.

All did not produce normal data distribution curves with p-values greater than 5%. Again, the underlying assumption for the test is H_0 : Distribution is Normal and H_a : Distribution is nonparametric or not normal. The researcher's initial thinking was the data outliers from the original data set was causing the failures but as the sample sizes grew larger and larger, the nonparametric curves continued to appear even with sample sizes as high as 1,750 points. All total there were 105 tests completed for normality with only 5 showing nonparametric behavior. The results can be found in Table 5.9 for Anderson-Darling normality checks. Thinking through this, the normality generator also has a confidence level (assumed to be 95%) for generating a normal distribution curve so it should be no surprise that some may be nonparametric as the simulation started with nonparametric data in every grouping.

Conclusions are that increasing the sample size for each combination will increase the precision of the results. Precision is the ability of the statistical study to detect smaller and smaller data differences. This prevents the researcher from making a Type I Error - rejecting the null when the null is true. However, this action does not provide for the result being investigated (that is, correlation to developmental training).

The researcher then went through set of simulation runs with the data but used just the T-statistic test and the Wilcoxon Rank-Sign tests for training correlation p-values. Results showed samples less than 75 data points had variation in their p-values but as the sample size grew, this became less an issue. When the sample size got to 500, consistent results

Table 5.9 – Simulation Study, p-values for Test Runs

Simulation Study	PPM	PPM	PPM	PPM	PPM	PPM	PPM
	ABC	BC	AC	AB	C	B	A
Sample Size; N=25	0.379	0.950	0.918	0.502	0.902	0.457	0.115
Sample Size; N=50	0.878	0.536	0.550	0.254	0.567	0.734	0.330
Sample Size; N=75	0.406	0.665	0.989	0.922	0.570	0.542	0.746
Sample Size; N=100	0.763	0.717	0.261	0.341	0.232	0.108	0.238
Sample Size; N=125	0.196	0.451	0.030	0.431	0.890	0.871	0.860
Sample Size; N=150	0.505	0.818	0.531	0.941	0.604	0.186	0.551
Sample Size; N=250	0.847	0.363	0.486	0.199	0.919	0.551	0.082
Sample Size; N=500	0.740	0.204	0.615	0.814	0.641	0.037	0.315
Sample Size; N=800	0.327	0.416	0.794	0.088	0.221	0.656	0.951
Sample Size; N=1,000	0.698	0.660	0.395	0.880	0.009	0.146	0.678
Sample Size; N=1,200	0.319	0.075	0.260	0.843	0.527	0.918	0.998
Sample Size; N=1,400	0.586	0.771	0.135	0.957	0.928	0.435	0.620
Sample Size; N=1,500	0.316	0.979	0.420	0.966	0.828	0.400	0.599
Sample Size; N=1,750	0.891	0.245	0.117	0.561	0.020	0.546	0.043
Sample Size; N=2,000	0.718	0.942	0.810	0.553	0.535	0.213	0.180
Sample Size; N=3,000	0.613	0.643	0.785	0.674	0.740	0.549	0.296

Notes:

Number of Samples, Nonparametric 5 A-D Ho: Graphs are normal
 Number of Samples, Parametric 100 A-D Ha: Graphs are nonparametric
 Total number of Samples Tested 105
 Percentage of Samples nonparametric = $(5 / 105) (100) = 4.8\%$
 Results are Anderson-Darling p-values for normality; 95% C.L. nonparametric ≤ 0.05

appeared in terms of the p-values for the test statistic in both the T-test and the Wilcoxon Rank-Sign (all were 0.0000 with the exception of BC which showed no correlation). The results are shown below in (Table 5.10 and 5.11). It should be noted that the sample run for the actual statistics reported for the correlations in the next section are a different simulation run and also included the Sign Test as part of the study.

Data Simulation for Smaller Sample Groups

Statistically the better indicators for the actual data seemed to be the nonparametric tests – the Sign and Wilcoxon Rank-Sign Test. However, the Wilcoxon method ignores zero difference values in the matched-pair data so statistical results are, in some ways, less meaningful since it excludes a significant piece (16.2%) of the data. If the zero differences are ignored, this lowers the number of data points in the sample and, consequently, can lower the power of the test. The smaller groups were explored through data simulation. As it was simple and easy to do, the larger group sizes were included as well. There was an additional reason to include them and discussed later. Consequently, the data simulations that were completed included combinations A, B, C, AB, AC, BC, & ABC (all seven combinations). The findings for these simulations are shown later for the PPM and 3MIS data respectively. It was not surprising to see no meaningful information extracted from the original groups with the small sample size. For example, the smallest group had a sample size of six. For that sample to be statistically significant, all suppliers within this group would have to post reductions for a positive correlation and that was not the case with the data. The research interest here was to determine what the data would show if the sample sizes were larger.

Table 5.10 – p-values for T-distribution Assessment for Correlation

P-values for T-Distribution	PPM	PPM	PPM	PPM	PPM	PPM	PPM
	ABC	BC	AC	AB	C	B	A
Sample Size; N=15	0.0004	0.7627	0.0069	0.0008	0.0246	0.1232	0.7436
Sample Size; N=25	0.0010	0.5772	0.0312	0.0060	0.0501	0.1862	0.3227
Sample Size; N=50	0.0001	0.0279	0.0064	0.0035	0.0141	0.1492	0.0984
Sample Size; N=75	0.0010	0.0776	0.0002	0.0019	0.0012	0.0361	0.0352
Sample Size; N=100	0.0002	0.1403	0.0000	0.0016	0.0007	0.0036	0.0177
Sample Size; N=125	0.0003	0.1637	0.0000	0.0001	0.0003	0.0034	0.0088
Sample Size; N=150	0.0000	0.2609	0.0000	0.0000	0.0003	0.0037	0.0121
Sample Size; N=250	0.0000	0.6120	0.0000	0.0000	0.0019	0.0002	0.0017
Sample Size; N=500	0.0000	0.3969	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5.11 – p-values for Wilcoxon Rank-Sign Assessment for Correlation

P-values for T-Distribution	PPM	PPM	PPM	PPM	PPM	PPM	PPM
	ABC	BC	AC	AB	C	B	A
Sample Size; N=15	0.0004	0.7627	0.0069	0.0008	0.0246	0.1232	0.7436
Sample Size; N=25	0.0010	0.5772	0.0312	0.0060	0.0501	0.1862	0.3227
Sample Size; N=50	0.0001	0.0279	0.0064	0.0035	0.0141	0.1492	0.0984
Sample Size; N=75	0.0010	0.0776	0.0002	0.0019	0.0012	0.0361	0.0352
Sample Size; N=100	0.0002	0.1403	0.0000	0.0016	0.0007	0.0036	0.0177
Sample Size; N=125	0.0003	0.1637	0.0000	0.0001	0.0003	0.0034	0.0088
Sample Size; N=150	0.0000	0.2609	0.0000	0.0000	0.0003	0.0037	0.0121
Sample Size; N=250	0.0000	0.6120	0.0000	0.0000	0.0019	0.0002	0.0017
Sample Size; N=500	0.0000	0.3969	0.0000	0.0000	0.0000	0.0000	0.0000

The data simulations provided some interesting results as (Tables 5.12 and 5.13) indicate. Of all seven combinations (A, B, C, AB, AC, BC, & ABC) for both the PPM and 3MIS data only four failed to show a correlation between training and defect reduction. In total, forty-two statistical tests were run on these combinations (Student-t, Sign, and Wilcoxon Rank Sign) for each set of classes (a total of 7 combinations times 3 tests per combination times 2 databases equaling 42 tests results).

In the simulations, if one test showed a positive correlation, all the test performed on the combination showed the same outcome. If the result was no correlation, all three confirmed the combination in the set to be no correlation. However, most of the combinations showed a positive significance and correlation. As can be seen from the data, the only simulated set that did not provide a positive result for the PPM data was the combination “BC” while the remaining six combinations (A, B, C, AB, AC, and ABC) provided a correlation as denoted by their p-values – all were less than 0.05. Within the 3MIS data, three combinations provided no correlation with their alpha values being greater than 0.05 (C, BC, and ABC). All these combinations delivered a p-value from a low of 0.9172 to a high of 1.0000. The normality of these simulations was also checked, and, as expected from a 500-point simulation, the data was normal.

Some of the explanation behind the negative correlations for the BC grouping can be explained in that the mean for the PPM data was very near zero with a large standard deviation (3.11, 371.16 respectively) while the means for the 3MIS data with no correlations (three separate groups) were actually negative values with significant standard deviations. Group B had a small negative and sizable standard deviation (-16.78, 124.13). Likewise, group ABC in 3MIS had a similar condition with a more negative

Table 5.12 – Simulated p-value Results for PPM & 3MIS Data, N=500

Summary of Simulation Runs for each Data Combination		Data Simulation Results; N = 500					
		PPM Matched Pair – p- value	PPM Sign Result One-Tail Test; α = 5%	PPM Wilcoxon Result; α = 5%	3MIS Matched Pair – p- value	3MIS Sign Result One-Tail Test; α = 5%	3MIS Wilcoxon Result; α = 5%
Data Set Description	Code						
PFMEA/CP (only)	A	0.0246	0.0178	0.0031	0.0000	0.0010	0.0000
8-D Problem Solving	B	0.0000	0.0007	0.0000	0.0000	0.0000	0.0065
Containment	C	0.0000	0.0001	0.0000	0.9893	0.9172	0.9827
PFMEA/CP & 8-D PS	AB	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
PFMEA/CP & Containment	AC	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000
8-D PS & Containment	BC	0.4685	0.2512	0.6299	1.0000	0.9510	1.0000
Attended all 3 Trg. Events	ABC	0.0000	0.0000	0.0000	0.9045	0.9027	1.0000

Table 5.13 – Significance Results for PPM & 3MIS Data, N=500

Summary of Simulation Runs for each Data Combination		Significant YES or NO					
		PPM T-Test	PPM Sign Result	PPM Wilcoxon Result	3MIS T-Test	3MIS Sign Result	3MIS Wilcoxon Result
Data Set Description	Code						
PFMEA/CP (only)	A	Yes	Yes	Yes	Yes	Yes	Yes
8-D Problem Solving	B	Yes	Yes	Yes	Yes	Yes	Yes
Containment	C	Yes	Yes	Yes	No	No	No
PFMEA/CP & 8-D PS	AB	Yes	Yes	Yes	Yes	Yes	Yes
PFMEA/CP & Containment	AC	Yes	Yes	Yes	Yes	Yes	Yes
8-D PS & Containment	BC	No	No	No	No	No	No
Attended all 3 Trg. Events	ABC	Yes	Yes	Yes	No	No	No

mean and larger standard deviation (-26.13, 330.40). Finally, group C for 3MIS also had a similar negative mean compared to B, but with a smaller standard deviation (-10.19, 97.42).

It is not surprising these combinations failed to deliver a useful correlation (a normal data profile based on these values is highly likely to create a mean less than or equal to zero so the researcher cannot reject null in these cases; therefore $H_0 \leq 0$). Additionally, groups ABC, BC, and C also had small sample sizes (C = 10 and BC = 7 and for 3MIS; BC = 9 for PPM) and ABC was also small equaling 27 for 3MIS. Sample size along with mean and standard deviation caused these negative correlations. The negative or near zero means are the biggest contributor to this effect. More actual data will be needed for these combinations to determine their true effect.

Information gained from this simulation run did provide some insight into the four sample combinations with insufficient data and also helped resolve an issue with one of the larger samples of actual data that produced borderline results in the original review. Of the four combinations with insufficient sample size (B, C, AC, and BC), combination “BC” failed to correlate to improved defect rate for either PPM or 3MIS in the original data. The same result existed for “C” and “ABC” combinations in 3MIS data as well.

The rest showed positive correlations – most of the combinations indicate significant correlations to lower defect rates for the supplier for both PPM (six of the seven combinations) and for 3MIS (four of the seven combinations). Noteworthy in this data are combinations that are longer running in terms of class launch. Also, noteworthy, is the fact 3MIS data lags producer data by 15 – 17 months so this may be an additional reason

for the non-correlations in 3MIS data. This was not accounted for in the initial research design.

The combination of “BC” for PPM data is the lone outlier to these combinations with a negative correlation. Interestingly, this combination has also had the shortest time for implementation compared to the others and with less data. Combinations of “AB,” “ABC,” and “AC” have in common the PFMEA / CP class (A) that is the longest running class. This does not, however explain the shortest running class “C” and the positive correlation of PPM data and the negative correlation for the 3MIS data. PPM data for group C did however have a positive mean relative to the negative mean in the 3MIS data. This is at least part of the explanation for the difference.

Another possibility is the time lag difference mentioned earlier. The explanation may lie in the fact that the data collected on defect rates at the assembly plant is immediate – if there is a defect, the supplier knows within twenty-four hours there is a problem and must work to correct it whereas 3MIS data takes much longer to see in terms of the results. This may explain why there are more negative correlations in the 3MIS data – an insufficient amount of time has elapsed for the information to be generated – accounting for an additional 15 to 17 months elapsed time before the 3MIS data is averaged may produce similar results for the PPM data.

For the 3MIS data that had positive results, they have a common element. They are in combination with “A” (the longest running class) which adds an extra year back to the time window or B (second longest running class). If the defect rates are down at the

supplier site, the producer may start to see results late in calendar year 2018 or early 2019 – past the time window of this Case Study.

In summary, the simulated data provided insights into the results that would otherwise have not been known to the researcher. From these results, it can be concluded that time plays an important part as to when to assess reductions. The 3MIS analysis becomes more difficult to assess as it depends a great deal on sales and marketing in terms of how fast vehicles move off dealers' car lots. In fact, the better indicator may simply be correlations between PPM rates and supplier training while ignoring 3MIS data because it removes the additional time lag from consideration. If these numbers are low and remain that way, the producer should expect declines sometime in the future for the 3MIS data after the vehicle is purchased by its owner.

Simulation Study for Determination of “Best Combinations”

The question of whether there were better classes or class combinations than others was also investigated with a second data simulation. To improve the precision of the result and provide sufficient sample size to narrow the confidence interval of the data, a simulation of size 1,000 was run. The simulation started with the same means and standard deviation for each combination as for the 500 data point simulation. Mathematically, it just took a little longer on computer computation time.

Combinations with higher differences in means and median were found in the data - they are shown below. The researcher ran two tests – the Welch ANOVA (Analysis of Variance) and One-Way ANOVA test on the data. The Welch ANOVA gave results on both the mean and median with confidence intervals for each combination and the one-

way ANOVA gave results on just the mean with confidence intervals. Again, all three results (Welch ANOVA for mean and the One-Way ANOVA for mean provided the same information in terms of combinations that were providing better results. (Figures 5.5 through 5.10) (next two pages) provide the results of the ANOVA studies.

As can be seen in the graphs, each class of data (PPM and 3MIS) have at least two groups that provide a better result in terms of larger defect reductions. It is important to note that each class of data (PPM and 3MIS) are different but with a result that points to time-related outcomes. (Figures 5.5, 5.7, and 5.9) (PPM data) all provide two groups that are above the rest in terms of performance with defect reductions (AC & B) for PPM.

