Multidimensional Visualization of Process Monitoring and Quality Assurance Data in High-Volume Discrete Manufacturing

by

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ABSTRACT

Advances in microcomputing hardware and software over the last several years have resulted in personal computers with exceptional computational power and speed. As the costs associated with microcomputer hardware and software continue to decline, manufacturers have begun to implement numerous information technology components on the shop floor. Components such as microcomputer file servers and client workstations are replacing traditional (manual) methods of data collection and analysis since they can be used as a tool for real-time decision-making. Server-based and web-based shop floor data collection and monitoring software applications are able to collect vast amounts of data in a relatively short period of time. In addition, advances in telecommunications and computer interconnectivity allow for the remote access and sharing of this data for additional analysis. Rarely, however, does the method by which a manager reviews production and quality data keep pace with the large amount of data being collected and thus available for analysis.

Visualization techniques that allow the decision maker to react quickly, such as the ability to view and manipulate vast amounts of data in real-time, may provide an alternative for operations managers and decision-makers. These techniques can be used to improve the communication between the manager using a microcomputer and the microcomputer itself through the use of computer-generated, domain-specific visualizations. This study explores the use of visualization

tools and techniques applied to manufacturing systems as an aid in managerial decision-making. Numerous visual representations that support process and quality monitoring have been developed and presented for evaluation of process and product quality characteristics. These visual representations are based on quality assurance data and process monitoring data from a high-volume, discrete product manufacturer with considerable investment in both automated and intelligent processes and information technology components. A computer-based application was developed and used to display the visual representations that were then presented to a sample group of evaluators who evaluated them with respect to their ability to utilize them in making accurate and timely decisions about the processes being monitored. This study concludes with a summary of the results and provides a direction for future research efforts.

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CHAPTER 1

INTRODUCTION

Personal computer users currently have at their fingertips processing capabilities that exceed the mainframe and mini-computing systems of previous decades. Further, the costs associated with microcomputer hardware and software continue to decline as microcomputing component technologies become increasingly more efficient. As a result, manufacturers have begun to implement numerous information technology components for data collection and processing on the shop floor. Components such as microcomputer file servers and microcomputer client workstations are now commonplace, replacing the traditional and sometimes manual methods of data collection and analysis. Of particular importance are shop floor data collection and monitoring software applications packages that can and are being used as a tool for real-time decision-making. Shop floor data collection and monitoring software applications, originally designed for expensive mainframe and mid-level computing systems, are now available on microcomputing platforms. These client-server and web-based data collection systems can typically accumulate vast amounts of data in a relatively short period of time. Further, advances in computer interconnectivity via company intranets and the Internet allow collection, remote access, and sharing of this data. Unfortunately, the methods by which a manager reviews production and quality data have remained the same. That is, a small subset of processes and/or quality characteristics is examined with no method available to analyze cause and effect on the entire manufacturing system as a whole.

Solutions for the problems created by cheaper and more powerful computer information systems and technology may be at hand. For example, the same personal computers that rapidly collect and store large quantities of data can be used to analyze and display this data quickly and efficiently given the correct set of applications tools. Recent advances in visualization tools and applications packages rely on increasingly powerful microprocessors to dynamically view and manipulate multidimensional data in real time. Visualization techniques, largely used in scientific applications to date, are finding their way into the business environment. Organizations are beginning to apply multidimensional visualization techniques to sales, cost, and performance data (Preston, et al., 1996). A logical extension would be to apply these same visualization techniques to process and quality data.

The primary purpose of this dissertation is to investigate whether the application of new visualization techniques and representations to high-volume manufacturing can improve manufacturing systems monitoring and thus reduce out-of-control condition response time. This reduction in response time should lead to a reduction in the amount of defective product being manufactured.

Advances in Data Collection

The data collection procedures of most organizations are domain-specific and have evolved as a result of the needs of a sublevel business function to aid in localized decision-making (Zhang, 1995). Each localized data collection system has the capability of collecting large volumes of data that does not easily lend itself to mental or pictorial visual representation. The relationships between the individual data pieces being collected are multidimensional which adds to the difficulty and complexity of developing suitable visual representations for decision-making. While computers and advances in computing power have aided in the manipulation of this data, a majority of the decision-making responsibility still rests with those human individuals assigned to manage a given business function. Many times this decision-making environment is dynamic and volatile, thus the decision-maker is under extreme pressure to make a correct decision in a timely manner. Decision-makers that understand the complexities and interrelationships between the various organizational and business functions have an advantage in making a timely and correct decision over those who are unfamiliar with the operating environment.

For the modern manufacturing organization of today, it is possible for an automated data collection system to record thousands of state changes per work shift. State changes occur when machines and equipment cycle on or off, change speed or direction, or alter levels of resource input or post-processing output. Shop floor process and quality assurance applications also record and store large quantities of data for a wide variety of process and product quality characteristics. This data, usually presented in the form of a statistical control chart, is typically stored to provide a quality history for a given machine or process characteristic. Decision-makers that have to react to ever-changing conditions on the shop floor are now faced with two distinct problems. First, shop floor data collection systems now provide an ever-increasing amount of data to be analyzed by the decision-maker. Second, shop floor data is coming from a multitude of data collection mechanisms with very little integration between them. As a result, the time required for a decision-maker to react to the data is less than the time needed for him/her to understand the information that is contained in the data.

Advances in Visual Representations

Along with advances in computing technology and speed, there have been numerous advances in both computer graphical user interfaces (GUI) and visualization technologies. Plotting and graphing programs of previous-generation computers required extensive programming knowledge with the resulting graph being based on a formula or collection of formulas, each representing a component of the plot. Programmers and scientists developed such graphical representations thus limiting the visual exploration of data to a select group of highly trained individuals in an organization. Graphical representations of data were rarely personalized to the individual desires of the decision-maker due to the high overhead associated with reformulation and reprogramming. Recent advances in computing show that graphically oriented programs have replaced command-driven application packages for file and data manipulation and presentation. Thus, the basic visualization of handwritten plots of points on a piece of paper has been replaced by the automated graphing capabilities of many software applications packages, graphics libraries, and graphic creation "wizards" available to the general personal computer user (Wolff and Yaeger, 1993). The resulting representations vary from the most basic two-dimensional black-and-white plot to multidimensional systems that use spatial objects, color, and time-series movement. However, while the personal computing tools exist to create visual representations of data, users of these applications packages are still required to have an understanding of the complexities of the graphical applications package itself, as well as the fundamentals and interrelationships of their business environment.

Though increasingly finding their way into the business realm, the majority of visualization tools and applications packages have been used to explore physical science phenomena and to increase scientific knowledge in that area (Tufte, 1990). Engineering and the physical sciences typically use visualization tools and techniques for such applications as finite element analysis, layering and cross-section presentation and analysis, and cause-and-effect presentation and analysis. Visualization tools also have been used extensively in the entertainment industry as evidenced by the seemingly endless number of movies and video games with visual and digital special effects. Visualization research pertaining to business functions has been limited until recently. With the exception of studies that address the advantages and disadvantages of using graphs rather than tables, research into the application of visual representations to organizations is relatively new. Visualization applied to manufacturing information systems and production/quality processes is in its infancy. Visual navigational tools exist yet there are no visual applications packages that currently address the production process as a whole.

Research Method and Tasks

Visual representations of process and quality data range from the simple statistical process control chart to more advanced representations of multidimensional dependencies between two or more process quality characteristics. These representations can also be static, as rendered by relatively simple statistical graphics packages, or dynamic through the use of visual animation. Given the broad spectrum of possibilities for creating the visual representations to be examined, much thought must be given to the appropriate types of visual representations to use in testing the effectiveness of visualization on decision-making. Two-dimensional visual representations that represent either groups of like processes (subsystems) or a broad perspective of the manufacturing system (i.e. no ability to access system details) can be developed using most any two-dimensional plotting package or visually-based programming language. Microsoft Excel and/or Visual Basic for Applications are well suited for this purpose.

Visual representations involving multiple dimensions are needed to depict the interaction between two or more process/quality variables with respect to either differing machines of a given process, differing machines for dissimilar processes, or past machine or process history depicted by advances along a time scale. While visualization software packages, such as SeeIt and In3D, provide three dimensional capabilities, they do not allow for real-time updating of data and the flexibility in formatting needed for this research. Therefore, this research used the Java programming language to create various visualizations of quality data, including 3-dimensional interactive quality mapping with ribbons for control limits.

Given the broad spectrum of possibilities for creating visual representations of quality data, much thought must be given to the types of data that should be visualized as well as the appropriate type of visualization. To help with this task, a case study was conducted of a high-volume, discrete product manufacturer with considerable investment in both automated intelligent processes and information technology components. The shop floor configuration, product/process type, and product/process control parameters included in this dissertation are representative of those found in the case study. The particular product and process characteristics on which quality data is collected and evaluated were determined from Quality Function Deployment (QFD) analysis of customer requirements, quality characteristics, and process characteristics.

Once an adequate set of visual representations has been created to represent the various manufacturing process and quality characteristics and multidimensional interactions, an electronic data collection instrument was developed and administered in a controlled laboratory environment to test the differences between the visual representations with regard to a subject's ability to make an effective decision. Timeliness and accuracy of the decision-making process were also tested to determine whether visual presentation of data results in response times different from those of traditional methods. Subject confidence of decision was also assessed.

Research Implications

This research addresses the effect of visual representations on decision-making in manufacturing process and product quality control systems. While visualization tools and techniques have been used to explore how a given business entity is organized in terms of structure, the efforts of this research focus on visual perceptions of the manufacturing process from a systems point of view. The benefits realized by other fields in the application of visual techniques to large and complex data sets can be extended to industrial and manufacturing organizations. Based on a case study from industry, this research will determine the extent to which visual representations provide an understanding of the relationships between multiple and complex process and quality data sets.

CHAPTER 2

LITERATURE REVIEW

This chapter begins with a discussion of what is meant by the term "visualization" both in the general sense and as it applies to the scientific and business community. Examples of classic visual representations are presented and a discussion of visual cognition is provided. To conclude, a review of the application of visual techniques applied to business data is provided along with a discussion of both statistical process control and multivariate analysis.

Visualization Concepts

Mankind has been creating visual images to represent information for thousands of years as evidenced by archaeological findings of cave drawings in both Europe and the Americas (Tufte, 1983). However, visual representations depicting multidimensional cartographic information did not appear until 1100 A.D. in China and not until approximately 5000 years later in Europe. Dr. John Snow created one of the better examples of multidimensional mapping in 1854. He plotted the location of deaths due to cholera in the central part of London, England for the month of September. The locations of deaths were marked with dots and the locations of the area's water pumps were marked with crosses (see Figure 2.1). From this mapping Dr. Snow was able to observe that a majority of the cholera deaths were concentrated around the Broad Street water pump. Removal of the pump handle ended the local cholera epidemic that had claimed over 500 lives.

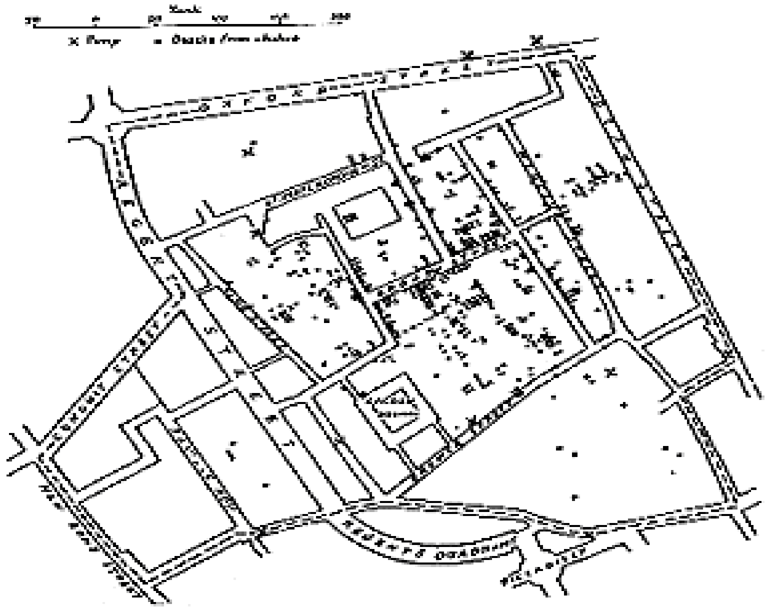


Figure 2.1 – Snow's Cholera Graphic
[This image is in the public domain.]

Charles Joseph Minard developed another excellent example of multidimensional visual representation in 1861. This graphic image depicted the catastrophic losses suffered by Napoleon's army during the Russian campaign of 1812. The size of Napoleon's army is depicted by the width of the respective band, the lighter band representing the march toward Moscow and the darker band representing the retreat from Moscow (see Figure 2.2). Beginning with 422,000 men in June 1812, only 100,000 men were left upon arriving at Moscow in September as much of the army had been deserted. Napoleon's retreat from Moscow is linked with a temperature scale at the bottom of the plot and shows that many of the men died from exposure during the brutal and cold winter. Of interest is the crossing of the Berezina River where the lives of many men were lost. Napoleon's army finally crossed back into Poland with only 10,000 of the original 422,000 men remaining. In this graphic, six variables are plotted on a two-dimensional surface: the size of Napoleon's army, their geographic location (latitude and longitude), the direction of movement, temperature, and date.

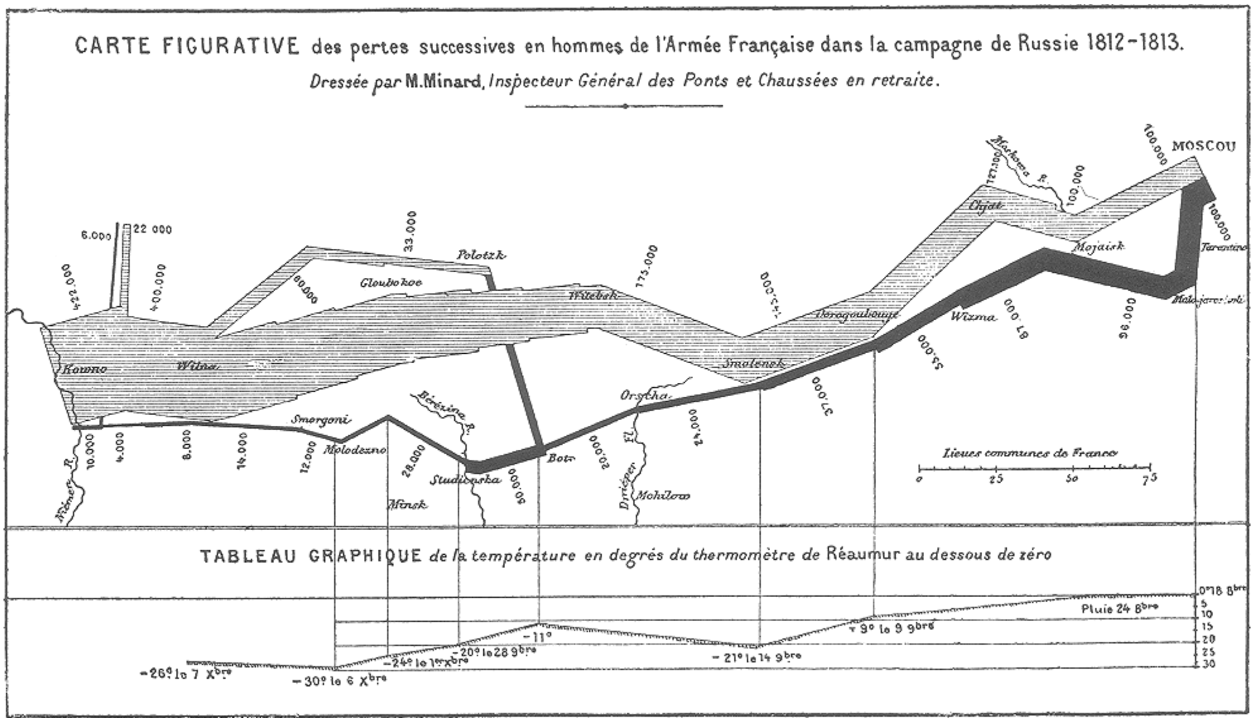


Figure 2.2 – Minard's Graphic of Napoleon's Moscow Campaign of 1812
[This image is in the public domain.]

Visualization and the process of creating visual imagery can be thought of as using "abstract, non-representational pictures to show numbers" as with the examples depicted above (Tufte, 1983). Visualization techniques typically involve using a combination of points, lines, coordinate systems, numbers, words, shading, and color to represent measurable quantities. Increasingly, creating visual representations involves the use of sophisticated computer hardware and software to display various types of information for the purpose of analysis. Visualization does not take the place of quantitative analysis but instead allows the quantitative analysis to become better focused (Grinstein and Ward, 1997). Visualization techniques and their resulting representations can be developed so that humans can extract information in a visual manner from underlying data using their cognitive reasoning abilities. Properly constructed visual representations can also be used to provide an overview of complex data, can assist in identifying relationships in data such as structure, patterns, trends, and anomalies, and can direct the user to other areas of interest in the underlying data set. Visualizations can be used to enhance the spatial and visual abilities of the user to allow the decision-maker to find the information contained in the data/visual representation.

The three general classes of visualization are scientific visualization, data or information visualization, and virtual reality (Tegarden, 1999). Scientific visualization focuses on the creation of visual imagery from engineering or scientific equations. An example of visualization techniques applied to scientific data would be the display of airflow over the wing of an aircraft or the contours of the human skull. Data or information visualization involves the creation of a visual image that is recognizable by the user and can be used to represent non-spatial data. A visual representation showing returns for a particular stock over the past thirty years would be an example of this type of visualization. Virtual reality (VR) uses a simulated environment that accepts user input and thus responds to user behavior. This three-dimensional computer-generated environment can either be non-immersive or immersive and is also known as artificial reality, cyberspace, or a virtual environment.

Visualization Technology and Visual Cognition

Visualization technology can be used by the decision-maker in determining relevant information that may otherwise be difficult to recognize. This has significant importance in time-sensitive environments associated with high-speed automated manufacturing. Cognitive research indicates that visual images, along with the process of creating a visual representation, enrich the problem-solving capabilities of the decision-maker. For both one-dimensional and multidimensional data, visual imagery can be used to enhance information processing capabilities. Results from Miller (1956) showed that subjects were able to perceive a greater amount of information through visual inputs. Subjects were able to distinguish between ten and fifteen locations of a mark on a line, were able to distinguish between seven and ten references of direction, and were able to distinguish between five and seven differences in size. Subjects were also able to distinguish between approximately nine different colors. Multidimensional results from Miller showed that subjects were able to distinguish between twelve different combinations when combining hue and saturation and were able to distinguish between seventeen different combinations when combining size, brightness, and hue. Further, subjects were able to differentiate between approximately twenty-four different images when asked to identify the location of a dot inside of a square.

Research on visual imagery also shows that visual mental images have counterparts that exist in the real world. In other words, concrete or naturally-occurring images depicting an item in the physical world are more easily recognized by the decision-maker than images that are abstract or those that do not have a real-world counterpart. This is the fundamental reason why visualization technology has been applied so often in the past to the physical sciences. The implications for visualizations in the business domain are that visual representations may have to be learned by a decision-maker which, in effect, will make the abstract images more concrete. For example, a statistical control chart used for process and quality monitoring has very little meaning to an individual unfamiliar with its purpose but can contain a wealth of information for a quality manager trained in its purpose and applicability.

Representations of Visualization Techniques

Tegarden (1999) describes eight visual examples that can be used as building blocks for multidimensional visualizations. These include: Kiviat Diagrams, Parallel Coordinates, 3-Dimensional Scattergrams, 3-Dimensional Line Graphs, Volume Rendering, Floors and Walls, Maps, and Surfaces:

- **Kiviat Diagrams -** For a Kiviat diagram, each variable of interest is plotted along a distinct axis according to its unit of measure (see Figure 2.3). Each axis is shown as a radius beginning from a common point in the middle of the Kiviat diagram. By connecting each of the plot points for each variable along the set of radii, a pattern is constructed. These patterns can then be compared. Kiviat diagrams are also known as radar charts, spider graphs, star graphs, and star glyphs.
- **Parallel Coordinates -** For Parallel Coordinates, each variable of interest is plotted on its own parallel line for a given set of data (see Figure 2.4). Similar patterns in the data are indicated by groupings of lines. For the given diagram, the two rightmost variables show two distinct groupings, one being the group of red lines and one being the group of blue lines.

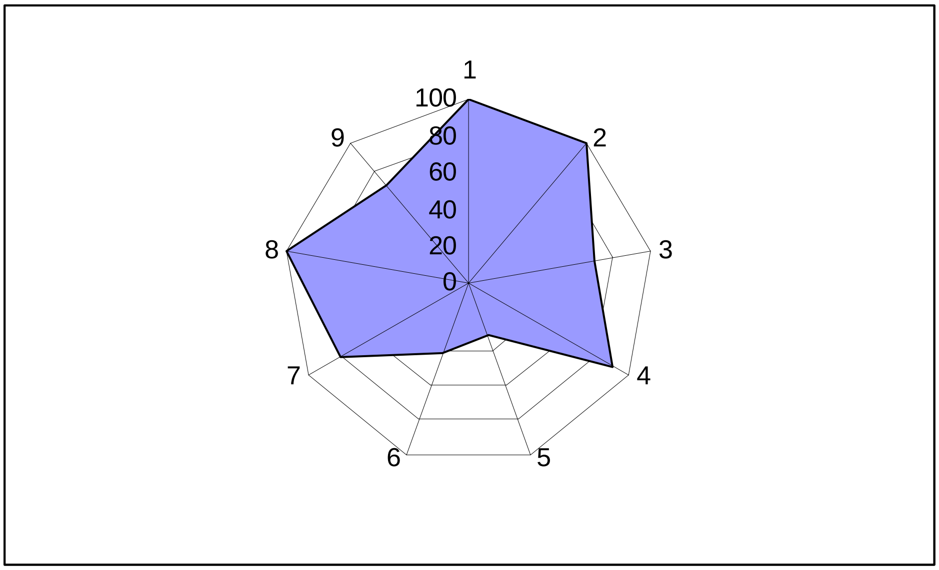


Figure 2.3 – Kiviat Diagram

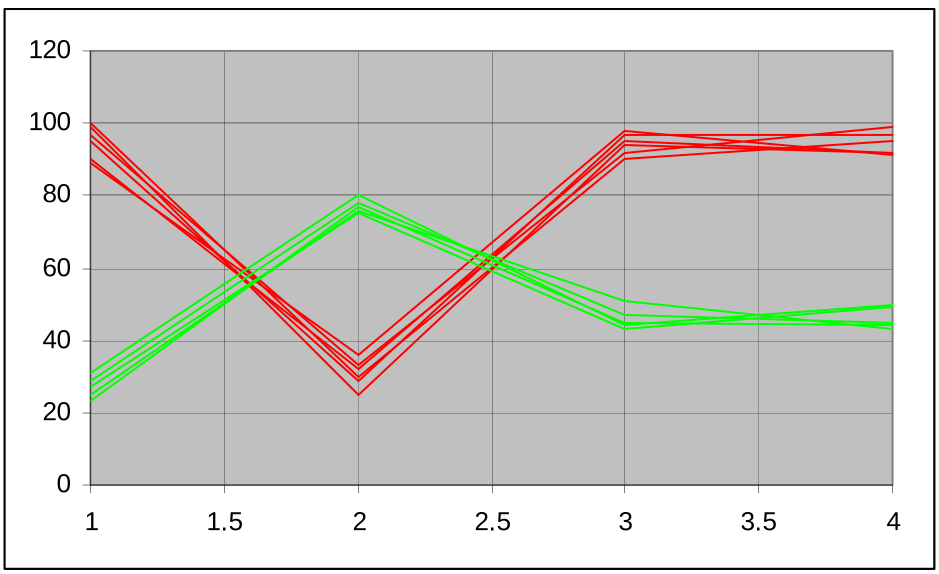


Figure 2.4 – Parallel Coordinates

- **3D-Scattergrams -** Three-dimensional scattergrams are similar to two-dimensional scatterplots in design (see Tegarden, 1999, p. 19). Multidimensional representation of three variables is possible with the value of each variable being plotted on each axis X, Y, and Z respectively. A fourth dimension can be plotted through the use of color.
- **3D-Line Graphs -** Three-dimensional line graphs are similar to two-dimensional line graphs (see Tegarden, 1999, p. 19). Four separate variables can be plotted. Three variables can be plotted in X,Y,Z coordinate space with a line connecting each of these points through the volume graph space. The fourth variable is represented through the use of color which changes as the line moves through three-dimensional space.
- **Volume Rendering -** Volume rendering uses a three-dimensional data set to represent number of observations of a dependent variable (see Tegarden, 1999, p. 20). Color is used to indicate the value of the dependent variable and opacity is used to indicate the number of observations for a particular X,Y,Z value.
- **Floor and Walls -** Floor and Walls diagrams project three-dimensional images contained in the body of a visual representation onto the floor and/or walls of the image respectively (see Tegarden, 1999, p. 21). This allows for comparison of two variables while holding the third variable constant. Visible Decisions SeeIT software allows the creation of floors and walls for its visual representations.
- **Maps -**Maps can be used as a concrete visual representation for the decision-maker so that data can be analyzed geographically (see Figure 2.5). Maps can be used for multivariable visual representations through the use of layering as with many of the Geographic Information System (GIS) software applications packages.

- **Surfaces -** Surfaces such as response surfaces can be used to find local optima (maximum and minimum) as well as global optima for business applications (see Figure 2.6). Such a visual representation requires a large amount of data since the image must appear to be continuous. Further, assumptions must be made concerning the business data to be analyzed such as linear interpolation between distinct (discrete) data points.

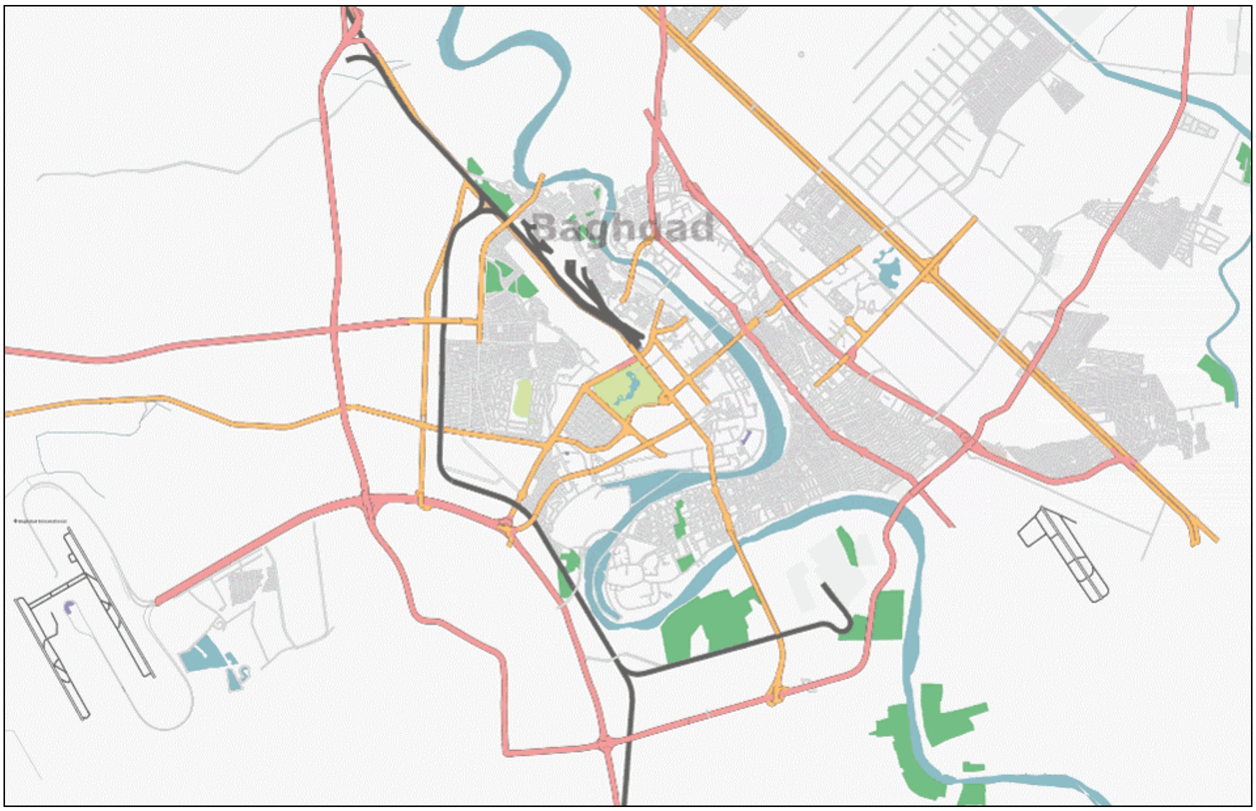


Figure 2.5 – Maps
[This image is in the public domain.]

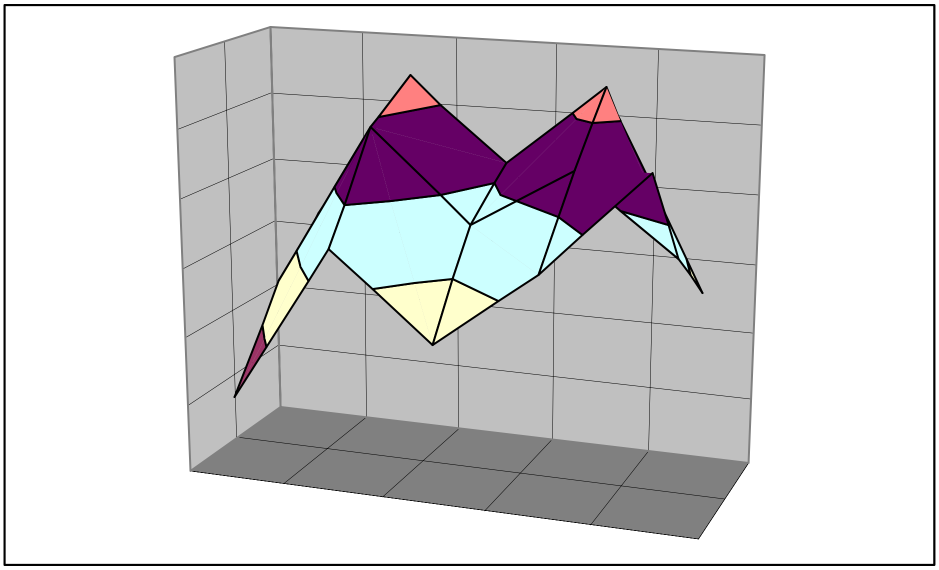


Figure 2.6 – Surfaces

Visualizing Business Data

Visualization applied to business information has taken the form of tables, outlines, pie charts, bar charts, line graphs, and the like and has existed in two-dimensional form for some time. However, as most business data is multidimensional and discrete, visual representations that address the abstract nature of business information and depict such information in real time are difficult to develop. Visualization can be used as a guide in the development of appropriate math models for business applications. It can show trends in data that may not be apparent using traditional methods of analysis. This is especially true of multivariate data where a variable, x, may not influence all members of the data set but instead only influences a subset of members. This is of primary importance to the analysis of quality and process data since product and process data collected at a subsequent state of manufacture may be taken from products processed on different machines at a preceding stage of manufacture. That is, if the preceding stage of manufacture has two machines X and Y that sends product to machine Z, data collected about the machine Z process contains samples from both machine X and machine Y. The variable in question may have significant influence if coming from machine X but may not be significant if coming from machine Y, effectively influencing only a subset of the data in question. Traditional statistical analysis using hypothesis tests may overlook these relationships.

Zhang (1995) conducted relevant visualization research in the development of an information visualization system (VIZ_planner) for manufacturing production planning. In the development of VIZ_planner, data is obtained from an MRPII software module and is presented in a series of multi-dimensional visual images in aggregate. Through a unified user interface, VIZ_planner allows a production planner to perform what-if analysis while evaluating potential solutions. Results and benefits derived from a controlled laboratory experiment utilizing VIZ_planner showed that users were able to generate a greater number of potential solutions (alternative production plans, in this case) than with the traditional methods of production planning. Users also experienced greater confidence in their decisions and expressed greater satisfaction with the outcomes of their production planning decisions.

Markham (1998) used scientific visualization techniques as a tool to gain insight into the complex intricacies of business organizations for the upcoming century. Visual representations of the organization were developed that extend beyond the traditional hierarchy of the organizational chart. This visual approach to organizational modeling allows for more in-depth analysis since key organizational variables can be visualized along with existing organizational entities. As with other visualization applications, visual representations are used to unmask processes and interdependencies that may not seem significant with other organizational modeling and evaluation techniques.

Research in Human Computer Interaction shows that primary cognitive abilities, specifically one's Spatial Visualization Ability (SVA), is a primary predictor of success in the ability to seek out and find information in electronic information systems. Individuals with low SVA take longer to navigate hierarchical menus systems database navigation, online learning environments, information archival systems, and internet websites (Downing, Moore, and Brown, 2005). The implication of this research is that by understanding the influence of SVA on information seeking, information systems can be designed to accommodate the individual differences of users.

Dull and Tegarden (1999) use three visual representations of multidimensional accounting information to test subject's ability to predict future values. Visual representations utilized in this research include 2-dimensional, 3-dimensional fixed, and 3-dimensional rotatable imagery and study participants made predictions on the graphics produced using accounting data from four different companies. Study participants using the 3-dimensional rotatable visualization type were found to produce the most accurate predictions.

Burkhard (2004) suggests that there is a difference between knowledge visualization and information visualization. The transfer of knowledge can be vastly improved through the use of the underlying abilities of humans to process visual representations. From a more pragmatic point of view, however, business managers are not well trained on using visualization methods for gaining insight into business data and business information affecting communication between business entities. The purpose of this research is to provide a framework and direction for knowledge visualization for the transfer of knowledge between at least two individuals.

Statistical Process Control

The term ‘quality control’ or ‘quality assurance’ is used to describe one of the fundamental functions of any business entity. As decision-makers, operators and managers monitor the various quality characteristics of the manufactured product in order to keep those quality characteristics within a specific set of boundaries as desired by the customer. In effect, decisions are made which assure the quality of a given product by controlling the processes used to manufacture that product. Assuring the product quality can be accomplished by inspecting each product once manufactured. However, 100% inspection of all manufactured goods can be expensive and time consuming. A better method of quality control and assurance is through the use of Statistical Process Control.

Statistical Process Control is a method for assuring the quality characteristics of a product or process fall within a given set of boundaries. Quality characteristics vary in their measurements because of the inherent variation that is present in all manufacturing processes. Variations that have assignable causes can be eliminated by adjusting the manufacturing process. Random variation, i.e. those with no assignable cause, cannot be eliminated through process adjustment. Statistical process control is a tool that uses statistics to determine whether variation is random or assignable.

Dr. Walter Shewhart of Bell Telephone Laboratories developed the theory behind statistical process control in the late 1920’s. He identified random or natural variation as that variation which is present in a process due to the effects of the design of the manufacturing system itself. This type of variation can be adjusted out of the manufacturing system since it is predictable, i.e.

machines can be adjusted and/or the methods used in manufacturing can be made more accurate and robust. Variation that is caused by factors external to the manufacturing system, however, is not predictable and can include such causes as machine and tool wear, inadequate operator training, inadequate or inferior raw materials or component items. Thus, statistical process control can be used to differentiate variation attributable to assignable causes from variation attributable to random causes.

Statistical process control implementation requires the measurement of a variable of output from a process, a quality characteristic, which is then compared to a standard. Process or product parameters that are typically measured include temperature, thickness, diameter, viscosity, or number of defects. Before measurements can be taken, a sampling plan is usually determined which states how often a sample is to be taken from the process and the size of the sample group. A typical sampling plan may require that diameter measurements of ten (10) units of product need to be taken every two hours. It is important that the sample group be taken from a single distinct population such as one machine, one shift, or one operator. This ensures that the variation within the group is minimized which maximizes the chance of detecting variation between groups, i.e. maximizes the chance of detecting variation due to an assignable cause. Figure 2.7 provides an example of a statistical process control chart.

Multivariate analysis and statistical process control can be used to monitor several variables in a process (Prabhu and Runger, 1997). Multivariate control charts are advantageous over simple control charts in that they are able to sense assignable causes between multiple variables that are either poorly detected or undetected by their univariate counterparts. This is usually accomplished through the use of an algorithm or procedure that amplifies or distorts the multivariate interrelationship.