The One-Way ANOVA for the PPM data failed to produce as much separation for “AC” as did the Welch ANOVA test, but the graph still shows a significant piece of the confidence interval above the others, so it was included as a desirable combination. (Figures 5.6, 5.8, and 5.10) (3MIS data) also provided two groups that are above the rest in terms of performance with greater defect reductions (AB & B). Considering the results, they both (PPM & 3MIS) have the common class of 8-D Problem Solving (B) and they have one common element of PFMEA (A) in the double class combination (AB & AC). This result infers the two longer running programs are having the largest impact on improvement (reductions) for defect rates found at the assembly plant and for defect rates after the car is sold – 3MIS.

This is not surprising; the effect the manufacturer is looking for does not appear instantaneously but occurs over time – crossing three or more years. Mentioned earlier,

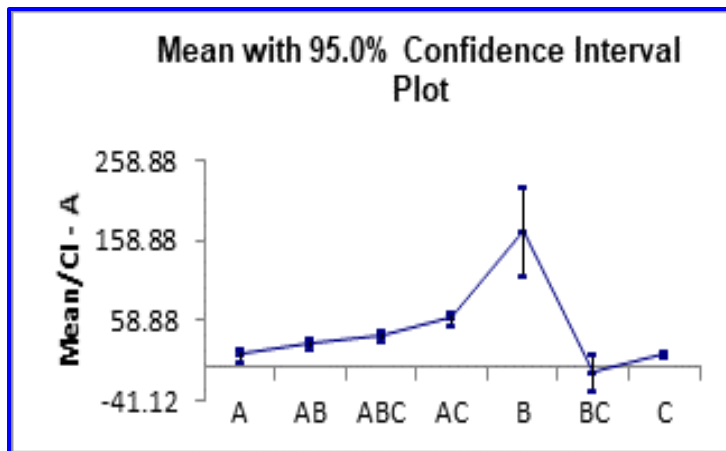


Figure 5.5 – PPM (Welch ANOVA)

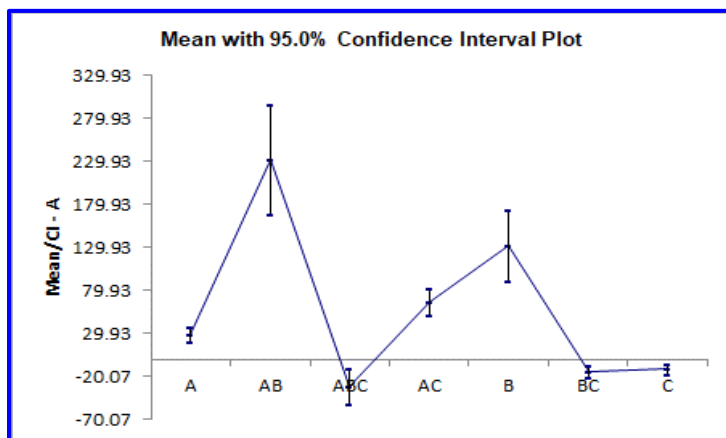


Figure 5.6 – 3MIS (Welch ANOVA)

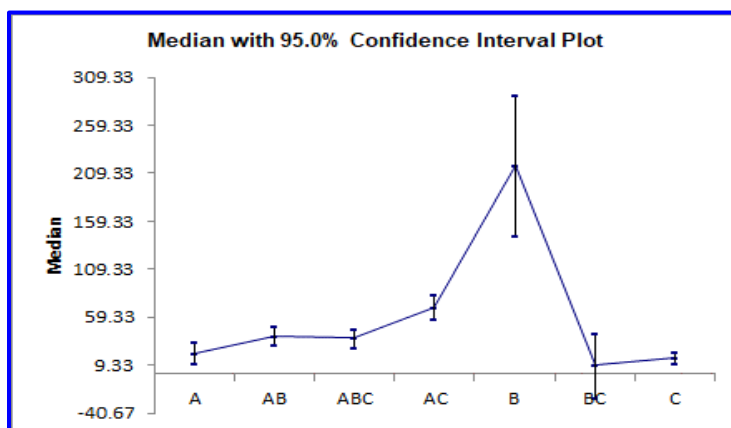


Figure 5.7 – PPM (Welch ANOVA)

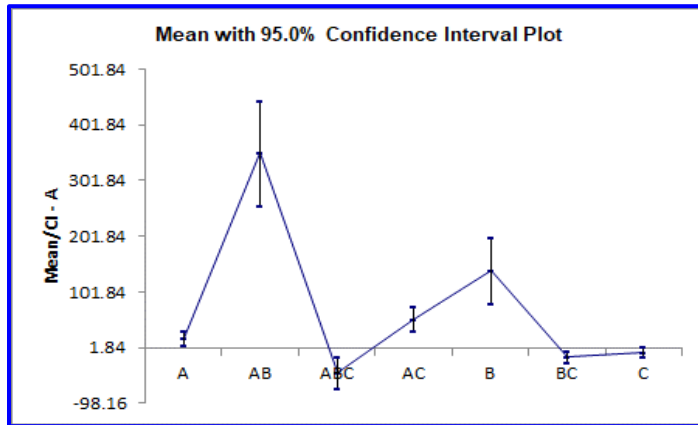


Figure 5.8 – 3MIS (Welch ANOVA)

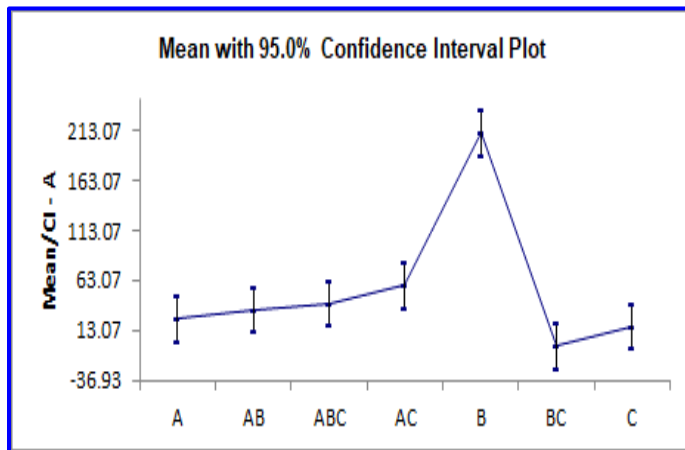


Figure 5.9 – PPM (1-Way ANOVA)

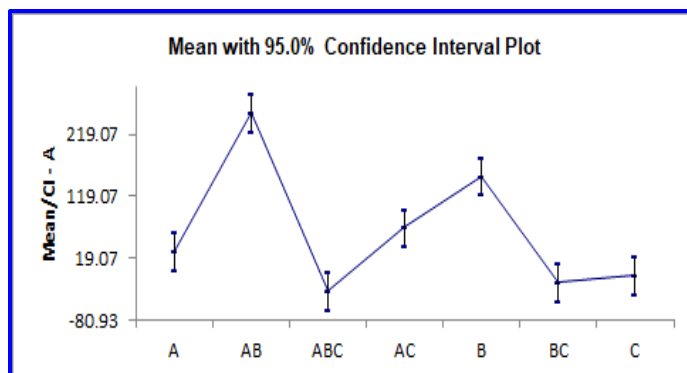


Figure 5.10 – 3MIS (1-Way- ANOVA)

change in any organization is as much about training and learning as it is about the will to change and move to a different level of understanding. The data tells the researcher that some organizations have been unwilling to change (a relative minority). Still others appear to have changed (the majority). Making a “culture shift” would be a more appropriate descriptor. Suppliers and the OEM must view slow-change as part of this long-term objective. This change is a transformation leading to lower defects in future years. The transition is already visible statistically.

Review of the Results of the Original Data

The original data is presented last rather than first because it was the least revealing. There is evidence in the actual data of correlations between defect reductions and the supplier related training events that have been conducted across this span of time (2013 to 2017). However, four of the original combinations failed to show any correlation due to their sample size.

The remaining three combinations provided another line of thought for investigation during the data simulations for the larger samples. If the simulated data was the same for the original large samples as the simulated data, inference can be made relative to the small sample results discussed earlier. In other words, if the simulation for the larger samples agreed with the original data analysis, it is acceptable to infer the correlations yielded by the small sample simulation were significantly different as compared to the original data analysis. The results of these tests on original data are show in (Tables 5.14 and 5.15) for PPM and 3MIS data.

Table 5.14 – p-Values; T-Test, Sign & WRS Studies – Original Data

p-values for Tests	PPM	PPM	PPM	3MIS	3MIS	3MIS
Data Set Description	T-test Result	Sign Result	Wilcoxon Result	T-test Result	Sign Result	Wilcoxon Result
PFMEA/CP	0.1454	0.6563	0.2008	0.1521	0.3633	0.2206
8-D PS & Containment	0.1960	0.2539	0.3178	0.2495	0.2266	0.1763
Containment	0.3884	0.6367	0.4168	0.1136	0.6230	0.3417
8-D Problem Solving	0.1960	0.3877	0.5468	0.2495	0.5958	0.3525
PFMEA/CP	0.1151	0.0416	0.0524	0.0559	0.0013	0.0053
PFMEA/CP & 8-D PS	0.0314	0.5000	0.1130	0.1485	0.1002	0.0385
Attended all Three	0.0267	0.0378	0.0347	0.2860	0.0610	0.0714
All Suppliers with 2 of 3 Training Events	0.0275	0.3179	0.0465	0.0922	0.0362	0.0135
All Suppliers with 1 of 3 Training Events	0.1890	0.2329	0.1192	0.0320	0.0083	0.0107
All Training in Any Combination	0.0080	0.0450	0.0040	0.0140	0.0003	0.0172

Table 5.15 – Indicators for t-test, Sign and WRS – Original Data

p-values for Tests	PPM	PPM	PPM	3MIS	3MIS	3MIS		PPM	3MIS
Data Set Description	T-test Result	Sign Result	Wilcoxon Result	T-test Result	Sign Result	Wilcoxon Result		Finding	Finding
PFMEA/CP	No	No	No	No	No	No		SSTS	SSTS
8-D PS & Containment	No	No	No	No	No	No		SSTS	SSTS
Containment	No	No	No	No	No	No		SSTS	SSTS
8-D Problem Solving	No	No	No	No	No	No		SSTS	SSTS
PFMEA/CP	No	Yes	BL	BL	Yes	Yes		Yes =1	Yes = 1
PFMEA/CP & 8-D PS	Yes	No	No	No	No	Yes		Yes =1	Yes =1
Attended all Three	Yes	Yes	Yes	No	No	No		Yes =3	No
All Suppliers with 2 of 3 Training Events	Yes	No	Yes	No	Yes	Yes		Yes =2	Yes =2
All Suppliers with 1 of 3 Training Events	No	No	No	Yes	Yes	Yes		No	Yes =3
All Training in Any Combination	Yes	Yes	Yes	Yes	Yes	Yes		Yes =3	Yes =3

The same three test (Student-t, Sign, and Wilcoxon Rank-Sign tests) were run on the data after an attempt to normalize the data so the Student-t distribution could be used. The normalization improved the result of the student-t distribution and did not impact the other two tests as they are nonparametric tests and are not affected by distribution normality. Note these studies are one-tailed significance test where the null hypothesis is that the mean or median is equal or less than zero and the alternate hypothesis is that the mean or the median is greater than zero.

Recall from the earlier discussion the median value is a better indicator for skewed left or skewed right data than the mean. The seven combinations are the same seven that were under consideration in all the previous sections of this chapter (A, B, C, AB, AC, BC, & ABC). In the initial effort to see correlations, over half the data was not expected to yield a usable result. Consequently, the researcher looked at other data combinations to see whether other groupings yielded any significant results. The researcher looked at three additional groupings shown below the horizontal orange line in the figures:

- 1) The data block of suppliers with double classes (AB, AC, or BC) taken.
- 2) The data block of suppliers with just single classes (A, B, or C) taken.
- 3) The entire data block (all 148 suppliers) as a single group.

These combinations produced correlations as well but are not included as part of the data simulations which considered just the original seven combinations. They also are not reported as part of the conclusions. Upon review of the larger groups (all singles, all doubles, and the whole data base) – only suppliers taking a single class for the supplier PPM data failed to produce a positive correlation. One of the conclusions from this effort with the larger combinations of data was larger samples tend to produce results inferring

positive correlations. This was confirmed in the 500-sample data simulation providing information that inferred correlation on six of seven PPM and four of seven for the 3MIS groupings.

Mentioned earlier, four combinations failed to show any correlation with reductions for either the PPM or the 3MIS PPM data (B, C, AC, and BC). Of the remainder (A, AB, and ABC), there were mixed results. There were some correlations, with one, two or three of the tests showing positive results. In a few cases, results in (Table 5.14) were borderline with the p-values just barely over 0.0500. These appear in (Table 5.15) as borderline (BL) – highlighted in yellow.

In (Table 5.14), there are an equal number of negative to positive correlations (8 to 8) – counting the other two values 0.0610 and 0.0714 as too high to label as borderline and marked negative. The initial strategy was to use any of the three-test showing a positive correlation as reason to infer a connection between training and defect reduction. If this premise is used, the combination “ABC” for 3MIS data showed a negative correlation as shown in (Table 5.16).

Using the data for the 500-run simulation, the results of both analyses can now be compared. In the original data, the reader can see no correlation in (Table 5.16) for B, C, AC, and BC but in the simulated run five of the eight for PPM and 3MIS show a correlated result. In the larger samples for the A, AB, and ABC we see the correlations to be the same with the original data showing fewer correlations with for the three tests. Exclusive of the four groupings with insufficient data size, the conclusions from the review of tests on the actual data are there are correlations between training and defect reduction on

Table 5.16 – Comparison of Actual Data Run against Simulated Data Run

Comparison Study		Original Data		Simulated Data	
		PPM	3MIS	PPM	3MIS
Data Set Description	Code	Finding	Finding	Finding	Finding
8-D Problem Solving	B	No = 3	No = 3	Yes = 3	Yes = 3
Containment	C	No = 3	No = 3	Yes = 3	No = 3
PFMEA/CP & Containment	AC	No = 3	No = 3	Yes = 3	Yes = 3
8-D PS & Containment	BC	No = 3	No = 3	No = 3	No = 3
PFMEA/CP	A	Yes = 1	Yes = 2	Yes = 3	Yes = 3
PFMEA/CP & 8-D PS	AB	Yes = 1	Yes = 1	Yes = 3	Yes = 3
Attended all 3 Events	ABC	Yes = 3	No = 3	Yes = 3	No = 3

three of the three combinations – PPM data (A, AB, and ABC) and for two of the three combinations for 3MIS data (A, AB, and ABC). Only the combination of ABC for 3MIS data showed a negative correlation of the three combinations which has already been explained in an earlier section.

Comparing Actual to Simulated Data

A comparison was made between the groupings with small sample sizes (four) and the larger samples (three) for the combinations of A, B, C, AB, AC, BC, and ABC. The results are shown in Table 5.16 above. The first four on the left were the sample groupings in the original data that were too small. Data simulation expanded their size and allowed an inference of a positive correlation for three of four for PPM supplier data and two of four for the 3MIS data. For the larger samples – both the actual and simulated data agreed.

Conclusions reached from this comparison are that if the three larger samples (A, AB, and ABC) agree with each other, then it is not a stretch in the mathematical sense to infer the four combinations with insufficient sample size producing a different result for the simulated run can be accepted as a positive correlation as well.

The researcher can now infer that of the seven PPM combinations and the seven 3MIS combinations, 71.4% (10 of 14) of the training combinations produced a favorable result in the reduction of supplier defects either onsite or three months after the car was sold to the customer. These results agree well with the earlier high-level look at the data indicating 7 in 10 had implemented the training and education.

Of the four smaller samples, the ones showing the negative correlations are also the ones having the later class launch dates and having starting means for the simulations that were negative or very close to zero. C also has the least amount of time since launch and the combination BC as well with the B portion of the combination only being older by one year. The reason behind why C has a positive correlation for PPM data and for 3MIS has a negative correlation was explored. This grouping was also of a small sample size in the original data. For both the PPM and 3MIS groupings, 3MIS data had a negative mean but with a standard deviation within 30 points of the PPM data but PPM data had a positive mean. For data simulation, this can account for why the positive correlation shows up for OEM site defects (PPM) and a negative correlation occurred for the 3MIS data.

It is the only group and class in the fourteen that was different. If time since development and launch has a significant connection to the data results, this also likely impacts the results. This combination should be revisited as the database grows.

DOE Experiment - Actual Case Study Results

The DOE testing of the original data produced one significant result for both the PPM data and the 3MIS data. Class “A” (PFMEA / CP) shown in Tables 5.17 and 5.18 below for the DOE results showed a significant correlation between the class and defect reductions at the assembly plant (PPM) and after the vehicle was in service (3MIS). The observed statistic (4.344 and 14.094 respectively), in both cases, exceeded the critical F-statistic value (4.080). Consequently, there is enough evidence to infer Class A is having a significant impact on defect reduction in both instances (PPM & 3MIS data). No additional significant correlations were noted in the DOE study.

Note: The DOE with 6 replicates (two level full factorial) has an assumption in the data that was discussed briefly in Chapter 4. Not anticipating a DOE analysis of data, the researcher did not ask nor look for data on similar suppliers that took no classes. A discussion with the creator of the OEM database (Mr. J. Graves) indicated this would be time consuming and difficult to go back and generate so an alternative was needed for the negative values (see Table 4.9) of A, B, and C – that is, no classes taken.

The basic assumption here was many of the suppliers had been requested to attend these classes because their supplier ratings were poor. Said differently, this is an indication their performance results on defects were rising as opposed to declining. Therefore, the matched pair differences would be negative rather than positive. A decision to randomly sample negative findings for matched pair differences (non-implementers) would be the same as not taking a class. Consequently, this is a significant underlying assumption for the DOE generators for AB, AC, BC, and ABC.

Table 5.17 – DOE Assessment of PPM Original Data

Parameter	SS	d.f.	MS	Fo	Fc	Significant
A	205125	1	205125	5.541	4.08	Yes
B	9	1	9	0.000	4.08	No
AB	12332	1	12332	0.333	4.08	No
C	64478	1	64478	1.742	4.08	No
AC	5026	1	5026	0.136	4.08	No
BC	1994	1	1994	0.054	4.08	No
ABC	68533	1	68533	1.851	4.08	No
Error	1480875	40	37022			
Total	1838373	47				

Table 5.18 – DOE Assessment of 3MIS Original Data

Parameter	SS	d.f.	MS	Fo	Fc	Significant
A	639596	1	639596	17.276	4.08	Yes
B	3611	1	3611	0.098	4.08	No
AB	21338	1	21338	0.576	4.08	No
C	115398	1	115398	3.117	4.08	No
AC	3714	1	3714	0.100	4.08	No
BC	13751	1	13751	0.371	4.08	No
ABC	4501	1	4501	0.122	4.08	No
Error	463419	40	11585			
Total	1265326	47				

Kirkpatrick Model, Level I and Level II Results

Class performance metrics have been consistently good for classes spanning the training period from 2013 to 2017 and beyond. At the end of each class, the students are asked to provide a class assessment (evaluation). The evaluation does not require a student's name so the evaluation is anonymous, and individuals can be candid about the class and usually are. Only one class is shown as part of this dissertation, but the information provided by this class is nominal for results throughout the entirety of supplier training.

The student evaluation is completed on a scale of 1 to 5 (Likert scale with 5 being excellent, 4 being good to above average, 3 being average, 2 being below average and 1 being unsatisfactory. It's extremely common to see the evaluations for a specific evaluation category to be 90% or greater for four's and five's (above average to excellent). These results are shown in (Figure 5.11 through 5.16). The Likert score is calculated for each graph with the exception of student comments. Scores of 4.5, 4.6, 4.7, 4.6, and 4.6, respectively, were obtained with an average overall rating of 4.6. The number of students submitting evaluations for this class was 48.

Test Scores can also be found in (Figures 5.17 & 5.18). Norms for the before and after test scores have routinely been in the high 60's to low 70's and low to mid 90's, respectively since the inception of the training efforts by UT CIS. It is also not uncommon for students to score 100% of the final test. This provides an excellent indication the material was understood and learned. Outliers, as seen in the boxplot (Figure 5.18) are those students having no experience with the subject matter before class; however, all passed the course after the material was delivered and the final was taken so a significant increase in understanding for those not schooled in the subject matter.

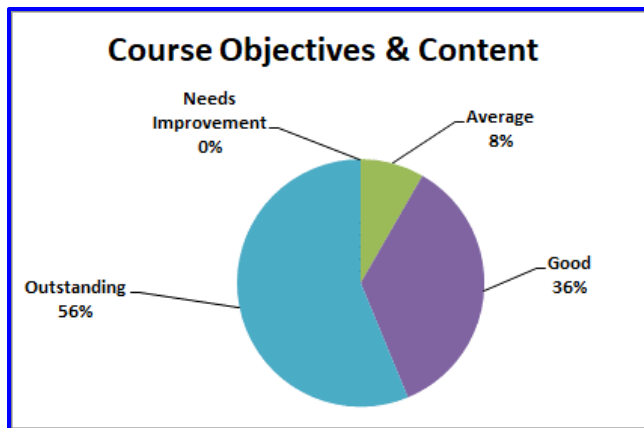


Figure 5.11 – Course Objectives & Content

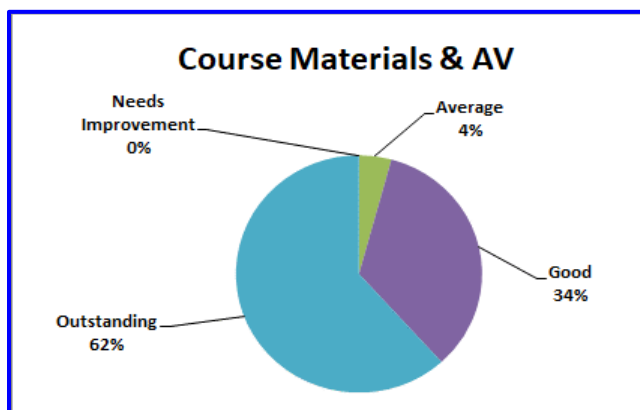


Figure 5.12 – Course Materials & AV

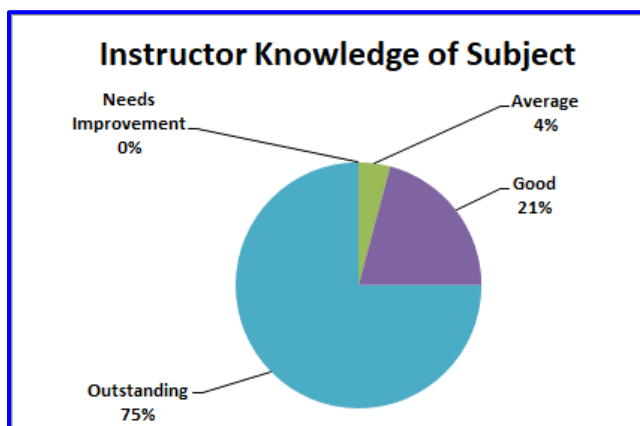


Figure 5.13 – Instructor Knowledge

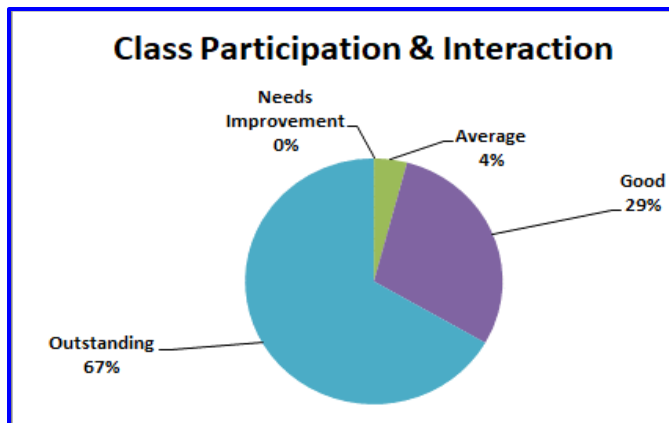


Figure 5.14 – Class Participation

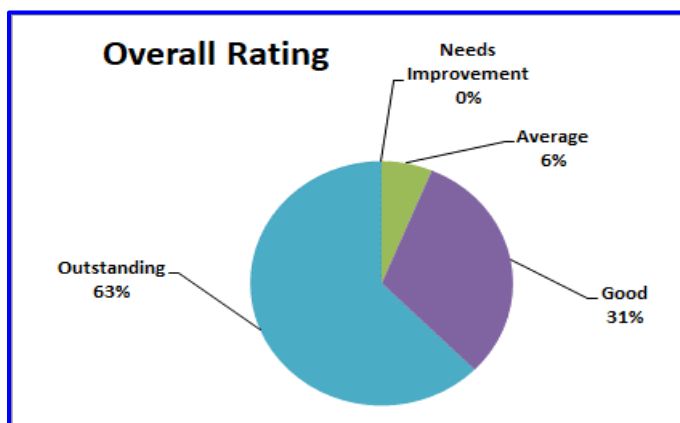


Figure 5.15 – Overall Rating

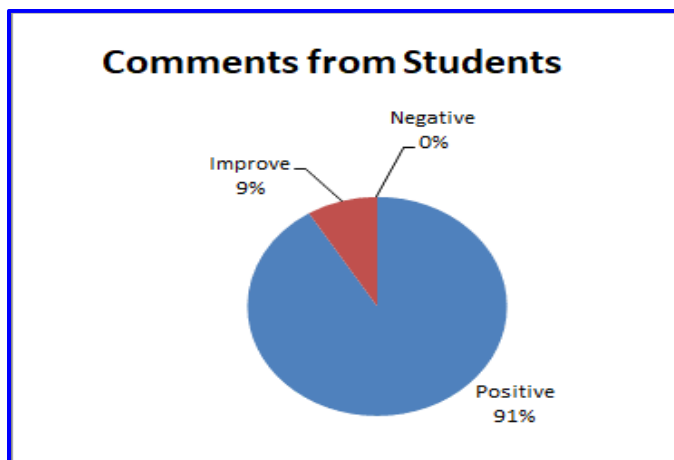


Figure 5.16 – Student Comments

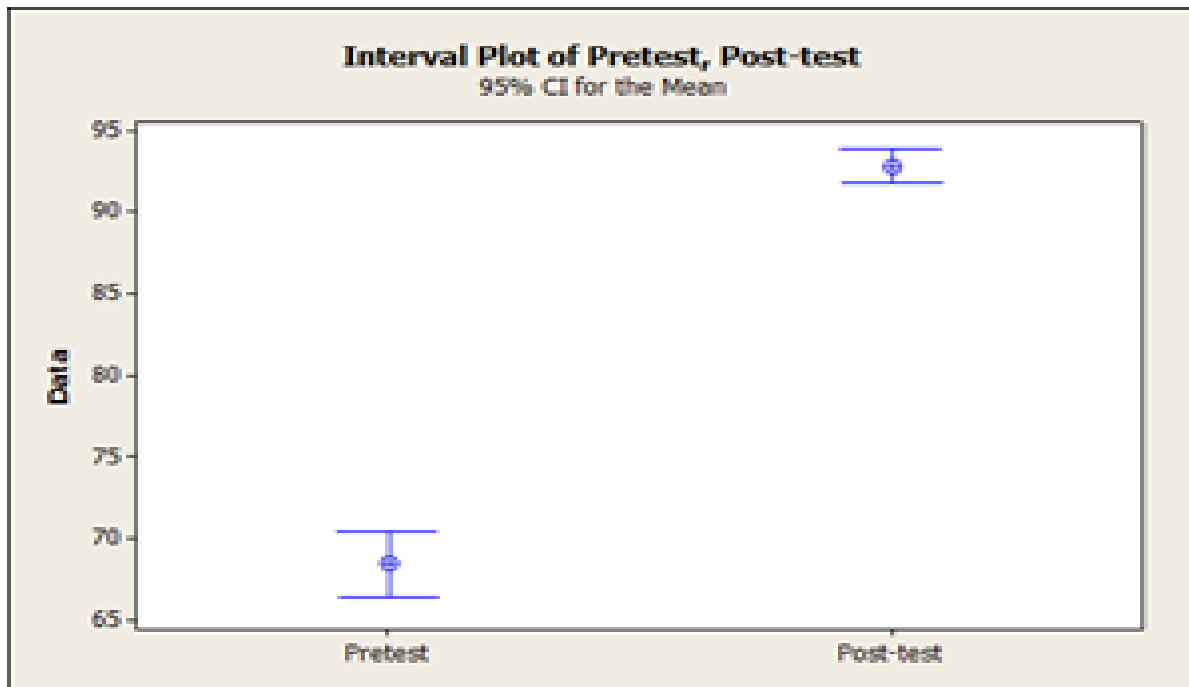


Figure 5.17 – Test Scores Before and After Class

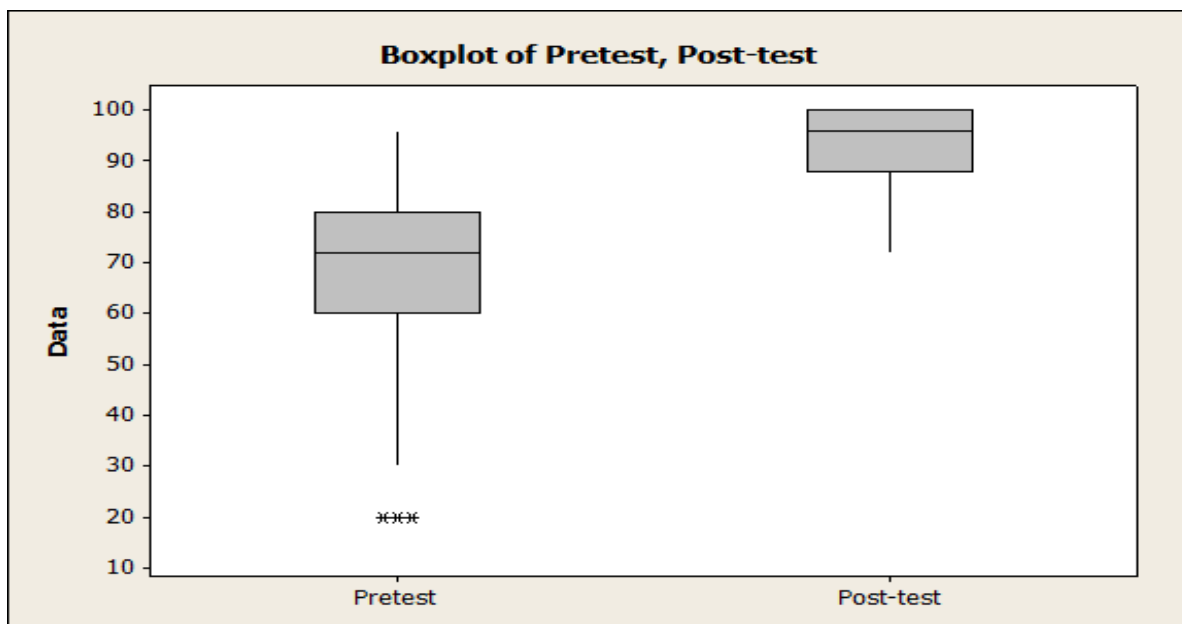


Figure 5.18 – Boxplot of Test Scores from Figure 5.17

Summary

Based on the cumulative results of these research studies, the researcher is confident the data analysis has shown a significant correlation between training and defect rate reduction at the assembly plant (PPM) and after the vehicle is sold to the customer (3MIS) for the 148 suppliers contained in the data set. This change on the part of the suppliers represents a significant culture shift away from their past “reactive” posture and towards a more “proactive” stance in quality. The long-range OEM goal is being realized.