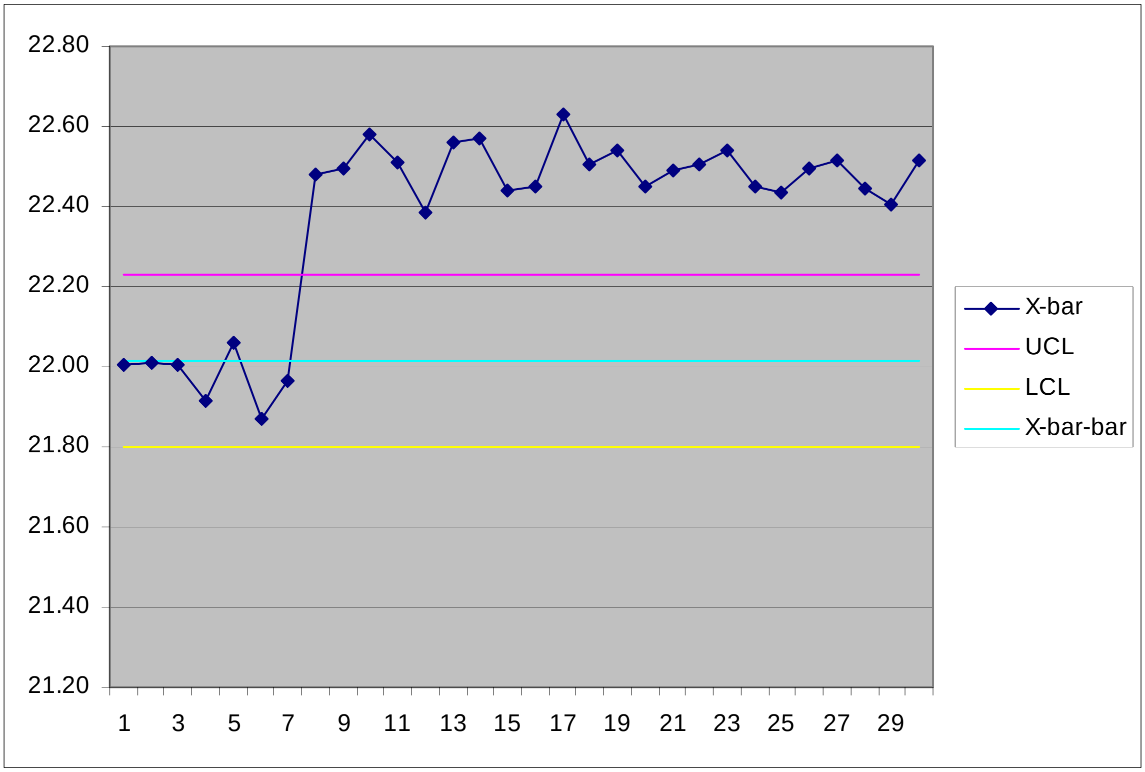


Figure 2.7 – Statistical Process Control (SPC) Chart

The field of quality control has for some time relied on the analysis of quantitative data. Visual representations of quality data became prevalent in the total quality management (TQM) era with its emphasis on worker-controlled quality. In addition to statistical process control charts, Pareto analysis, flow charts, defect checksheets, histograms, scatterplots, and cause-and-effect diagrams were introduced. Each of these visual tools applies quantifiable measurement techniques to data associated with quality and process monitoring. While these simple tools have been used with much success in monitoring single processes, their applicability to complex automated manufacturing systems collecting large amounts of quality and process data is limited. This research will test the effectiveness of advanced visual representations in addressing the complex issue of high-volume, discrete-product automated production system quality and process monitoring. The next chapter presents the research methodology for this dissertation, beginning with a description of the manufacturing facility that served as a case study for this research.

CHAPTER 3

RESEARCH METHODOLOGY

This chapter begins with a description of the quality and process monitoring data collection systems of a typical aluminum can and end manufacturer, Ball Metal Container (formerly Reynolds Metals Company). The domestic aluminum can and end manufacturing facilities of this company served as a prototype for this research. The steps involved in the aluminum can manufacturing process are discussed, along with process and product quality characteristics typically collected at each manufacturing facility. The quality function deployment (QFD) process used to obtain a subset of quality characteristics to be visually examined in this study is described. The chapter concludes with a description of the experimental design and experimental conditions under which this research is conducted.

Case Study: Ball Metal Container

The case study for this research was conducted at the sixteen original aluminum can and end manufacturing facilities of the Aluminum Can Manufacturing Division of Reynolds Metals Company. Ball Metal Container purchased Reynolds Metals Can Division in mid-1998, forming the largest can manufacturing operation in North America. Ball Metal Container now operates twenty-five aluminum can and end plants and supplies 38% of the North American beverage can market.

At the time of purchase, the former Reynolds Metals Company aluminum can manufacturing plants were capable of producing approximately 18 billion aluminum cans per year of various sizes across the original sixteen manufacturing facilities in North America. Each facility is highly automated in that programmable logic controllers are used to start, adjust, and stop a majority of the process equipment used to manufacture an aluminum can or end.

Process data is collected directly from the programmable logic controllers (PLC's) for those facilities that are equipped with Class 5 (intelligent) PLC's. Quality assurance data is manually collected by shop floor operators at discrete points in time during the two-shift, twenty-four hour per day operation of each facility. PLC state changes can easily number in the thousands per shift with each state change being recorded in an ODBC-compliant database. Shop floor operators enter approximately one-thousand individual units of data per shift into the control charts which make up the Quality Assurance Gauging System. Shop floor operators and operations supervisors alike are unable to process this volume of data in a timely fashion as the response times for process intervention are substantially shorter than the time required for data comprehension.

Each manufacturing facility has a local area network (LAN) originally equipped with an Ethernet backbone and one or more file servers running Windows 2000 Server as the Network Operating System (NOS). Interconnectivity between can and end manufacturing facilities and to Can Division Headquarters is provided using dedicated T1 (or greater) telephone lines for data transmission. Virtual Private Networking is not used. Company servers were originally connected in a hub-and-spoke arrangement to the corporate information services automation facility in Richmond, Virginia. This hub-and-spoke arrangement is still in place though the hub has been relocated and is now at Ball Metal Container headquarters in Boulder, Colorado. Wide area networking (WAN) connectivity is possible such that a user in one facility can share physical and logical resources, and thus view process and quality data located in another facility.

Users authenticate to their respective server from any personal computer connected to the LAN. Once authenticated, a user profile script file is used to establish connections to file volumes, printing devices, and other peripherals as needed by the user and as deemed necessary by corporate IT personnel. One of the standard file volumes available on each of the individual aluminum can and end manufacturing facility servers contains shop floor applications, such as the Quality Assurance Gauging System software and the Process Monitoring System software.

The Quality Assurance Gauging System. As the can and end manufacturing plants operate on a twenty-four hours per day continuous schedule, the workstations that are installed on the shop floor to collect quality assurance data are continuously logged into the network. They are connected only to the quality assurance gauging software application.

The applications package that collects quality assurance data, STATNET/2, is a DOS-based package which stores data in flat file format. STATNET/2 allows a user to enter data either through the PC keyboard or through the use of communications port-type (RS-232) devices. Data is displayed in quality assurance control chart form for the various process and product quality characteristics of interest. A historical record of the sample data collected over time for various process and/or product characteristics is available to users of the STATNET/2 applications package. Users are able to display either control charts or histograms of historical data for one characteristic at a time. Users are also able to print out copies of quality control charts and histograms. Samples of tabular and control chart reports from the system are shown in Figures 3.1 and 3.2, respectively.

Exception Report - Salisbury Can Plant

START DATE: 10-01-1998 **START TIME:** 07:00

STOP DATE: 10-01-1998 **STOP TIME:** 19:00

21-Mar-99

WORK STATION	MACHINE	PART	OPERATION	CHARACTERISTIC LABEL	SUBGRP	PLOT POINT	LOWER TOL	UPPER TOL	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
20	D&I 11	BM 11	12oz 20x/211	(FT) Flange Thickn	3215	0.00627	0.00589	0.00651	0.00629	0.00635	0.0059	0.00653	0	0	0	0	0	0
20	D&I 12	BM 12	12oz 20x/211	(FT) Flange Thickn	3190	0.00631	0.00589	0.00651	0.00643	0.00614	0.00653	0.00616	0	0	0	0	0	0
20	D&I 12	BM 12	12oz 20x/211	(WT) Wall Thickne	3205	0.004	0.00389	0.00441	0.004	0.00401	0.00389	0.00410	0	0	0	0	0	0
20	D&I 13	BM 13	12oz 20x/211	(WT) Wall Thickne	3158	0.00391	0.00389	0.00441	0.00395	0.00389	0.00391	0.00392	0	0	0	0	0	0
20	D&I 13	BM 13	12oz 20x/211	(WT) Wall Thickne	3157	0.00389	0.00389	0.00441	0.00388	0.00388	0.00398	0.00382	0	0	0	0	0	0
20	D&I 14	BM 14	12oz 20x/211	(FT) Flange Thickn	3211	0.00613	0.00589	0.00651	0.00608	0.00584	0.00647	0.00612	0	0	0	0	0	0
20	D&I 14	BM 14	12oz 20x/211	(WT) Wall Thickne	3188	0.00389	0.00389	0.00441	0.00393	0.00380	0.00403	0.00381	0	0	0	0	0	0
20	D&I 14	BM 14	12oz 20x/211	(WT) Wall Thickne	3189	0.00391	0.00389	0.00441	0.004	0.00379	0.00389	0.00395	0	0	0	0	0	0
20	D&I 14	BM 14	12oz 20x/211	(WT) Wall Thickne	3190	0.00387	0.00389	0.00441	0.00383	0.00379	0.00385	0.00401	0	0	0	0	0	0
20	D&I 22	BM 22	12oz 20x/211	(WT) Wall Thickne	2908	0.00394	0.00389	0.00441	0.00410	0.0039	0.00387	0.00388	0	0	0	0	0	0
20	D&I 23	BM 23	12oz 20x/211	(FT) Flange Thickn	2878	0.00622	0.00589	0.00651	0.00609	0.00604	0.00622	0.00654	0	0	0	0	0	0
20	D&I 23	BM 23	12oz 20x/211	(WT) Wall Thickne	2858	0.00397	0.00389	0.00441	0.004	0.00389	0.00397	0.00401	0	0	0	0	0	0
20	D&I 24	BM 24	12oz 20x/211	(FT) Flange Thickn	2848	0.00613	0.00589	0.00651	0.00648	0.00587	0.00598	0.00622	0	0	0	0	0	0
20	D&I 25	BM 25	12oz 20x/211	(FT) Flange Thickn	2864	0.00612	0.00589	0.00651	0.00605	0.00588	0.00618	0.00639	0	0	0	0	0	0
20	D&I 25	BM 25	12oz 20x/211	(WT) Wall Thickne	2828	0.00391	0.00389	0.00441	0.00401	0.00387	0.00391	0.00386	0	0	0	0	0	0
20	D&I 25	BM 25	12oz 20x/211	(WT) Wall Thickne	2827	0.00392	0.00389	0.00441	0.00393	0.00385	0.00398	0.00393	0	0	0	0	0	0
20	Trimmer 11	Pocket 1-5	12oz 202/211	(TH) Pocket 1 Trim	1167	4.84254	4.8389	4.8431	4.84336	4.84222	4.84205	0	0	0	0	0	0	0
20	Trimmer 22	Pocket 1-5	12oz 202/211	(TH) Pocket 3 Trim	1108	4.83985	4.8389	4.8431	4.84002	4.84098	4.83857	0	0	0	0	0	0	0
21	Washer 1	Random	12oz	(CN) Deion'd Water	3453	6	0.5	2.5	6	0	0	0	0	0	0	0	0	0
21	Washer 1	Random	12oz	(CN) Deion'd Water	3454	6	0.5	2.5	6	0	0	0	0	0	0	0	0	0
21	Washer 1	Random	12oz	(CN) Deion'd Water	3455	5.8	0.5	2.5	5.8	0	0	0	0	0	0	0	0	0
21	Washer 1	Random	12oz	(TP) Zone 1 Oven	3620	383	339.9	380.1	383	0	0	0	0	0	0	0	0	0
21	Washer 1	Random	12oz	(TP) Zone 1 Oven	3621	384	339.9	380.1	384	0	0	0	0	0	0	0	0	0
21	Washer 1	Random	12oz	(TP) Zone 1 Oven	3622	383	339.9	380.1	383	0	0	0	0	0	0	0	0	0
23	Ln 1 Spin'l	Pocket 1-30	12oz 202	(FH) Pocket 17 Fla	771	4.80967	4.8039	4.8201	4.8035	4.81335	4.81215	0	0	0	0	0	0	0
24	Palletizer 1	Isotonic	12oz 202	(ME) Metal Exposu	311	3.49	-0.1	15	2.8	7	15.1	4.2	0.5	0.4	0.6	0.9	0.8	2.8

Figure 3.1 – Exception Report from Salisbury Can Plant

Compliance Report - Salisbury Can Plant

Start Date: 10/1/98 Start Time: 7:00

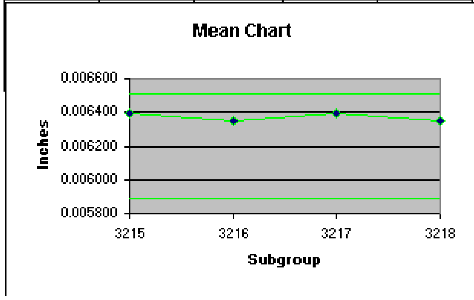
Stop Date: 10/1/98 Stop Time: 19:00

21-Mar-99

WORK STATION	MACHINE	PART	OPERATION
20	D&I 11	BM 11	2oz 20x/211

(FT) Flange Thickness	
Completed	4
Required	4
% Completed	100
Out of Control	
% Out of Control	

Subgroup	3215	3216	3217	3218
	0.00629	0.00627	0.00631	0.00628
	0.00640	0.00628	0.00637	0.00634
	0.00654	0.00651	0.00657	0.00645
	0.00636	0.00634	0.00632	0.00634
Average	0.006398	0.006350	0.006393	0.006353
Range	0.000250	0.000240	0.000260	0.000170



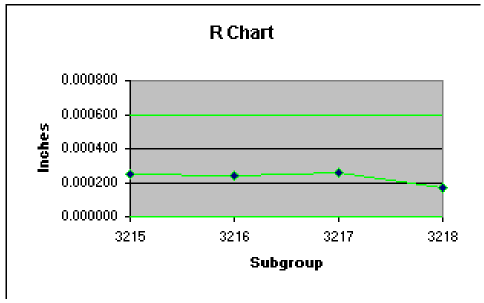


Figure 3.2 – Altered Compliance Report for Salisbury Can Plant showing 2-D Control Charts

The Quality Assurance Gauging System provides shop floor operators with quality information in the form of statistical process control charts that are used to determine whether to continue production or to stop and readjust the process. This system, however, does not provide an operator with the ability to view data across numerous quality characteristics or process control charts at the same time. Thus, operators cannot easily visualize interactions between process and product quality characteristics at a given stage in the manufacturing process. The same is true concerning the visualization of interactions between process and quality characteristics that span one or more steps in the manufacturing process.

The Process Monitoring System. Process monitoring captures dynamic state changes from programmable logic controllers that control the various machines and processes that make aluminum cans. State changes include machine processing speeds, conveyor speeds, counts of cans as inputs to machines for processing, counts of cans as outputs from machines once processed, and counts of cans moving past a particular point in the manufacturing process measured over a particular period of time.

The process monitoring system is comprised of several information systems components that have been integrated and customized for the aluminum can manufacturing process. Data collection from manufacturing line PLC's is provided by a dynamic data exchange (DDE) module running under Windows 2000. Schematics of shop floor processes that show real-time state changes and can counts are provided to users of the process monitoring system through a continuously updated Microsoft Excel spreadsheet. The cells in this spreadsheet are linked to objects in these schematics. Users visualize state changes by monitoring changes in the color of a linked object. Objects representing machines and conveying change from green (operating normally) to yellow (ready state) to red (machine down). Typically, both can counts and machine speeds are also displayed.

Process monitoring data is stored in a collection of ODBC-compliant relational databases developed under SQL Server. They reside on a Windows 2000 file server and RAID technology is used to ensure that data structures and tables can be rebuilt should a single-component disk drive fail. Reporting mechanisms are currently web-portable across the company intranet so that this information can be accessed remotely in real-time.

Machine processing speeds and counts relate directly and are vital to ensure product and process quality assurance since they provide information regarding the quantity of good and bad product that have passed through a machine and/or process and ultimately to the customer. Decisions regarding the suitability of in-process cans for further processing or finished cans for shipment are a logical and desired outcome of the shop floor monitoring systems. However, machine speeds for certain equipment can reach as high as 1200 cans per minute with the typical can manufacturing line being able to produce approximately 1 million (1,000,000) cans per day. Thus, the opportunity exists for a large number of defective cans to be produced if a critical process, product, or quality defect goes unnoticed. To date, the process monitoring system and quality assurance gauging system do not interact.

Knowledge of the can manufacturing process is essential to designing a more effective quality monitoring system. The next section describes the basic steps in the can manufacturing process, the plant layout, and the specific quality data that is collected.

Aluminum Can Manufacturing Process

The can manufacturing process consists of six basic steps:

Step 1. Aluminum sheet stock is punched or pressed into aluminum cups at the beginning of the can manufacturing process. Rolls of aluminum sheet stock are fed into a cupping press after being coated with a cupping lubricant to reduce heat and tool wear. The thickness or gage of the aluminum sheet stock varies according to the dimensions of the finished can being manufactured. For example, a 16 ounce aluminum can requires thicker sheet stock than a 12 ounce aluminum can. Cup dimensions also vary by the size of the can being produced with larger cans requiring cups of larger diameter. See Figure 3.3.

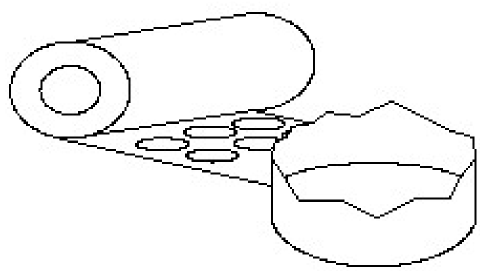


Figure 3.3 – Aluminum Sheet Stock Pressed into Cups

Step 2. Once aluminum cups are pressed, they are conveyed by single line track work to the Draw and Iron (D&I) process. Cups are fed into a machine called a body maker where they are drawn and ironed into an actual can body. The bottom of the can, critical to the columnar strength of the can, is formed at this step. Also, this process determines the thickness of the sidewall of the can. Sidewalls are thinnest in the middle part of the outside can wall and become substantially thicker towards both the top and the bottom of the can. Sidewall thickness is also critical to the columnar strength of the can. See Figure 3.4.

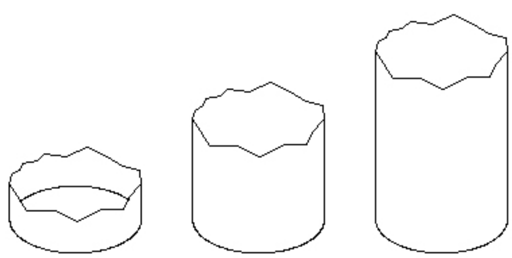


Figure 3.4 – Cups Drawn and Ironed into Can Bodies

Once drawn and ironed, the can body passes through a trimming machine (trimmer) which removes the rough edges of the can and trims the top edge to the correct height specification. While D&I aluminum can body makers use one set of tooling punches to perform operations on each can, trimmers are multi-tooled machines in that they have a number of tooling cells or pockets, each pocket with its own set of trimming tools. See Figure 3.5.

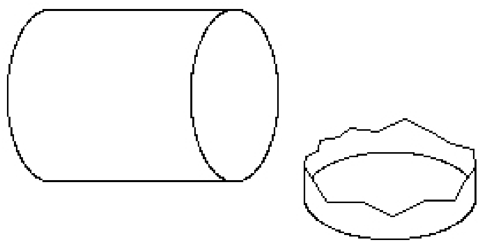


Figure 3.5 – Excess Metal Trimmed From Can Body

Lubricant, called soluble oil, is used in the D&I and trimming processes to reduce both heat and tool wear due to friction. Soluble oil, a mix of water and oil, is pumped through the tooling and sprayed onto the cup as it is being drawn, ironed, and trimmed. Soluble oil is then collected and the metal fragments are filtered out so that the lubricant can be reused.

Step 3. Aluminum cans are then conveyed to a washer that cleans and etches the can and removes any foreign material, including the soluble oil residue. Cans are conveyed to a printer where ink is applied in several coats using an offset printing process. Label specifications are provided by the customer which typically consist of ink colors, ink placement, and plate registration. A coating of overvarnish lacquer is applied to the can exterior before the can is conveyed to the exterior drying oven to be dried. This oven is called a pin oven since the cans are placed on pins before passing through the oven. This keeps the ink and overvarnish lacquer from becoming smeared since there is no physical contact with the outside of the can. See Figure 3.6.

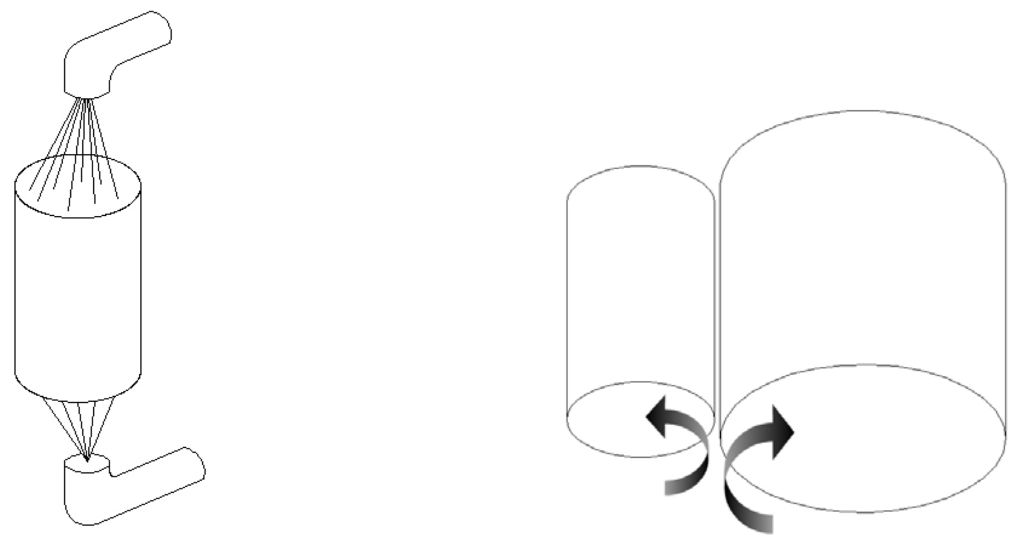


Figure 3.6 – Washing and Printing of Aluminum Can

Step 4. After exiting the pin oven, cans are distributed to a bank of spraying machines which spray enamel onto the interior walls of the can. The inside spray process utilizes one bank of spray machines per manufacturing line with five (5) or six (6) spray machines per bank. Spray machines can have one or two nozzles (guns) depending on the inside spray pattern desired. Once sprayed, cans are then conveyed to the bake oven where the inside spray enamel is cured. Inside spray coverage varies by type of fill product and is critical to keep the contents of the filled can from reacting with the aluminum. Highly acidic products such as colas and juices require a greater amount of inside spray material with proper distribution on the sides and the bottom of the can. Products with lower acidity, such as beer, do not need as much inside spray coverage though proper distribution is still important.

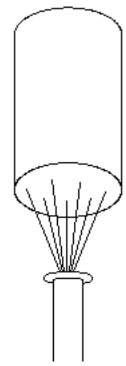


Figure 3.7 – Applying Enamel to Inside of Aluminum Can

Step 5. Once cans have passed through the bake oven, they are conveyed to the necker/flanger area. A straight-walled can must have its opening properly sized to accept the respective cover or end once it is filled with consumer product. It is the necking process which sizes this opening by drawing the aluminum at the top of the can into a smaller diameter than the straight-walled can itself. This drawing down into a smaller diameter occurs in one necking step or a series of necking steps. A flange is also drawn onto the can in order to properly accept and seal the cover or end. Both the diameter of the neck and the width of the flange are critical for proper end acceptance and seal. The height of the can once the flange is drawn is also important since it affects the filling operations at the customer. Once necked and flanged, finished product cans are 100% inspected by a light tester for pinholes and split flanges. This is to protect the customer from leaking cans once they are filled and sealed.

Figure 3.8 – Necked and Flanged Finished Aluminum Cans Pass Through Light Tester

Step 6. The finished cans are conveyed to a palletizer once properly necked and flanged. Cans are placed on wooden or plastic pallets one layer at a time and separated with either cardboard or plastic sheet stock. This sheet helps to keep the layers of cans clean since the cans are loaded upright. This sheet also helps to stabilize the next layer of cans. The top layer of cans has a wooden or plastic frame placed on top of the sheet. Plastic strapping is then vertically banded around the palletized layers of cans for shipment. In addition, some customers require their palletized cans to be wrapped in plastic for shipment. Cans are now ready for shipment to the customer’s filling operations.

Facility Layout

Figure 3.9 shows a typical two-line plant layout. A sample of the various quality characteristics that are monitored at each step in the aluminum can manufacturing process are provided in Table 3.1. As individual aluminum cups move from the cupping press, they are routed to one of a series of D&I bodymakers for conversion to can bodies. Each bodymaker has an associated trimmer that can have from one to five trimming heads. Once trimmed, the can bodies are then again aggregated to pass through the washing, etching, and printing processes. They are then arranged serially to pass through the pin oven for drying/curing. Once again grouped in aggregate, the labeled aluminum cans are routed to one of a series of spray machines for interior enamel coating. They are then grouped in aggregate in order to pass through the bake oven that cures the interior coating. Upon exiting the bake oven, aluminum can bodies enter the necking and flanging process. Much like a trimmer, the necker/flanger can have either fifteen or thirty tool sets or heads that perform the necking and flanging operations. Finished aluminum cans pass serially through the light tester for 100% inspection of pinholes. The final stage in the manufacturing process aggregates the finished aluminum cans one last time for placement on pallets for shipment to the customer.

As shown in Figure 3.9, quality at subsequent stages of production is affected by one or more stages of previous production processes. The current Quality Assurance Gauging System makes it difficult to identify the source of a quality problem. Operators cannot view multiple control charts easily, nor can they detect interactions across processes. The sheer volume of information generated is also a problem.

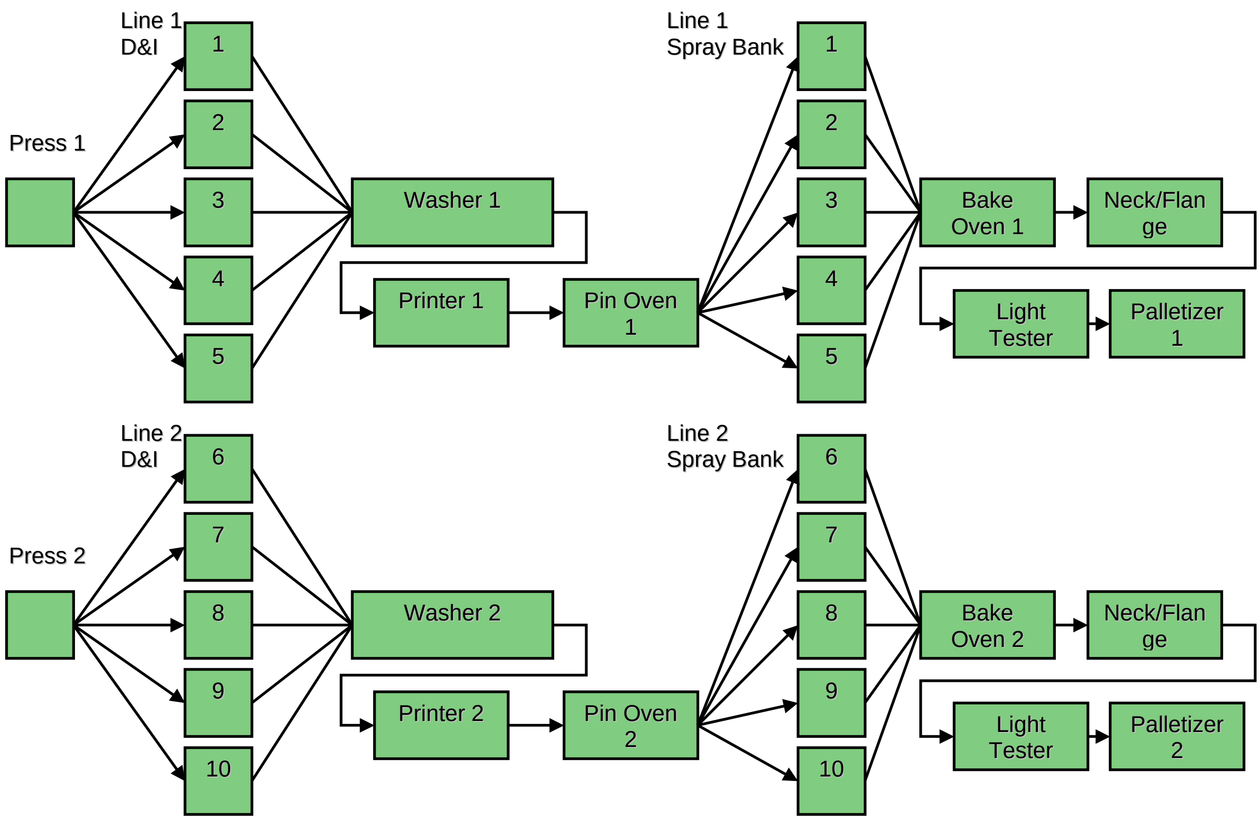


Figure 3.9 – Two-Line Can Plant Layout

Table 3.1 – Monitored Quality Characteristics

Characteristic	Code	Taken	Units
Cup Weight	(CU)	Press Area	grams
Cupping Lube Thickness	(LT)	Press Area	microns
Flange Wall Thickness, In-process	(FT)	D&I area	inches
Midwall Thickness, In-process	(WT)	D&I area	inches
Bottom Bulge, In-process	(BB1)	D&I area	psi
Column Strength, In-process	(CS1)	D&I area	lbs
Bottom Panel Depth	(BP)	D&I area	inches
Countersink Depth	(CO)	D&I area	inches
Trimmed Height	(TH)	D&I area	inches
(Inside) Spray Weight	(SW)	Spray area	grams
(Inside) Spray Thickness	(ST)	Spray area	microns
(Outside) Varnish Weight	(OW)	Spray area	grams
(Outside) Varnish Thickness	(OT)	Spray area	microns
Can Weight	(CW)	Spray area	grams
Metal Exposure, In-process	(ME1)	Spray area	millivolts
Flange Width	(FW)	Necker area	inches
Neck Plug Diameter	(NP)	Necker area	inches
Flanged Height	(FH)	Necker area	inches
Bottom Bulge, Finished can	(BB2)	Palletizer area	psi
Column Strength, Finished Can	(CS2)	Palletizer area	lbs
Metal Exposure, Finished Can	(ME2)	Palletizer area	millivolts

Data representing a two-week collection period and collected from the Quality Assurance Gauging System at the Salisbury, North Carolina aluminum can manufacturing facility were analyzed for the case study. The collected data could not be used in its raw form due to the presence of inaccurate sampling techniques and erroneous data. The data, however, did provide a basis for the creation of visual representations displayed using a simulated data set. To determine which quality characteristics and process interactions to include in the experiment, a QFD (quality function deployment) analysis was performed. The next section details that analysis.

Quality Function Deployment

The selection of quality and process characteristics to be included in the visualization experiment is based on the matrix framework of Quality Function Deployment (QFD). Quality tables, the basis for QFD, originated in the Kobe shipyards of Japan in the early 1970's as a method for planning and coordinating a modular approach to ship production. At the same time, other Japanese industries, pleased with the production capabilities of their management systems, were searching for methods to improve the planning capabilities of their systems. The design process was identified as especially wasteful given the time, money and effort expended and the number of "reworks" that were required in product design before and after production. The quality tables were refined and extended by Toyota and other Japanese firms into what is now known as Quality Function Deployment (QFD). With a set of interrelated tables that deploy customer requirements through design, manufacture and delivery, QFD has become an effective approach for product and process design. Plans extending from the nebulous "voice of the customer" to exact settings on production machines ensure that the impact of complex design decisions is communicated, coordinated and consistently enacted at each state of the design and manufacture process.

QFD came to America in the early 1980’s through such companies as Ford, Omark, and 3M. Now the technique is popular in both manufacturing and service industries worldwide, primarily in design. QFD actually consists of twenty interrelated matrices, but most companies use only the first matrix (called the House of Quality) which relates customer requirements to design characteristics. Although the real power of QFD lies in utilizing the entire spectrum of matrices, managers cannot realistically handle the explosion of decisions that need to be made as data cascades through the various “houses.”

Making wise choices in process control and quality assurance requires knowledge of the detailed ramifications of each decision. The layered tabular format of QFD is well-suited to the interlaced decisions of product and process quality, the application of visualization techniques, and the speed with which managers and operators must make decisions. The merger of QFD with visualization will enable a manager to quickly examine the projected effect of process adjustments on several layers of operations before defects occur on the manufacturing floor. With such foresight, bad decisions can be avoided, and process problems solved before they significantly affect the quality of the finished product.

A series of QFD-like matrices have been constructed to describe the interaction of product and process quality characteristics and to identify key interactions to be included in the visualization experiment. The first matrix begins with customer requirements. A global soft drink manufacturer was chosen as a representative customer. Typical production runs for this customer consist of one production line operating 24 hours a day, 7 days a week for 10 to 15 weeks to produce 70 to 100 million cans. Defective cans are scrapped as there is no rework. Table 3.2 describes the customer requirements and rates their importance. Table 3.3 relates the customer requirements to quality characteristics. It is important to be able to quantify customer requirements in the form of quality characteristics. The units of measure are shown on the bottom of the matrix. Actual values and deviations are confidential and cannot be revealed in this document. In the center of the matrix, a plus sign represents a positive relationship between a customer requirement and a quality characteristic. For example, the thickness of the aluminum can flange wall and the midwall is directly proportional to the strength of the aluminum can. This is depicted in Table 3.3 as a positive relationship between the customer requirement of Can Strength and the quality characteristics of Flange Wall Thickness and Midwall Thickness. The trimmed height of the aluminum can, as well as the width of the necked flange and the diameter of the neck are directly related to the customer requirement of Dimensional Integrity, i.e. the ease at which the aluminum cans pass through the filling operation.

Discussions with management and hourly personnel at the Salisbury Can Plant revealed numerous quality issues with the Dimensional Integrity customer requirement. Specifically, if an aluminum can becomes jammed in the filling process, customer filling operations can be shut down for a length of time from several hours to several days depending on the severity of the jam. This leads to lost filling time on the part of the customer and typically requires a major cleanup effort to remove gallons of fill product, i.e. syrup and beverage, from the filling operations machinery and work area. Charges for lost fill time and filling operations cleanup have been charged back to the Salisbury Can Plant in the past. Plant personnel felt that, while the customer requirements of Coating Adhesion, Aesthetics, and Can Strength were important, quality issues in these areas did not have the potential to shut down the customer filling operations. Typically, aluminum cans with quality issues in these areas can still be filled and ultimately sold. Also, while other aluminum can manufacturing facilities are more advanced in the statistical process control implementation efforts and track many additional quality characteristics than those provided in Table 3.1, the quality characteristics associated with the customer requirement of Aesthetics is not electronically tracked with the Quality Assurance Gauging System at the Salisbury facility. The customer requirement that was the focus of this study is highlighted in Table 3.2 below.

Table 3.2 – Customer Requirements

Requirement	**Importance**	**Description**
Coating Adhesion	4	Product doesn't eat through aluminum No thin spots when cans rub against each other
Aesthetics	3	Product label placed correctly on can Ink color true to color standard Ink color consistent across product
Dimensional Integrity	5	Cans don't leak Cans don't jam customer filling operation Ends attach correctly to can
Can Strength	4	Minimize shipping damage Minimize damage at point of use

Importance Rating: 1 (not important) to 5 (very important)

The Dimensional Integrity customer requirement has an effect on multiple product quality characteristics as shown in Table 3.3. Specifically, the product quality characteristics of Cup Weight, Flange Wall Thickness and Midwall Thickness of the aluminum can, and Trimmed Height of the aluminum can affect the dimensional integrity of the in-process can. Product quality characteristics affecting the dimensional integrity of the finished can include Flange Width and Flanged Height of the aluminum can as well as Column Strength of the aluminum can. While Column Strength can be measured for an in-process aluminum can, only finished can Column Strength was electronically tracked at the Salisbury Can Plant and thus included in this study.