For those suppliers not showing improvements, further work between OEM and supplier is needed to understand the implementation barriers standing in the way of what they learned. A probable cause was postulated in the body of this document but not verified. Data from the classroom indicates the material was understood by the supplier. However, lack of implementation is not necessarily the fault of the student.

This failure should be directed towards each supplier’s corporate management. Either they decided on a conscious level not to implement the classroom materials or they lacked implementation resources. In either case, this was a supplier management decision and a significant concern for the OEM.

CHAPTER 6. CONCLUSIONS

- 1) The encryption process used by the OEM to maintain data security for its organization does not impact the results and outcomes of the research study. The data encryption process can be reversed, and the original data returned to its actual values if the encryption algorithm values (M and b) are known.
- 2) Data simulation of the three larger sample combinations agree with the statistical study of the original data analysis so the four small sample simulation results can be accepted as a valid inference of correlations to defect reductions even though the original data analysis did not indicate a correlation.
- 3) There is statistical evidence inferring six of seven combinations (exclusive of classes coded BC) are having a positive correlation on defect reductions discovered for the assembly plants (PPM level) – that is, the results of the supplier development training reduced defects the OEM received directly from these 148 suppliers studied. These findings were discussed in detail in the previous chapter, Chapter 5.
- 4) There is statistical evidence inferring that of the seven combinations, four have shown positive correlation (exclusive of classes coded C, BC, and ABC) and are having a positive impact on defect reductions after the vehicle is sold to the customer (3-MIS) – that is, the results of the supplier development training reduced OEM 3MIS defects from the 148 suppliers studied. Likewise, detailed findings were discussed in Chapter 5.
- 5) The longer running classes (PFMEA and 8-D – Class A & B respectively) are providing better performance results than containment. Containment (Class C) is the shortest running class and, with the added time lag of 3MIS data (15–17 months or more till sold), shows poorer performance compared to PFMEA & 8-D.

- 6) There is mathematical evidence that 70 to 80% of the suppliers taking the training classes are implementing what they learned over the course of time and that the majority of them are deploying the OEM's developmental training.
- 7) The best combinations for performance are classes involving PFMEA and 8-D (A and B) leading to an indication that development training is highly time-related. This does not mean the Containment training class does not belong as part of the developmental training. The implication is simply the shortest running of the three classes has yet to produce any statistical evidence of correlation.
- 8) The DOE (6 random replicates) taken from the original data showed a positive data correlation for Class A (PFMEA & CP) compared to defect reductions found at the OEM and with defects after the vehicle is in service (3MIS). None of the other combinations showed a positive correlation. Note: the correlation assumes the suppliers with defects trending upward or on the rise rather than in decline correlates to no classes taken (no data was collected for companies before the training initiative was implemented by the OEM – see Chapter 5 explanation).

CHAPTER 7. FUTURE STUDIES & RECOMMENDATIONS

- 1) The reason underlying why the 20 to 30% of supplier non-implementers have failed to implement their training is unknown and should be explored as part of the future work for the OEM quality team members. The most likely cause as to why it is not implemented is the shop “cultural environment.” However, this theory has not been verified or validated.
- 2) A follow-up survey of all suppliers taking the developmental training should be considered to gauge the level of implementation for each supplier relative to the classes that their plant participated in. This would also create a sense of urgency the OEM places on developmental training and reinforce the need for more extensive implementation.
- 3) It would be an interesting exercise to compare supplier overall scorecard scores with those suppliers not implementing training. This suggested exercise was never an objective of the original research, but the hypothesis might be (Ho: non-implementers = high scores) with the alternative (Ha: non-implementers = low scores) with the OEM determining the acceptable lower bound for the high score before it is started and how the overall score is viewed over time. There is very likely a correlation between the two. This type of control (low scores) could be used as a supplier mandate for completion of these courses and other future classes or, if serious enough, for removing the supplier from the supply chain.
- 4) The researcher sees no reason why future assessments cannot include multi-part providers (suppliers). Each part provided should be a stand-alone assessment and treated the same as the single part provider. It would be a measure of horizontal deployment at the factory level. Results if implemented should, over time, be similar.

- 5) There are indications that treating 3MIS data the same way the assembly plant defect data was treated was an incorrect choice in initial planning. The PPM data and the 3MIS PPM data are offset by as much as a year or more. There is an additional time lag to vehicle sales after production and this should have been accounted for and should be included in the next iteration of this analysis.
- 6) The longer running classes tend to show a correlation suggesting longer planning horizons are needed to see these correlation effects. The shorter the class training window, the greater the evidence of non-correlation.
- 7) The fact that student numbers taking the Containment class are far fewer compared to those that participated in the PFMEA and 8-D classes provides one plausible reason as to why there may be a lack of correlation evidence. This should be revisited later as the student numbers taking this class grows in order to determine if it too provides a meaningful correlation in defect reduction results.
- 8) As a year has elapsed since the beginning of this statistical analysis, the assembly plant may just be starting to see defect reductions from suppliers taking the Containment training. This should be verified at some point.
- 9) Future studies of this nature should ignore the “b” add-on to the encryption algorithm for matched-pair data sets as it eliminates itself in the subtraction process to obtain the matched-pair difference. This was an unanticipated twist in the data during the analytical steps and the fault of the researcher for not seeing it ahead of time.

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APPENDIX

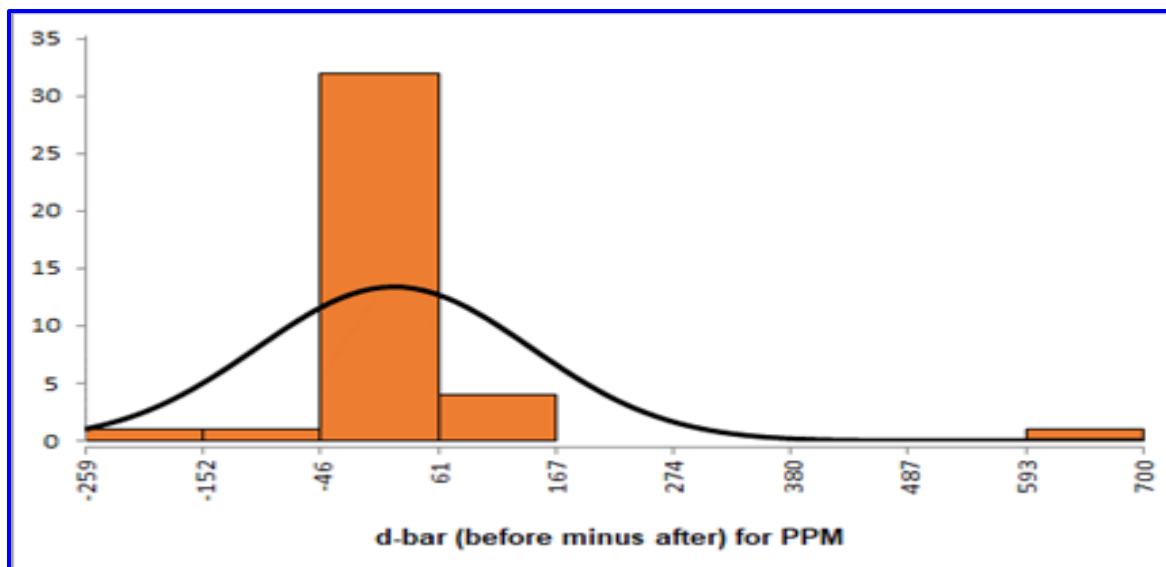


Figure AF-5.1 – PPM – Histogram for “A” – Original Data – Nonparametric

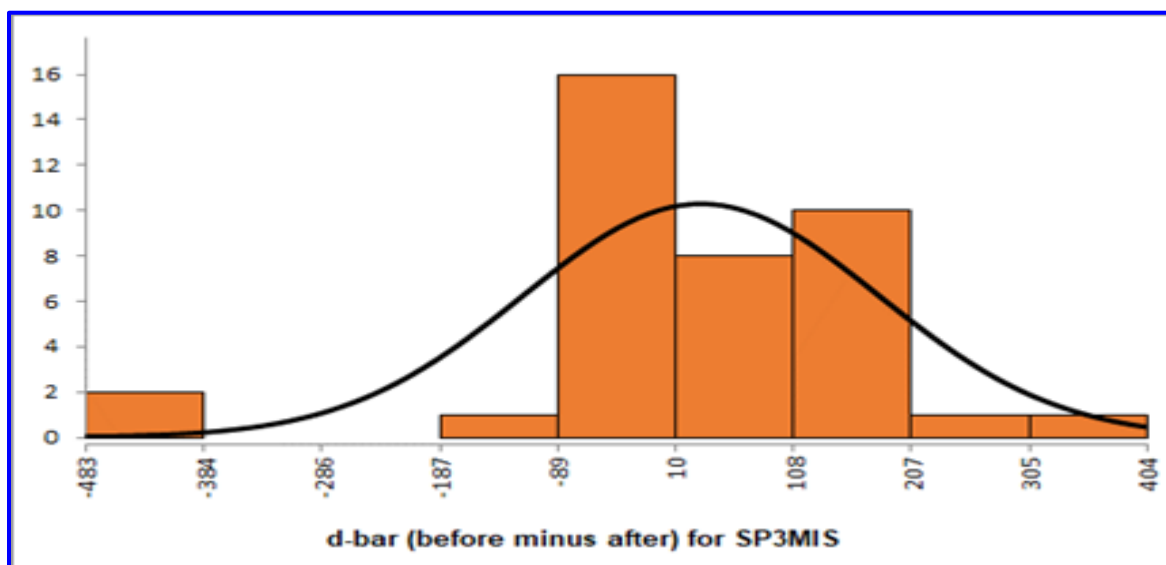


Figure AF-5.2 – 3MIS – Histogram for “A” – Original Data – Nonparametric

Note: For Statistical Normality Plots, see AF-5.22 & 5.23

Normalization Attempts for Original Data

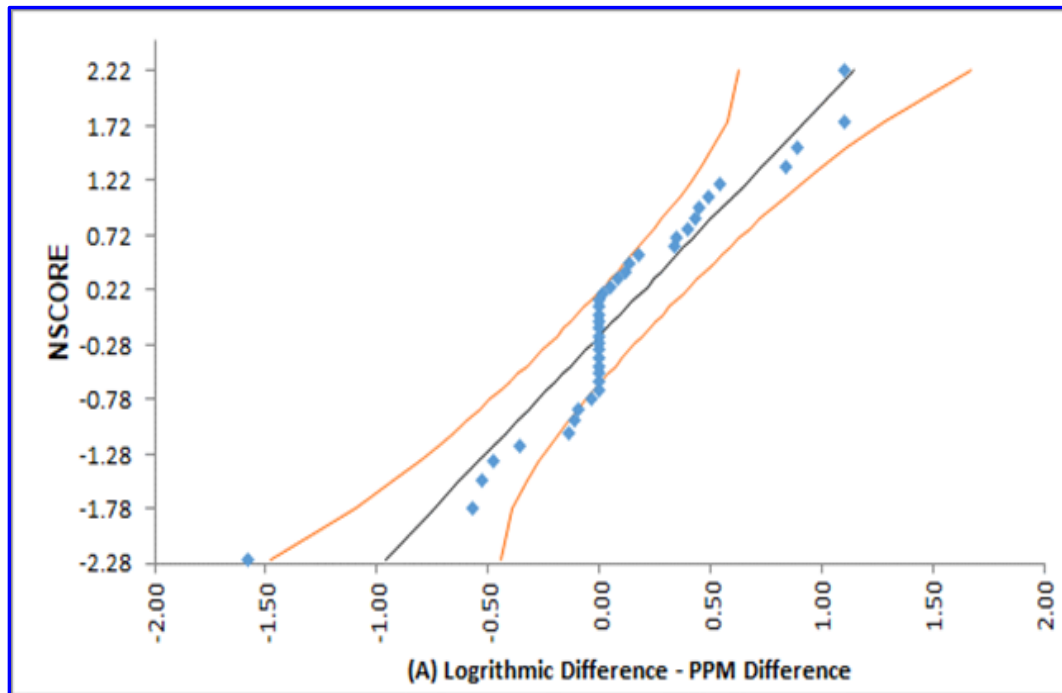


Figure AF-5.3 – PPM – Combo “A”

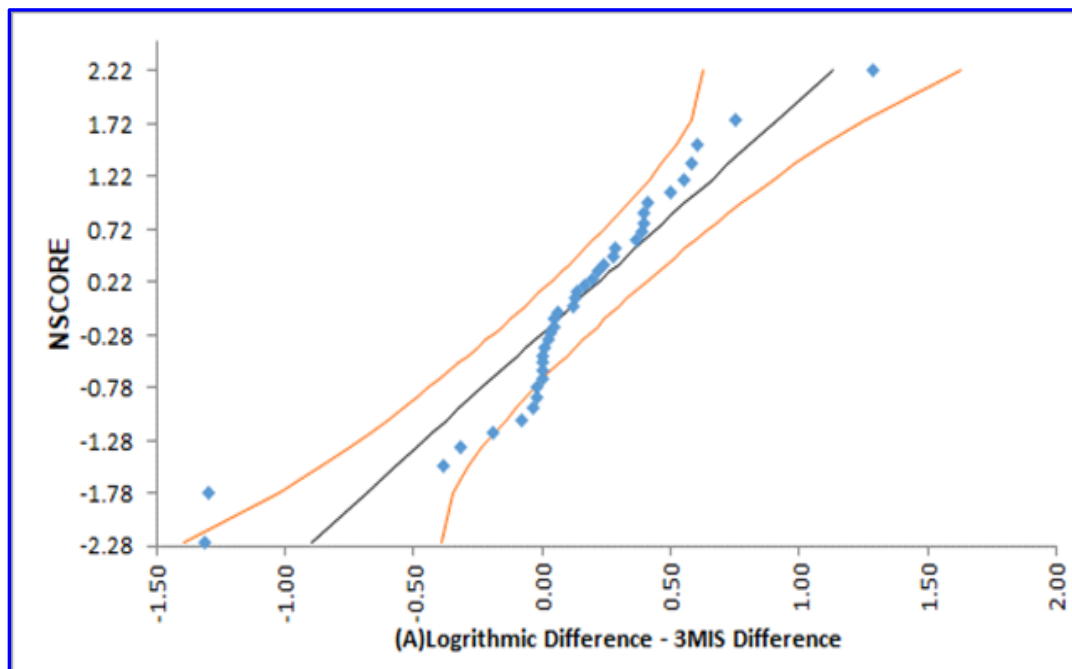


Figure AF-5.4 – 3MIS – Combo “A”

Normalization Attempts for Original Data (CONTINUED)

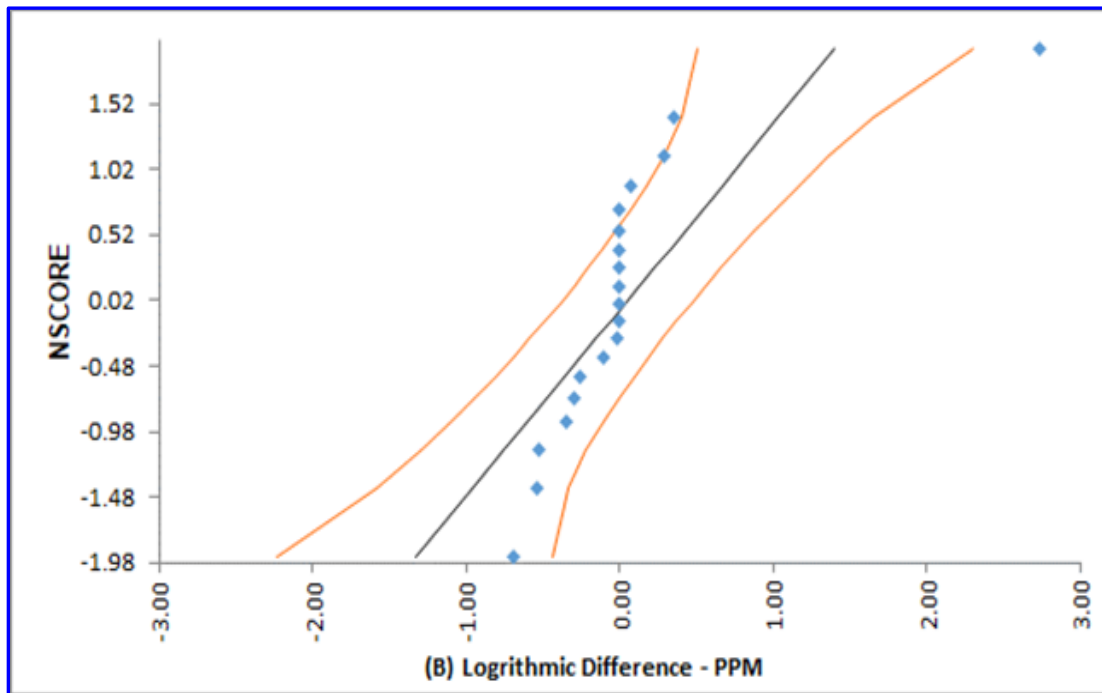


Figure AF-5.5 – PPM – Combo “B”

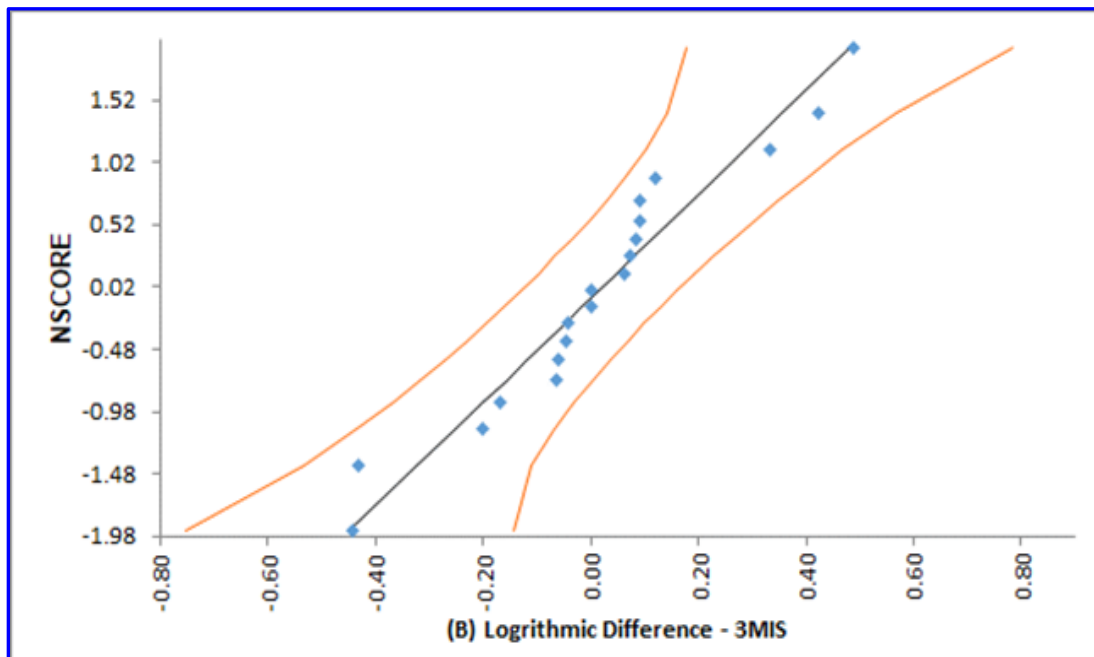


Figure AF-5.6 – 3MIS – Combo “B”

Normalization Attempts for Original Data (CONTINUED)

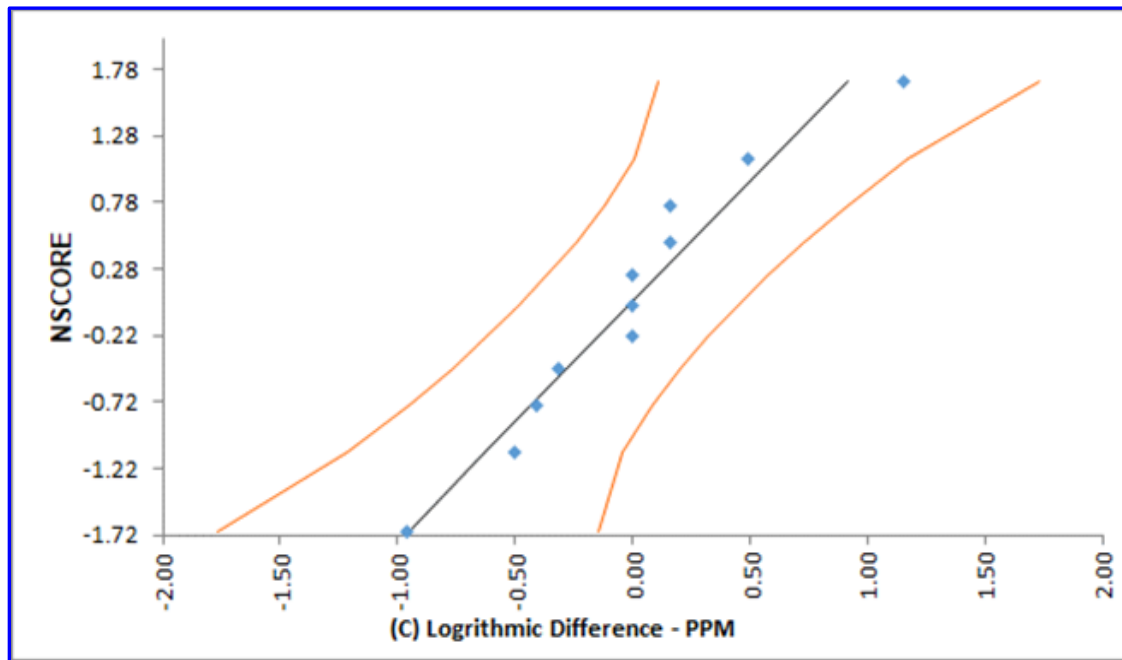


Figure AF-5.7 – PPM – Combo “C”

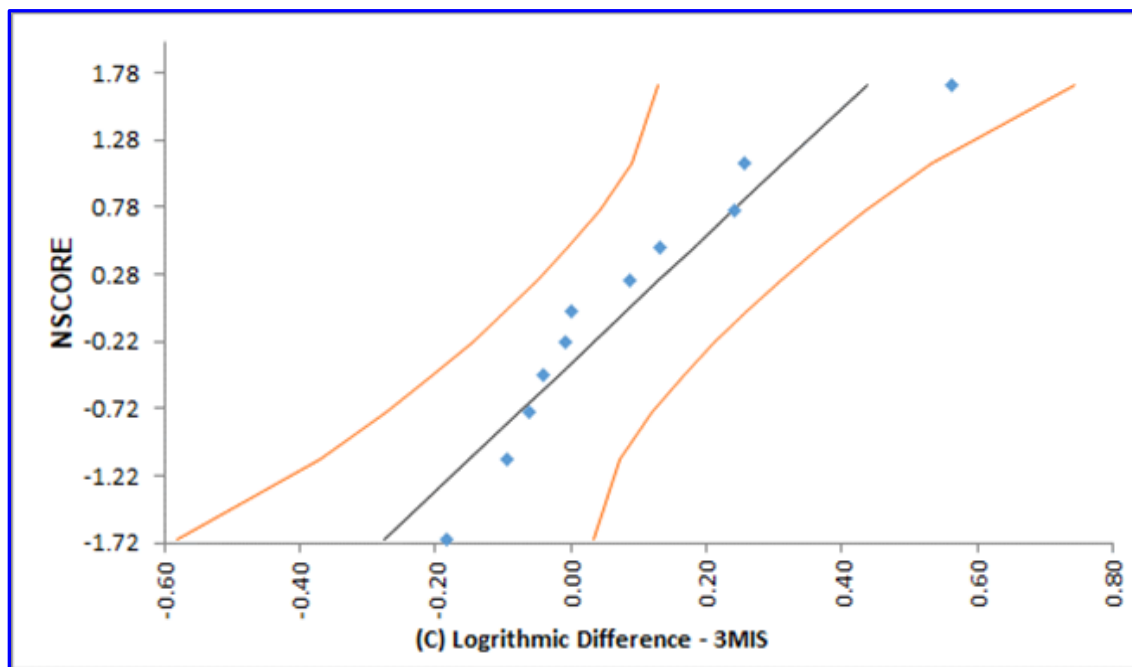


Figure AF-5.8 – 3MIS – Combo “C”

Normalization Attempts for Original Data (CONTINUED)

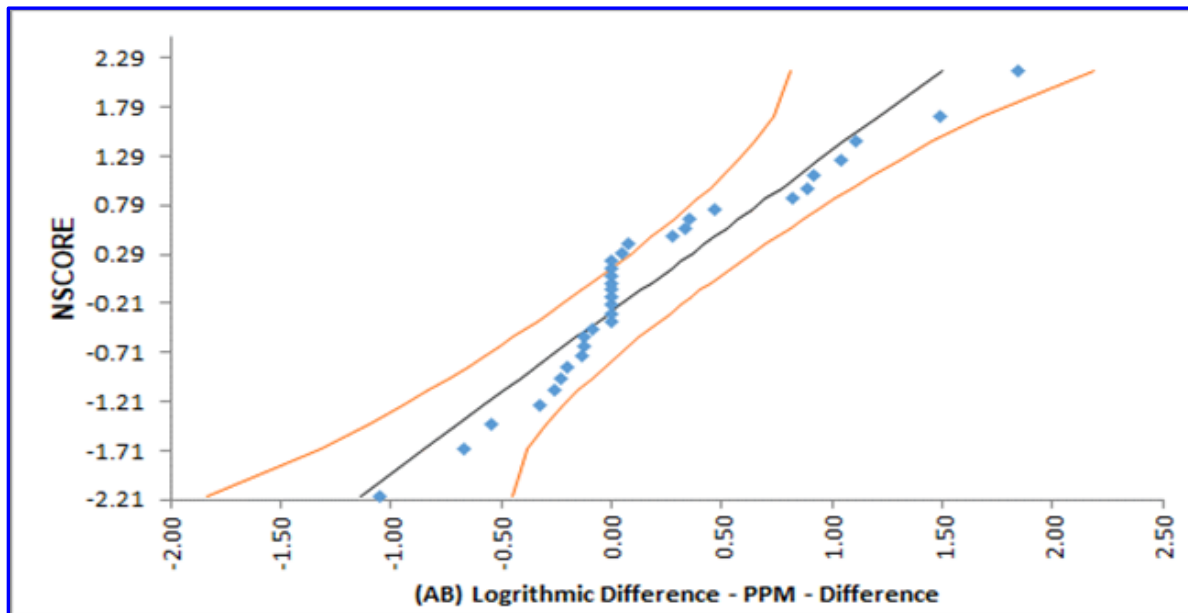


Figure AF-5.9 – PPM – Combo “AB”