Table 3.3 – Customer Quality Matrix

	Product Characteristics																				
Customer Requirement	Cup Weight	Lube Thickness	Flange Wall Thickness	Midwall Thickness	Bottom Bulge, In-process	Column Strength, In-process	Bottom Panel Depth	Countersink Depth	Trimmed Height	(Inside) Spray Weight	(Inside) Spray Thickness	(Outside) Varnish Weight	(Outside) Varnish Thickness	Can Weight	Metal Exposure, In-process	Flange Width	Neck Plug Diameter	Flanged Height (Finished)	Bottom Bulge, Finished	Column Strength, Finished	Metal Exposure, Finished
Dimensional Integrity	+		+	+		+			+							+		+		+	
Can Strength	+		+	+	+	+	+	+						+					+	+	
Coating Adhesion										+	+	+	+		+						+
Aesthetics																					
Units of Measure	gm	mc	in	in	psi	lb	in	in	in	gm	mc	gm	mc	gm	mv	in	in	in	psi	lb	mv
Target	CONFIDENTIAL																				
Deviation	CONFIDENTIAL																				

Key: + - Quality Characteristic Included in Study

Table 3.4 depicts the interrelationships among quality characteristics. Quality characteristics that exhibit multiple dependencies represent increasing data complexity. The relationships shown in this table will be used to develop the visualizations. Discussions with personnel at the Salisbury facility revealed multiple visibility issues in that operators and supervisors at the beginning stages of the manufacturing process were unaware of quality problems that were occurring at the finishing stages of the manufacturing process. Plant personnel were interested in pursuing visual methods of interaction between these two groups of operators and thus quality interrelationships were included in this study.

Table 3.4 – Interrelationship of Quality Characteristics

	Cup Weight	Lube Thickness	Flange Wall Thickness	Midwall Thickness	Bottom Bulge, In-process	Column Strength, In-process	Bottom Panel Depth	Countersink Depth	Trimmed Height	(Inside) Spray Weight	(Inside) Spray Thickness	(Outside) Varnish Weight	(Outside) Varnish Thickness	Can Weight	Metal Exposure, In-process	Flange Width	Neck Plug Diameter	Flange Height (Finished)	Bottom Bulge, Finished	Column Strength, Finished	Metal Exposure, Finished
Cup Weight			+	+	+	+								+					+	+	
Lube Thickness																					
Flange Wall Thickness					+	+													+	+	
Midwall Thickness					+	+													+	+	
Bottom Bulge, In-process																			+	+	
Column Strength, In-process																			+	+	
Bottom Panel Depth																			+	+	
Countersink Depth																					
Trimmed Height																+	+	+			
(Inside) Spray Weight											+				+						+
(Inside) Spray Thickness															+						+
(Outside) Varnish Weight													+		+						+
(Outside) Varnish Thickness															+						+
Can Weight																					
Metal Exposure, In-process																					
Flange Width																		+			
Neck Plug Diameter																					
Flange Height (Finished)																					
Bottom Bulge, Finished																					
Column Strength, Finished																					
Metal Exposure, Finished																					

Key: + - Interrelationship Included in Study

Table 3.5 describes the process characteristics that should be monitored at each machine. Although these are not included in the experiment, they are provided here to illustrate how the series of QFD matrices can be extended.

Table 3.5 – Process Characteristics

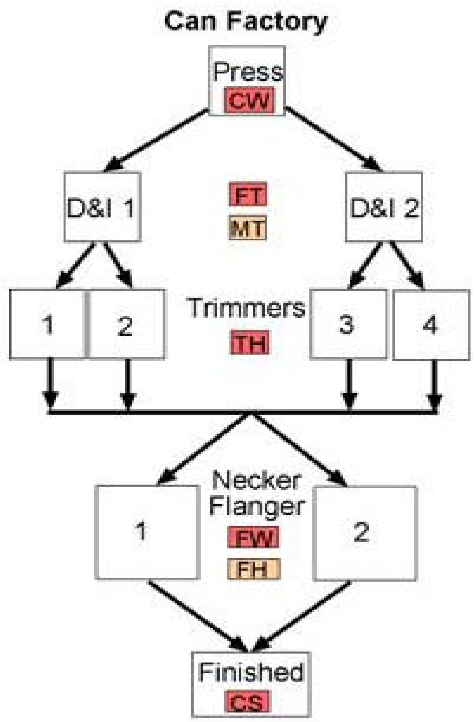
Process	Characteristic
Press	Speed, feed rate; Tool wear, placement; Lube thickness, placement
D&I Body Maker Trimmer	Speed, feed rate; Tool pack, wear, placement, stops; Soluble oil temperature, pH, tramp
Washer	Water pH, temperature, acid concentration; Chemical content; Mat speed
Printer	Speed; Printer head plate registration, temperature; Ink color, consistency; Varnish consistency
Pin Oven	Chain speed; Temperature, humidity
Spray Bank	Spray coverage, amount, consistency; Spray gun positioning, cleanliness
Bake Oven	Mat speed; Temperature, humidity
Necker/Flanger	Speed, feed rate; Tool wear, placement
Light Tester	Calibration; Speed
Palletizer	Speed

The quality/process matrix, shown in Table 3.6, relates each quality characteristic to the process where they are measured or to subsequent processes that are affected by that measurement. From the matrix, it is apparent that many of the quality characteristics are affected by the operation of the D&I body maker and the spray bank. The D&I body maker is instrumental in determining dimensional integrity, the customer requirement that is the focus of this study. The necker/flanger is also an important process. The sprayer has less of an impact on those requirements, thus, it is will not be included per se in the visualization experiment.

Table 3.6 – Quality/Process Matrix

QUALITY CHARACTERISTIC	Press	D&I Body Maker	Trimmer	Washer	Printer	Pin Oven	Spray Bank	Bake Oven	Necker/Flanger	Light Tester	Finished
Cup Weight	+	+									
Lube Thickness	+	+									
Flange Wall Thickness		+	+								
Midwall Thickness		+	+								
Bottom Bulge, In-process		+									
Column Strength, In-process		+									
Bottom Panel Depth		+									
Countersink Depth		+									
Trimmed Height			+						+		
(Inside) Spray Weight							+				
(Inside) Spray Thickness							+				
(Outside) Varnish Weight							+				
(Outside) Varnish Thickness							+				
Can Weight							+				
Metal Exposure, In-process								+			
Flange Width			+						+		
Neck Plug Diameter									+		
Flanged Height (Finished)			+						+		
Bottom Bulge, Finished						+		+			+
Column Strength, Finished						+		+			+
Metal Exposure, Finished											+

The series of QFD matrices helped to narrow down the choice of quality characteristics to be included in the visualization experiment. For example, important interactions within processes and across processes can be tested with the following characteristics: Cup Weight and its interaction with Flange Wall Thickness and Midwall Thickness, Trimmed Can Height and its interaction with Flange Width, Neck Plug Diameter, and Finished Can Height. The highlighted rows in Table 3.6 are the quality characteristics included in this study, along with the corresponding processes. The simulated factory layout, then, is reduced from that shown in Figure 3.1, to the revised layout shown in Figure 3.10.



Key:	
CW	Cup Weight
FT	Flangewall Thickness
MT	Midwall Thickness
TH	Trimmed Height
FW	Flange Width
FH	Flanged Height
CS	Column Strength

Figure 3.10 – Revised Can Factory Layout

The Visualization Experiment

For this research, the investigator used a laboratory experiment to examine simulated data sets which were then used by subjects to make decisions. The interactive data collection software was developed with the assistance of the Virginia Tech multimedia laboratory using the Java Developers Toolkit and the Java 3D Runtime Environment. Use of the Java Developers Toolkit (JDK) allowed for the real-time rendering of the visual representations used in this experiment such that no static imagery had to be created or stored. JDK also was used to build the user interface screens used to collect the data and verify the accuracy of respondents' results for the training phase of the experiment. The Java 3D Runtime Environment was used to create the 3-dimensional visualizations and to make them both sizeable and rotatable for the user. Again, rendering of the visual imagery occurred in real-time and eliminated the creation and storage of numerous 3-dimensional static images. The laboratory experiment was loaded onto six (6) computer test stations located in the Marketing Behavioral Laboratory at Virginia Tech. Subject participants were then able to proceed with the experiment in a controlled setting.

A simulated set of quality data was used for this experiment rather than using actual production data for the various quality characteristics from the Salisbury facility. Quality data was generated using the random number generating capabilities in Microsoft Excel and the RAND( ) function. Each Excel spreadsheet contained thirty (30) data points on which to calculate control limits and then an additional thirty (30) data points representing measurements for a given quality characteristic. Out of control conditions were then introduced into each of the spreadsheets as required to represent the particular quality characteristic to be displayed.

The experiment used undergraduate college students enrolled in the introductory operations management course as subjects. The students had recently covered statistical process control in class. Two points extra credit added to the final grade for the course were given as incentives for participating. No points were given for incomplete sessions. The web-based laboratory experiment included briefing instructions, demographic questions, and a series of visualizations where subjects were asked a subset of questions relating to that particular visual representation. Specifically, subjects were asked to assess whether a process is out-of control and, if so, to determine the source of the out-of-control condition. Sample screen captures from student training sessions are included in the appendix.

Subjects participating in the laboratory experiment were given one specific type of visual representation from the four developed (i.e. Table, 2D, 2DA, 3D discussed in the next section) for all datasets presented to them for analysis. It would have been difficult to train a subject on more than one type of visual representation without biasing the results. For training purposes, a subject could receive as many as five (5) training scenarios in which their results were presented at the end of each scenario along with the correct answers. Subjects were allowed to proceed to the test portion of the experiment once they had successfully completed three training scenarios. They were then given a total of five different test scenarios of the same visualization type to assess. The entire experimental process took approximately 45 minutes.

Experimental Design

The visual representations were tested under a variety of experimental conditions based on a four-factorial experimental design. The experimental design is shown in Table 3.7. Factors include the data representation method to be displayed to the subject, the complexity of the data, process quality, and the visual acuity of the subject. Performance measures include the accuracy of the decision made by the subject decision-maker, the timeliness of the decision made by the subject decision-maker, and the confidence of the decision made by the subject decision-maker. The factors and factor levels are described in the next section.

Table 3.7 – Experimental Design

Factor A - Visual Representation	
	1. Tabular Data
	2. 2D Image
	3. 2D Animated Image
	4. 3D Interactive Image
Factor B - Process Complexity	
	1. In Control
	2. Single Process Out of Control
	3. Parallel Processes Out of Control
	4. Serial Processes Out of Control
Factor C - Quality Issue	
	1. In Control
	2. Shift in Mean
	3. Shift in Variation
	4. Pattern in Data
Factor D - Visual Acuity of Decision Maker	
	1. Low
	2. Medium
	3. High

Visual Representations. Examples of visual representations of process and quality data include:

Tabular data - Data presented in tabular format includes standard, non-image reporting methods generated through the use of queries and reports (see Figure 3.11).

Two-dimensional images - Data presented in two-dimensions consists of statistical quality control charts, specifically X-bar charts and R-chart (see Figure 3.12).

Two-dimensional animated images - Data presented using two-dimensional animation builds the data points as time progresses from some time period, t, to some other time period in the future, t + n, where n is the number of time periods to be animated.

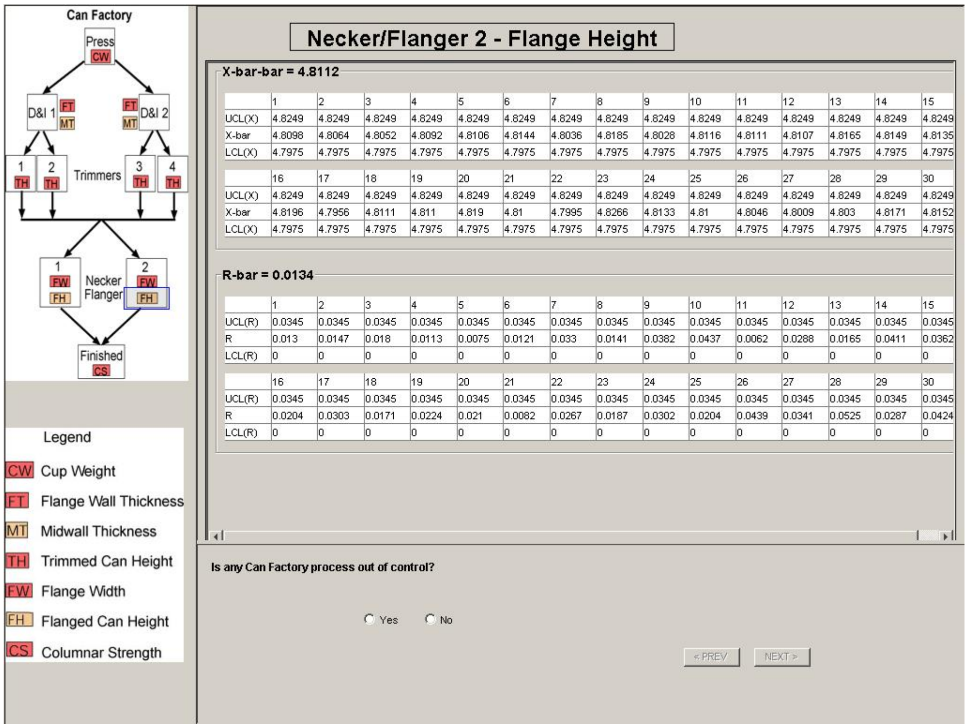


Figure 3.11 – Table of Quality Data

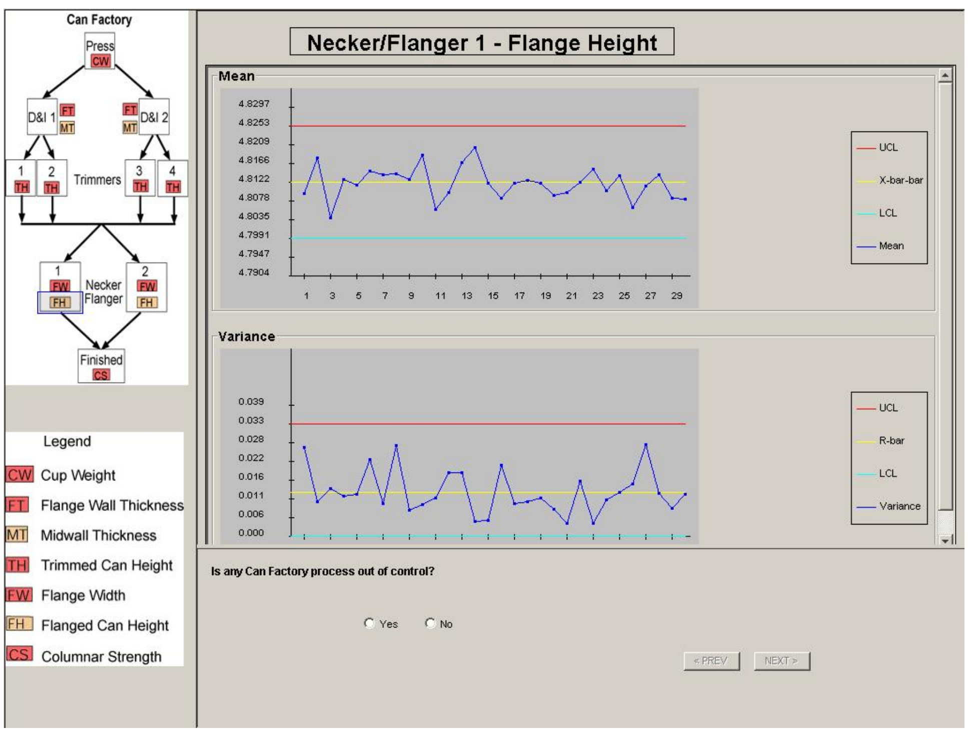


Figure 3.12 – Two-Dimensional Image

Three-dimensional image - Figure 3.13 presents quality data in three-dimensions with ribbon mean and control limits. The image can be manipulated and scaled both vertically and horizontally.

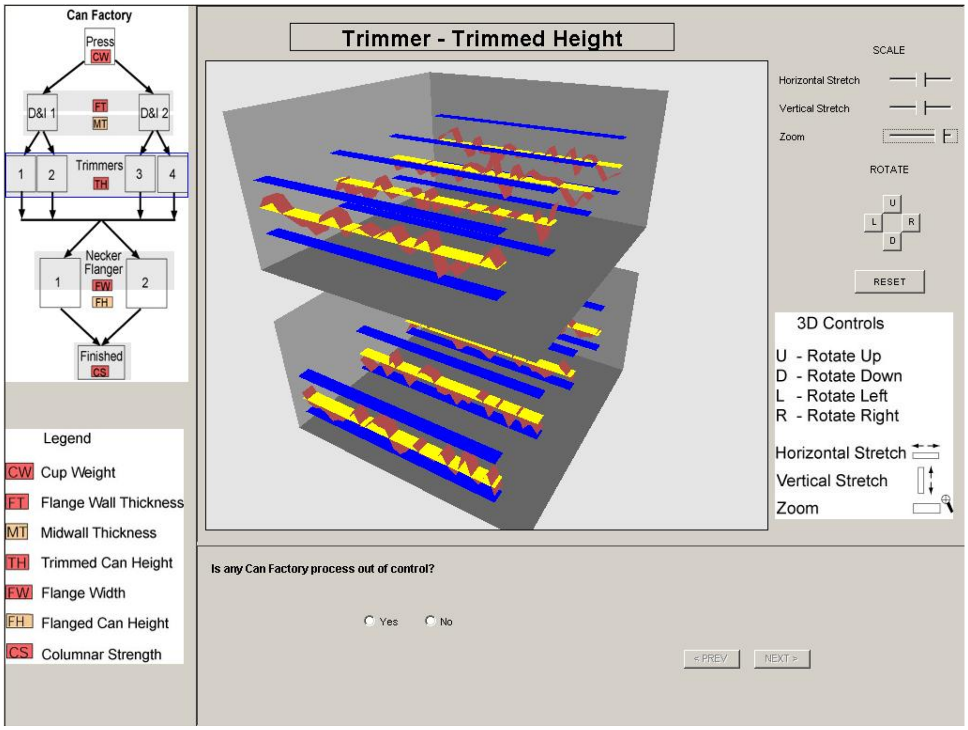


Figure 3.13 – Three-Dimensional Interactive Image

Process Complexity. A set of nine (9) case scenarios were created for this study based on the most common quality problems identified in the case study data and the QFD analysis. Case 0 represents the scenario where all processes of the Can Factory are in control. Cases 4, 6, and 9 represent the scenario where only one process of the Can Factory is out-of-control, i.e. a single process. Cases 3, 5, and 8 represent the scenario where two or more like processes of the Can Factory are out-of-control, i.e. parallel machines of the same process. Cases 1, 2, and 7 represent the scenario where one upstream process is out-of-control, affecting a subsequent out-of-control downstream process, i.e. serial processes (see Figure 3.14).

Can Factory Case	Process Complexity
Case 0:	In Control
Can Factory In Control	
Case 1: Press Out of Control which Affects All D&I	Serial
Case 2: Press Out of Control which Affects Finished	Serial
Case 3: All D&I Out of Control	Parallel
Case 4: One D&I Out of Control	Single
Case 5: All Trimmers Out of Control	Parallel
Case 6: One Trimmer Out of Control	Single
Case 7: All Trimmers Out of Control which Affects All Neckers	Serial
Case 8: All Neckers Out of Control	Parallel
Case 9: One Necker Out of Control	Single
Key:	In Control
	Single
	Serial
	Parallel

Figure 3.14 – Process Complexity Case Scenarios

Quality Issue. Similar to the process complexity factor, the different levels of quality issues are represented in the case scenarios. Case 0 represents the scenario where all processes of the Can Factory are in control. For each of the cases 1 through 9, the respective mean or means are above or below mean control limits for the Mean Out of Control quality issue. For each of the cases 1 through 9, the respective range or ranges are above or below range control limits for the

Variance Out of Control quality issue. For the Pattern quality issue, a pattern has been introduced into the data, specifically a run of seven data points. The Pattern quality issue exists for Single process complexity only, i.e. cases 4, 6, and 9.

Visual Acuity. Visual Acuity is measured using the Vividness of Visual Imagery Questionnaire referenced in Marks (1973). The VVIQ consists of sixteen statements concerning objects or events to be visualized by the study participant. Each participant responds to the statements with an integer ranging from one to five indicating how vivid the image represented by the statement is to them (1= no image at all; 2 = image vague and dim; 3 = image moderately clear and vivid; 4 = image clear and reasonably vivid; 5 = image perfectly clear and vivid as normal vision). The VVIQ score was calculated by averaging the responses to the sixteen (16) visualization statements. The VVIQ classification was based on this average (Low = 1, 2; Medium = 3; High = 4, 5).

Randomized Block Design

A full factorial for this study yields 192 experimental conditions and thus potentially 192 different visualizations (assuming one visualization per combination of factors). An experiment of this magnitude is deemed infeasible given the use of human subjects. It is preferable to use a random block design to test the interactions between the various factors.

Subjects participating in the laboratory experiment were given one specific type of visual representation from the four developed (i.e. Table, 2D, 2DA, 3D) for all datasets presented to them for analysis. The reason for this is for training purposes as it would be impossible to train a subject on more than one type of visual representation without biasing the results. For training purposes, a subject could receive as many as five (5) training scenarios in which their results were presented at the end of each scenario along with the correct answers. Subject were allowed to proceed to the test portion of the experiment once they had successfully completed three training scenarios or once they had completed five training scenarios irrespective of correctness. They were then given a total of five test scenarios of the same visualization type as their training scenarios.

While the visualization type was fixed for a given subject for all dataset scenarios received, both process complexity (Factor B) and quality issue (Factor C) were allowed to vary by scenario. Thus, Factor A was controlled at the subject level while Factors B and C were controlled at the dataset scenario level, making for a split-plot design. The experiment was also a random factor experiment in that not all scenarios were possible. For example, the In Control process complexity condition was not applicable to the quality issue (Factor C) conditions of Mean, Variance, and Pattern. Further, the In Control quality issue condition was not applicable to the process complexity (Factor B) conditions of Single, Serial, and Parallel. Finally, the Pattern quality issue condition was not applicable to either the Serial or Parallel process complexity condition. See Table 3.8.

Table 3.8 – All Possible Combinations of Factors For Laboratory Experiment

Factors		C: In Control			C: Mean		
		D: Low	D: Med	D: High	D: Low	D: Med	D: High
A: Table	B: In Control	X	X	X			
	B: Single				X	X	X
	B: Serial				X	X	X
	B: Parallel				X	X	X
A: 2D	B: In Control	X	X	X			
	B: Single				X	X	X
	B: Serial				X	X	X
	B: Parallel				X	X	X
A: 2DA	B: In Control	X	X	X			
	B: Single				X	X	X
	B: Serial				X	X	X
	B: Parallel				X	X	X
A: 3D	B: In Control	X	X	X			
	B: Single				X	X	X
	B: Serial				X	X	X
	B: Parallel				X	X	X

Factors		C: Variance			C: Pattern		
		D: Low	D: Med	D: High	D: Low	D: Med	D: High
A: Table	B: In Control						
	B: Single	X	X	X	X	X	X
	B: Serial	X	X	X			
	B: Parallel	X	X	X			
A: 2D	B: In Control						
	B: Single	X	X	X	X	X	X
	B: Serial	X	X	X			
	B: Parallel	X	X	X			
A: 2DA	B: In Control						
	B: Single	X	X	X	X	X	X
	B: Serial	X	X	X			
	B: Parallel	X	X	X			
A: 3D	B: In Control						
	B: Single	X	X	X			
	B: Serial	X	X	X			
	B: Parallel	X	X	X			

Key: X - Possible Combination of Random Factors

Experimental Hypotheses

The hypotheses that will be tested in this study are listed below:

Hypothesis One: The ability of a decision-maker to detect process quality is not affected by the type of Visual Representation being displayed.

Hypothesis Two: The ability of a decision-maker to assess process quality and to respond in a timely manner is not affected by the type of Visual Representation being displayed.

Hypothesis Three: The confidence with which a decision-maker is able to detect process quality is not affected by the type of Visual Representation being displayed.

Hypothesis Four: The ability of a decision-maker to detect process quality is not affected by the complexity of the data being visualized.

Hypothesis Five: The ability of a decision-maker to detect process quality is not affected by the quality issue being visualized.

Hypothesis Six: The ability of a decision-maker to detect process quality is not affected by the visual acuity of the subject as categorized by their VVIQ score.

Personnel at the Salisbury facility were very interested in determining if the presentation of quality data in differing visual representations would have an effect on decision-making response times due past occurrences of large number of defective cans being produced. They were also interested both accuracy and confidence, especially for operators who had only recently been hired at the facility and thus had very little experience in the aluminum can manufacturing process. Chapter 4 continues with the results of the visualization experiment.

CHAPTER 4

EXPERIMENTAL ANALYSIS AND RESULTS

This section begins with a description of the collected sample data set and the analytical procedures used in the statistical analysis of that data. Each of the proposed hypotheses is discussed in detail and evidence is provided showing whether the particular hypothesis being analyzed should be rejected or not. This section also includes a discussion of the interactions that are shown to exist between certain collected variables of interest.

Description of the Sample Data Set

As described in the previous chapter, the amount of time a subject took to view a can plant dataset and make a decision was recorded, along with the accuracy of the decision and subject confidence in the decision. Decision accuracy incorporated subject answers concerning whether the can plant was in or out of control, whether the primary/secondary processes were in or out of control, and whether one or all of the machines of a particular process were in or out of control. A visualization index, called VVIQ, was also measured for each study participant after the subject had viewed multiple can plant datasets. There were 59 subject participants in the study and statistics were collected on a total of 295 datasets. Demographic data collected on the experiment participants included age, gender, computer experience, work experience, education level, highest degree earned, statistical training or background, operations management training or background, and major in college. This demographic data is shown in Table 4.1 and is organized by visual representation type. The visual representation types are data table (TABLE), 2-dimensional control chart (2D), 2-dimensional animated control chart (2DA), and 3-dimensional interactive control chart (3D).

Table 4.1 – Demographic Data by Visualization Type

Demographic Measurement		Visualization Type				
		TABLE	2D	2DA	3D	Total
Age (years)	20	7	6	8	7	28
	21	6	4	4	7	21
	22	1	5	1		7
	23				2	2
	24			1		1
	Total	14	15	14	16	59
Gender	Female	5	6	6	4	21
	Male	9	9	8	12	38
	Total	14	15	14	16	59
Computer Experience (years)	2 to 3	1			2	3
	4 to 5	2	1			3
	5+	11	14	14	14	53
	Total	14	15	14	16	59
Work Experience (years)	0 to 1		3	1	1	5
	2 to 3	3	4	2	6	15
	4 to 5	5	4	4	3	16
	5+	6	4	7	6	23
	Total	14	15	14	16	59
College Level	Junior	5	6	8	6	25
	Senior	9	9	6	10	34
	Total	14	15	14	16	59
Highest Degree Earned	Secondary	12	14	12	13	51
	Assoc	2		2	2	6
	BS		1		1	2
	Total	14	15	14	16	59
Formal Training: Statistics	Yes	13	15	14	16	58
	No	1				1
	Total	14	15	14	16	59
Formal Training: Operations	Yes	12	6	9	6	33
	No	2	9	5	10	26
	Total	14	15	14	16	59
Undergraduate Major	ACIS		3	2	3	8
	BIT	3	3	4	3	13
	ECON				2	2
	FIN	4	4	1	3	12
	HTM	2	1	1	1	5
	MGT	4	2	1	3	10
	MKT	1	1	5		7
	Other		1		1	2
	Total	14	15	14	16	59

The experimental data was processed to determine the accuracy of the subject responses for each of their observed datasets. Accuracy was measured as the number of correct answers given by a subject for a case-specific dataset. Cases where only a subset of questions was valid were standardized so that accuracy could be compared across all cases. Figure 4.1 shows the network flow diagram of the decision-making process for this experiment.

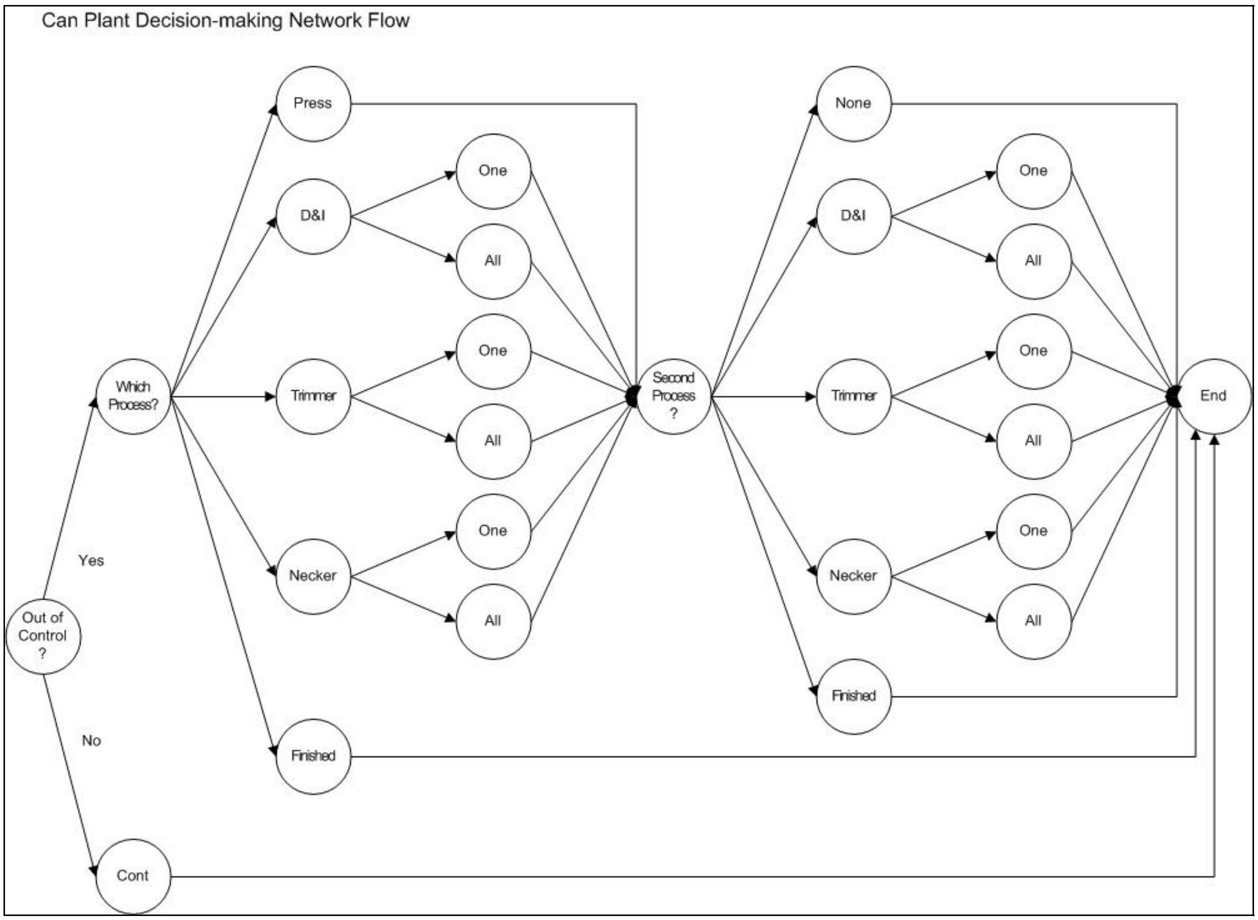


Figure 4.1 – Network Flow Diagram of Decision-making Process

Study participants could accumulate up to five (5) points based on the accuracy of their respective answers as they make their decisions in response to the questions displayed onscreen in the experiment. Accuracy of their responses depends on which of the ten (10) experiment cases is being displayed onscreen for the study participant. Table 4.2 shows which questions were valid for each of the cases and the standard points given for each question.

Table 4.2 – Accuracy Score by Case

Case (points awarded in parentheses)	Question 1: Is Any Process Out of Control?	Question 2: Which Process Caused Problem?	Question 3: All of That Process?	Question 4: Subsequent Process Out?	Question 5: All of That Process?
Case 0: In Control	No (5) Yes (0)	N/A	N/A	N/A	N/A
Case 1: Press Affects All D&I	Yes (1) No (0)	Press (2) All other (0)	N/A	D&I (1) All other (0)	All (1) One (0)
Case 2: Press Affects Finished	Yes (1) No (0)	Press (2) All other (0)	N/A	Finished (2) All other (0)	N/A
Case 3: All D&I	Yes (1) No (0)	D&I (1) All other (0)	All (1) One (0)	None (2) All other (0)	N/A
Case 4: One D&I	Yes (1) No (0)	D&I (1) All other (0)	All (0) One (1)	None (2) All other (0)	N/A
Case 5: All Trimmers	Yes (1) No (0)	Trimmer (1) All other (0)	All (1) One (0)	None (2) All other (0)	N/A
Case 6: One Trimmer	Yes (1) No (0)	Trimmer (1) All other (0)	All (0) One (1)	None (2) All other (0)	N/A
Case 7: All Trimmers Affects All Neckers	Yes (1) No (0)	Trimmer (1) All other (0)	All (1) One (0)	Necker (1) All other (0)	All (1) One (0)
Case 8: All Neckers	Yes (1) No (0)	Necker (1) All other (0)	All (1) One (0)	None (2) All other (0)	N/A
Case 9: One Necker	Yes (1) No (0)	Necker (1) All other (0)	All (0) One (1)	None (2) All other (0)	N/A

Descriptive statistics on Completion Time, Accuracy, and Confidence for each of the visual representations is shown in Table 4.3. Procedures selected for analysis and hypothesis testing were chosen based on these descriptive statistics and the underlying distribution of the data.

Table 4.3 – Descriptive Statistics by Visual Representation

Visual Representation		TABLE	2D	2DA	3D
Completion Time	n	70	75	70	80
	Mean	265.36	60.25	231.33	68.83
	StDev	188.09	47.77	258.25	46.02
Accuracy	n	70	75	70	80
	Mean	3.30	3.03	3.01	3.70
	StDev	1.85	2.10	2.05	1.88
Confidence	n	70	75	70	80
	Mean	2.34	2.20	2.23	2.13
	StDev	0.93	0.93	0.76	0.93

Statistical Model

A model was developed so that the relevant factors could be examined with respect to significance. Completion Time, Accuracy, and Confidence were chosen as the response variables which are a function of the following four factors:

Completion Time, Accuracy, Confidence = *f* (A, B, C, D)

where A = Visual Representation,

B = Process Complexity,

C = Quality Issue, and

D = Visual Acuity of the subject.

Timeliness is a continuous variable which records the time, in seconds, for the subject to view and review a can plant dataset and answer questions about the process. Accuracy is an integer score, ranging from 0 to 5, based on the correctness of the subject's answers about the process. Confidence is a response given by the subject, ranging from 1 (low confidence) to 5 (high confidence), based on their perception of how well they performed on a given dataset.

The first factor is the visual representation displayed to the subject in the experiment, specifically a Data Table (TABLE), a 2-Dimensional control chart (2D), a 2-Dimensional animated control chart (2DA), or a 3-Dimensional interactive control chart (3D). The second factor is the complexity of the process being displayed, specifically a Single Process being affected by a quality control issue, a Parallel Process being affected by a quality control issue (i.e. all machines of a given process), or a Serial Process being affected by a quality control issue (i.e. a machine from one process affecting a subsequent downstream process). This factor is not applicable to the in-control condition. The third factor is the quality issue being displayed, specifically a Shift in Mean, a Shift in Variance, or a Pattern (or run) in the data. This factor is also not applicable to the in-control condition. The fourth factor is the visual acuity of the subject as measured by the Vividness of Visual Imagery Quotient (VVIQ). While a total of five (5) datasets were displayed to each of the subjects, a subject has only one VVIQ. For this study, the VVIQ scores were categorized into Low, Medium, and High scores. Ratings of 1 or 2 were considered low scores, 3 was a medium score, and 4 or 5 a high score. Table 4.4 summarizes the three response variables and four factors.