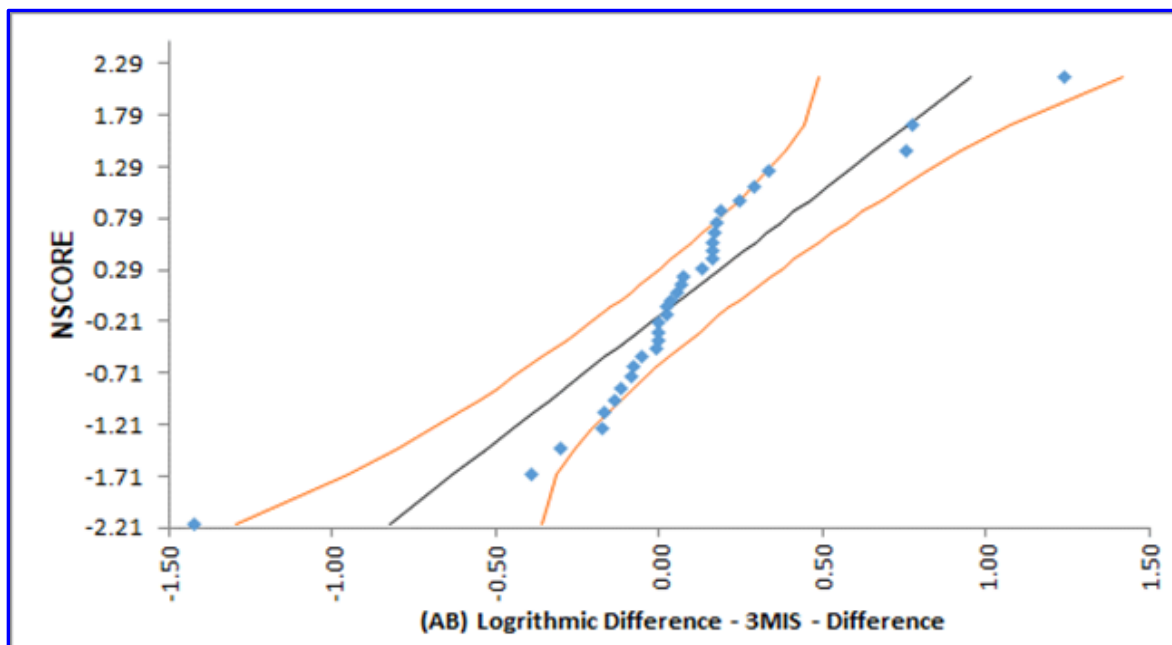


Figure AF-5.10 – 3MIS – Combo “AB”

Normalization Attempts for Original Data (CONTINUED)

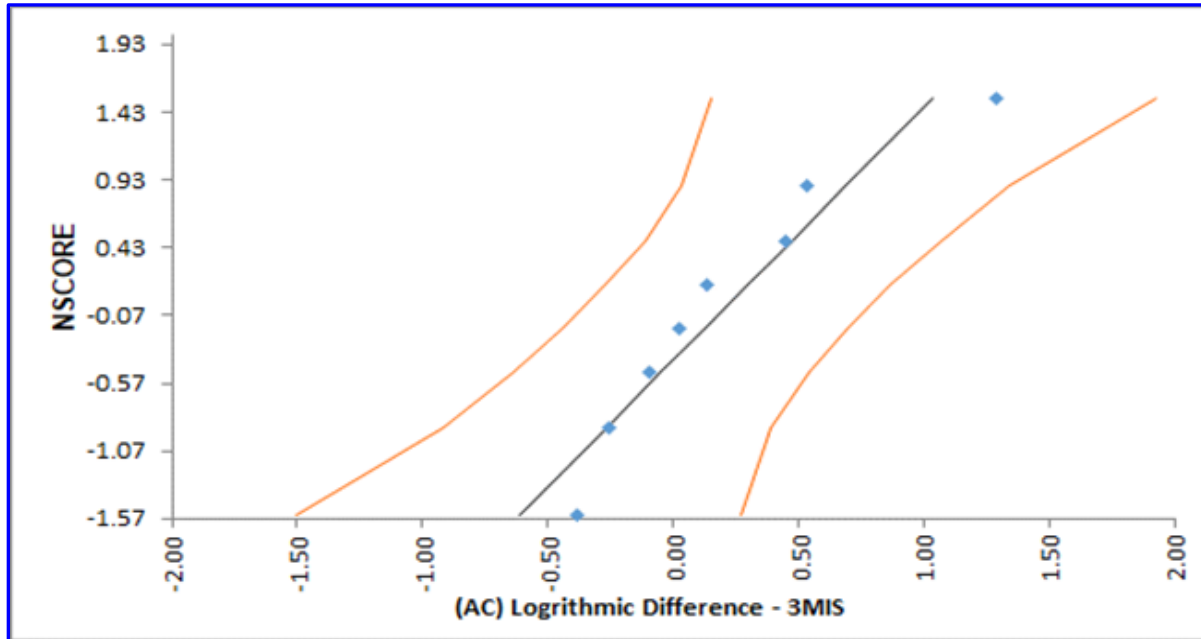


Figure AF-5.11 – PPM – Combo “AC”

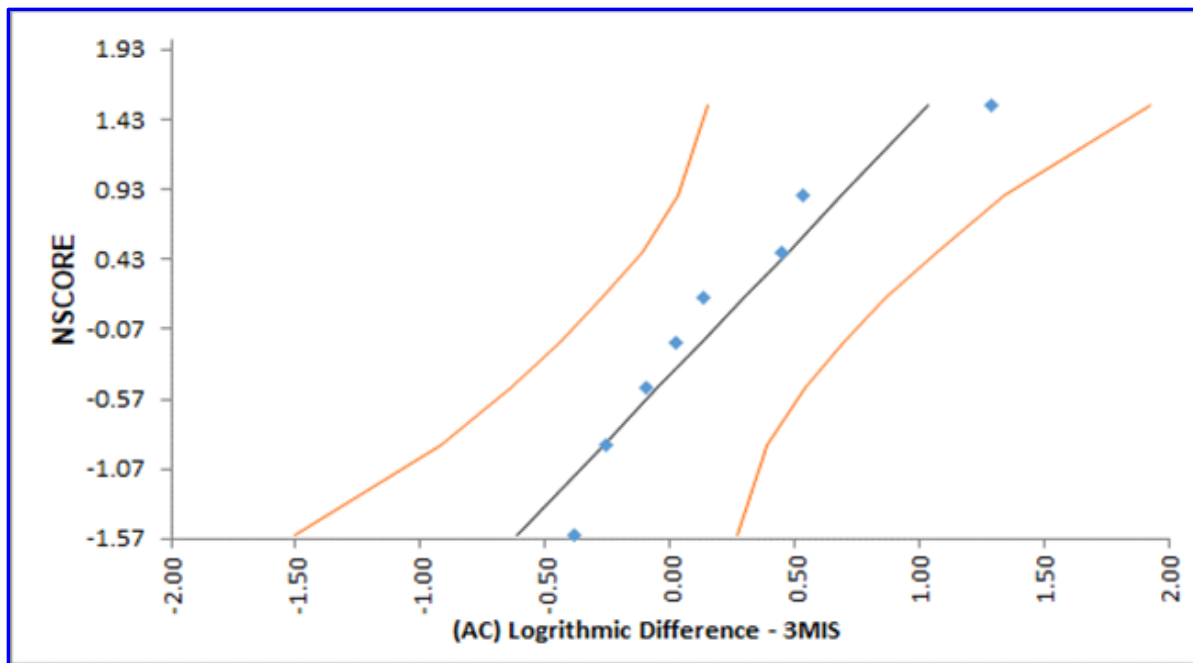


Figure AF-5.12 – 3MIS – Combo “AC”

Normalization Attempts for Original Data (CONTINUED)

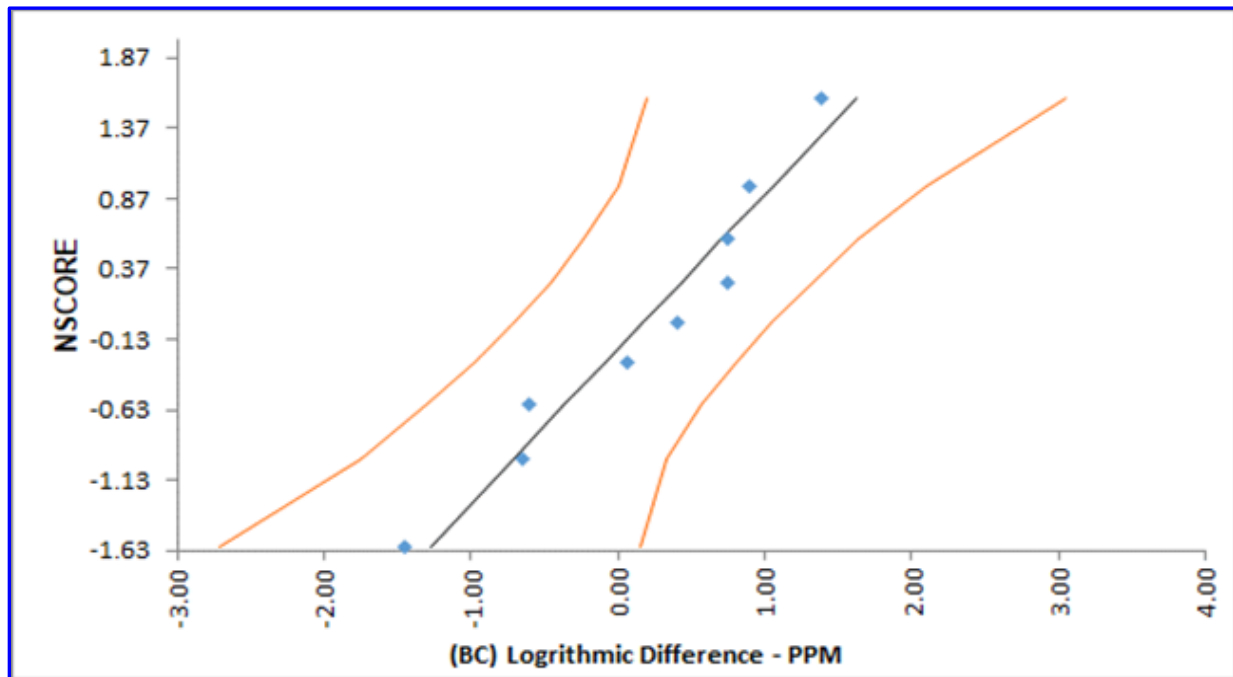


Figure AF-5.13 – PPM – Combo “BC”

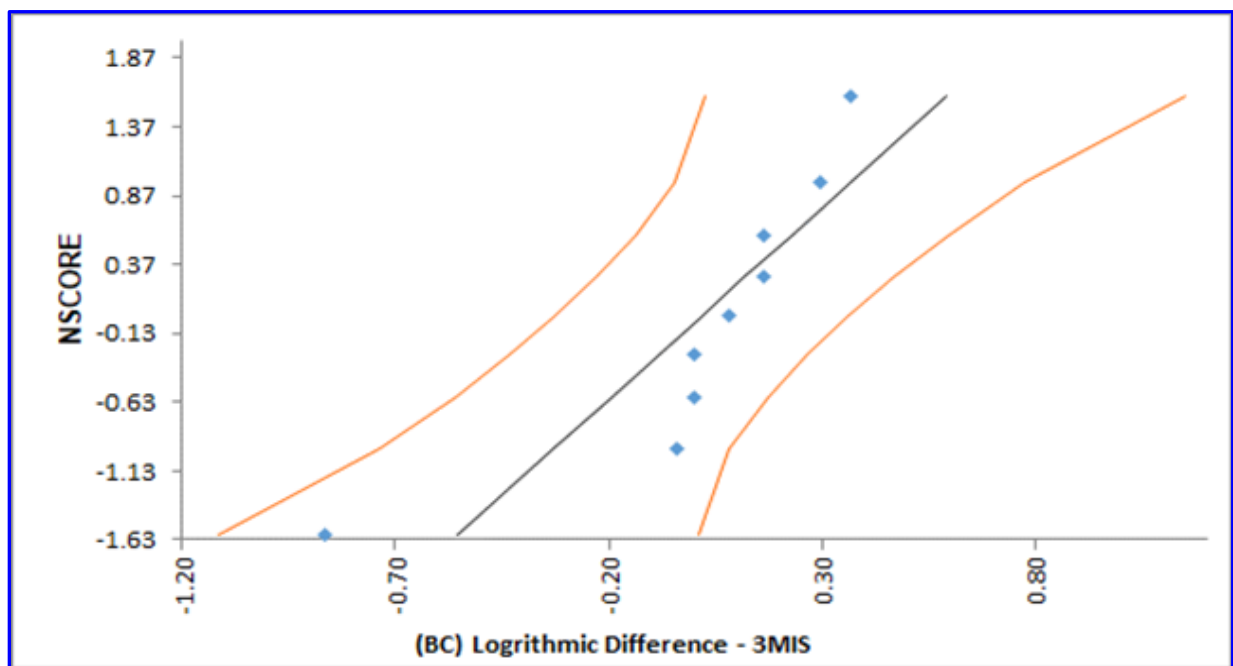


Figure AF-5.14 – 3MIS – Combo “BC”

Normalization Attempts for Original Data (CONTINUED)

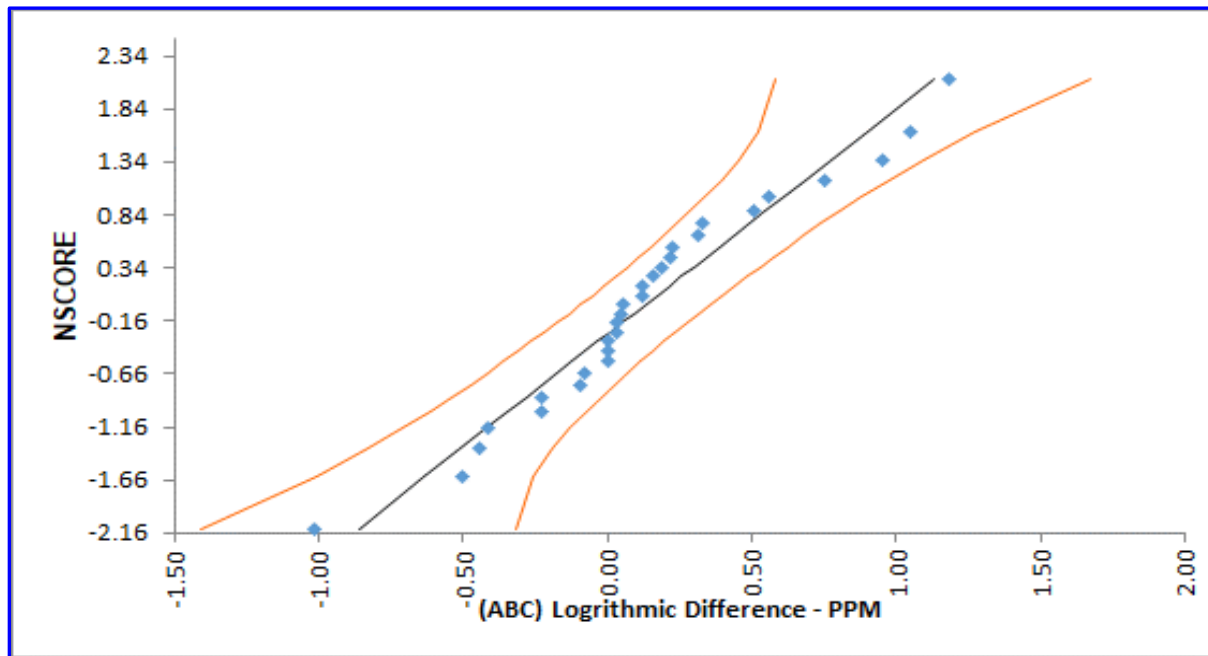


Figure AF-5.15 – PPM – Combo “ABC”