Table 4.4 – Response Variables and Factor Levels

Response Variables				
Completion Time (seconds)				
Accuracy Score (points)				
Confidence (ordinal scale)				
	Levels			
Factors	1	2	3	4
A: Visual Representation	TABLE	2D	2DA	3D
B: Process Complexity	In Control	Single	Serial	Parallel
C: Quality Issue	In Control	Mean Out	Variance Out	Pattern
D: Visual Acuity	Low	Medium	High	

The mixed model procedure was used in SAS (version 9.1) to analyze the model for the three response variables since SAS can analyze both continuous and discrete variables simultaneously. Each of the individual factors was included in the model along with all possible two-way, three-way, and four-way interactions. The mixed model procedure (PROC MIXED) was used since the model is a split-plot model, i.e. factors B and C vary by dataset while factors A and D vary by subject. For example, a subject sees all 2D datasets but the process complexity and quality issue varies between displayed datasets. The mixed model procedure addresses the autocorrelation that may occur between the five datasets displayed to a subject (i.e. the learning effect) and adjusts the various respective error terms in determining which factors and interactions are significant in the model. PROC MIXED also allows for unbalanced designs and missing data, as in the case where the process is in control and thus factors B and C are not valid. Least squares means cannot be calculated for factor combinations where there are no observations and thus the general linear model SAS procedure (PROC GLM) cannot be used.

Table 4.5 – SAS Mixed Model Procedure Results by Response Variable

	Probability (> F-statistic)		
Effect	Completion Time	Accuracy	Confidence
A	< 0.0001	0.0567	0.6323
B	0.5051	0.5128	0.3439
C	0.6313	0.2515	0.9982
D	0.0057	0.2905	0.0008
A x B	0.2421	0.3123	0.5068
A x C	0.5231	0.0068	0.3372
A x D	< 0.0001	0.1265	0.4535
B x C	0.3770	0.1322	0.9096
B x D	0.8231	0.3490	0.0912
C x D	0.8668	0.5933	0.0998
A x B x C	0.0493	0.5293	0.5162
A x B x D	0.0034	0.6447	0.6209
A x C x D	0.1510	0.3576	0.2208
B x C x D	0.9595	0.4687	0.5169
A x B x C x D	0.0127	0.7850	0.0982

Key:	Significant at 10% level
	Significant at 5% level
	A = Visual Representation
	B = Process Complexity
	C = Quality Issue
	D = Visual Acuity

Results for the SAS mixed model procedures for the three response variables are given in Table 4.5 and are discussed below. With respect to Completion Time, the main effect factors that are significant at the 0.05 level include A (Visual Representation) and D (Visual Acuity) with p-values of < 0.0001 and 0.0057 respectively. The A x D two-way interaction (Visualization Representation x VVIQ) is significant at the 0.05 level with a p-value of < 0.0001. The three-way interactions that are significant at the 0.05 level are: A x B x C: Visualization Type x Complexity x Condition (p-value of 0.0493); A x B x D: Visualization Type x Complexity x VVIQ (p-value of 0.0034). The four-way interaction of A x B x C x D (Visualization Representation x Process Complexity x Quality Issue x Visual Acuity) is also significant at the 0.05 level with a p-value of 0.0127.

With respect to Accuracy, there are no main effect factors that are significant at the 0.05 level. However, there is one main effect factor that is significant at the 0.10 level, A: Visualization Type with a p-value of 0.0567. There is only one two-way interaction that is significant at the 0.05 level, specifically A x C: Visualization Type x Condition with a p-value of 0.0068. There are no three-way or four-way interactions that are significant at either the 0.05 or 0.10 level.

With respect to confidence, the only main effect that is significant at the 0.05 level is D: VVIQ with a p-value of 0.0008. There are two two-way interactions that are significant at the 0.10 level, specifically BD (Complexity x VVIQ) with a p-value of 0.0912, and CD (Quality Issue x VVIQ) with a p-value of 0.0998. While there are no three-way interactions that are significant at either the 0.05 or 0.10 level, the four-way interaction ABCD (Visualization Type x Complexity x Quality Issue x VVIQ) is significant at the 0.10 level with a p-value of 0.0982.

Hypothesis Tests

The first hypothesis to be tested concerns the ability of a decision-maker to detect process quality according to the type of Visual Representation being displayed. Stated in null form:

$H1_0$: The ability of a decision-maker to detect process quality is not affected by the type of Visual Representation being displayed.

Results from the SAS mixed model discussed earlier did show that, while Visualization Type was not extremely significant at the 0.05 level with respect to Accuracy, the p-value for this main effect was 0.0567. Comparisons of the means for the four Visualization Types were conducted using respective t-tests for independent means. The results are shown in Table 4.6.

Table 4.6 – Means Comparisons for Accuracy by Visualization Type

Comparison	p-value
TABLE vs 2D	0.4064
TABLE vs 2DA	0.3880
TABLE vs 3D	0.1920
2D vs 2DA	0.9714
2D vs 3D	0.0375
2DA vs 3D	0.0352

Key:	
	Significant at 10% level
	Significant at 5% level

Visual Representation		2DA	2D	TABLE	3D
Accuracy	n	70	75	70	80
	Mean	3.01	3.03	3.30	3.70
	StDev	2.05	2.10	1.85	1.88
		Grouped Means			
				Grouped Means	

While there was not enough evidence to reject $H1_0$ at the 0.05 level across all Visualization Types, results from the t-tests show that differences in mean accuracy between the 2D and 3D Visualization Types as well as between the 2DA and 3D Visualization Types are significant at the 0.05 level with p-values of 0.0375 and 0.0352 respectively. Mean Accuracy is not significantly different between the 2DA, 2D, and TABLE Visualization Types at the 0.05 level of significance and thus those means are grouped together in Table 4.6. Mean Accuracy is also not significantly different between the TABLE and 3D Visualization Types at the 0.05 level of significance and those means are grouped together in Table 4.6 as well.

The second hypothesis to be tested concerned the response time of a decision-maker in detecting process quality with respect to the type of Visual Representation being displayed. Stated in null form:

H2$_0$: The ability of a decision-maker to assess process quality and to respond in a timely manner is not affected by the type of Visual Representation being displayed.

The SAS mixed model discussed earlier did show that Visualization Type was significant with respect to Timeliness with a p-value of less than 0.0001. There is enough evidence to reject H2$_0$ at the 0.05 level of significance. Comparisons of the means for the four Visualization Types were conducted using respective t-tests for independent means. The results are shown in Table 4.7.

Table 4.7 – Means Comparisons for Timeliness by Visualization Type

Comparison	p-value
TABLE vs 2D	< 0.0001
TABLE vs 2DA	0.3746
TABLE vs 3D	< 0.0001
2D vs 2DA	< 0.0001
2D vs 3D	0.2576
2DA vs 3D	< 0.0001

Key:	
	Significant at 10% level
	Significant at 5% level

Visual Representation		2D	3D	2DA	TABLE
Completion Time	n	75	80	70	70
	Mean	60.25	68.83	231.33	265.36
	StDev	47.77	46.02	258.25	188.09
		Grouped Means			
				Grouped Means	

Shorter response times are associated with both the 2D and 3D Visualization Types while the 2DA and TABLE Visualization Types show longer response times. With respect to grouped means, Mean Completion Time is not significantly different between the 2D and 3D Visualization Types at the 0.05 level of significance. Mean Completion Time is also not significantly different between the 2DA and TABLE Visualization Types at the 0.05 level of significance. It is important to note the practical interpretation of these results. For 2D and 3D Visualization Types, at one-million cans per shift per line, approximately 1500 defective aluminum cans would be processed before the quality problem was identified. For TABLE and 2DA Visualization Types, approximately 6500 defective aluminum cans would be processed before the quality problem would be identified, a difference of 5000 aluminum cans.

The third hypothesis to be tested concerned the confidence of the decision-maker in making the correct analysis from the Visual Representations. Stated in null form:

$H3_0$: The confidence with which a decision-maker is able to detect process quality is not affected by the type of Visual Representation being displayed.

The SAS mixed model discussed earlier did not indicate that Visualization Type was significant with respect to Confidence (p-value of 0.6323). There is not enough evidence to reject $H3_0$ at the 0.05 level of significance. Comparisons of the means for the four Visualization Types using respective t-tests for independent means verify this conclusion. The results are shown in Table 4.8. With respect to grouped means, Mean Confidence is not significantly different between the 3D, 2D, 2DA, and TABLE Visualization Types at the 0.05 level of significance.

Table 4.8– Means Comparisons for Confidence by Visualization Type

Comparison	p-value
TABLE vs 2D	0.3571
TABLE vs 2DA	0.4287
TABLE vs 3D	0.1553
2D vs 2DA	0.8397
2D vs 3D	0.6171
2DA vs 3D	0.4563

Key: Significant at 10% level; Significant at 5% level

Visual Representation		3D	2D	2DA	TABLE
Confidence	n	80	75	70	70
	Mean	2.13	2.20	2.23	2.34
	StDev	0.93	0.93	0.76	0.93
		Grouped Means			

The fourth hypothesis to be tested concerned the ability of a decision-maker to detect process quality according to the complexity of the data being displayed. Stated in null form:

$H4_0$: The ability of a decision-maker to detect process quality is not affected by the complexity of the data being visualized.

The SAS mixed model discussed earlier did not indicate that Process Complexity was significant with respect to Accuracy (p-value of 0.2515). There is not enough evidence to reject $H4_0$ at the 0.05 level of significance. Comparisons of the means for the four levels of Process Complexity using respective t-tests for independent means are shown in Table 4.9 and appear to be conflicting. Accuracy of subject scores between Single and Serial are significant at the 0.05 level (p-value of 0.0005), likewise between Serial and Parallel at the 0.05 significance level (p-value of 0.0134). Thus, while the SAS model did not show Process Complexity as a significant main effect, there is significance between two of the means. With respect to grouped means, Mean Accuracy is not significantly different between the Single, Parallel, and In Control Process Complexities at the 0.05 level of significance. Mean Accuracy is also not significantly different between the In Control and Serial Process Complexities at the 0.05 level of significance.

Table 4.9– Means Comparisons for Accuracy by Process Complexity

Comparison	p-value
In Control vs Single	0.3259
In Control vs Serial	0.6713
In Control vs Parallel	0.5410
Single vs Serial	0.0005
Single vs Parallel	0.3819
Serial vs Parallel	0.0134

Key:	
	Significant at 10% level
	Significant at 5% level

Process Complexity		Single	Parallel	In Control	Serial
Accuracy	n	117	82	14	82
	Mean	2.91	3.16	3.57	3.85
	StDev	2.13	1.91	2.34	1.64
		Grouped Means	Grouped Means	Grouped Means	
				Grouped Means	Grouped Means

The fifth hypothesis to be tested concerned the ability of a decision-maker to detect process quality according to the underlying quality issue contained in the sample data. Stated in null form:

$H5_0$: The ability of a decision-maker to detect process quality is not affected by the quality issue being visualized.

The SAS mixed model discussed earlier did not indicate that Quality Issue was significant with respect to Accuracy (p-value of 0.5128). There is not enough evidence to reject $H5_0$ at the 0.05 level of significance. Comparisons of the means for the four Quality Issue levels using respective t-tests for independent means are shown in Table 4.10 and verify this conclusion. With respect to grouped means, Mean Accuracy is not significantly different between the Pattern, Mean, Variance, and In Control Quality Issues at the 0.05 level of significance.

Table 4.10– Means Comparisons for Accuracy by Quality Issue

Comparison	p-value
In Control vs Mean Out	0.6713
In Control vs Variance Out	0.7802
In Control vs Pattern	0.2622
Mean Out vs Variance Out	0.6951
Mean Out vs Pattern	0.1774
Variance Out vs Pattern	0.1159

Key:	
	Significant at 10% level
	Significant at 5% level

Quality Issue		Pattern	Mean	Variance	In Control
Accuracy	n	38	124	119	14
	Mean	2.74	3.29	3.39	3.57
	StDev	2.26	1.91	1.91	2.34
		Grouped Means			

The sixth hypothesis to be tested concerned the ability of a decision-maker to detect process quality according to his or her visual acuity. Stated in null form:

$H6_0$: The ability of a decision-maker to detect process quality is not affected by the visual acuity of the subject as categorized by their VVIQ score.

The SAS mixed model discussed earlier did not indicate that VVIQ classification was significant with respect to Accuracy (p-value of 0.2905). There is not enough evidence to reject $H6_0$ at the 0.05 level of significance. Comparisons of the means for the three VVIQ classifications using respective t-tests for independent means are shown in Table 4.11 and verify this conclusion.

Accuracy of subject scores between Medium VVIQ classification subjects and High VVIQ classification subjects are significant at the 0.10 level (p-value of 0.0648). With respect to grouped means, Mean Accuracy is not significantly different between the Medium, High, and Low VVIQ Classifications at the 0.05 level of significance.

Table 4.11– Means Comparisons for Accuracy by VVIQ Classification

Comparison	**p-value**
Low vs Medium	0.2580
Low vs High	0.6095
Medium vs High	0.0648

Key:	
	Significant at 10% level
	Significant at 5% level

VVIQ Classification		Medium	High	Low
Accuracy	n	185	100	10
	Mean	3.09	3.54	3.90
	StDev	2.00	1.91	2.08
		Grouped Means		

Two–Way Interactions

Two–way interactions among the four factors and three response variables are discussed in this section. (Table 4.4 is repeated below for reference.)

Table 4.4 – Response Variables and Factor Levels

Response Variables:				
Completion Time (seconds)				
Accuracy Score (points)				
Confidence (ordinal scale)				
Factors:				
A: Visualization Type	TABLE	2D	2DA	3D
B: Process Complexity	In Control	Single	Serial	Parallel
C: Quality Issue	In Control	Mean Out	Variance Out	Pattern
D: Visual Acuity	Low	Medium	High	

AB Interaction for Completion Time.

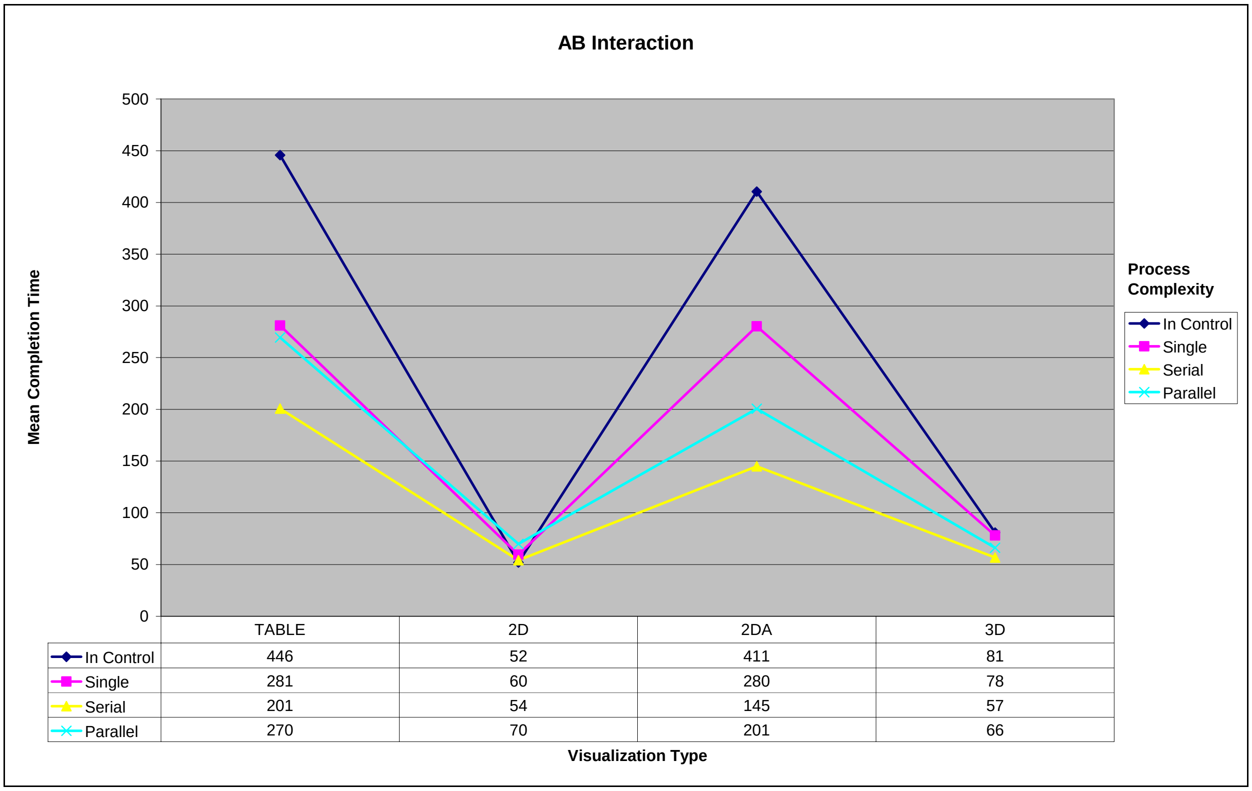


	TABLE	2D	2DA	3D
In Control	446	52	411	81
Single	281	60	280	78
Serial	201	54	145	57
Parallel	270	70	201	66

Figure 4.2 – AB Interaction for Completion Time Response Variable

From Figure 4.2, the AB interaction indicates that there is no significant difference in mean completion time for the Single or Parallel process complexity for the Table or 2D visualization type. Process complexity also has no effect on mean completion time for the 2D or 3D visualization type. In Control process complexity takes longer to detect for the Table and 2DA visualization type. This may be due to subjects taking extra time to search for a quality problem that does not exist. Single process complexity takes longer to detect than Serial process complexity for the Table visualization type. Single process complexity also takes longer to detect than both Serial and Parallel process complexity for the 2DA visualization type. Both of these findings are somewhat counterintuitive given the assumption that more complex datasets should take longer to detect.

AC Interaction for Completion Time.

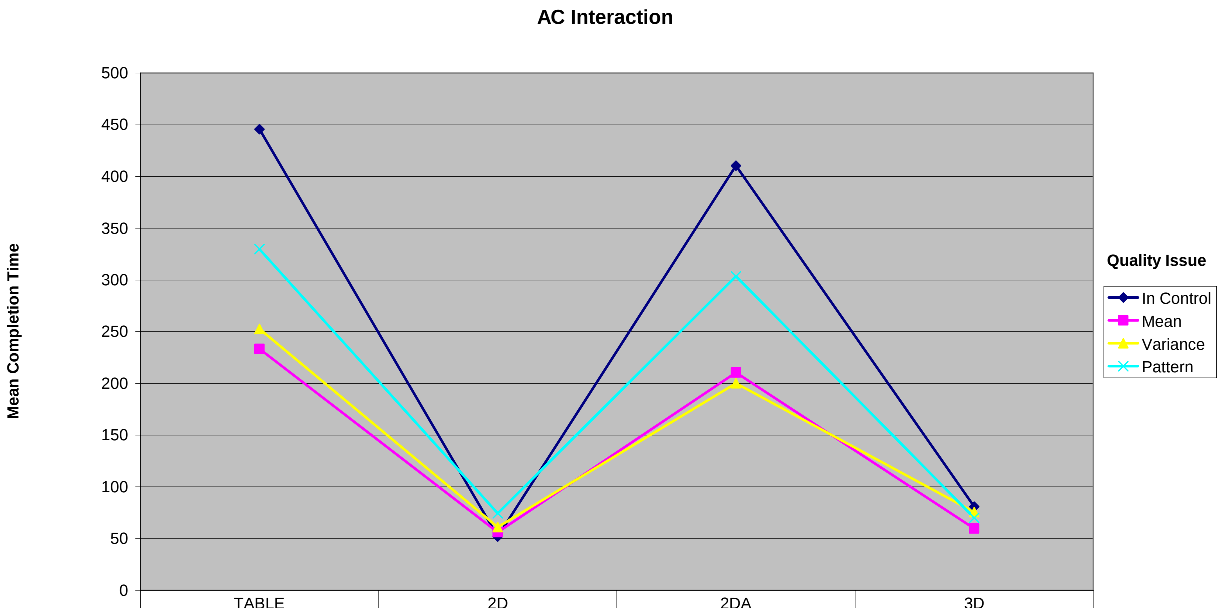


	TABLE	2D	2DA	3D
In Control	446	52	411	81
Mean	233	56	211	60
Variance	253	61	200	76
Pattern	330	74	304	70

Figure 4.3 – AC Interaction for Completion Time Response Variable

From Figure 4.3, the AC interaction indicates that there is no significant difference in mean completion time for the Mean or Variance quality issue regardless of the visualization type being displayed. Quality issue also has no effect on mean completion time for either the 2D or 3D visualization type. Patterns take longer to detect with both the Table and 2DA visualization type. While this makes sense for the Table visualization type (i.e. it is difficult to detect a pattern in a table of numbers), it is somewhat counterintuitive for the 2DA visualization type since a pattern would be highlighted as it is drawn onscreen. In control quality issues take longer to detect with either the Table or 2D visualization type. This may be because subjects are taking extra time to search for a quality problem that does not exist.

<u>AD Interaction for Completion Time.</u>

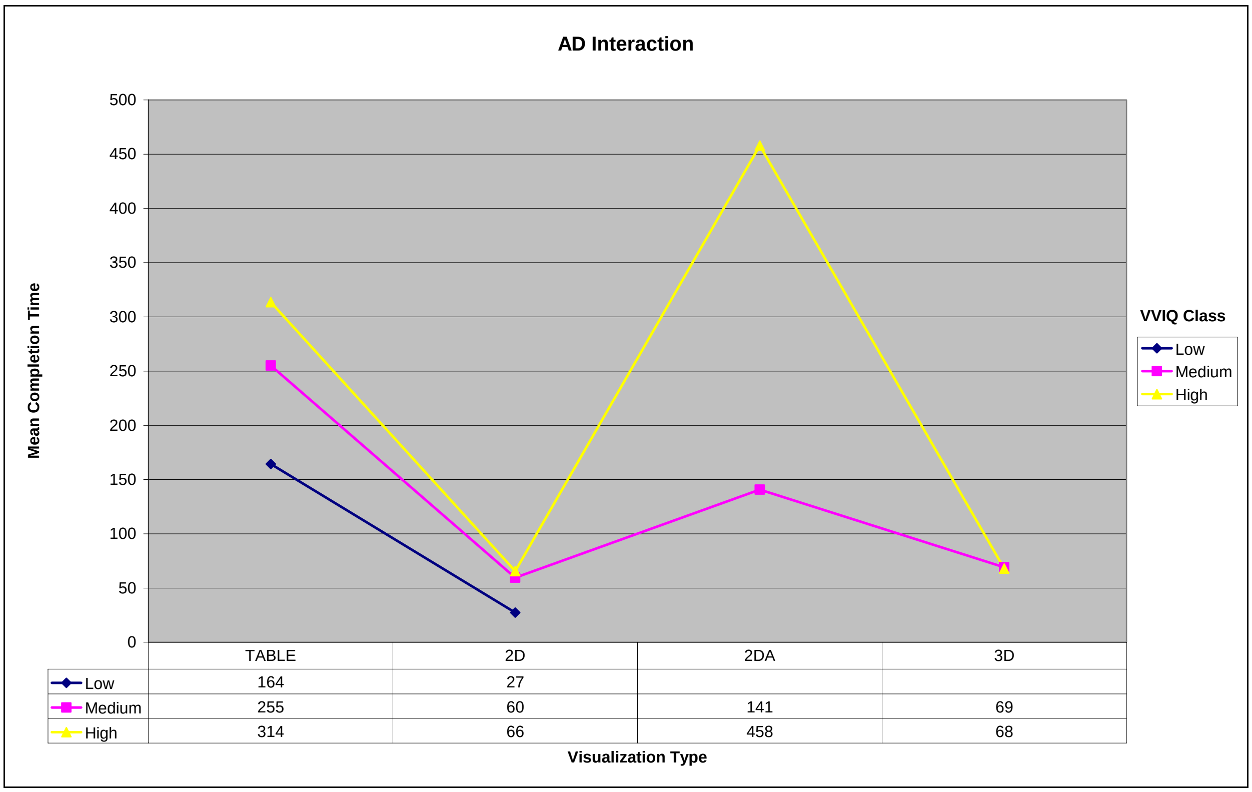


Figure 4.4 – AD Interaction for Completion Time Response Variable

From Figure 4.4, the AD interaction indicates that for both Table and 2D visualization types, subjects classified as having low VVIQ actually have smaller mean completion times than subjects having either medium or high VVIQ. While there is no difference in mean completion time for both the 2D and 3D visualization types for those subject with medium and high VVIQ classifications, mean completion time for the 2DA visualization type for subjects having high

VVIQ is of much greater duration than mean completion time for the 2DA visualization type for subjects having medium VVIQ.

<u>BC Interaction for Completion Time.</u>

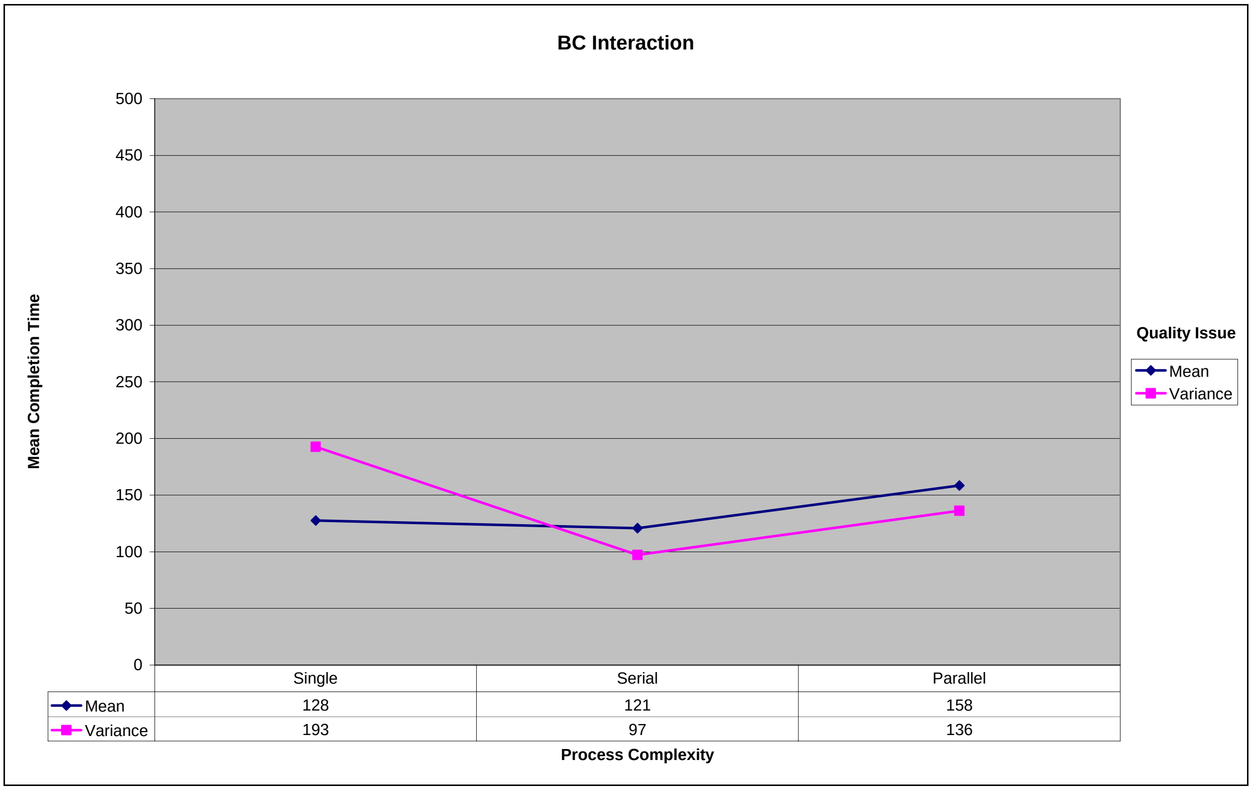
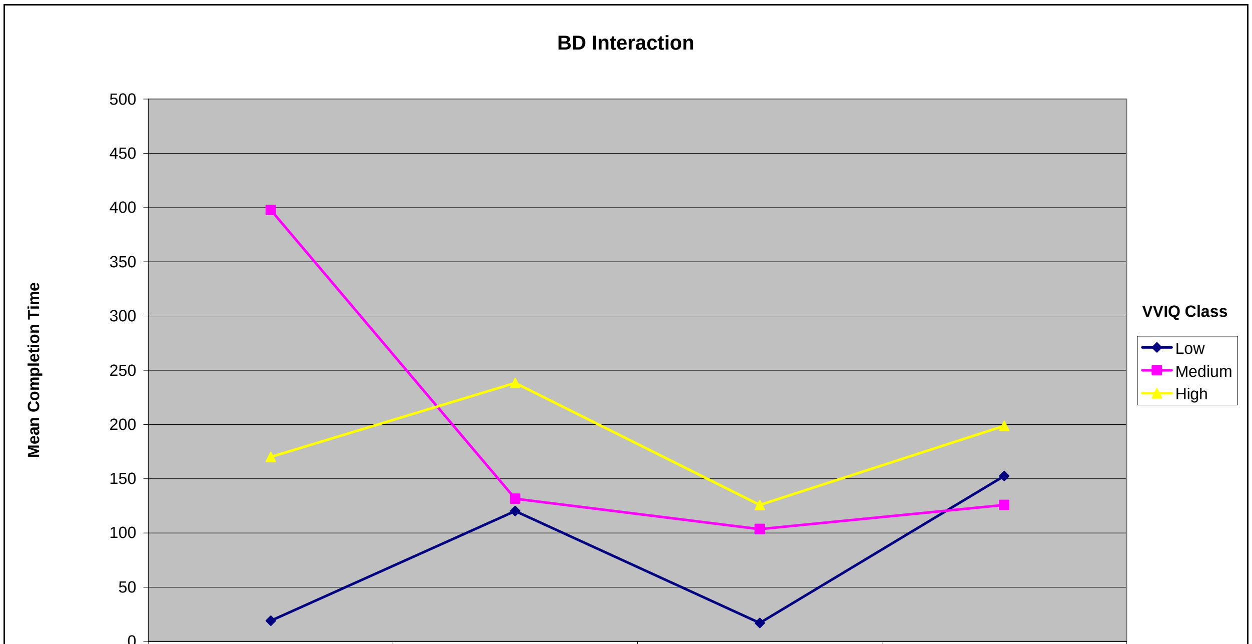


Figure 4.5 – BC Interaction for Completion Time Response Variable

From Figure 4.5, the BC interaction indicates that for Single process complexity, the Variance quality issue takes longer to detect. However, mean completion time for both the Serial and Parallel process complexity is of shorter duration for the Variance quality issue.

<u>BD Interaction for Completion Time.</u>



	In Control	Single	Serial	Parallel
Low	19	120	17	153
Medium	398	132	104	126
High	170	238	126	199

Figure 4.6 – BD Interaction for Completion Time Response Variable

From Figure 4.6, the BD interaction indicates that the In Control and Serial process complexity has the lowest mean completion time for subjects with a Low VVIQ. The In Control process complexity has a lower mean completion time for subjects with a High VVIQ than for subject with a Medium VVIQ. For Single, Serial, and Parallel process complexity, however, subjects with a Medium VVIQ have a lower mean completion time than subjects with a High VVIQ. Subjects with a Medium VVIQ have similar mean completion times for Single, Serial, and Parallel process complexity.

CD Interaction for Completion Time.

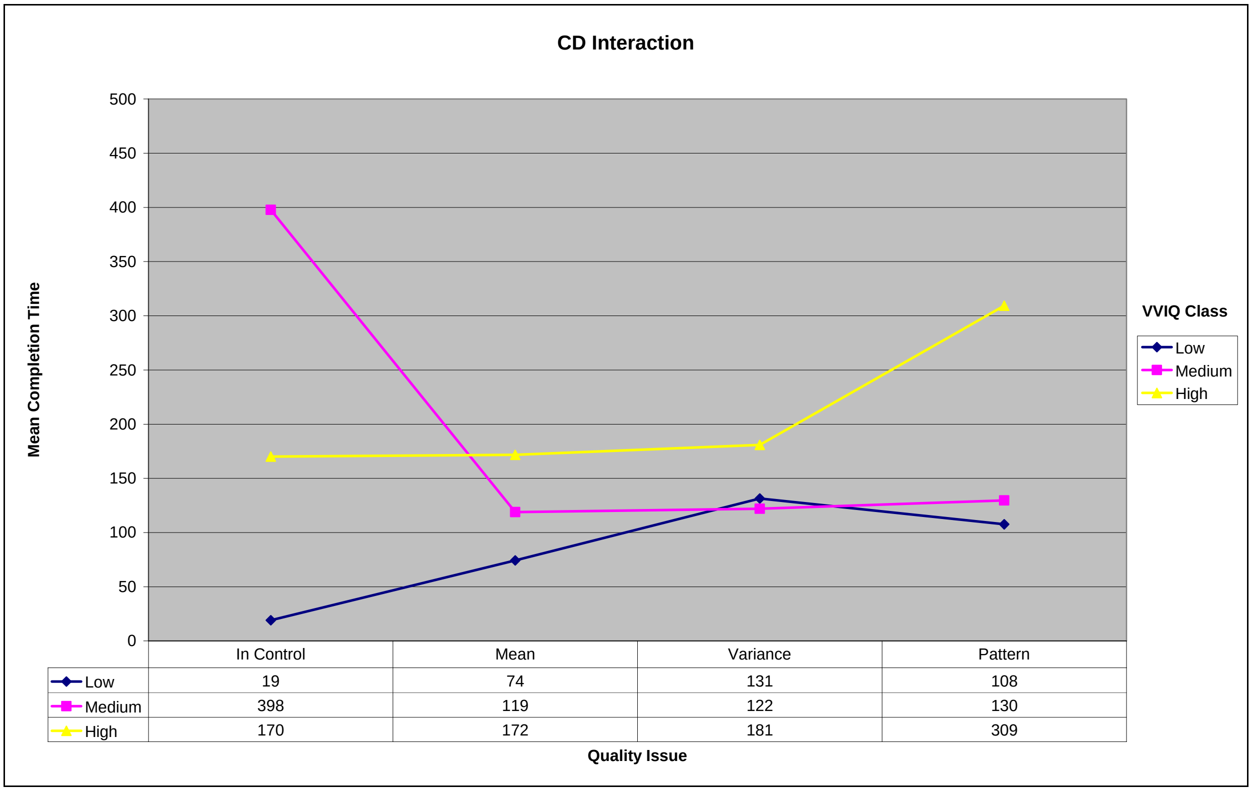


Figure 4.7 – CD Interaction for Completion Time Response Variable

From Figure 4.7, the CD interaction indicates that, for Low VVIQ, mean completion time increases with In Control, Mean, and Variance quality issues and then remains approximately the same for the Pattern quality issue. While subjects with High VVIQ have shorter mean completion times for the In Control quality issue than subjects with Medium VVIQ, the opposite holds true for the Mean, Variance, and Pattern quality issues. Subjects with a Medium VVIQ have similar mean completion times for Single, Serial, and Parallel process complexity.

AB Interaction for Accuracy.