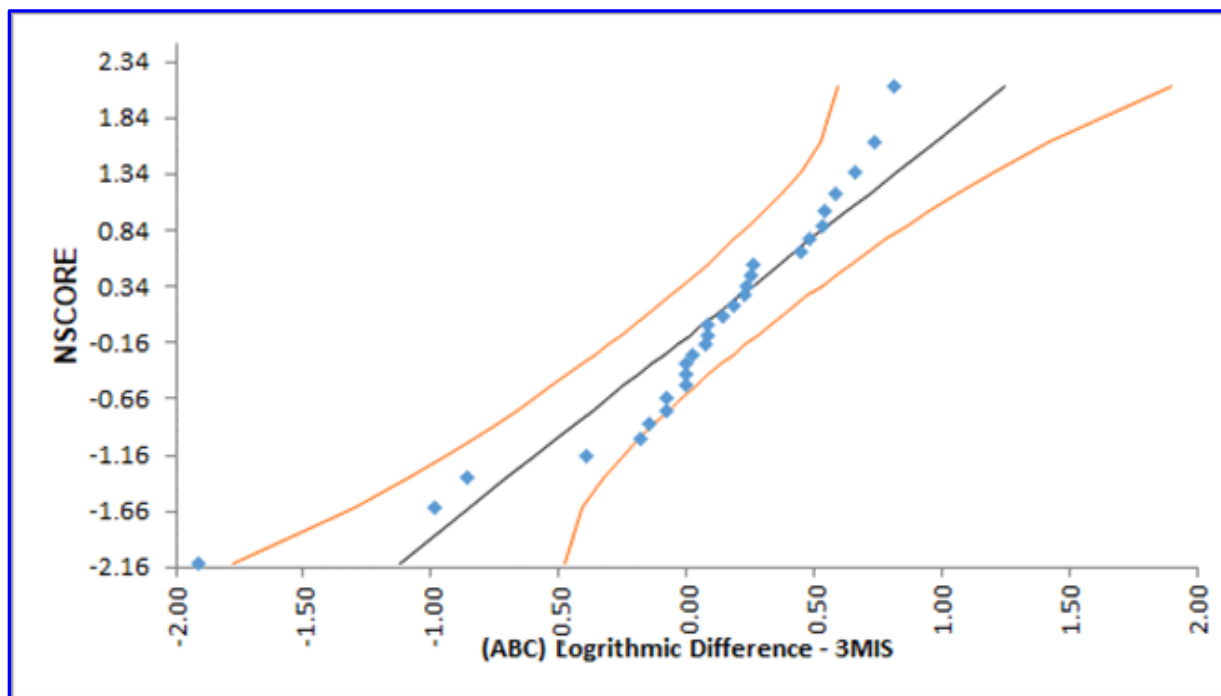


Figure AF-5.16 – 3MIS – Combo “ABC”