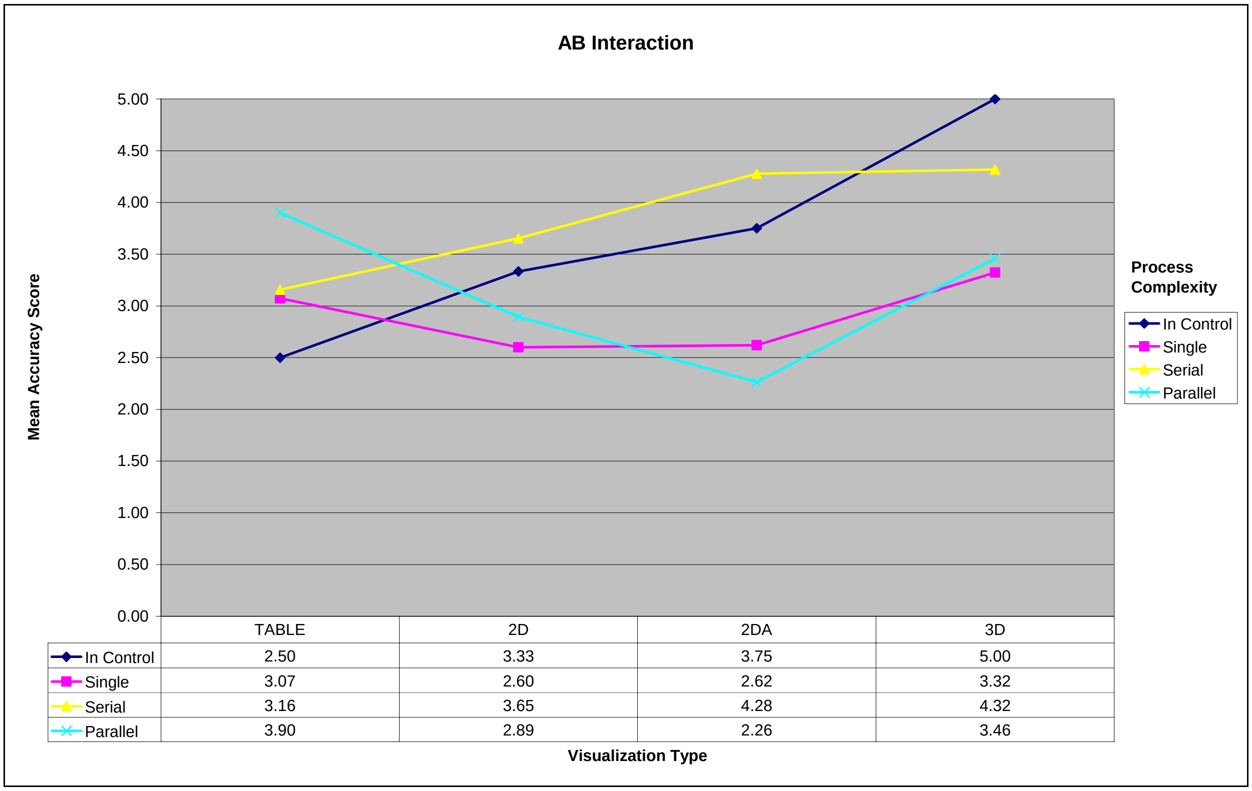


Figure 4.8 – AB Interaction for Accuracy Response Variable

From Figure 4.8, the AB interaction indicates that, for the In Control and Serial process complexity, accuracy increases as the visualization type becomes more sophisticated from Table to 2D to 2DA to 3D. Accuracy for the Single and Parallel process complexity shows either flat or decreasing accuracy as the visualization type becomes more sophisticated from Table to 2D to 2DA. However, for the 3D visualization type, accuracy increases for the Single and Parallel process complexity. Thus, increased accuracy is associated with increased visualization type sophistication for all four process complexity factor levels.

AC Interaction for Accuracy.

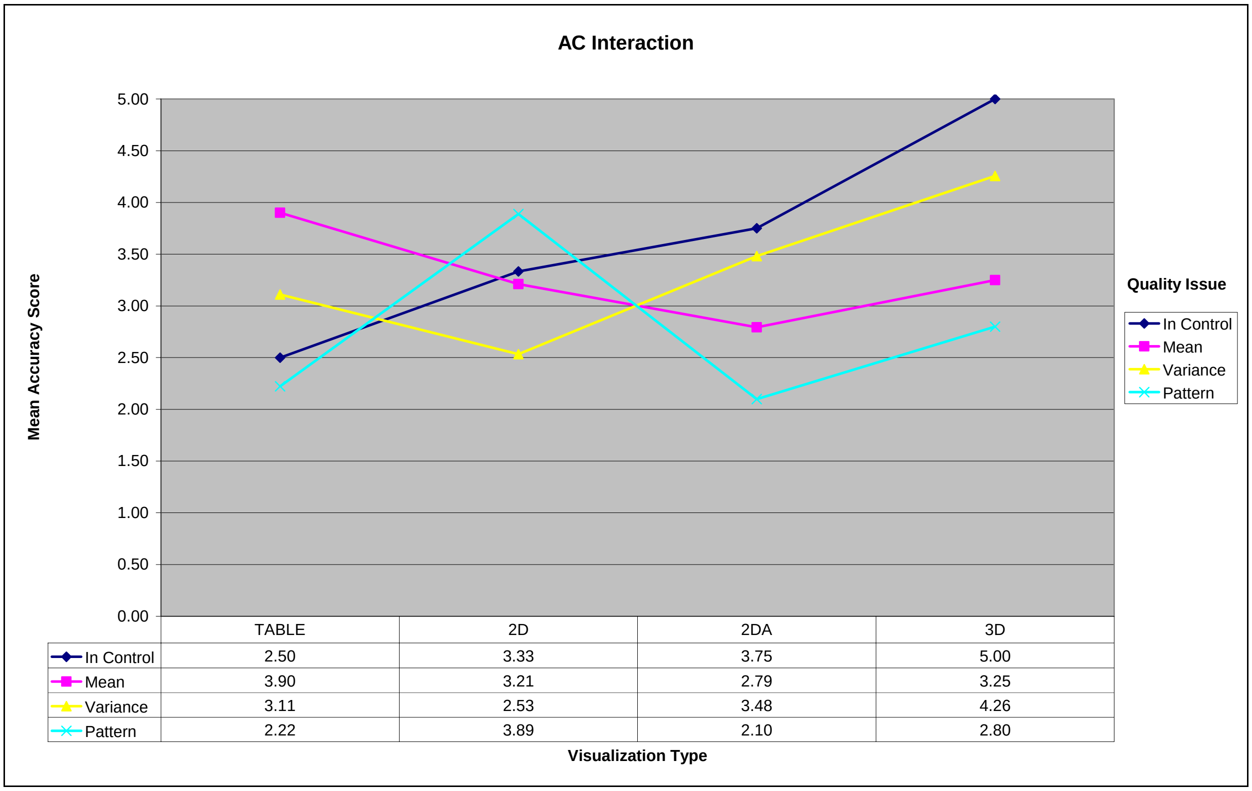


	TABLE	2D	2DA	3D
In Control	2.50	3.33	3.75	5.00
Mean	3.90	3.21	2.79	3.25
Variance	3.11	2.53	3.48	4.26
Pattern	2.22	3.89	2.10	2.80

Figure 4.9 – AC Interaction for Accuracy Response Variable

From Figure 4.9, the AC interaction indicates that, for the In Control quality issue, accuracy increases with increased visualization types from Table to 2D to 2DA to 3D. This holds true for the Variance quality issue with the exception of a slight decrease in accuracy for the 2D visualization type. Patterns are easier to detect with 2D visualizations. For the Mean and Pattern quality issue, however, the results are a bit unclear. The Mean quality issue shows a decrease in accuracy as the visualization type becomes more sophisticated from Table to 2D to 2DA. Accuracy does increase for the Mean quality issue for 3D. The results are even more profound for the Pattern quality issue since accuracy first increases from Table to 2D visualization type, then decreases for 2DA visualization type. Accuracy for the Pattern quality issue does again increase for the 3D visualization type.

AD Interaction for Accuracy.

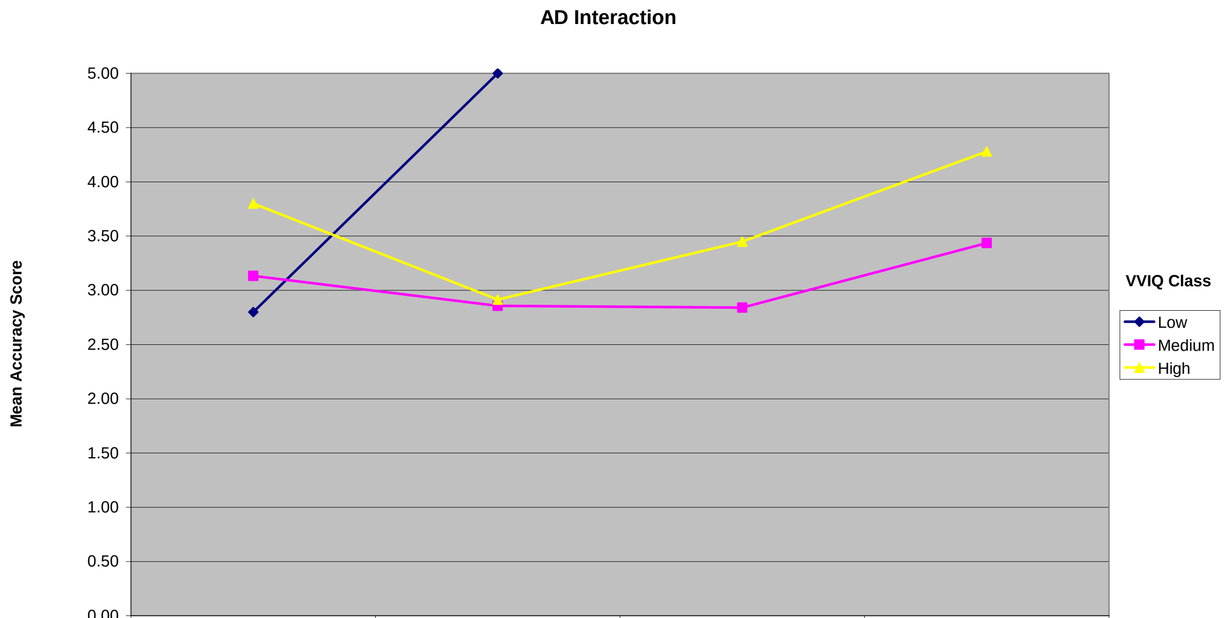


	TABLE	2D	2DA	3D
Low	2.80	5.00		
Medium	3.13	2.86	2.84	3.44
High	3.80	2.91	3.45	4.28

Figure 4.10 – AD Interaction for Accuracy Response Variable

From Figure 4.10, the AD interaction indicates that the Table visualization type has the lowest accuracy for subjects with Low VVIQ and highest accuracy for subjects with High VVIQ. There is also the somewhat surprising result that, for subjects with Low VVIQ, a perfect accuracy score is obtained with the 2D visualization type. Further investigation shows that this is due to the small number of subjects that are categorized as having Low VVIQ. Subjects with Medium and High VVIQ respectively show a decrease in accuracy moving in visualization type sophistication from Table to 2D, then an increase in accuracy moving from 2D to 2DA to 3D. Again, 3D shows the highest accuracy measurements for the Medium and High VVIQ.

BC Interaction for Accuracy.

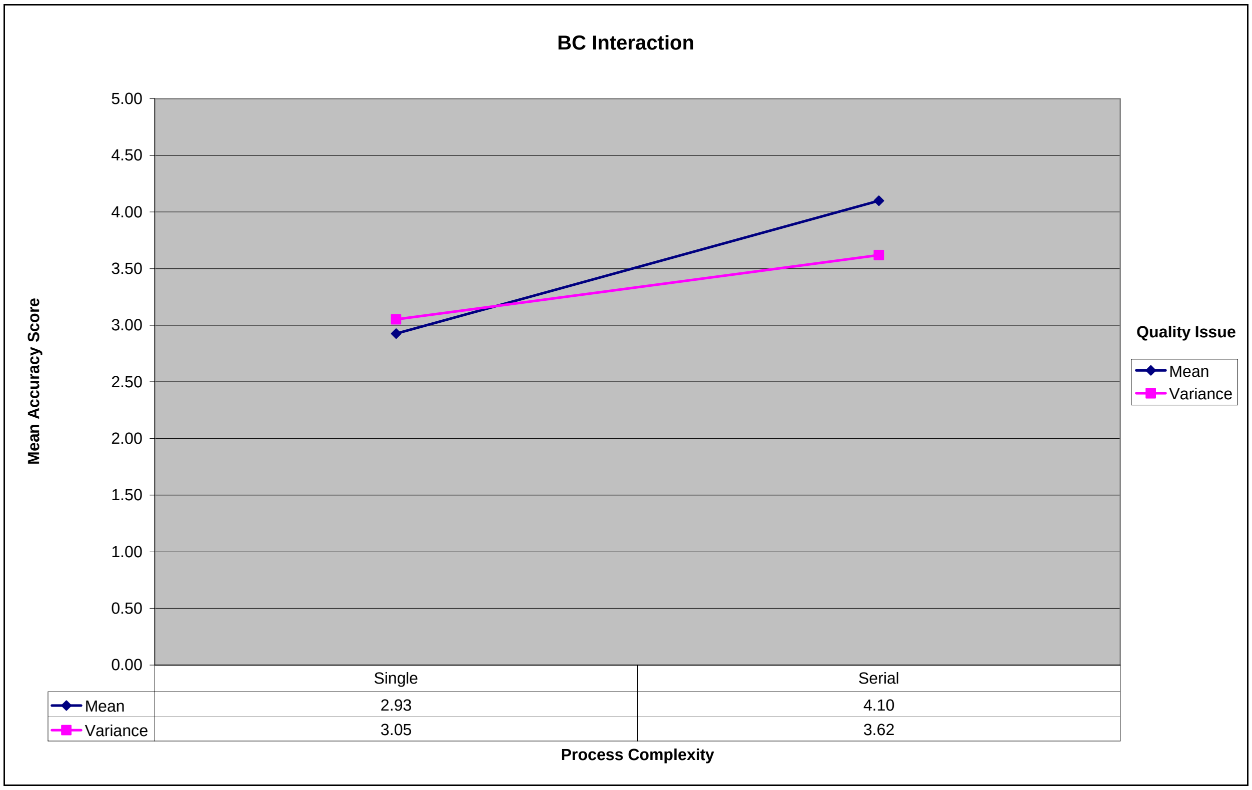


Figure 4.11 – BC Interaction for Accuracy Response Variable

From Figure 4.11, the BC interaction indicates that accuracy is approximately the same for the Single process complexity for both the Mean and Variance quality issue. However, for the Serial process complexity, accuracy is greater for the Mean quality issue than the Variance quality issue. It may be more difficult to detect variance quality issues in upstream-downstream processes.

BD Interaction for Accuracy.

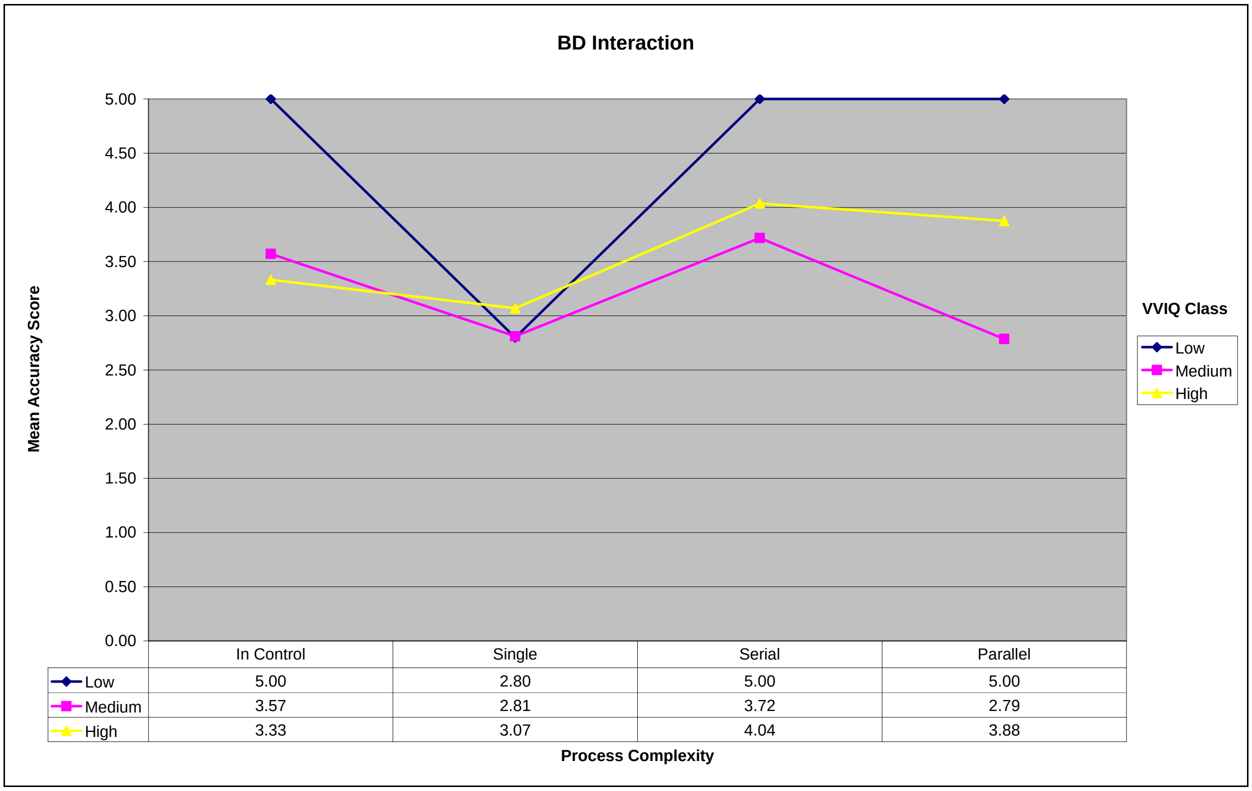
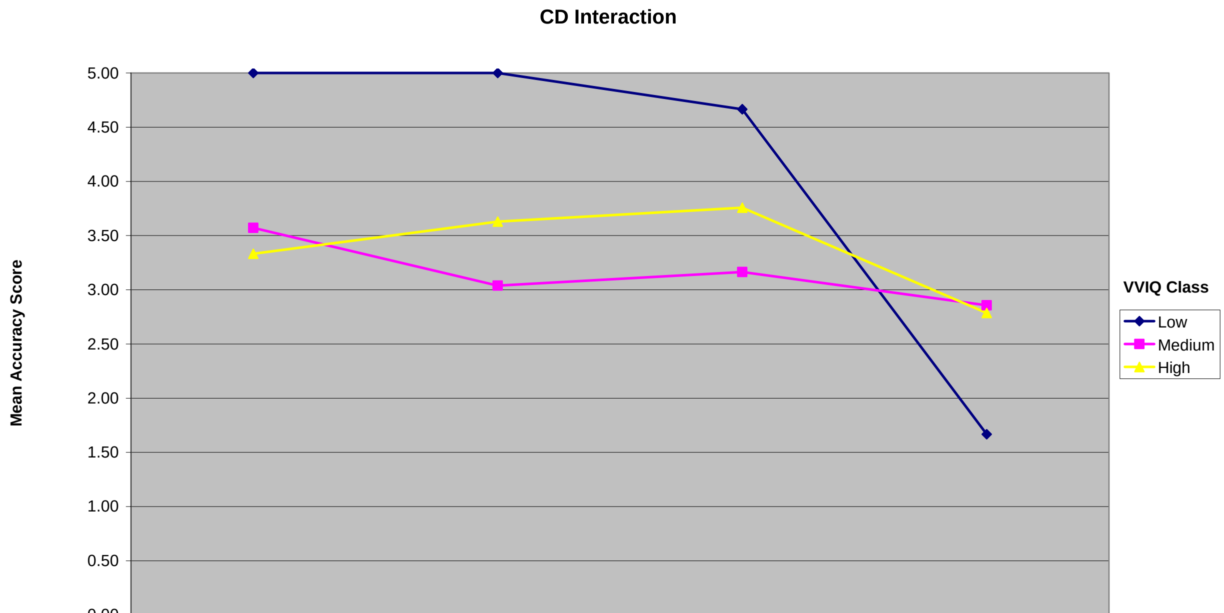


Figure 4.12 – BD Interaction for Accuracy Response Variable

From Figure 4.12, the BD interaction shows that, for subjects with Medium VVIQ, accuracy is greater for the In Control process complexity. Accuracy is greater for the Single, Serial, and Parallel process complexity for subjects with a High VVIQ. For both the Single and Serial process complexity, accuracy increases for subjects with either Medium or High VVIQ. For the Parallel process complexity, however, accuracy decreases for subjects with either Medium or High VVIQ. Of particular interest are subjects with Low VVIQ. In Control, Serial, and Parallel process complexity show perfect accuracy while Single process complexity shows lower accuracy. Again, this is most likely due to the small number of subjects classified as having Low VVIQ.

CD Interaction for Accuracy.



	In Control	Mean	Variance	Pattern
Low	5.00	5.00	4.67	1.67
Medium	3.57	3.04	3.16	2.86
High	3.33	3.63	3.76	2.79

Figure 4.13 – CD Interaction for Accuracy Response Variable

From Figure 4.13, the CD interaction indicates that subjects having either Medium VVIQ or High VVIQ have approximately the same accuracy for the In Control, Mean, and Variance quality issue. However, those same subjects show a decrease in accuracy with the Pattern quality issue. Patterns may be difficult to detect irrespective of the VVIQ of the subject. Again, subjects with a Low VVIQ are of interest. In Control and Mean quality issues show perfect accuracy for those subjects with Low VVIQ. Low VVIQ subjects show exceptionally high accuracy for the Variance quality issue as well. Low VVIQ subjects, however, have the lowest accuracy for the Pattern quality issue which again provides evidence that patterns may be difficult to detect.

AB Interaction for Confidence.

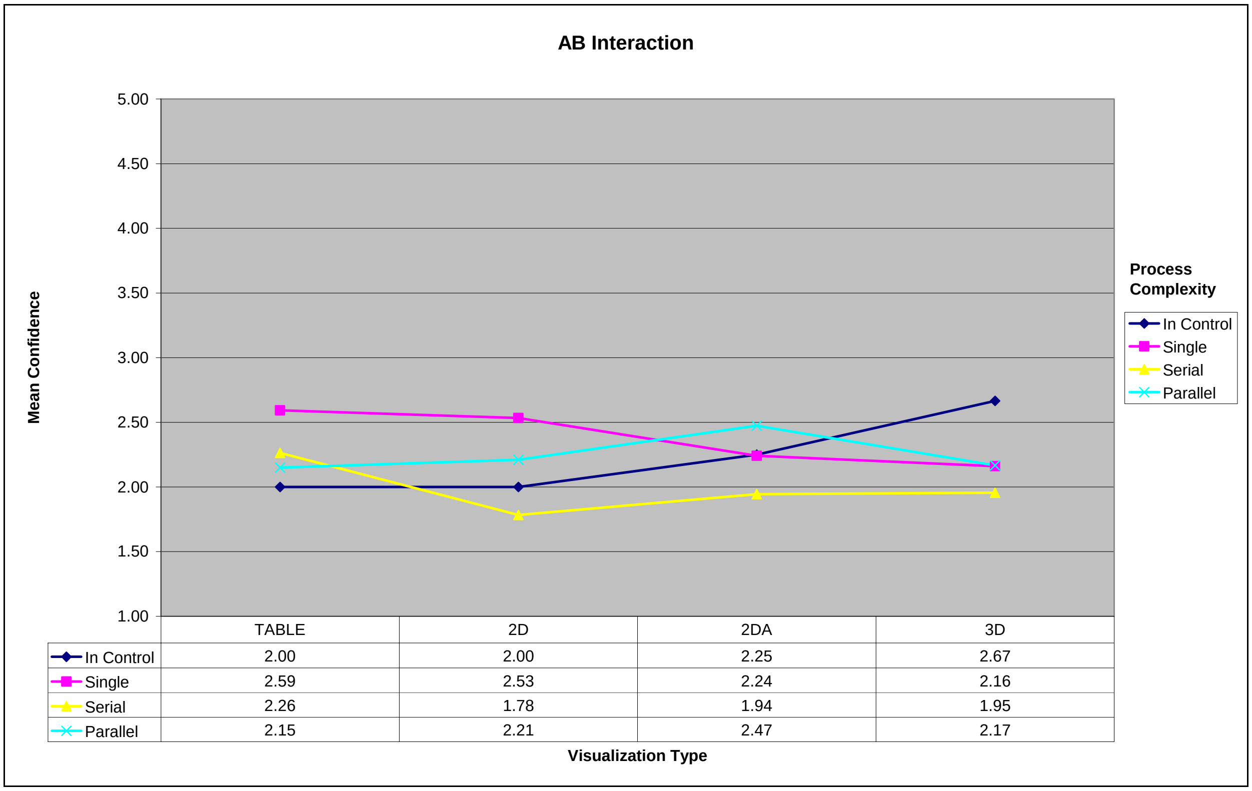


	TABLE	2D	2DA	3D
In Control	2.00	2.00	2.25	2.67
Single	2.59	2.53	2.24	2.16
Serial	2.26	1.78	1.94	1.95
Parallel	2.15	2.21	2.47	2.17

Figure 4.14 – AB Interaction for Confidence Response Variable

From Figure 4.14, the AB interaction indicates that subject confidence is approximately equal regardless of the complexity of the process for each of the four visualization types.

AC Interaction for Confidence.

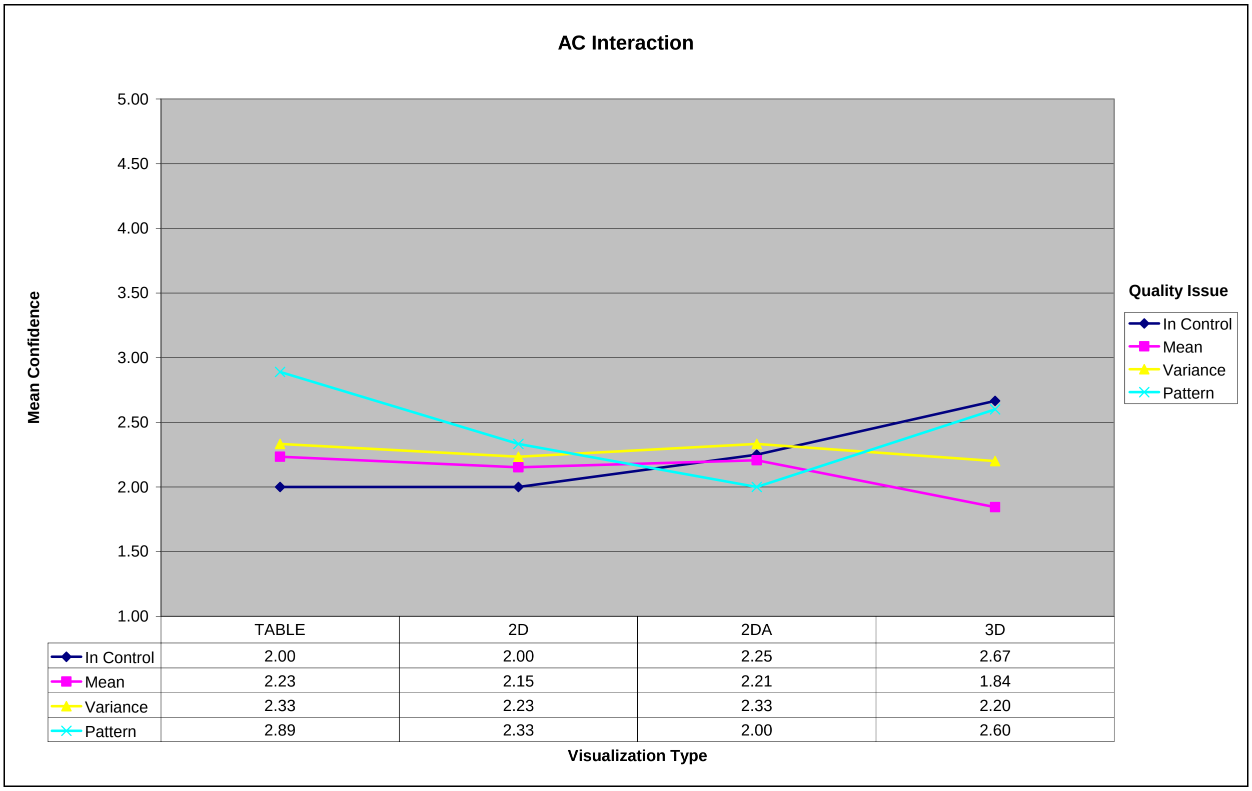


	TABLE	2D	2DA	3D
In Control	2.00	2.00	2.25	2.67
Mean	2.23	2.15	2.21	1.84
Variance	2.33	2.23	2.33	2.20
Pattern	2.89	2.33	2.00	2.60

Figure 4.15 – AC Interaction for Confidence Response Variable

From Figure 4.15, the AC interaction indicates that subject confidence is approximately equal regardless of the quality issue for each of the four visualization types.

AD Interaction for Confidence.

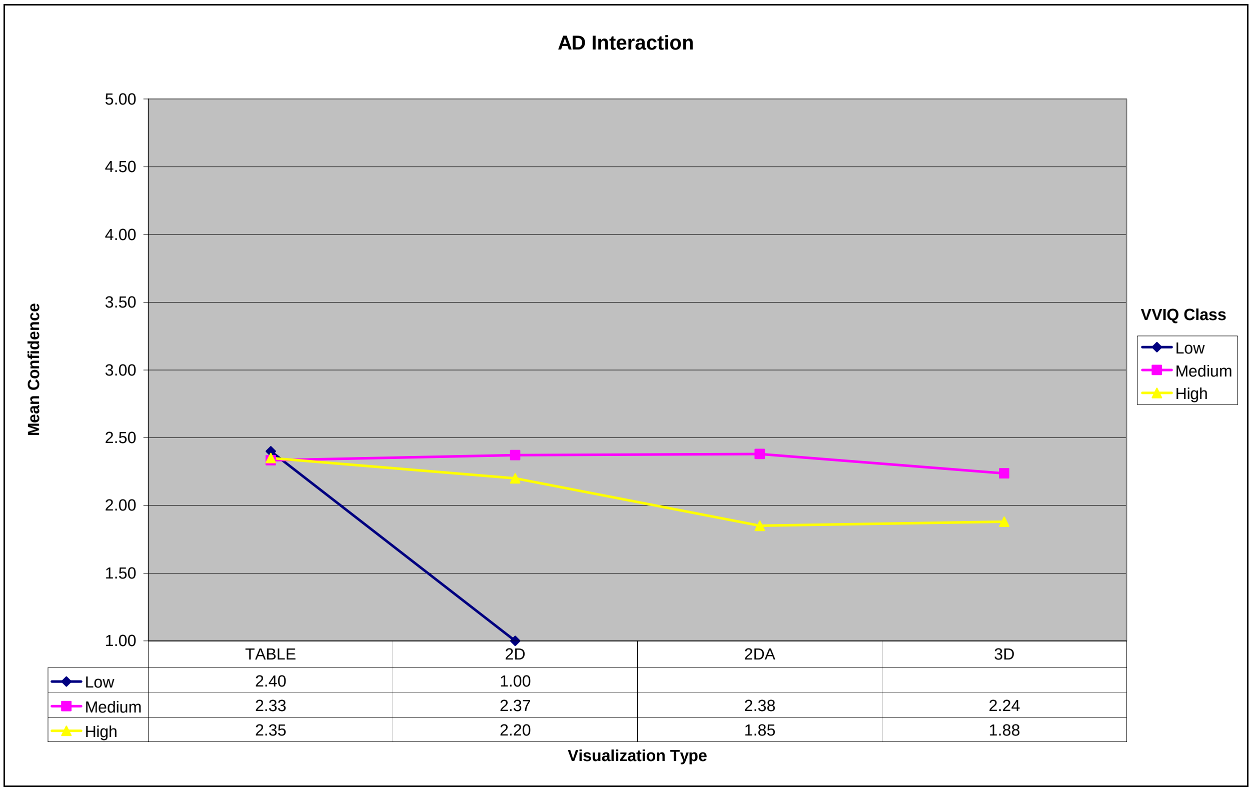
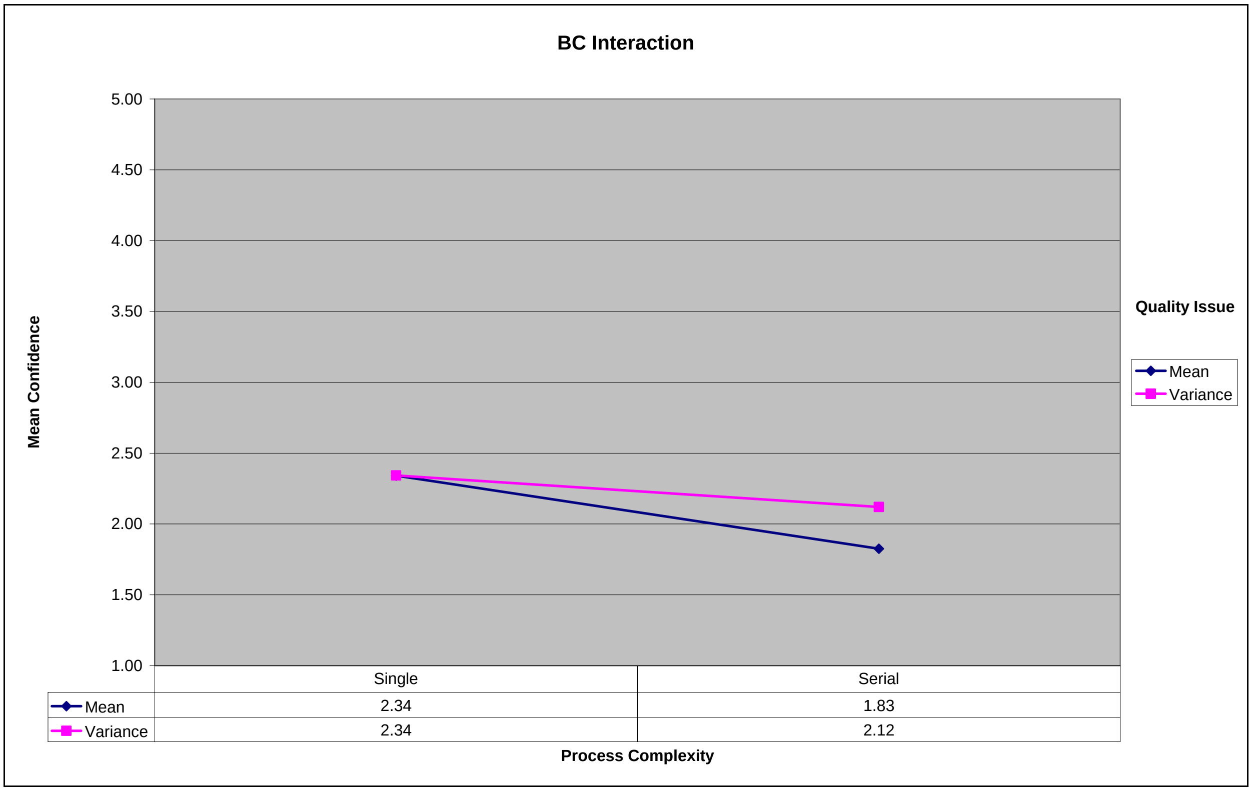


Figure 4.16 – AD Interaction for Confidence Response Variable

From Figure 4.16, the AD interaction indicates that subject confidence is approximately equal for subjects with either Medium VVIQ or High VVIQ for each of the four visualization types. For subjects with Low VVIQ, subject confidence for the Table visualization type is approximately the same as subjects with either Medium VVIQ or High VVIQ. However, Low VVIQ subjects have much lower confidence for the 2D visualization type than Medium or High VVIQ subjects.

BC Interaction for Confidence.

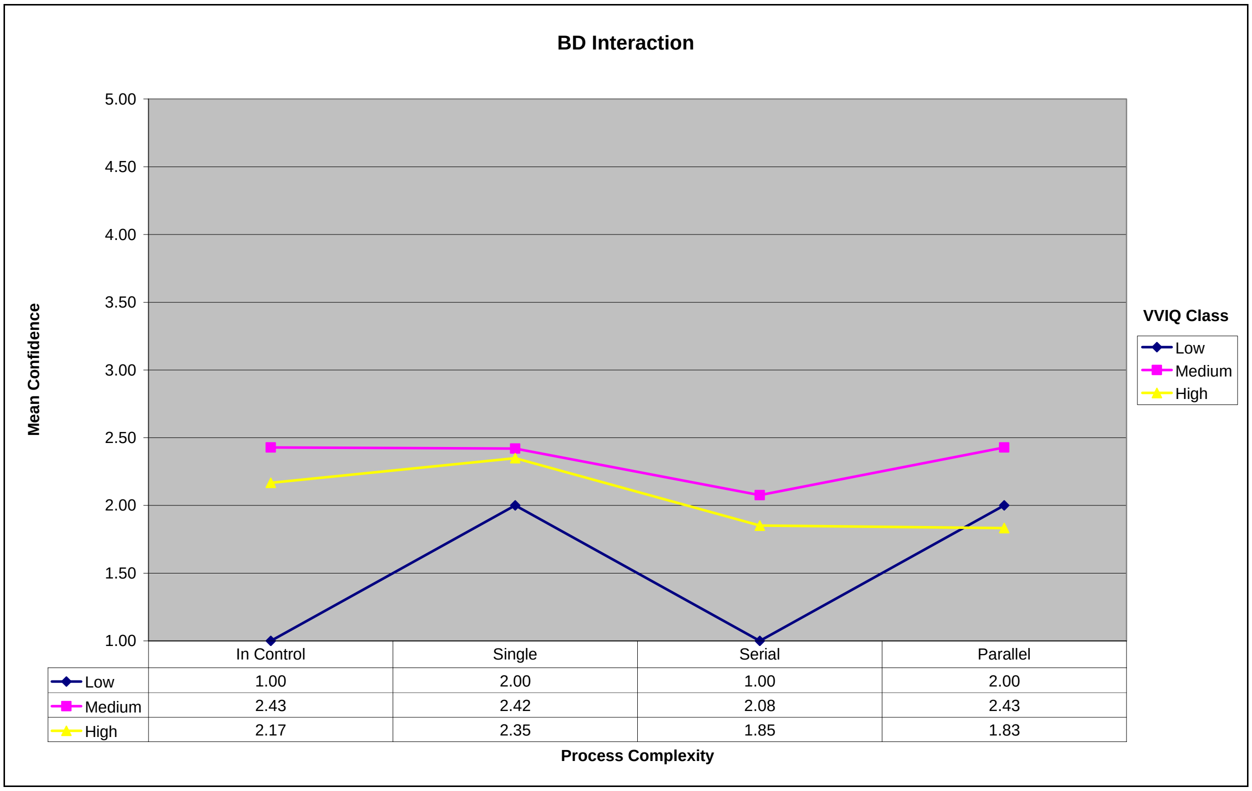


	Single	Serial
Mean	2.34	1.83
Variance	2.34	2.12

Figure 4.17 – BC Interaction for Confidence Response Variable

From Figure 4.17, the BC interaction indicates that confidence is equal for the Single process complexity for both the Mean and Variance quality issue. For the Serial process complexity, however, confidence is higher for the Variance quality issue than the Mean quality issue.