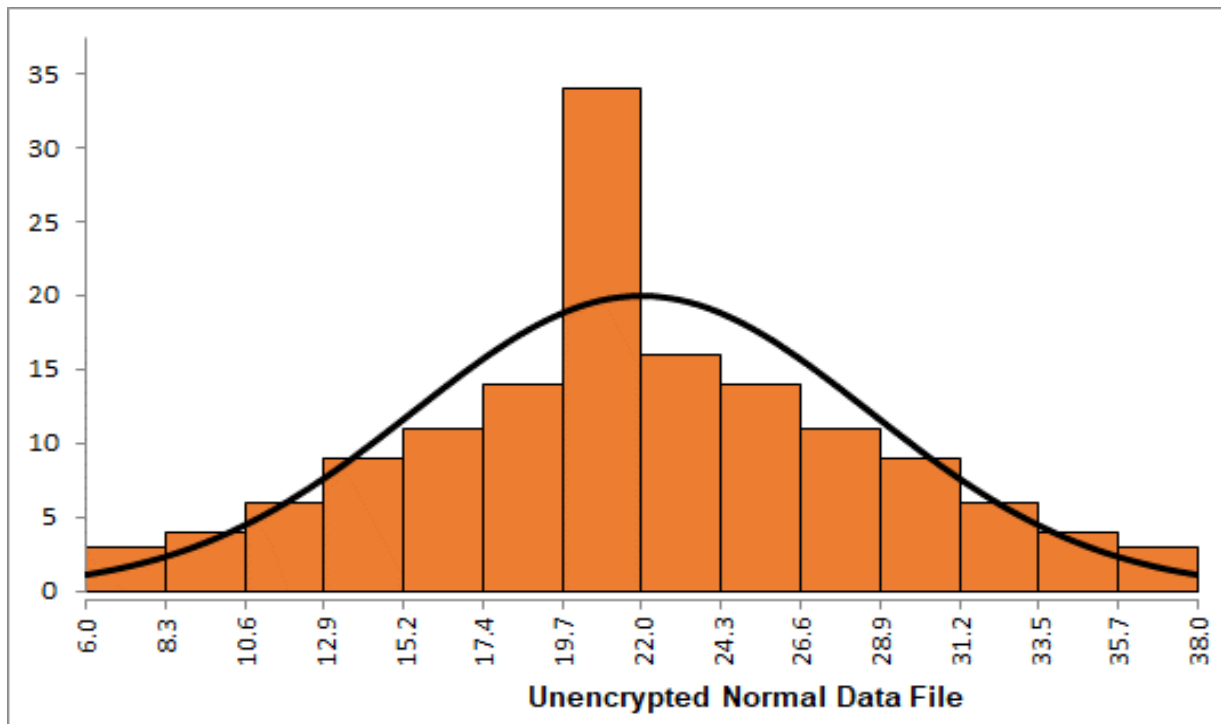


Figure AF-5.17 – Histogram – Plot of Normal Data before Encryption

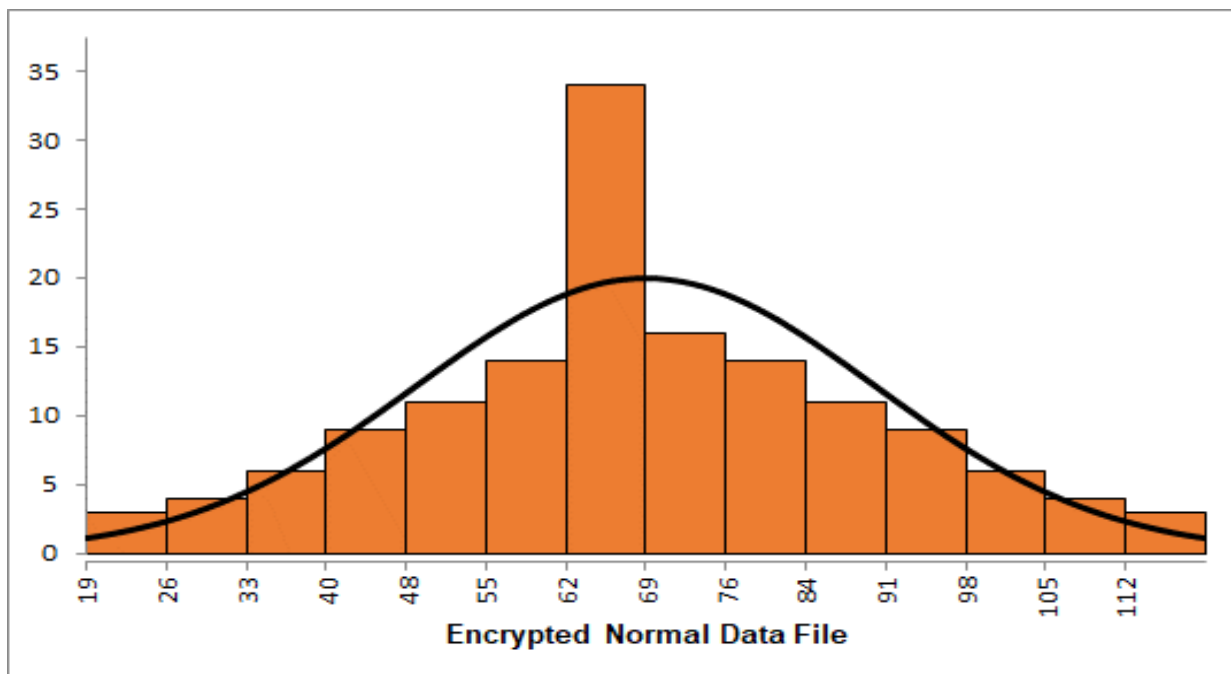


Figure AF-5.18 – Histogram – Plot of Normal Data after Encryption

Note: For Statistical Data on these two Histograms – see below, AF-5.23 & 5.24

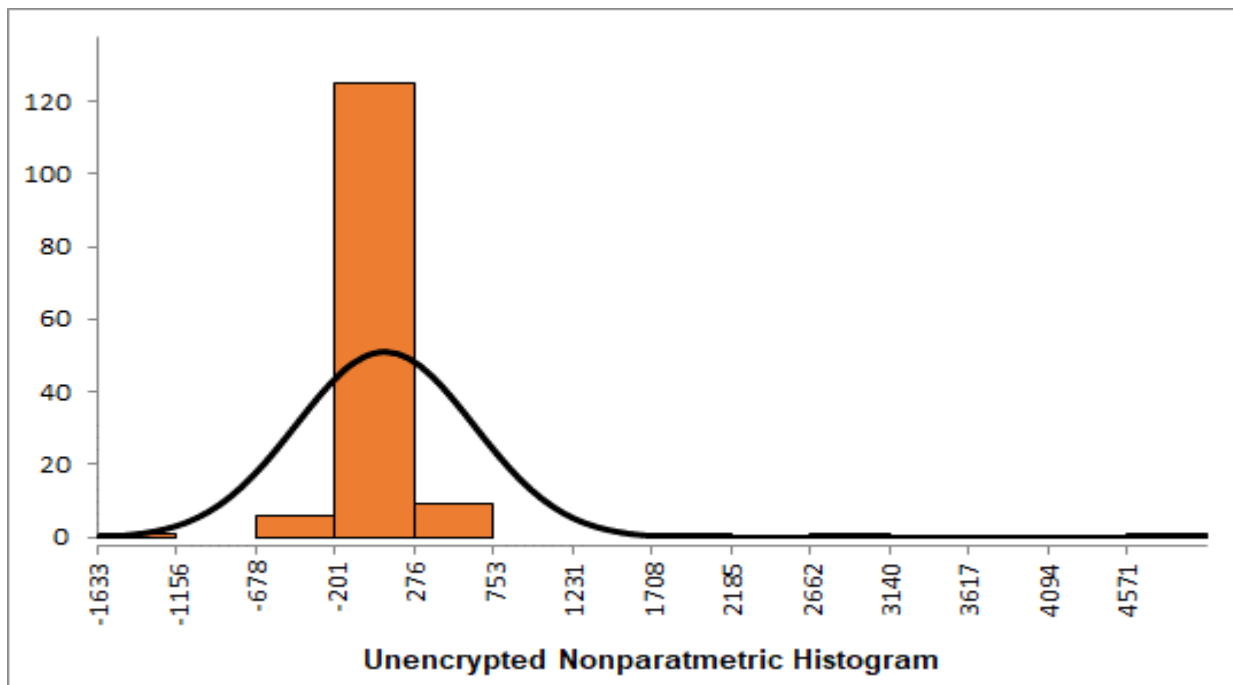


Figure AF-5.19 – Histogram – Plot of Nonparametric Data before Encryption

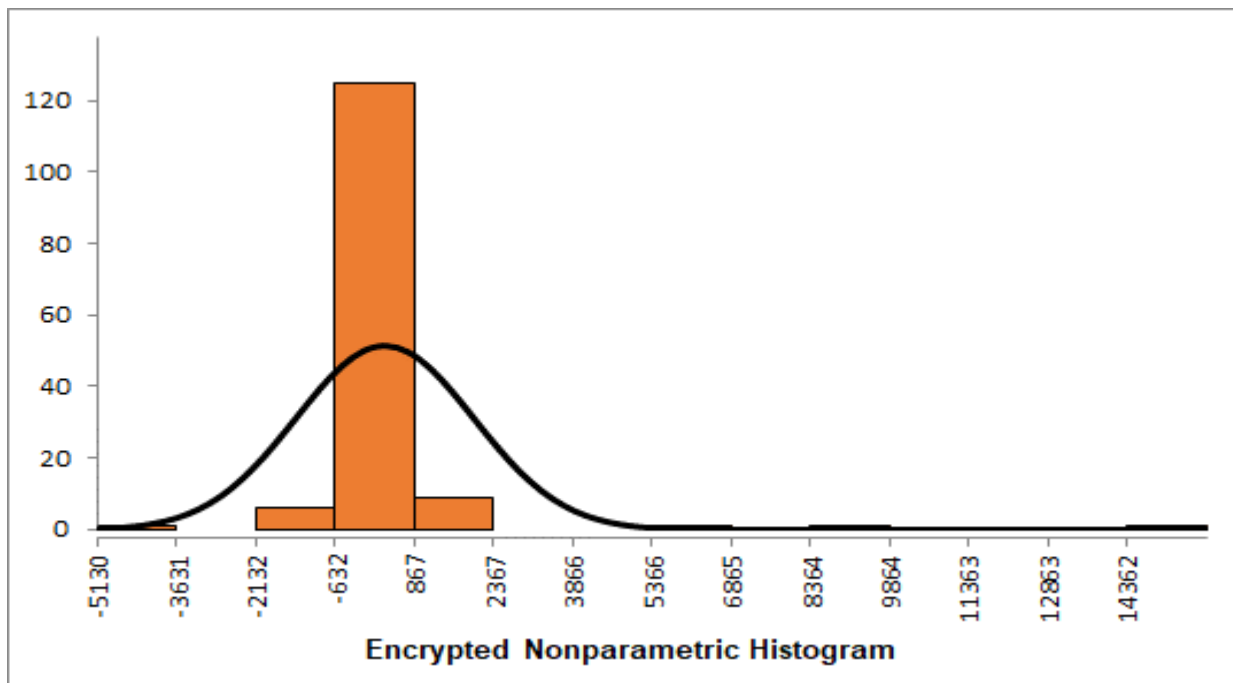


Figure AF-5.20 – Histogram – Plot of Nonparametric Data before Encryption

Note: For statistical data on these histograms – see below; AF-5.25 & 5.26

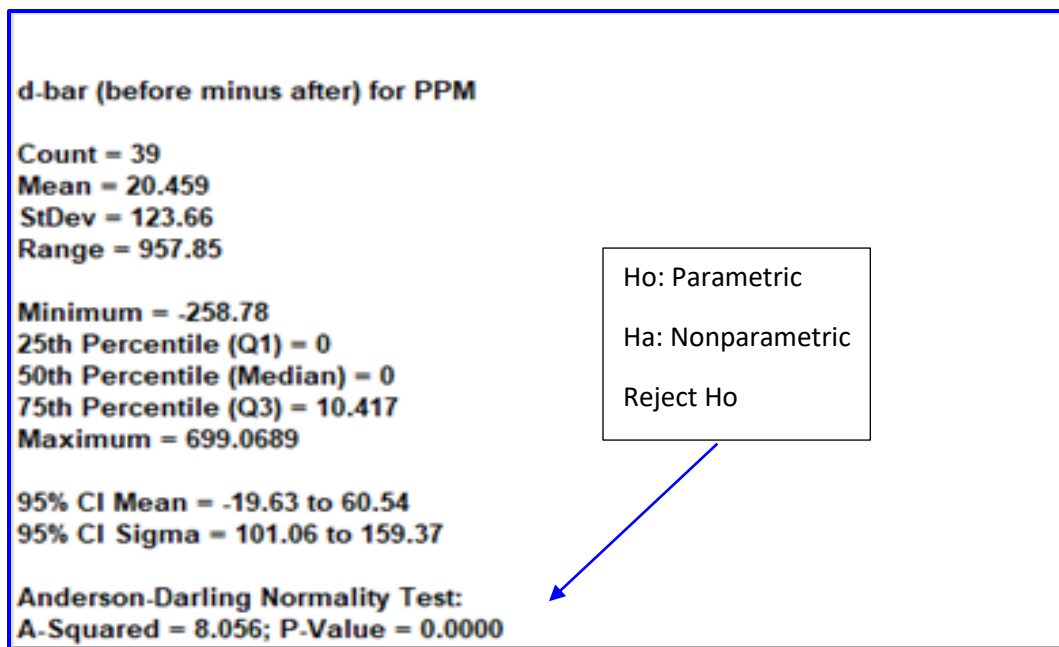


Figure AF-5.21 – Class “A” (PPM) – Original Data – Nonparametric

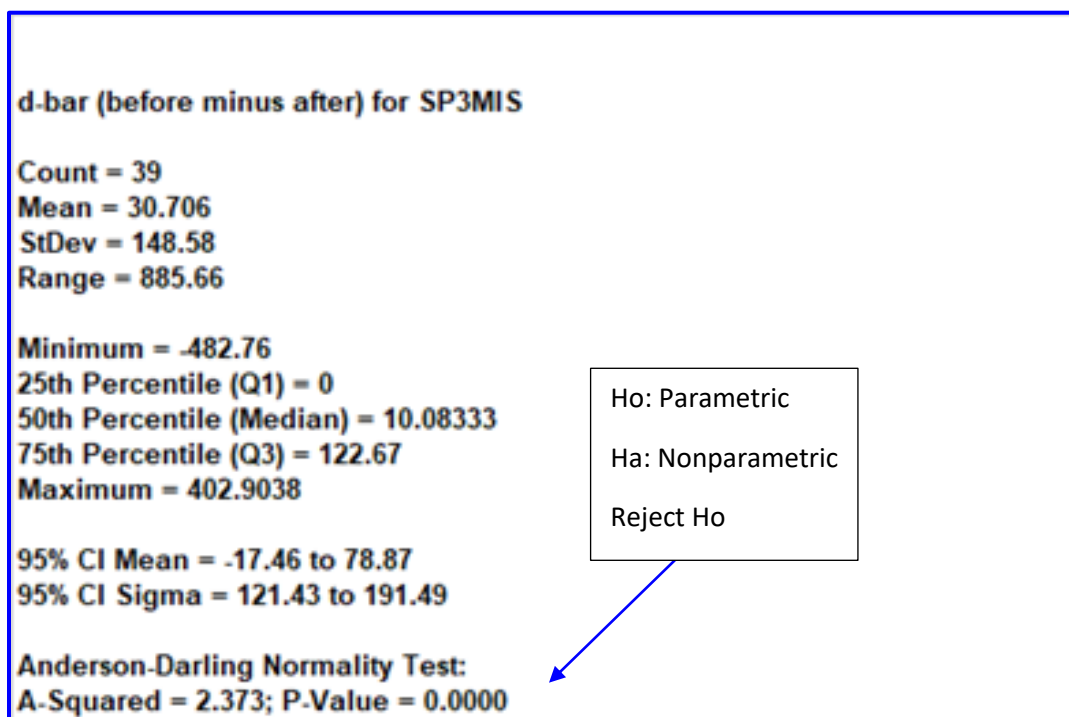


Figure AF-5.22 – Class “A” (3MIS) – Original Data - Nonparametric

Normal Data - Unencrypted

Count = 144
Mean = 22
StDev = 6.568
Range = 32.00

Minimum = 6
25th Percentile (Q1) = 18
50th Percentile (Median) = 22
75th Percentile (Q3) = 26
Maximum = 38

95% CI Mean = 20.92 to 23.08
95% CI Sigma = 5.89 to 7.43

Anderson-Darling Normality Test:
A-Squared = 0.571889; P-Value = 0.1355

Ho: Parametric
Ha: Nonparametric
Do Not Reject Ho

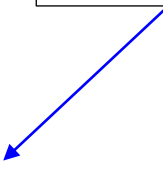


Figure AF-5.23 – Statistical Data on Normal Unencrypted Data File

Normal Data Encrypted

Count = 144
Mean = 69.117
StDev = 20.633
Range = 100.53

Minimum = 18.850
25th Percentile (Q1) = 56.551
50th Percentile (Median) = 69.117
75th Percentile (Q3) = 81.684
Maximum = 119.3846

95% CI Mean = 65.72 to 72.52
95% CI Sigma = 18.49 to 23.34

Anderson-Darling Normality Test:
A-Squared = 0.571889; P-Value = 0.1355

Ho: Parametric
Ha: Nonparametric
Do Not Reject Ho

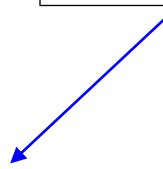


Figure AF-5.24 – Statistical Data on Normal Encrypted Data File

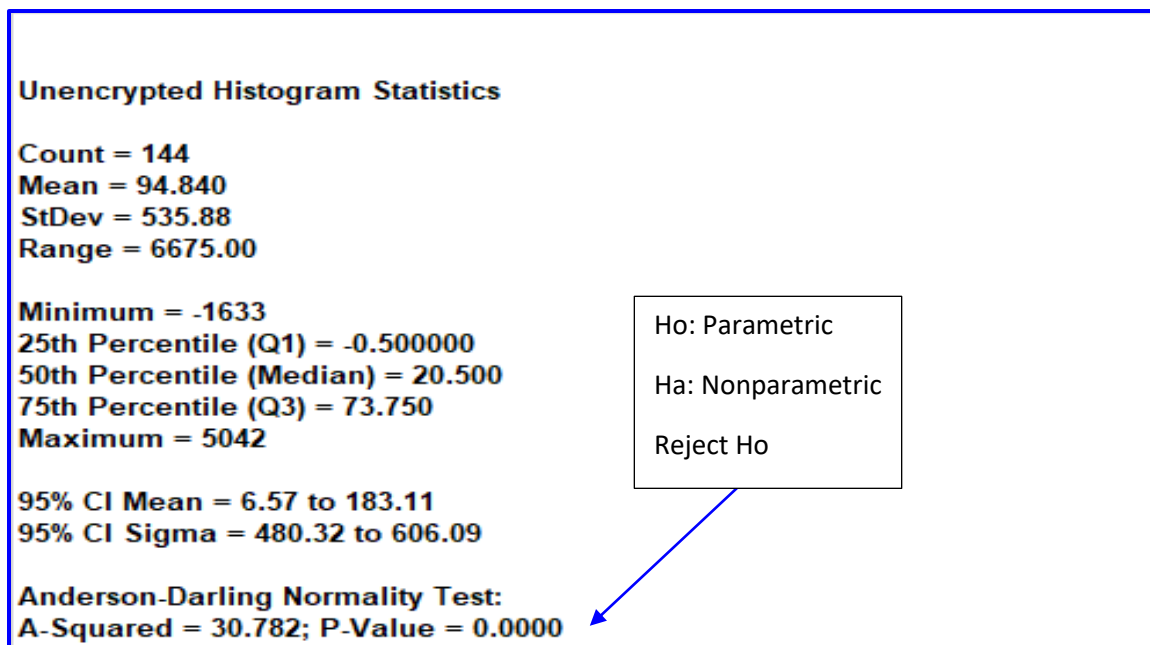


Figure AF-5.25 – Statistical Data on Nonparametric Unencrypted Data File

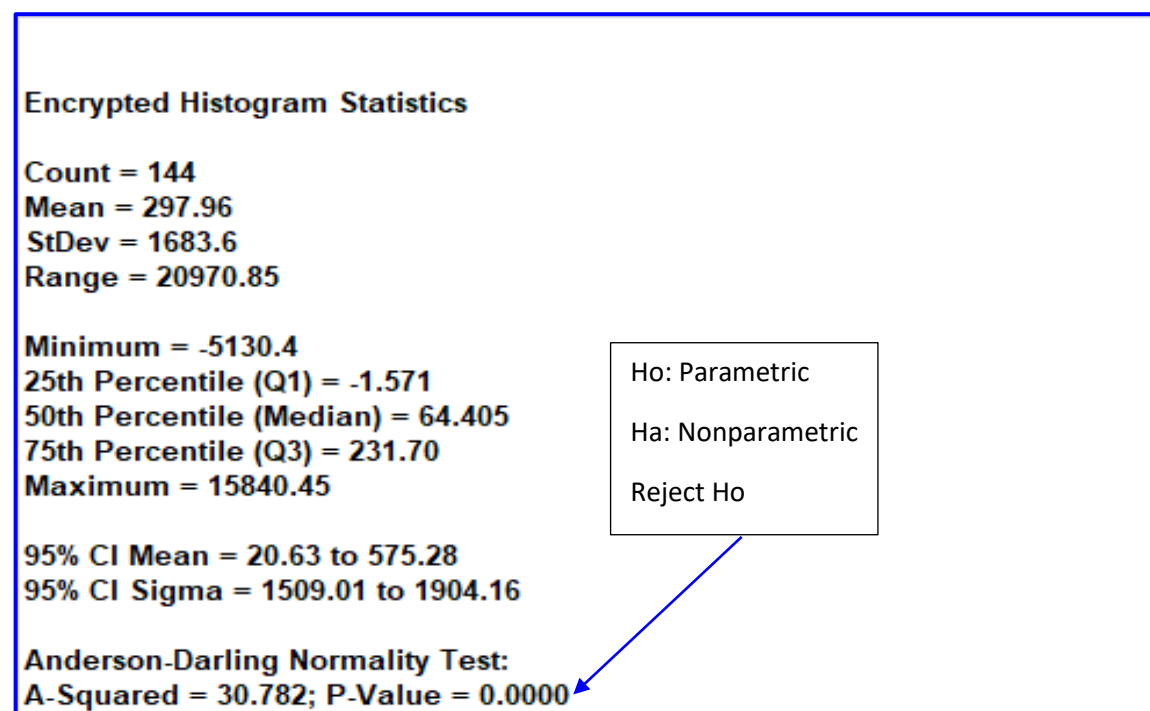


Figure AF-5.26 – Statistical Data on Nonparametric Encrypted Data File

Table AT-5.1 – Normalized Data used for Encryption Impact Study

Data File, Normal Data; Encryption Impact Study											
6	18	28	36	12	20	30	22	18	10	34	28
14	22	14	20	24	28	10	22	28	32	18	18
18	16	32	26	34	18	20	32	16	24	30	22
28	24	20	22	20	14	28	26	12	28	26	20
22	34	26	18	30	8	24	22	34	24	14	28
12	24	22	14	26	22	18	30	12	32	16	24
14	332	24	30	20	26	10	22	18	22	30	26
20	26	8	28	22	18	24	26	20	14	24	16
18	28	30	20	12	16	22	28	26	16	26	22
16	20	22	16	26	32	24	16	20	22	20	18
10	24	20	38	18	14	16	12	24	36	24	26
20	30	26	16	22	24	18	24	14	22	30	20

Note: This data file has all positive numbers; no zero values; no negative numbers

Table AT-5.2 – Nonparametric Data used for Encryption Impact Study

Data File, Nonparametric Data; Encryption Impact Study											
145	73	163	-4	-3	72	111	38	57	6	8	19
6	7	206	-2	5042	2840	21	72	138	6	-1	55
33	-64	11	31	170	2	79	437	129	26	-336	50
242	1816	-76	223	16	133	6	-13	10	-373	2	127
20	-19	112	2	33	5	6	-1633	-13	35	31	-133
123	403	-2	-2	5	-114	14	144	2	39	64	54
29	8	2	-121	405	32	-2	-23	428	2844	23	23
24	-4	133	13	-2	-44	-2	-61	21	22	-283	67
5	187	-387	-107	44	17	4	-315	-6	37	43	89
2	3	17	-3	326	132	160	558	-346	15	15	22
-137	-3	483	2	1	7	74	326	-55	98	63	34
129	110	10	42	35	135	-3	37	1	46	17	-12

Note: This data file has both negative and positive values; no zero values

VITA



Lynn Edward Reed was born in Peoria, Illinois in 1951 and has been a Tennessee resident since age two. He received his Bachelorate degree in Chemical Engineering from the University of Tennessee, Knoxville, in 1974. He spent 44 years working with Tennessee industries in various engineering and management capacities. He applied and was accepted to graduate school in 2009 and received a Masters of Science (M.S.) degree in Industrial Engineering Management in 2012 from the University of Tennessee Space Institute (UTSI). He is currently completing his Doctoral (Ph.D.) degree in Industrial Engineering from UTSI and The University of Tennessee, Knoxville.

From 1974 to 1995, Lynn worked as a engineer for Imperial Chemical Industries (ICI), a chemical facility in Mt. Pleasant, TN. He worked primarily in manufacturing management overseeing one-third of the complex and responsible for training, manufacturing, scheduling, safety, personnel, engineering, maintenance, and environmental activities for this area. From 1995 to 1996, he taught high school mathematics and algebra before joining the University of Tennessee Center for Industrial Services (UT CIS) as a Center technical resource and consultant.

From 1996 to the present, Lynn has worked for the UT CIS located in their Nashville office as an engineering resource to industry. His most recent efforts at UT CIS have been in quality management strategies in collaboration with a Tennessee OEM. His current work includes quality and environmental management systems, risk management, energy,

statistics, automotive core tools training, environmental and regulatory law. Lynn has held positions in administrative management in addition to being an engineering consultant and trainer for the Center addressing plant industrial engineering needs across Tennessee and, in some cases, industries located in other states or overseas and outside United States territory.

His professional interests lies in furthering knowledge in industrial product excellence, risk management, and facility cost reduction. Lynn is convinced that if our country is to compete globally, our manufacturers must find ways to lower cost through the elimination of waste and non-value-added activities. Lynn sees cost reduction and quality improvement as the two most significant national and global challenges facing American manufacturers and suppliers in the 21st Century. He also feels that learning to manage risk at the factory and enterprise level is a close second to the these challenges on cost and quality.