BD Interaction for Confidence.



	In Control	Single	Serial	Parallel
Low	1.00	2.00	1.00	2.00
Medium	2.43	2.42	2.08	2.43
High	2.17	2.35	1.85	1.83

Figure 4.18 – BD Interaction for Confidence Response Variable

From Figure 4.18, the BD interaction indicates that confidence is approximately equal for Medium and High VVIQ for the In Control, Single, and Serial process complexity. For the Parallel process complexity, confidence is higher for the Medium VVIQ than for the High VVIQ. For the Low VVIQ, the results are unique in that Single and Parallel process complexity show greater confidence while In Control and Serial process complexity show less confidence. Again, this may be due to the low number of subjects classified as Low VVIQ.

CD Interaction for Confidence.

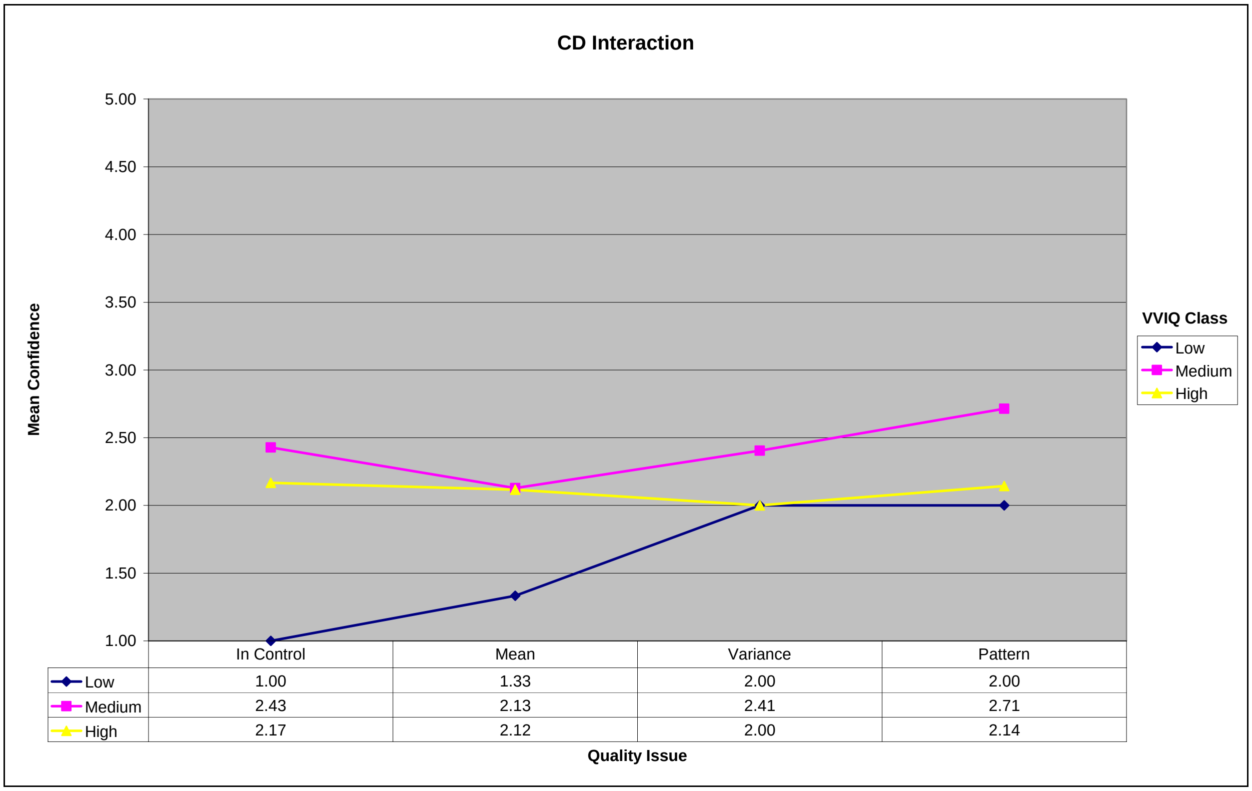


Figure 4.19 – CD Interaction for Confidence Response Variable

From Figure 4.19, the CD interaction indicates that confidence is approximately equal for the Mean quality issue for both Medium VVIQ subjects and High VVIQ subjects. Confidence is higher for the Medium VVIQ subjects than it is for the High VVIQ subjects for the In Control, Variance, and Pattern quality issue. For Low VVIQ subjects, the In Control and Mean quality issues show lower confidence than the Variance and Pattern quality issues.

Three – Way Interactions

Significant three–way interactions among the four factors and three response variables are discussed in this section. (Table 4.4 is repeated below for reference.)

Table 4.4 – Response Variables and Factor Levels

Response Variables:				
Completion Time (seconds)				
Accuracy Score (points)				
Confidence (ordinal scale)				
Factors:				
A: Visualization Type	TABLE	2D	2DA	3D
B: Process Complexity	In Control	Single	Serial	Parallel
C: Quality Issue	In Control	Mean Out	Variance Out	Pattern
D: Visual Acuity	Low	Medium	High	

ABC Interaction for Completion Time.

From Figure 4.20, the change in quality issue from Mean to Variance shows little difference in the mean completion time for subject responses for the 2D and 3D visualization types across Single, Serial, and Parallel process complexity. The change in quality issue from Mean to Variance does show a slightly greater effect on mean completion time for subject responses for the Table and 2DA visualization types across Single, Serial, and Parallel process complexity.

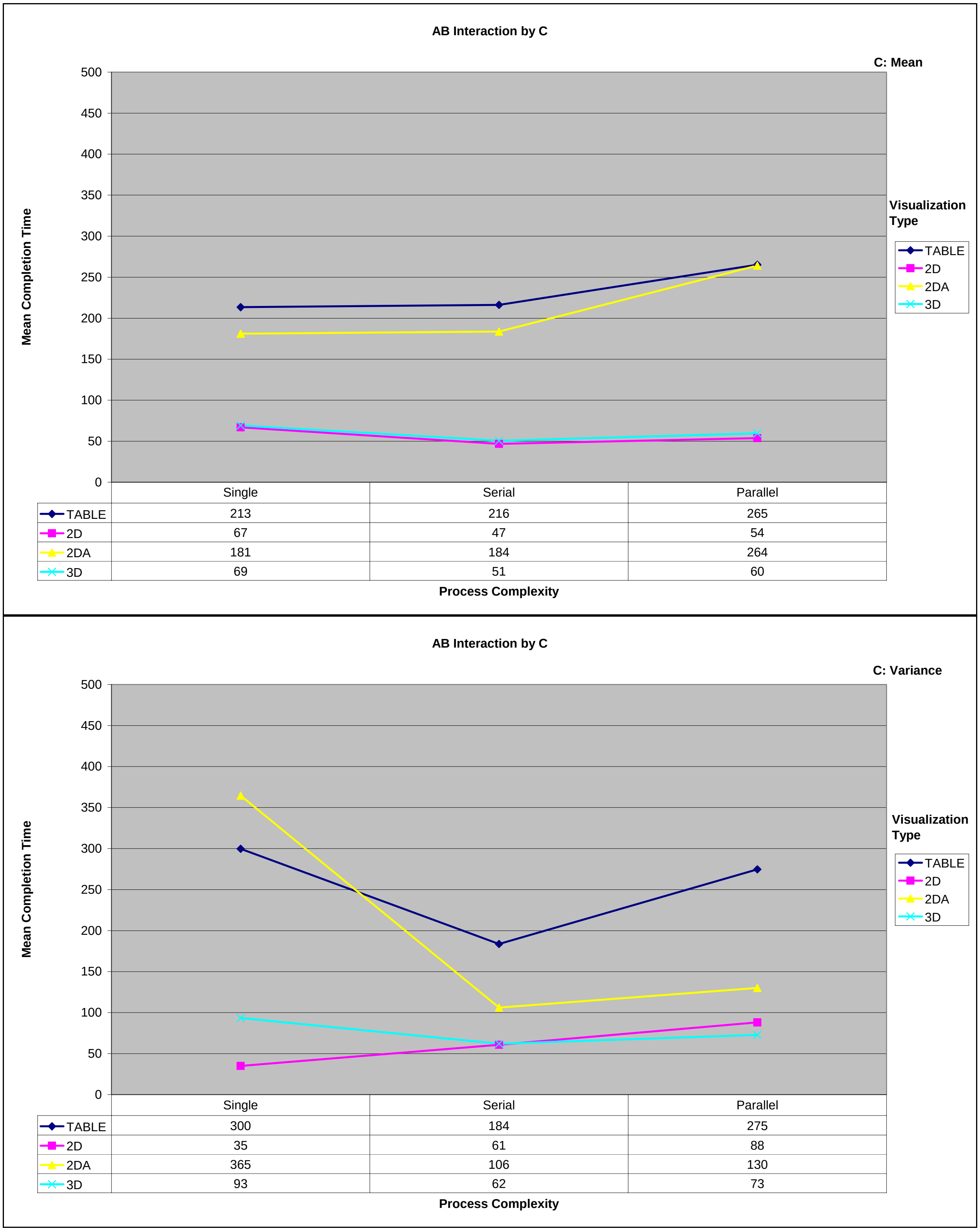
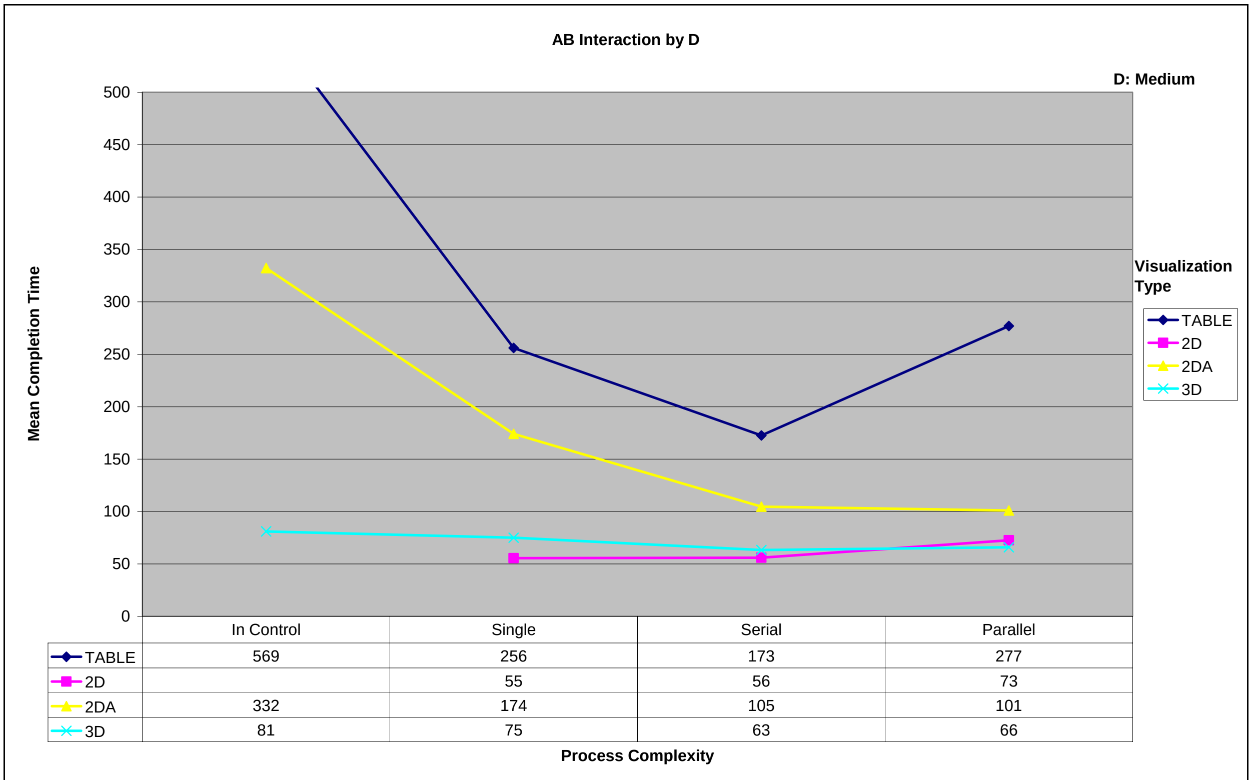


Figure 4.20 – AB Interaction by C for Completion Time Response Variable

ABD Interaction for Completion Time



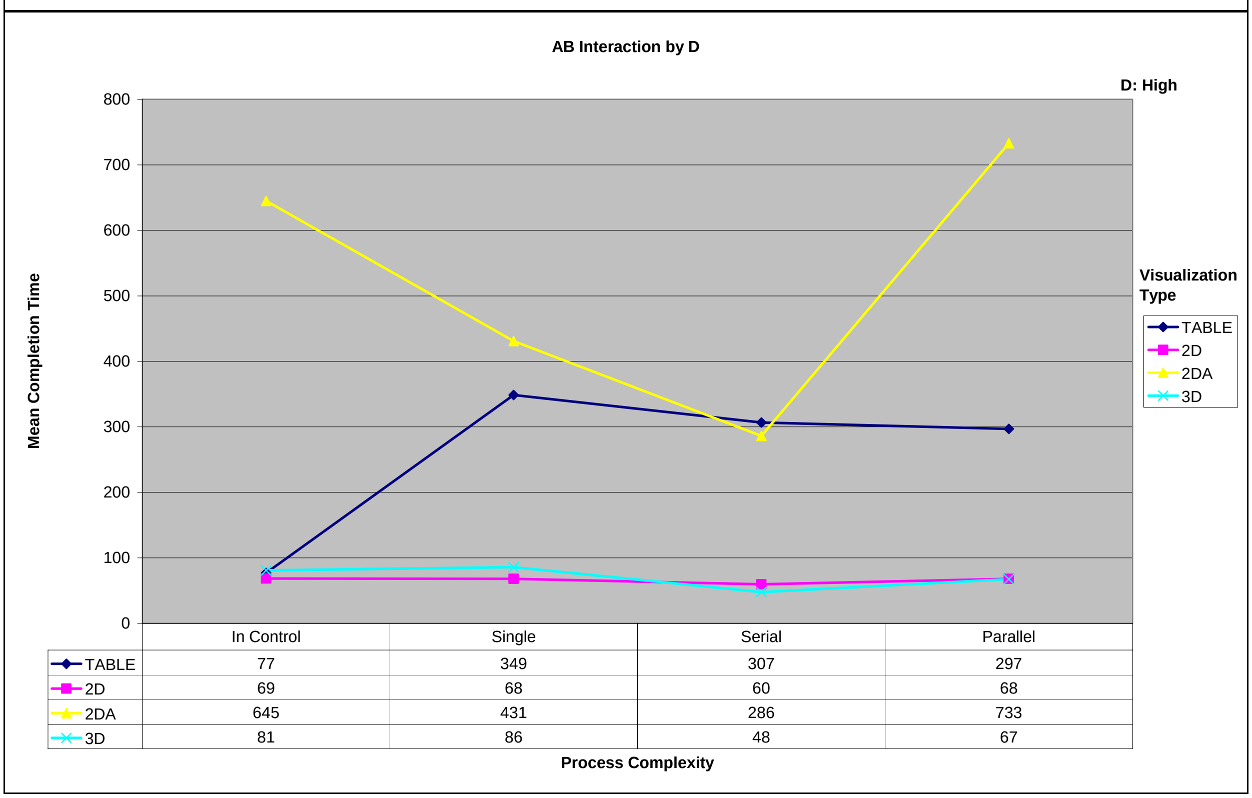


Figure 4.21 – AB Interaction by D for Completion Time Response Variable

From Figure 4.21, the change in VVIQ from Medium to High shows little difference in the mean completion time for subject responses for the 2D and 3D visualization types across In Control, Single, Serial, and Parallel process complexity. The change in VVIQ from Medium to High does show an effect on mean completion time for subject responses for the Table and 2DA visualization types across In Control, Single, Serial, and Parallel process complexity. Specifically, for each process complexity, the Table visualization type shows longer mean completion times for Medium VVIQ while the 2DA visualization type shows longer mean completion times for the High VVIQ.

There were no three way or four way significant interactions for the accuracy response variable. There were no significant three way interactions for the confidence response variable.

Network Flow Diagrams by Case

Network flow diagrams were developed for each of the Can Factory cases presented to the subject participants. For each network flow diagram, paths representing the correct decision at each node are shown in green and paths representing incorrect decisions are shown in red. The width of the path represents the percentage of subjects traversing that given path. Thicker green paths indicate a larger percentage of subjects selecting the correct answer at a given node for a given case while thicker red paths indicate a larger percentage of subjects selecting an incorrect answer at a given node for a given case. Examining Figures 4.22 through 4.31, in most cases, the respondents were able to reach the correct answer, although they were more successful in making the initial decisions than the second phase decisions. The exception is case 1 in which a majority of respondents incorrectly identified the source of the quality problem. In this case, all of the D&Is were out of control. This indicates that more significant results may have occurred if there were a broader range of quality problems represented in the test scenarios.

Chapter 5 discusses such limitations in this research, as well as future research efforts and overall conclusions of the dissertation.

Case 0 – Can Factory In Control.

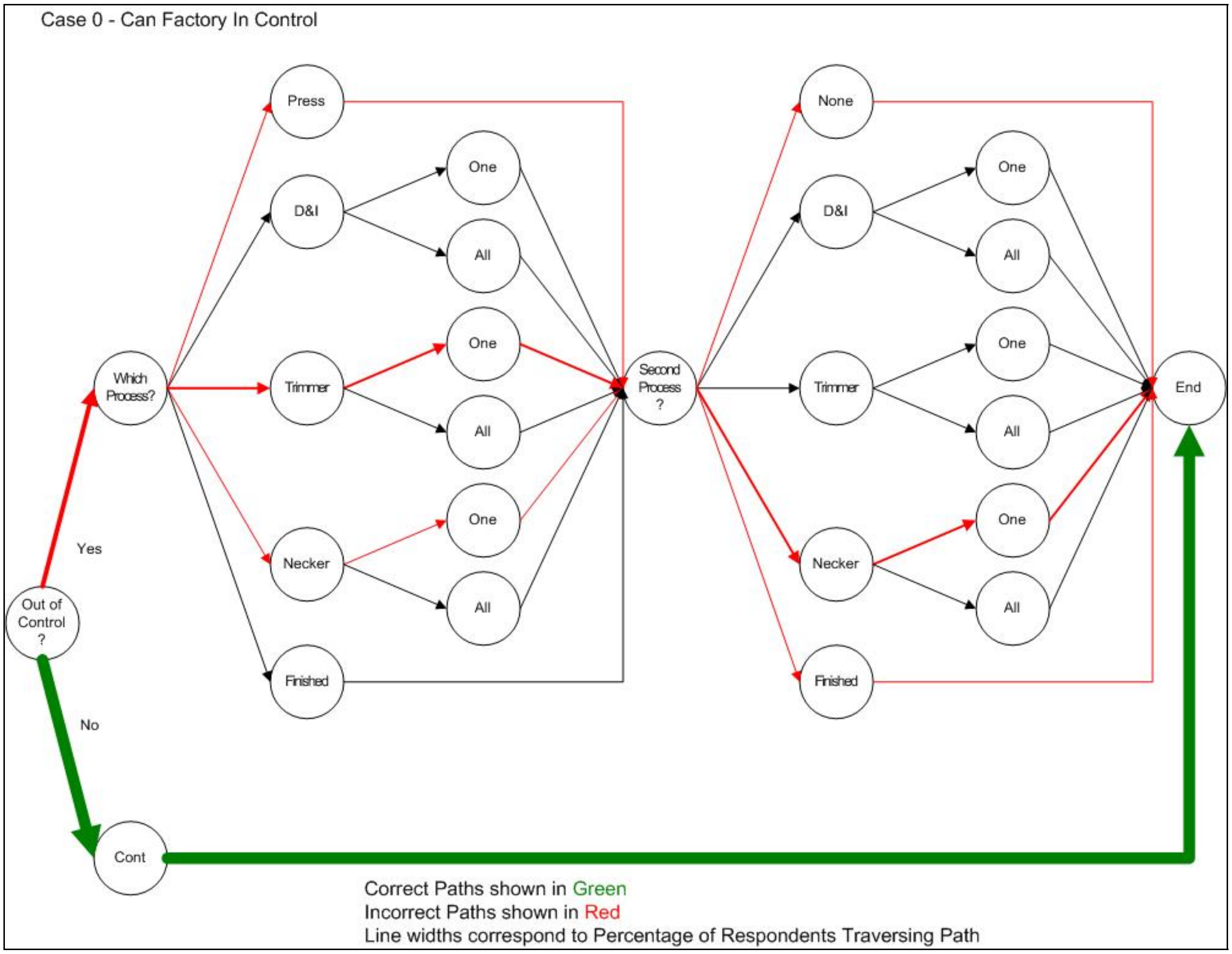


Figure 4.22 – Case 0 Decision–Making Network Flow Diagram

Case 1 – Press Out of Control Affecting All D&I.

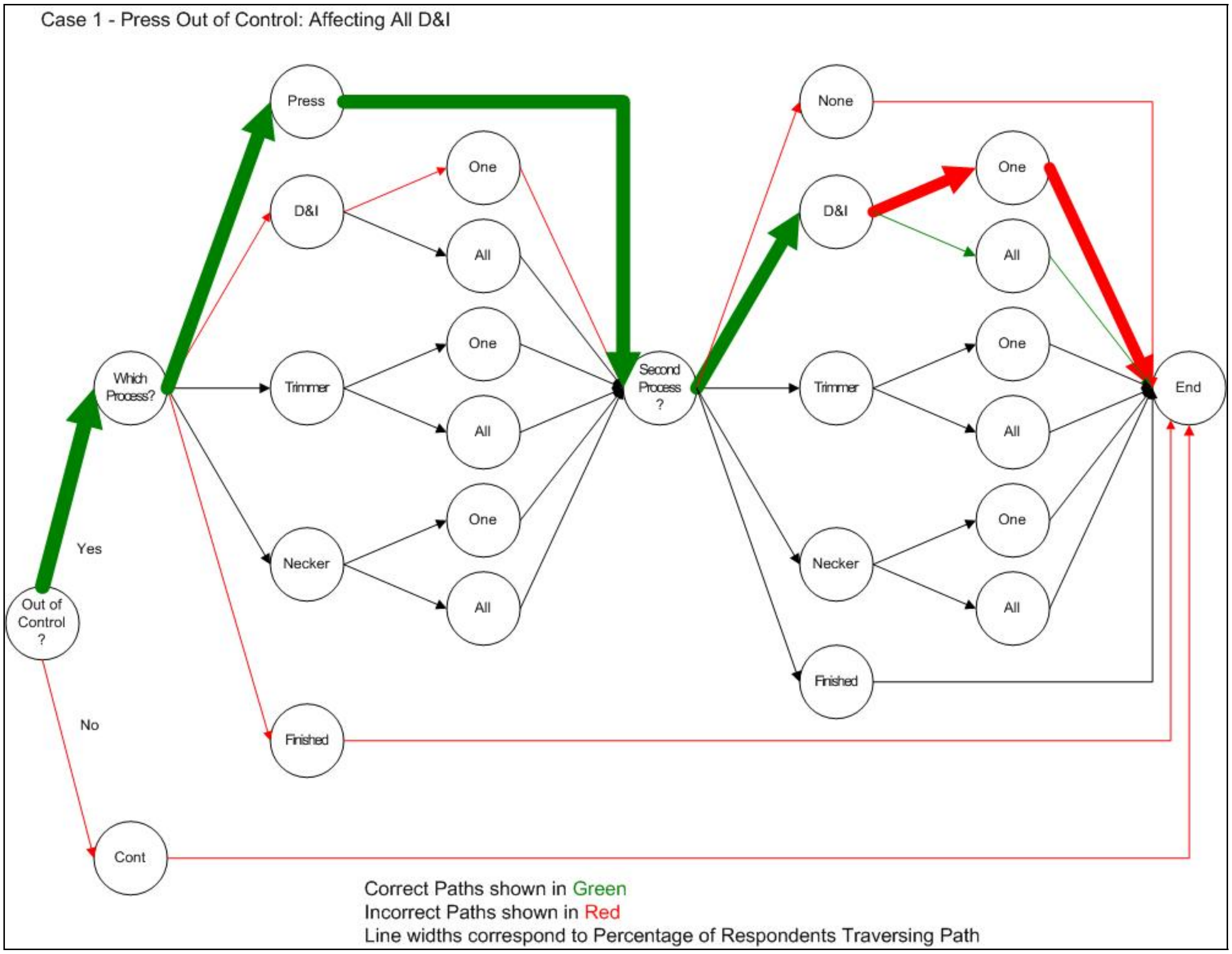


Figure 4.23 – Case 1 Decision–Making Network Flow Diagram

Case 2 – Press Out of Control Affecting Finished.

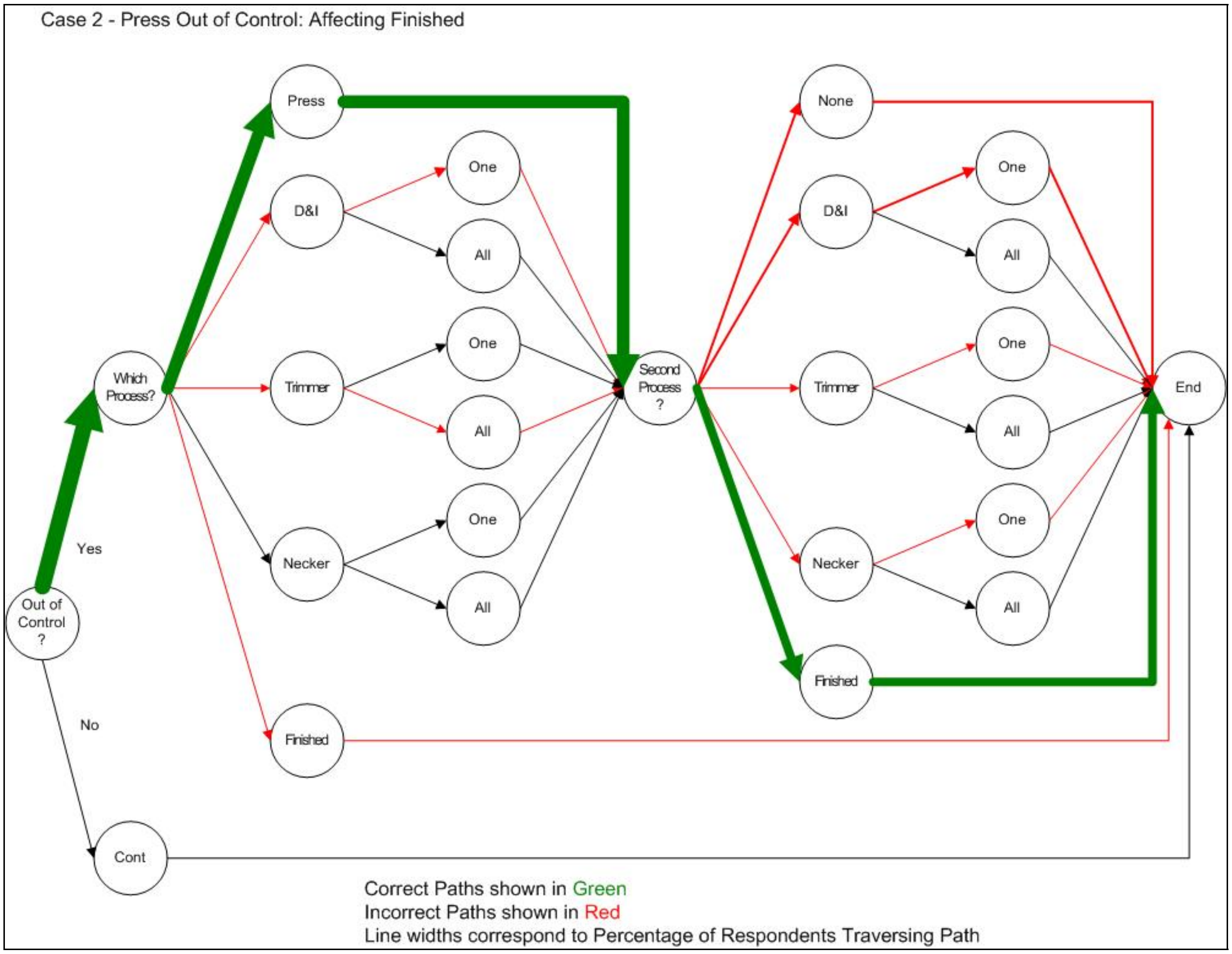


Figure 4.24 – Case 2 Decision–Making Network Flow Diagram

Case 3 – All D&I Out of Control.

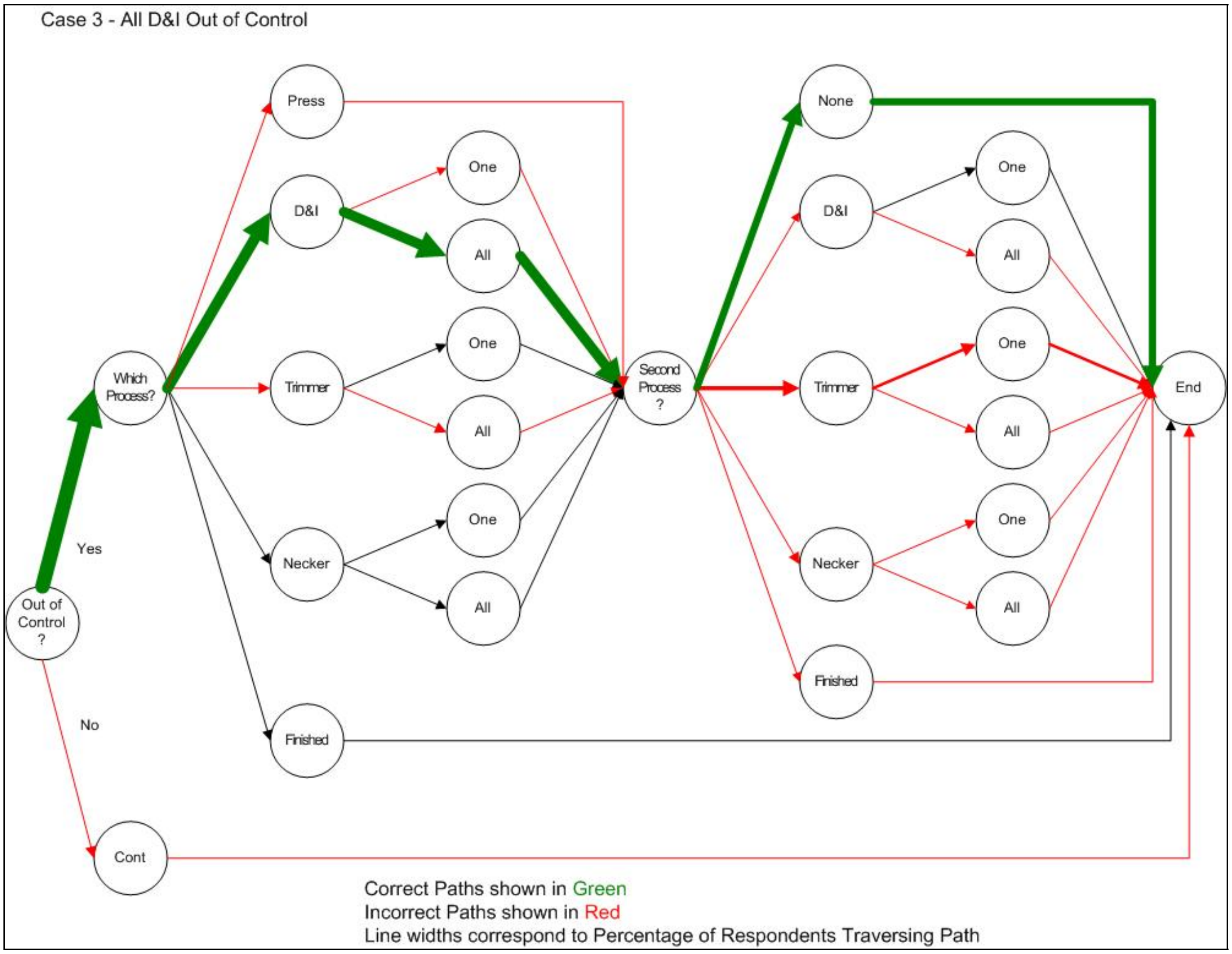


Figure 4.25 – Case 3 Decision–Making Network Flow Diagram

Case 4 – One D&I Out of Control.

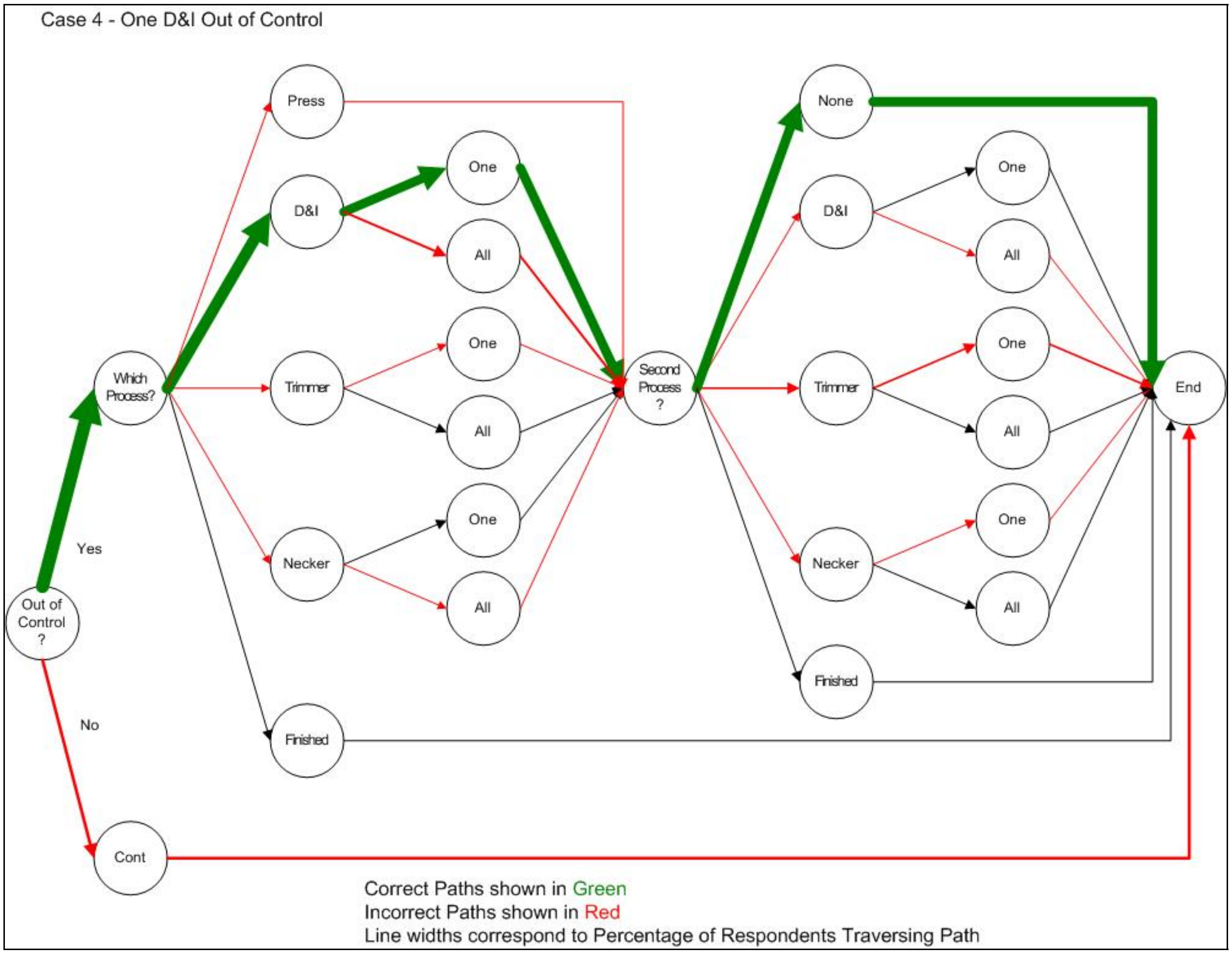


Figure 4.26 – Case 4 Decision–Making Network Flow Diagram

Case 5 – All Trimmers Out of Control.

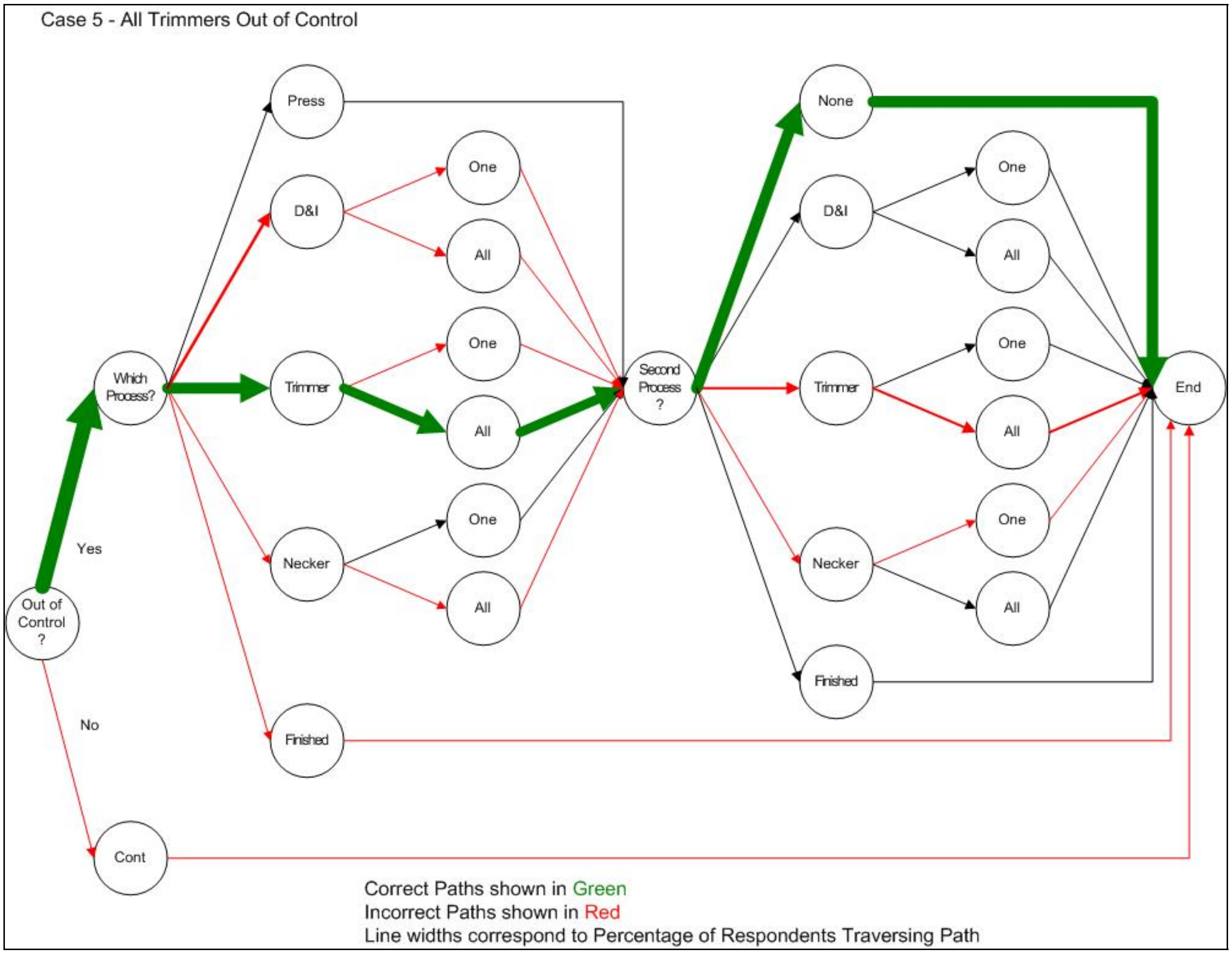


Figure 4.27 – Case 5 Decision–Making Network Flow Diagram

Case 6 – One Trimmer Out of Control.

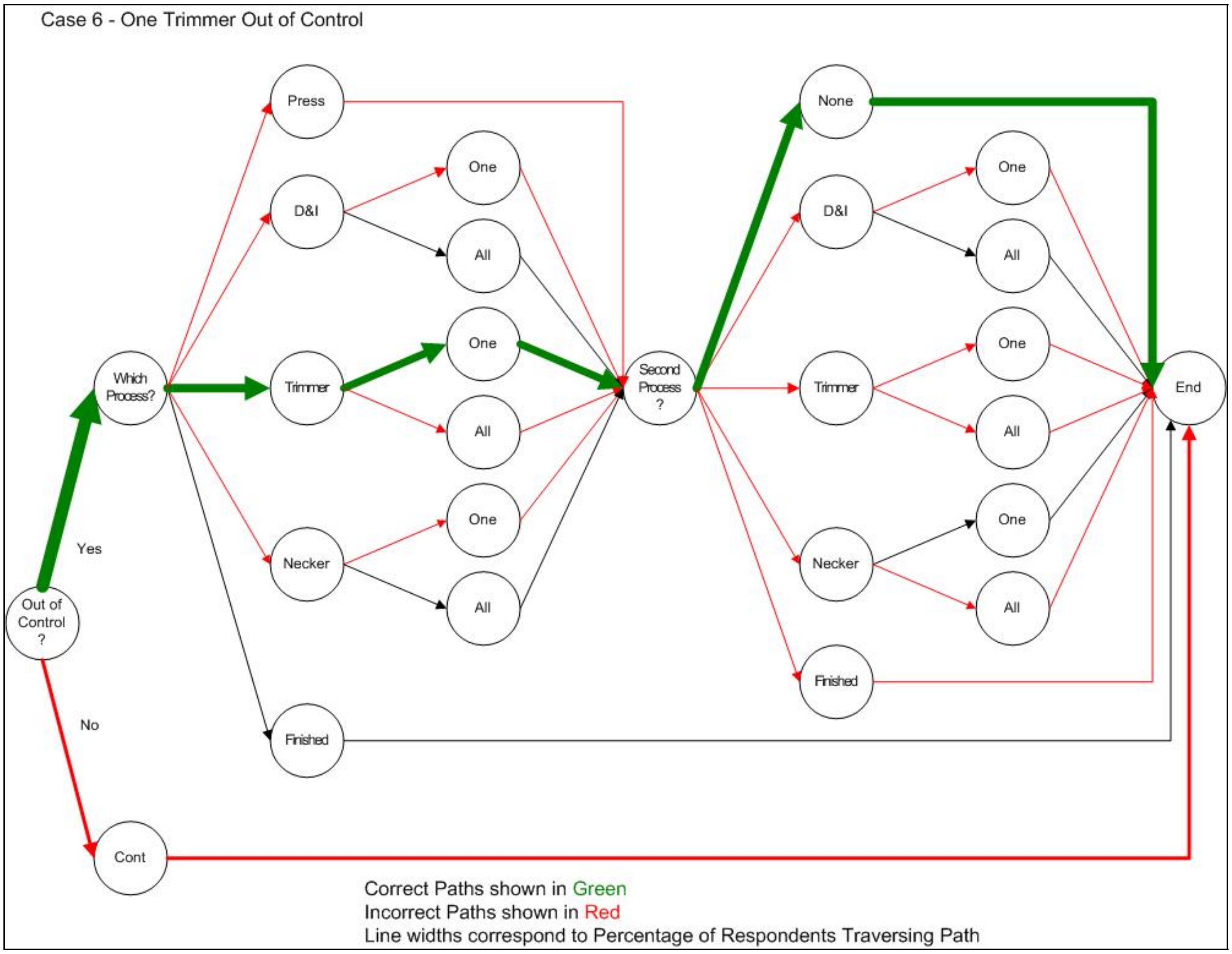


Figure 4.28 – Case 6 Decision–Making Network Flow Diagram

Case 7 – All Trimmers Out of Control Affecting All Neckers.

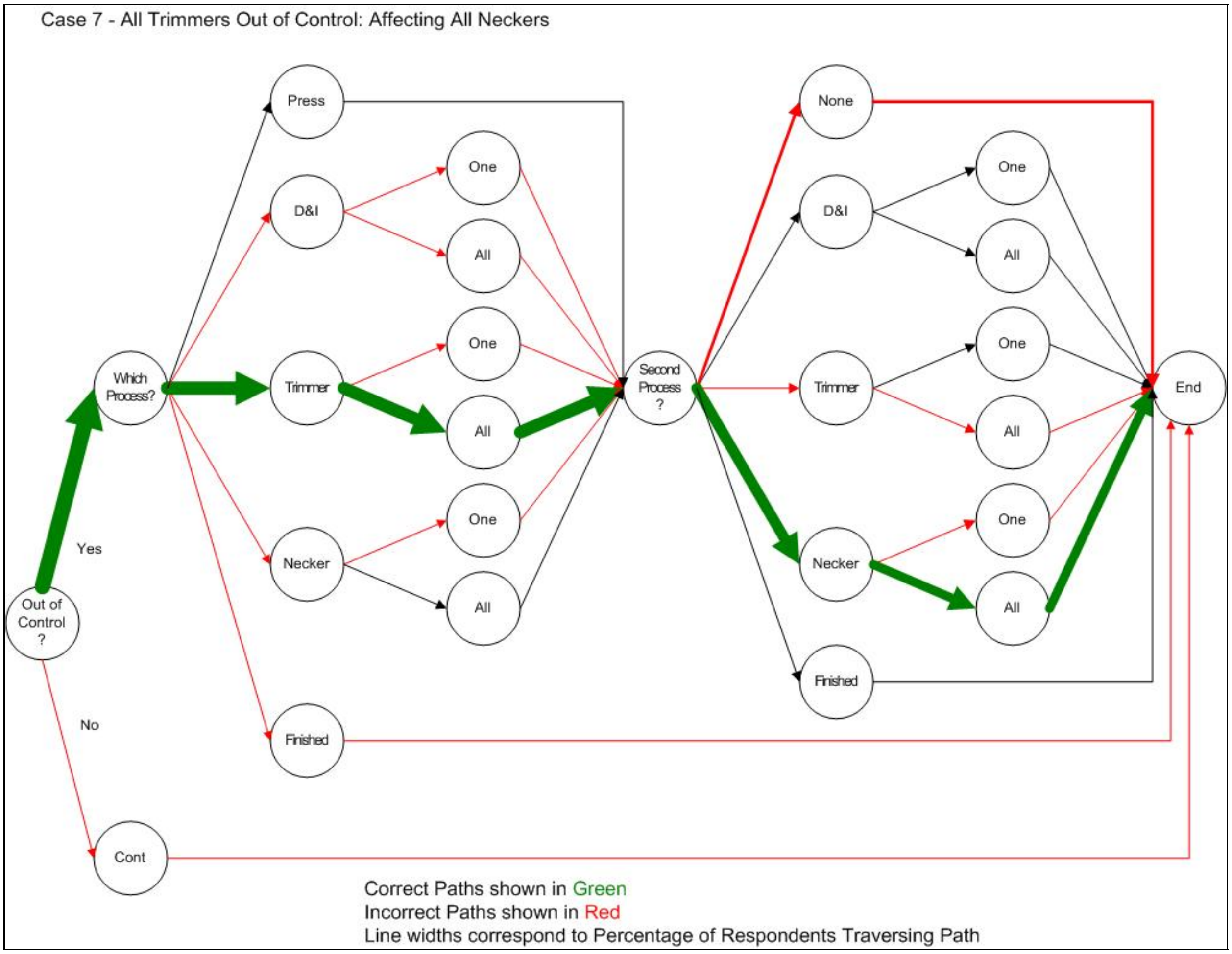


Figure 4.29 – Case 7 Decision–Making Network Flow Diagram

Case 8 – All Neckers Out of Control.

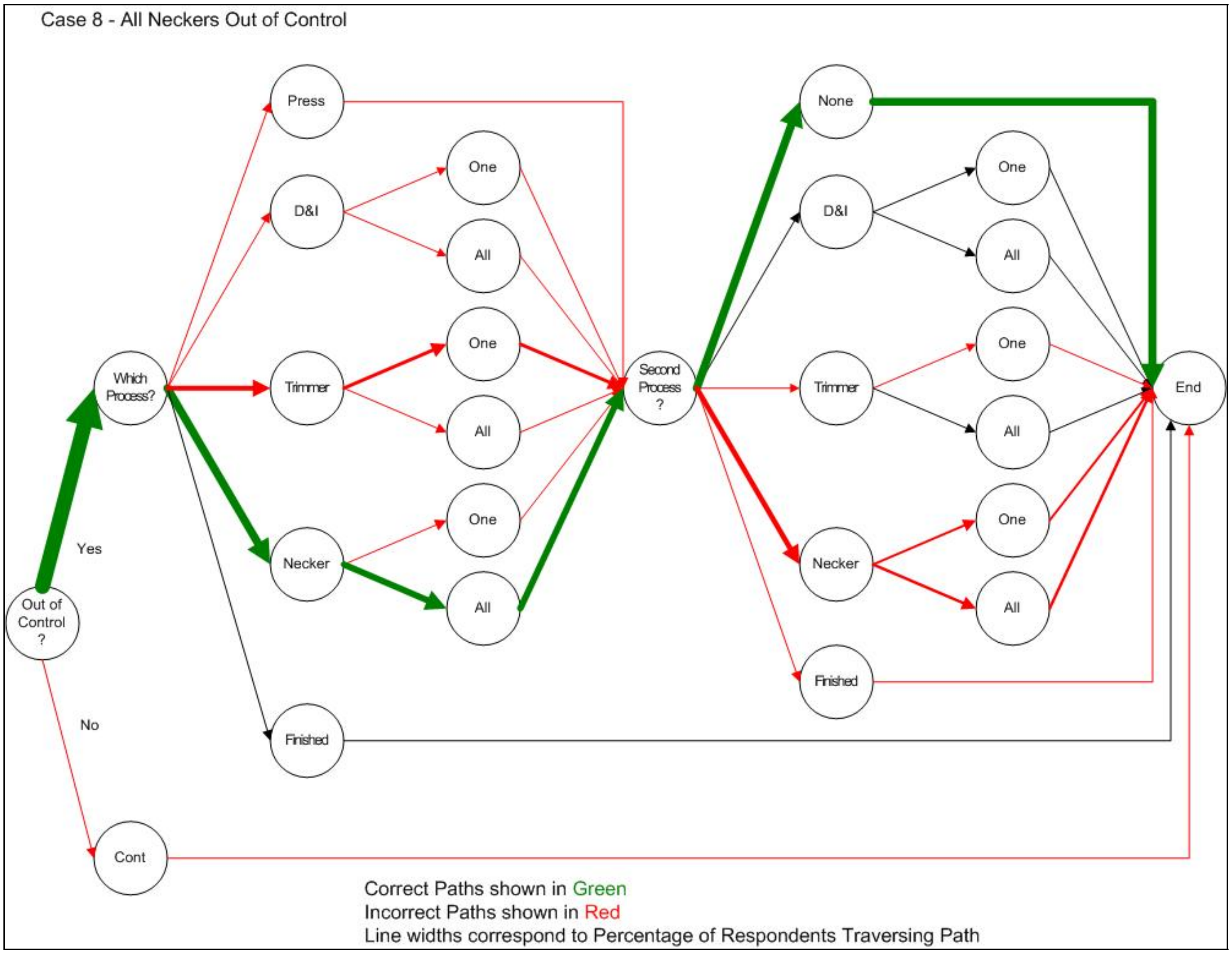


Figure 4.30 – Case 8 Decision–Making Network Flow Diagram

Case 9 – One Necker Out of Control.

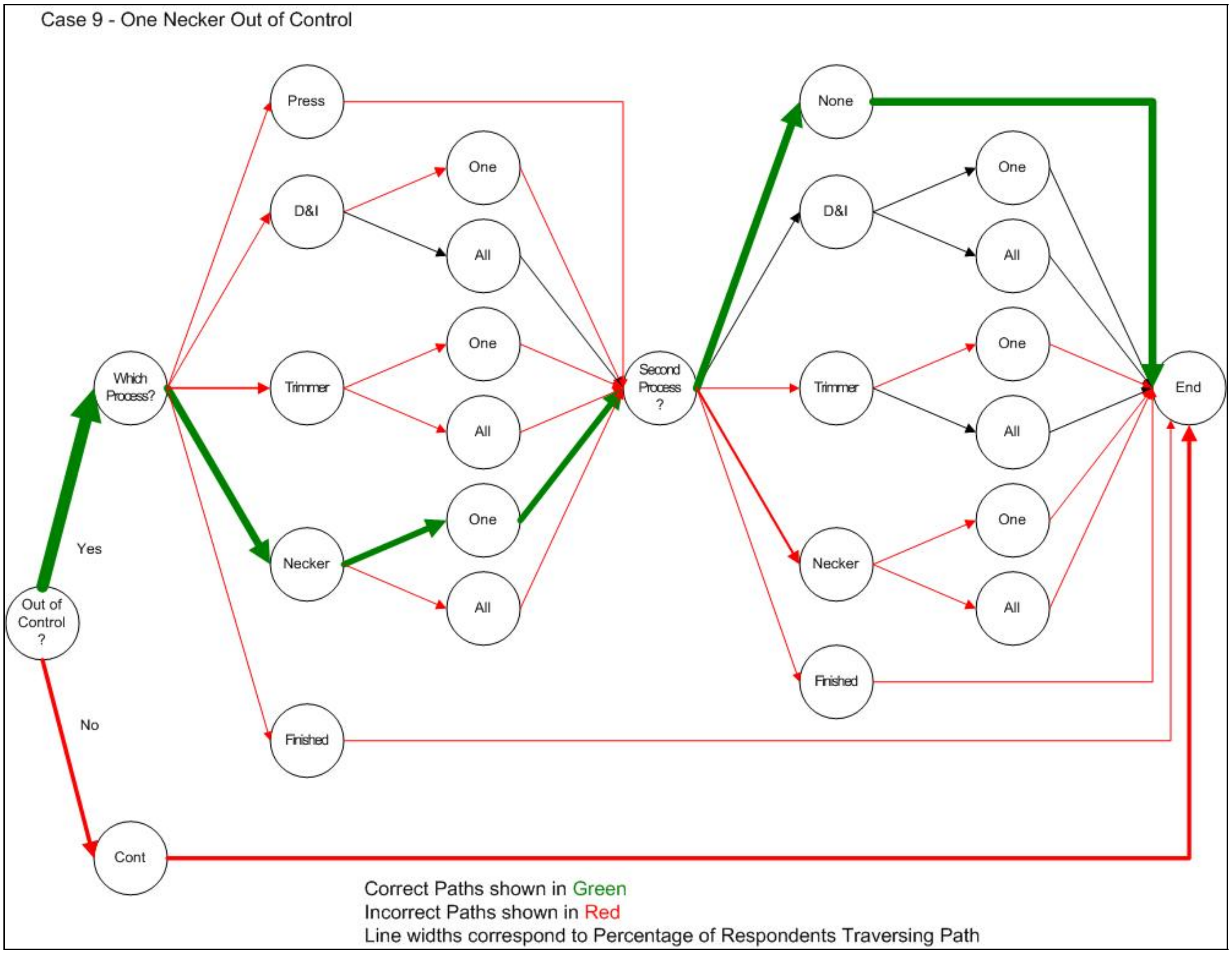


Figure 4.31 – Case 9 Decision–Making Network Flow Diagram

CHAPTER 5

CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

Chapter 4 presented the results of the experimental study, tested the hypotheses developed earlier, and discussed the relevance of these results. This chapter discusses the conclusions that can be derived from the results, discusses the limitations of those conclusions and this research, and suggests future research directions.

Conclusions

This research tested the ability of decision makers to detect quality problems using different visual representations across increasing levels of process complexity and varying quality issues for multiple classifications of visual acuity. The results were analyzed by the time required by a decision-maker to arrive at a decision, the accuracy of the decision made, and the perceived confidence of the decision-maker in arriving at that decision.

Several of the experimental results were expected. The type of visual representation was found to have a significant affect on completion time. Two-dimensional and three-dimensional visual representations take less time to assess than data tables and two-dimensional animated visual representations. Additionally, three-dimensional visual representations significantly improve decision-making accuracy over both two-dimensional and two-dimensional animated visual representations. Therefore, three-dimensional visual representations are superior to the other visual representation types tested in this experiment given their shorter completion times and improved decision-making accuracy.

Other experimental results were surprising. While process complexities were found to also significantly affect decision-making accuracy, the serial out of control condition is easier to assess than the single out of control condition or parallel out of control condition. It is interesting that decision-makers are most accurate in detecting quality problems for the most complex process. Further, subjects with low visual acuity were significantly less confident in their responses for both the in control and serial out of control condition.

Subjects with low visual acuity were significantly less confident in identifying in control and mean out of control quality issues. In control quality issues were significantly more accurate with three-dimensional visual representations. Mean quality issues were significantly more accurate with data table visual representations. Pattern quality issues were significantly more accurate with two-dimensional visual representations.

Visual acuity significantly affects decision-making completion time and confidence. Specifically, those with low visual acuity take significantly less time to assess quality problems than those with medium or high visual acuity. Subjects with medium visual acuity are more confident in their decisions than those with either low visual acuity or high visual acuity. Visual acuity significantly affects decision-making accuracy. Specifically, those with high visual acuity were more accurate than those with medium visual acuity. In terms of interaction effects, subjects with high visual acuity take significantly longer to assess two-dimensional animated visual representations.

With respect to confidence, many of the subjects taking the electronic experiment had limited experience with control charts and little to no experience in manufacturing. As with most learning situations, individuals become more confident in a procedure or technique as they utilize it more and more. Subject confidence may actually increase with long-term exposure to the different visualization types and manufacturing conditions.

Another surprising result concerns decision accuracy. In most cases, respondents were able to reach the correct conclusion; however, the time required to reach that conclusion varied significantly. Completion times were, therefore, the most significant experimental factor. Respondents were able to complete their tasks more quickly with two-dimensional and three-dimensional visual representations. Two-dimensional animated visual representations did not improve decision accuracy or completion times over that of a data table.

The results of this study indicate that complex visual representations can be used to make decisions that are more accurate as subjects can directly examine the multidimensional relationships contained in the data. This is important to high-volume, discrete manufacturing given its multivariate nature. As manufacturing begins to employ more intelligent machinery capable of collecting copious data, more complex visual representations should be developed to show the interactions among those variables and thereby aid decision-makers in making better and more accurate decisions.

In addition to affecting accuracy of subject responses, certain visualization types affect the completion time of subject responses. Multidimensional visualizations can be used to make more timely decisions of a multivariate nature for a given data set. High-volume manufacturing is capable of processing large numbers of discrete products in a relatively short time, thus any multidimensional visual representation that can support a more timely decision on the part of the decision maker is of critical importance.

Limitations

A key limitation that may have affected the electronic experiment was the choice of visual representations used in the study. The Table visualization type was included as many of the line workers and supervisors at the Salisbury Can Plant still prefer tabular data. While the two-dimensional control charts (static and animated) are typical of statistical process monitoring software found in manufacturing, the three-dimensional interactive control chart was a new approach. There is a very good possibility that one or more better visualizations exist that will assist decision-makers in making more accurate and faster decisions, perhaps with greater confidence.   Even with the addition of a new visualization type, the three-dimensional image was limited to three variables of interest, i.e. the quality characteristic being measured, the number of machines for which it is measured, and time. Allowing subjects to choose their own variables to be displayed on the three-dimensional image and, in fact, allowing for a fourth dimension to be added to the image through the use of color or hue may affect the appropriateness of the visualization type.

Other limitations can be identified with the electronic experiment such as the issue of visual impairment on the part of the subject. No attempt was made to screen subjects taking the experiment with respect to any eyesight issue such as colorblindness, nearsightedness, or lack of depth perception. Basic sight issues may impair the decision-making ability of a subject participant which may have affected at least some of the results. Future research may call for the screening of potential survey participants to allow for control of this limitation. The use of only one visual test, VVIQ, to assess the visual acuity of the subject is also a limitation of this study. No significance was found based on the VVIQ. Perhaps one of the other available visual tests that measure visual acuity may yield different results.

There also may exist substantial differences between the students that participated in the study and line operators and supervisors that work at the Salisbury Can Plant. While student subjects allow for the collection of large amount of research data in a controlled environment, their real-world practical experience with aluminum can manufacturing, and manufacturing in general, is limited at best. Further studies may be able to address this limitation by allowing those in high-volume, discrete product manufacturing to view the various visualization types and participate in an altered version of the study.

Future Research

This dissertation serves as an initial investigation of the application of multidimensional visualization techniques to high-volume, discrete product manufacturing. The data presented in the visual representations was simulated based on real-world aluminum can manufacturing data. From this, several opportunities exist with respect to further study of high-volume multidimensional visualization.

Research on which visualization types are more appropriate for different process areas of a manufacturing entity can be conducted. A system of visual representations that provide reliable information to decision-makers in a real-time environment would be an area for future development. A classification system for visualization types could be developed which allow users to choose those types best suited for a given manufacturing process or facility.

The visualizations such as those developed for this research could also be used to train operators in detecting quality problems in a facility, and serve as a basis for discussion about the causes of quality problems. Recall that in preparing the visual representations for this research, QFD was used to determine the interrelationship between customer requirements and quality characteristics, and then quality characteristics and process characteristics. For future research, neural networks might be employed on a larger data set to find those interrelationships that are not evident to operators and quality control managers.

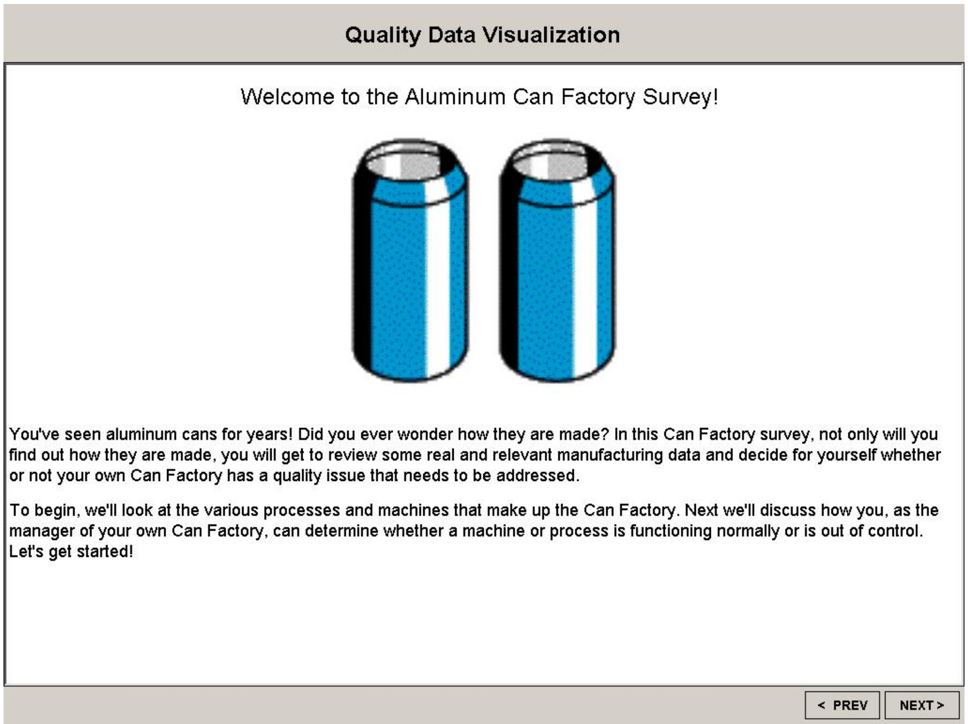
Differences exist among individuals based on their abilities to visually recognize and obtain information. Future research should include the adaptation of measures of these differences, other than the VVIQ, to better measure this difference and increase the understanding of how this affects the users of visually presented manufacturing information. On a broader scale, studies need to be developed that can accurately measure subject capabilities for comparison purposes in order to better understand the importance of this factor in the decision-making process.

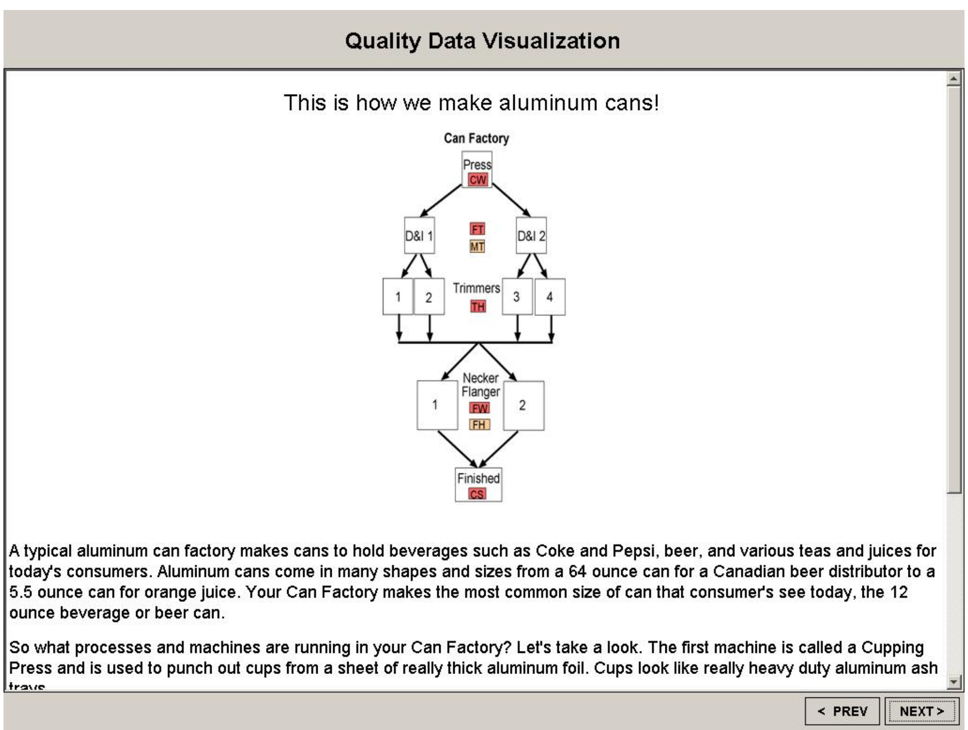
Finally, the application of data mining techniques to quality data, and the use of momentum accounting to assess changes in quality positions over time are fertile areas for future research.

Work is needed to investigate and develop information technology architectures that support visualization and visual representations as well as the investigation of web-based technologies for visual system integration into existing information technology infrastructures and legacy systems. The investigation and development of visual systems and representations that utilize and expand current organizational data mining and data warehousing capabilities is also an area for potential research given the current IT focus on enterprise systems and customer relationship management. The use of autonomous agents in both the development of visual representations and the delivery of visual images is also significant and provides another area for further research efforts.

APPENDIX

Screen Captures of the Visualization Experiment for 2D Visual Representations





Quality Data Visualization

These are the measurements we take at the different processes!

Listed below is each Can Factory process, some machine information about each process, and the data that you will be able to view for each machine:

- There is only one cupping Press and Cup Weights are measured to make sure there is an adequate amount of aluminum in the cup to make a can.
- There are two D&I machines to draw and iron the cups into can bodies. The thickness of the aluminum can sidewall is measured about halfway up the can body to determine the Midwall Thickness of the aluminum. At the top of the can body, the thickness of the aluminum can sidewall is measured to determine the Flange Wall Thickness of the aluminum. Why measure the thickness of the aluminum? Cans that are too thin will leak!
- There are four Trimmers to cut the rough edges from the tops of the aluminum cans. The Trimmed Height of the can body is measured since cans that are too tall won't properly pass through the Necker/Flanger.
- There are two Necker/Flangers to squeeze and flange the top of the aluminum can. The width of the flange (Flange Width) is measured as well as the Flanged Height. If the width of the flange is too small or too large, the lids won't fit properly. Also, finished cans that are too tall will jam up the machines that fill them with product (i.e. Pepsi or beer). Spilling large amounts of cola or beer makes a big mess and makes bottlers very upset!
- We crush aluminum cans (not all of them, just a few) at the one Finished process where the Columnar Strength is measured. Why? Aluminum cans have to withstand alot of vertical load when they're placed in warehouses and on store shelves. Cans that collapse and leak at the store also make a big mess and we want these customers to be happy too!

Information overload? Refer to your Can Factory handout!

< PREV | NEXT >

Quality Data Visualization

How do I know if my Can Factory is Out of Control?

In a few moments, you are going to be able to look at the data for each Can Factory process and machine. For each of the visual representations of this data, you will be comparing some sort of measurement, i.e. an average, to some set of limits for that measurement. These limits, usually called Upper Control Limits and Lower Control Limits, have been calculated beforehand using a statistical method called Statistical Process Control. You don't need to worry about how these control limits were calculated. You just need to know that if a measurement is within the control limits, then everything is OK. However, if a measurement is outside of the control limits, then the process on that given machine is out of control and your Can Factory has a problem.

Say, for example, we measured the Cup Weights of several cans and calculated the average or mean of the sample, X-bar. If X-bar is between the already calculated Upper Control Limit and Lower Control Limit, then everything is OK. If not, however, the the Press is Out of Control.

We can also calculate the Range of the Cup Weights we measured by subtracting the smallest Cup Weight value from the largest Cup Weight value. This value, R, can also be compared to its own set of already calculated Upper Control Limits and Lower Control Limits. If R is between these limits, then everything is OK. If not, however, this is another test showing the Press is Out of Control.

Sometimes patterns in data can indicate a quality problem for a process. For example, let's say that we take eight samples from the Press and calculate the mean (X-bar) for each Cup weight sample. Now, suppose that X-bar is for each sample is greater than the one before it. The process is slowly moving to an Out of Control condition! (Some subsequent sample will eventually be above the upper control limit...right?) For this survey, look for continuously increasing or continuously decreasing data. That's an Out of Control condition as well!

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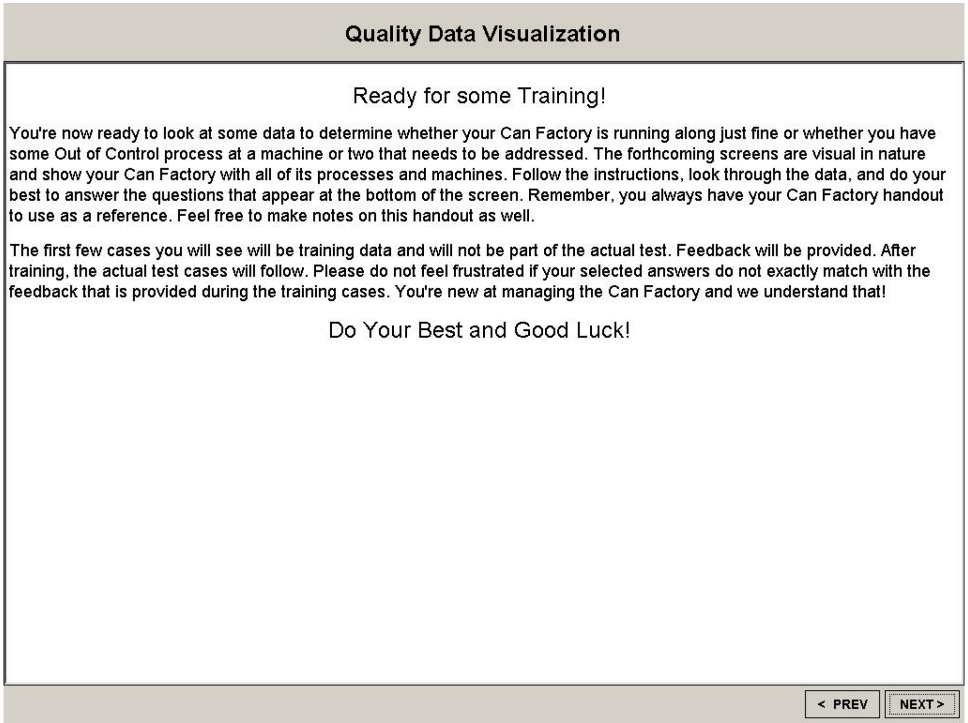
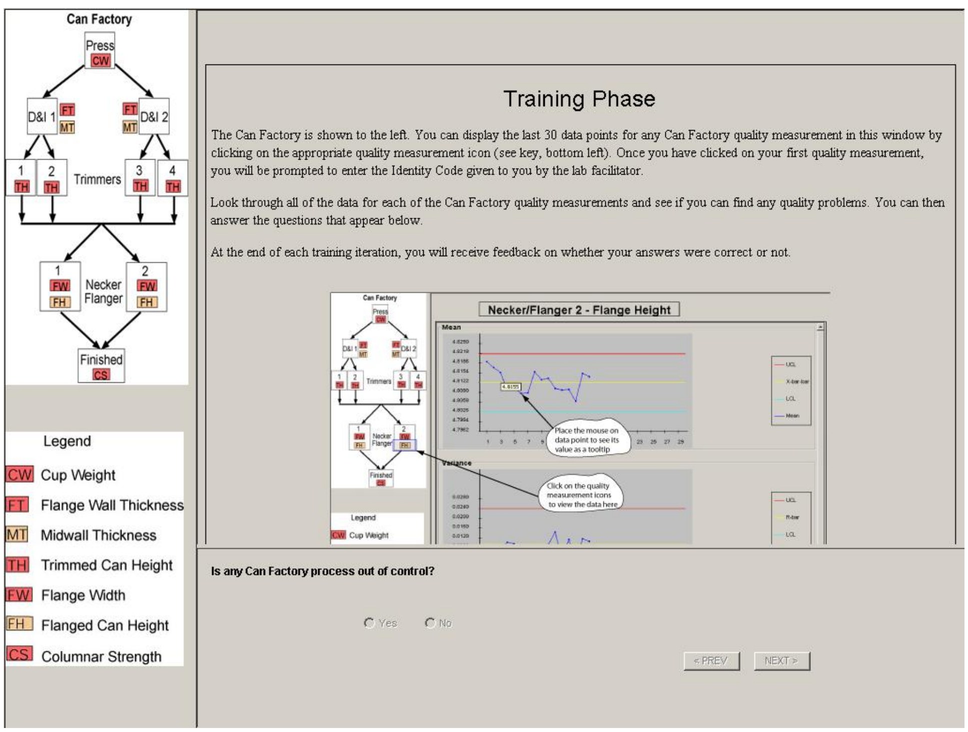
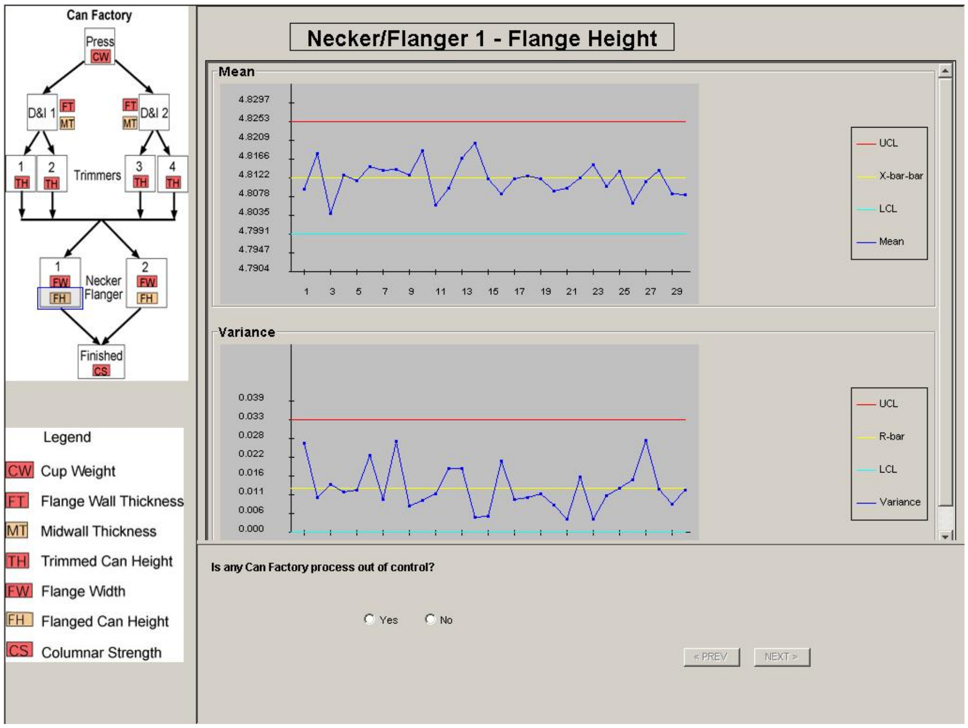
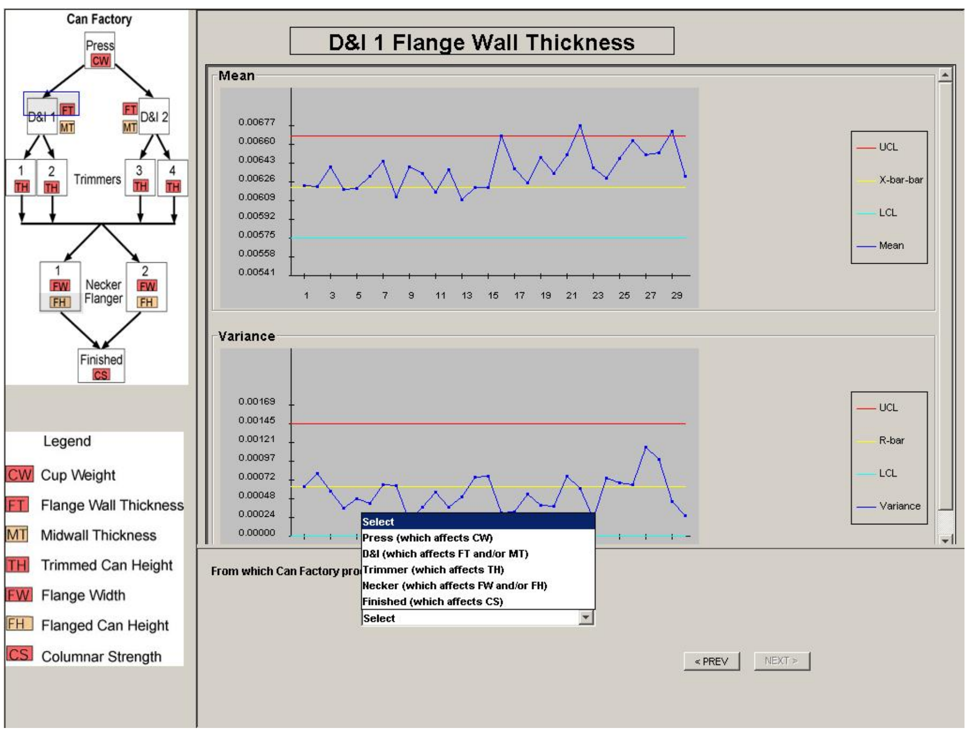
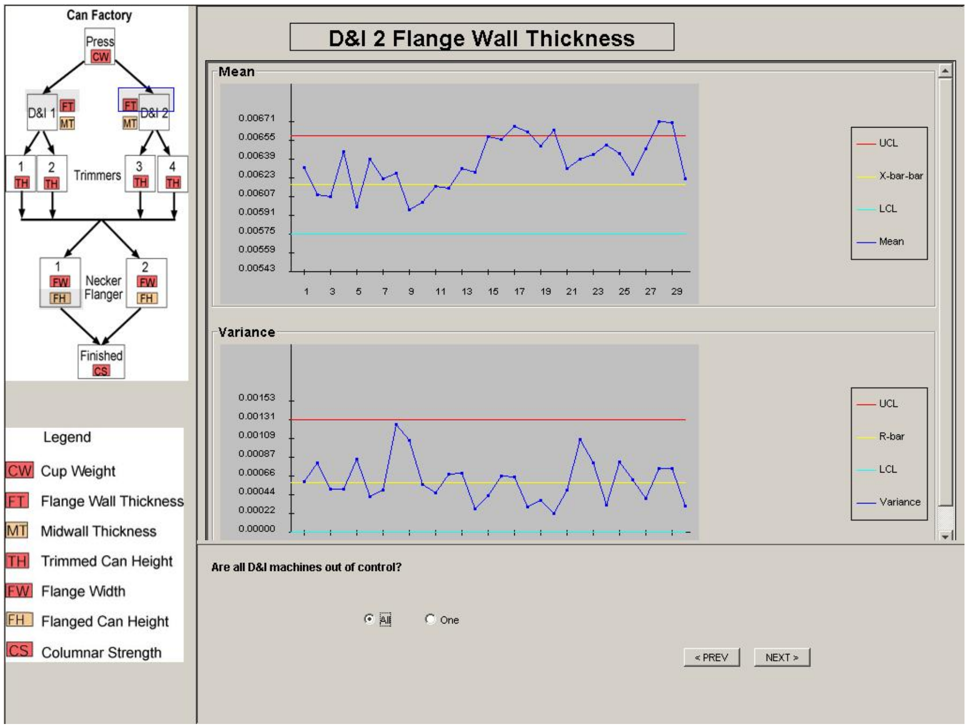
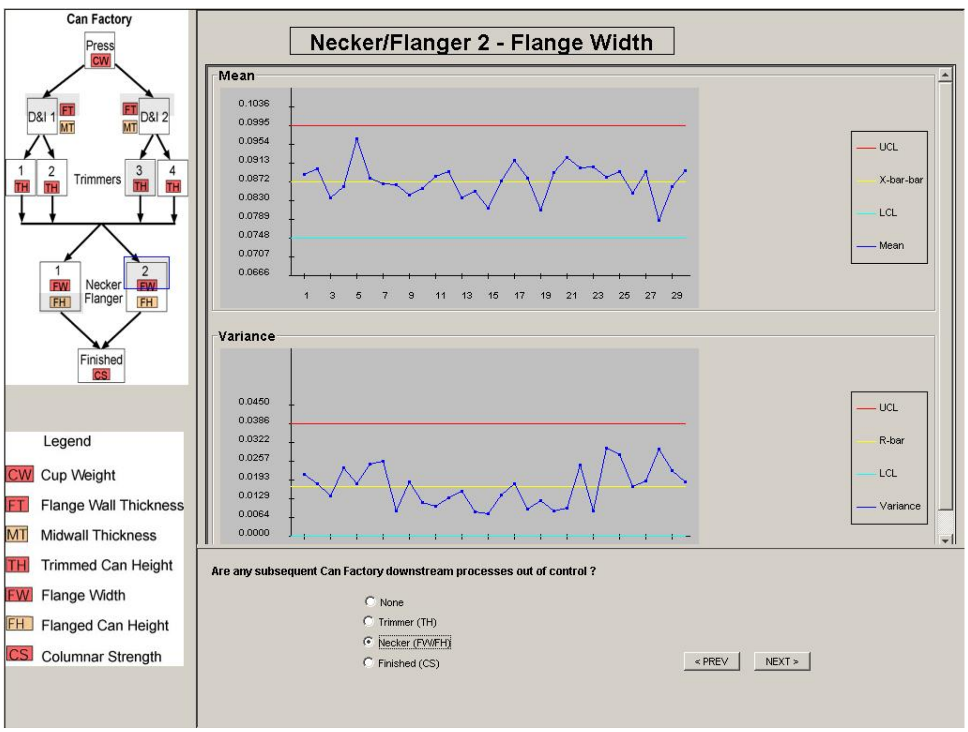

Quality Data Visualization
Ready for some Training!
You're now ready to look at some data to determine whether your Can Factory is running along just fine or whether you have some Out of Control process at a machine or two that needs to be addressed. The forthcoming screens are visual in nature and show your Can Factory with all of its processes and machines. Follow the instructions, look through the data, and do your best to answer the questions that appear at the bottom of the screen. Remember, you always have your Can Factory handout to use as a reference. Feel free to make notes on this handout as well.
The first few cases you will see will be training data and will not be part of the actual test. Feedback will be provided. After training, the actual test cases will follow. Please do not feel frustrated if your selected answers do not exactly match with the feedback that is provided during the training cases. You're new at managing the Can Factory and we understand that!
Do Your Best and Good Luck!
< PREV
NEXT >

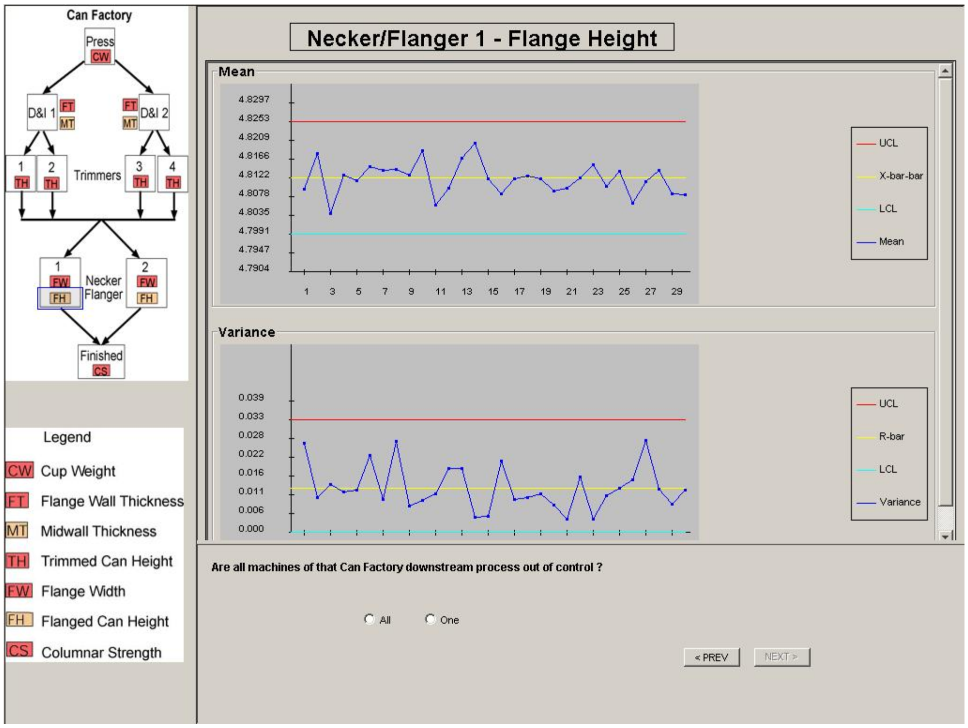

Can Factory
Press
CW
D&I 1
FT
MT
D&I 2
1
2
Trimmers
3
4
TH
1
2
Necker Flanger
FW
FH
Finished
CS
Legend
CW Cup Weight
FT Flange Wall Thickness
MT Midwall Thickness
TH Trimmed Can Height
FW Flange Width
FH Flanged Can Height
CS Columnar Strength
Training Phase
The Can Factory is shown to the left. You can display the last 30 data points for any Can Factory quality measurement in this window by clicking on the appropriate quality measurement icon (see key, bottom left). Once you have clicked on your first quality measurement, you will be prompted to enter the Identity Code given to you by the lab facilitator.
Look through all of the data for each of the Can Factory quality measurements and see if you can find any quality problems. You can then answer the questions that appear below.
At the end of each training iteration, you will receive feedback on whether your answers were correct or not.
Necker/Flanger 2 - Flange Height
Mean
Place the mouse on data point to see its value as a tooltip
Variance
Click on the quality measurement icons to view the data here
Is any Can Factory process out of control?
Yes
No
< PREV
NEXT >


Can Factory
Press
CW
D&I 1
FT
MT
D&I 2
Trimmers
TH
Necker
Flanger
FW
FH
Finished
CS
Legend
CW Cup Weight
FT Flange Wall Thickness
MT Midwall Thickness
TH Trimmed Can Height
FW Flange Width
FH Flanged Can Height
CS Columnar Strength
Necker/Flanger 1 - Flange Height
Mean
UCL
X-bar-bar
LCL
Mean
Variance
UCL
R-bar
LCL
Variance
Is any Can Factory process out of control?
Yes
No
< PREV
NEXT >

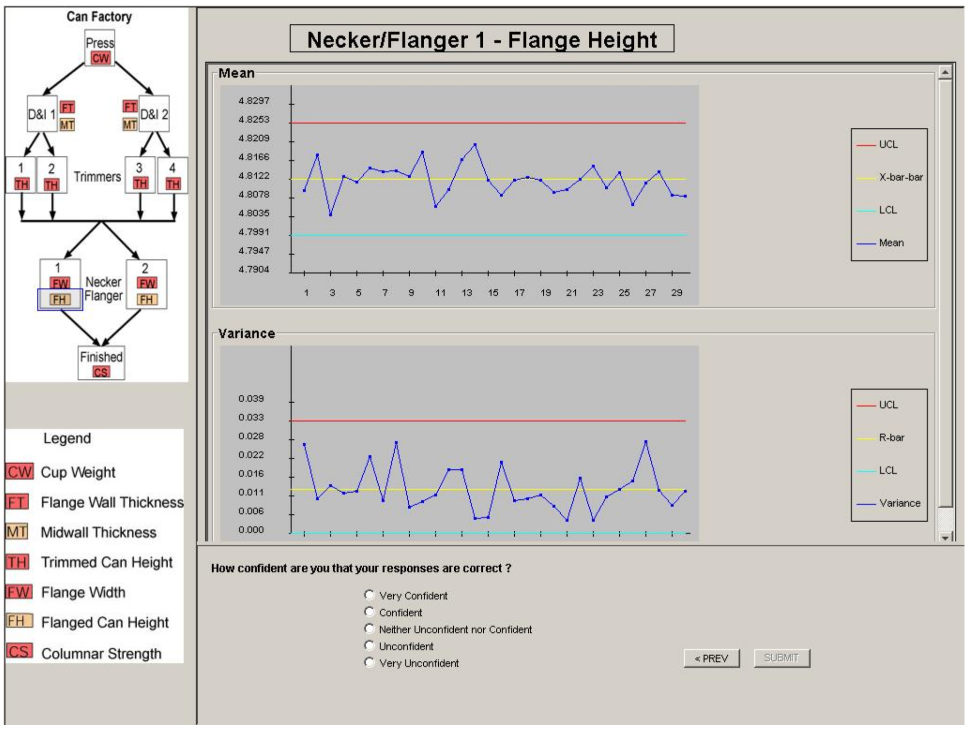

Can Factory
Press
CW
D&I 1
FT
MT
D&I 2
Trimmers
TH
Necker
Flanger
FW
FH
Finished
CS
Legend
CW Cup Weight
FT Flange Wall Thickness
MT Midwall Thickness
TH Trimmed Can Height
FW Flange Width
FH Flanged Can Height
CS Columnar Strength
D&I 1 Flange Wall Thickness
Mean
UCL
X-bar-bar
LCL
Mean
Variance
UCL
R-bar
LCL
Variance
From which Can Factory pro
Select
Press (which affects CW)
D&I (which affects FT and/or MT)
Trimmer (which affects TH)
Necker (which affects FW and/or FH)
Finished (which affects CS)
Select
< PREV
NEXT >


Can Factory
Press
CW
D&I 1
FT
MT
D&I 2
Trimmers
TH
Necker
Flanger
FW
FH
Finished
CS
Legend
CW Cup Weight
FT Flange Wall Thickness
MT Midwall Thickness
TH Trimmed Can Height
FW Flange Width
FH Flanged Can Height
CS Columnar Strength
D&I 2 Flange Wall Thickness
Mean
0.00671
0.00655
0.00639
0.00623
0.00607
0.00591
0.00575
0.00559
0.00543
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29
UCL
X-bar-bar
LCL
Mean
Variance
0.00153
0.00131
0.00109
0.00087
0.00066
0.00044
0.00022
0.00000
UCL
R-bar
LCL
Variance
Are all D&I machines out of control?
All
One
< PREV
NEXT >

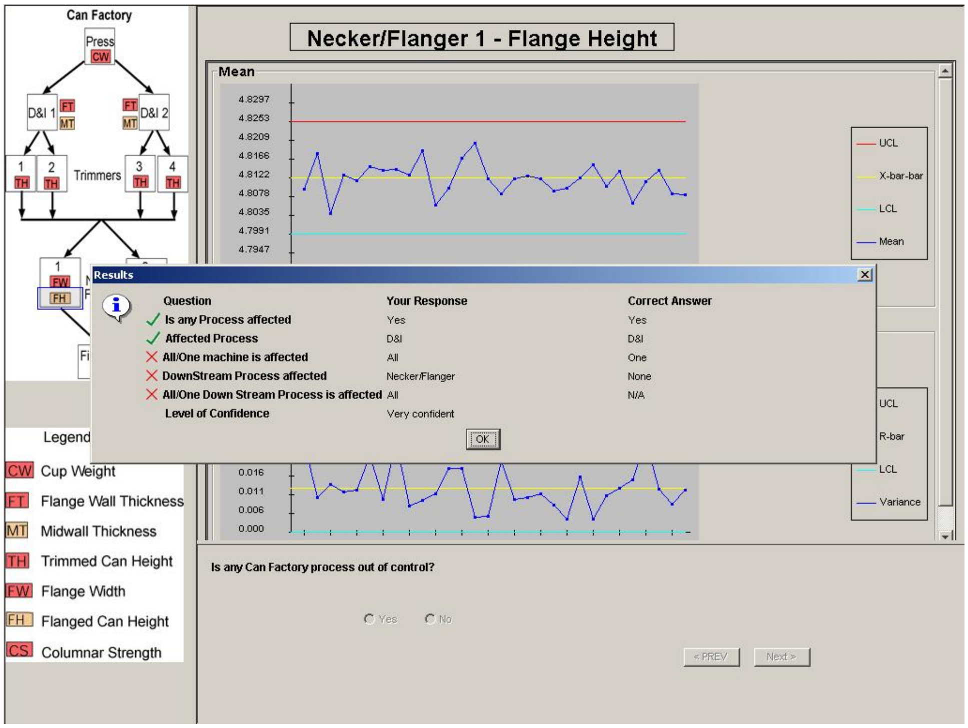

Can Factory
Press
CW
D&I 1
FT
MT
D&I 2
Trimmers
TH
Necker
Flanger
FW
FH
Finished
CS
Legend
CW Cup Weight
FT Flange Wall Thickness
MT Midwall Thickness
TH Trimmed Can Height
FW Flange Width
FH Flanged Can Height
CS Columnar Strength
Necker/Flanger 2 - Flange Width
Mean
0.1036
0.0995
0.0954
0.0913
0.0872
0.0830
0.0789
0.0748
0.0707
0.0666
1 3 5 7 9 11 13 15 17 19 21 23 25 27 29
UCL
X-bar-bar
LCL
Mean
Variance
0.0450
0.0386
0.0322
0.0257
0.0193
0.0129
0.0064
0.0000
UCL
R-bar
LCL
Variance
Are any subsequent Can Factory downstream processes out of control ?
None
Trimmer (TH)
Necker (FW/FH)
Finished (CS)
< PREV
NEXT >

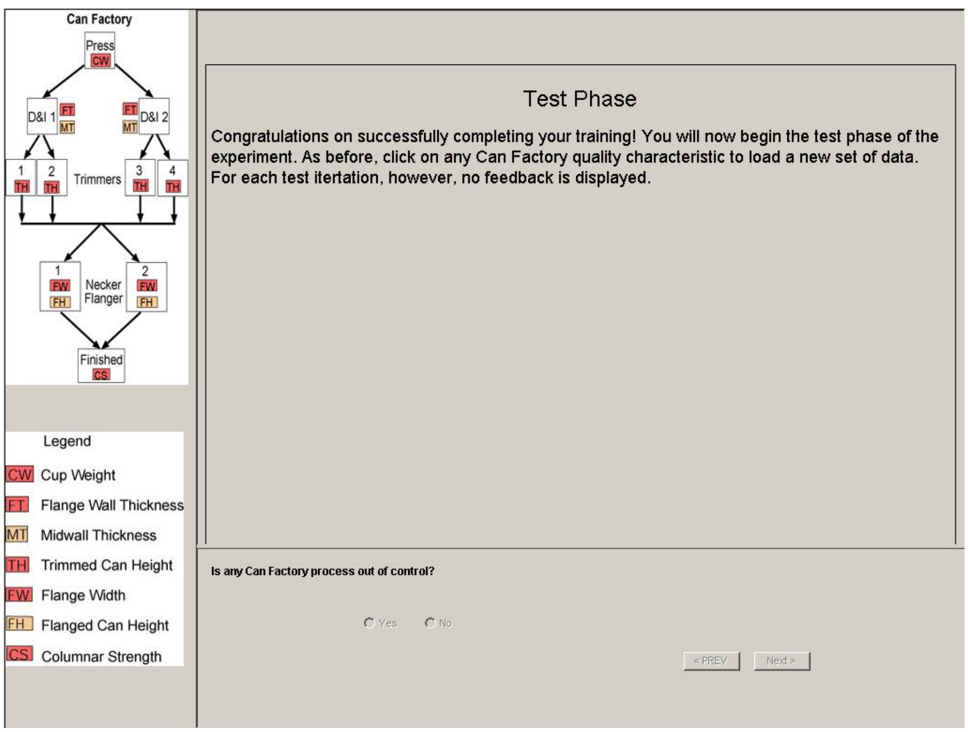


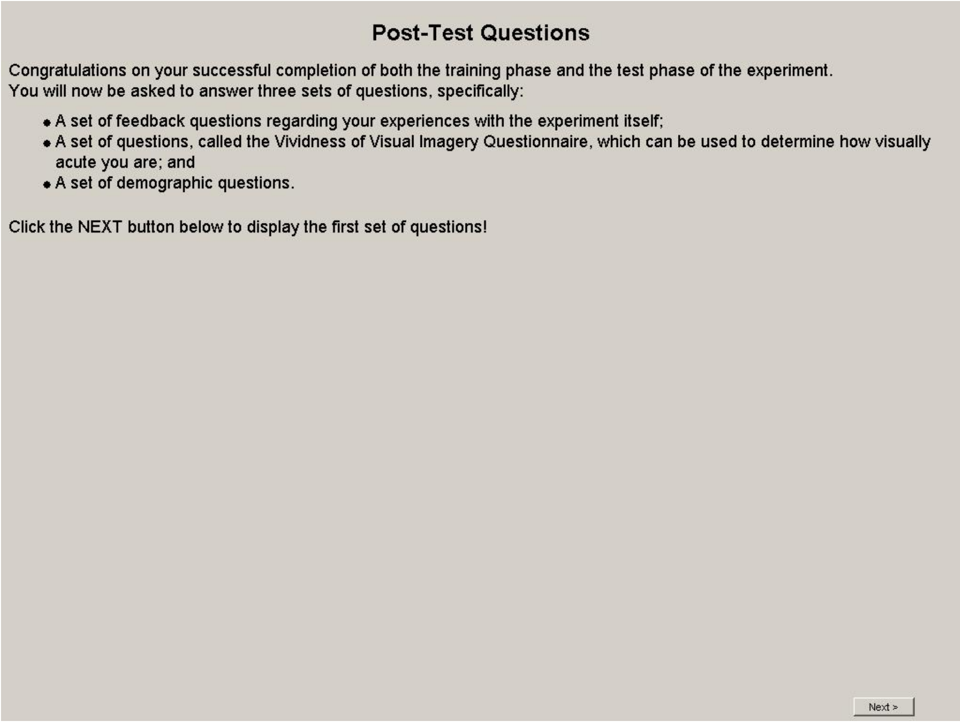
Can Factory
Press
CW
D&I 1
FT
MT
D&I 2
Trimmers
TH
Necker
Flanger
FW
FH
Finished
CS
Legend
CW Cup Weight
FT Flange Wall Thickness
MT Midwall Thickness
TH Trimmed Can Height
FW Flange Width
FH Flanged Can Height
CS Columnar Strength
Necker/Flanger 1 - Flange Height
Mean
UCL
X-bar-bar
LCL
Mean
Variance
UCL
R-bar
LCL
Variance
Are all machines of that Can Factory downstream process out of control ?
All
One
< PREV
NEXT >



Can Factory
Press
CW
D&I 1
FT
MT
D&I 2
Trimmers
TH
Necker
Flanger
FW
FH
Finished
CS
Legend
CW Cup Weight
FT Flange Wall Thickness
MT Midwall Thickness
TH Trimmed Can Height
FW Flange Width
FH Flanged Can Height
CS Columnar Strength
Necker/Flanger 1 - Flange Height
Mean
UCL
X-bar-bar
LCL
Mean
Variance
UCL
R-bar
LCL
Variance
How confident are you that your responses are correct ?
Very Confident
Confident
Neither Unconfident nor Confident
Unconfident
Very Unconfident
< PREV
SUBMIT


Can Factory
Press
CW
D&I 1
FT
MT
D&I 2
Trimmers
TH
FW
FH
Necker/Flanger 1 - Flange Height
Mean
UCL
X-bar-bar
LCL
Mean
Results
Question
Your Response
Correct Answer
Is any Process affected
Yes
Yes
Affected Process
D&I
D&I
All/One machine is affected
All
One
DownStream Process affected
Necker/Flanger
None
All/One Down Stream Process is affected
All
N/A
Level of Confidence
Very confident
OK
R-bar
Variance
Legend
Cup Weight
Flange Wall Thickness
Midwall Thickness
Trimmed Can Height
Flange Width
Flanged Can Height
Columnar Strength
Is any Can Factory process out of control?
Yes
No
« PREV
Next »


Can Factory
Press
CW
D&I 1
D&I 2
Trimmers
Necker Flanger
Finished
CS
Test Phase
Congratulations on successfully completing your training! You will now begin the test phase of the experiment. As before, click on any Can Factory quality characteristic to load a new set of data. For each test itertation, however, no feedback is displayed.
Legend
Cup Weight
Flange Wall Thickness
Midwall Thickness
Trimmed Can Height
Flange Width
Flanged Can Height
Columnar Strength
Is any Can Factory process out of control?
Yes
No
« PREV
Next »



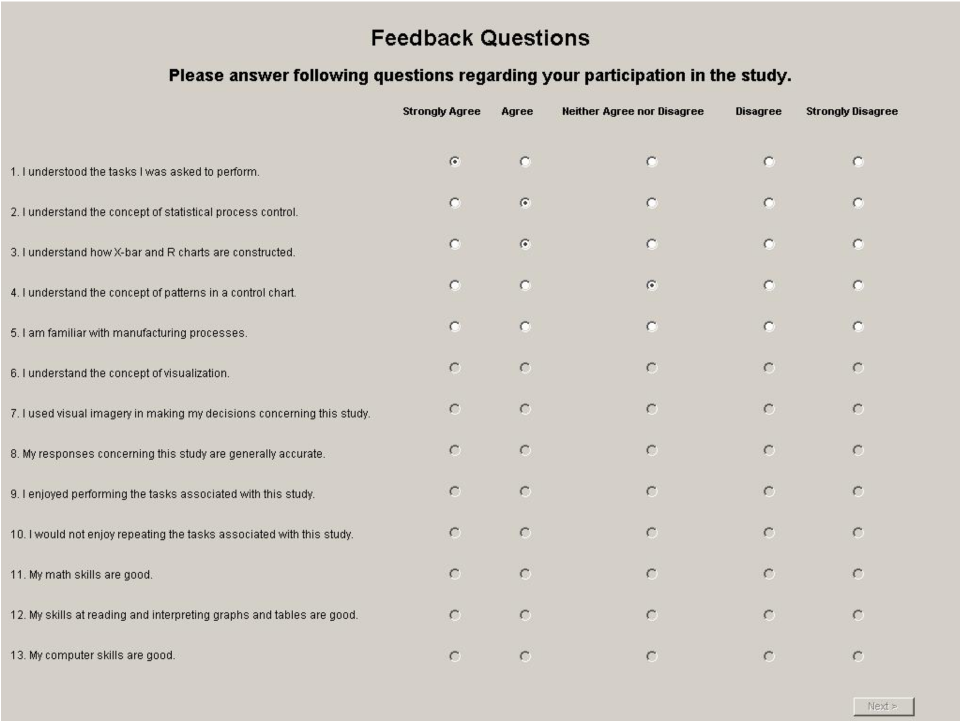
Post-Test Questions

Congratulations on your successful completion of both the training phase and the test phase of the experiment.
You will now be asked to answer three sets of questions, specifically:

- A set of feedback questions regarding your experiences with the experiment itself;
- A set of questions, called the Vividness of Visual Imagery Questionnaire, which can be used to determine how visually acute you are; and
- A set of demographic questions.

Click the NEXT button below to display the first set of questions!

Next >



Feedback Questions

Please answer following questions regarding your participation in the study.

	Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
1. I understood the tasks I was asked to perform.					
2. I understand the concept of statistical process control.					
3. I understand how X-bar and R charts are constructed.					
4. I understand the concept of patterns in a control chart.					
5. I am familiar with manufacturing processes.					
6. I understand the concept of visualization.					
7. I used visual imagery in making my decisions concerning this study.					
8. My responses concerning this study are generally accurate.					
9. I enjoyed performing the tasks associated with this study.					
10. I would not enjoy repeating the tasks associated with this study.					
11. My math skills are good.					
12. My skills at reading and interpreting graphs and tables are good.					
13. My computer skills are good.					

Next >

Vividness of Visual Imagery Questionnaire

Please answer each question to the best of your ability.
1 = No image at all; you only know that you are thinking of the object
2 = Mind's image is vague and dim
3 = Mind's image is moderately clear and vivid
4 = Mind's image is clear and reasonably vivid
5 = Mind's image is perfectly clear and as vivid as normal vision

For items 1 through 4, think of some friend whom you frequently see but who is not with you at present. Consider carefully the picture that comes before your mind's eye:

1. The exact contour of face, head, shoulders, and body.	1	2	3	4	5
2. Characteristic poses of head, attitude of body, etc.	1	2	3	4	5
3. The precise carriage, length of step, etc. in walking.	1	2	3	4	5
4. The different colors worn in some familiar clothes.	1	2	3	4	5

For items 5 through 8, visualize a rising sun. Consider carefully the picture that comes before your mind's eye:

5. The sun is rising above the horizon into a hazy sky.	1	2	3	4	5
6. The sky clears and surrounds the sun with blueness.	1	2	3	4	5
7. Clouds. A storm blows up, with flashes of lightning.	1	2	3	4	5
8. A rainbow appears.	1	2	3	4	5

For items 9 through 12, think of the front of a shop that you often go to. Consider carefully the picture that comes before your mind's eye:

9. The overall appearance of the shop from the opposite side of the road.	1	2	3	4	5
10. A window display including colors, shapes, and details of individual items for sale.	1	2	3	4	5
11. You are near the entrance. The color, shape, and details of the door.	1	2	3	4	5
12. Enter the shop and go to the counter. The assistant serves you. Money changes hands.	1	2	3	4	5

For items 13 through 16, think of a country scene which involves trees, mountains, and a lake. Consider carefully the picture that comes before your mind's eye:

13. The contours of the landscape.	1	2	3	4	5
14. The color and shape of the trees.	1	2	3	4	5
15. The color and shape of the lake.	1	2	3	4	5
16. A strong wind blows on the trees and on the lake causing waves.	1	2	3	4	5

Next >

Demographic Questions

Select the best responses from the dropdown boxes for the demographic questions that appear below.

How old are you ?	25+
Sex :	Male
How much computer experience do you have you ?	5 + years
How much work experience do you have ?	Select
What is your education level ?	Select
What is the highest degree you have earned ?	Select
Have you had formal classroom instruction in statistics ?	Select
Have you had formal classroom instruction in Prodcution/Operations Management ?	Select
What is your current major ?	

Next >

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