PREDICTIVE QUALITY ANALYTICS

by

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Dedicated to my wife Jennifer

Without her support, none of this would have been possible

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I wish my Father was here to see me walk and be awarded the Doctorate degree. His hard work and dedication in everything shaped my core and belief system. I am sure he is watching and beaming with pride. I am blessed to have my mother see me walk and point out “that is my son”. To my wife Jennifer, my daughter Maryam, my sons Ali, and Amir, you are all the reason why I do what I do. You give me purpose and pride. Without all of you, none of this would be possible. The idea of PQA was formed one afternoon in the office and a few years later, it’s my dissertation and a Global Quality Strategy of a Multinational Corporation. I’m grateful for all of the people along the way that helped make this dream a reality.

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Agha, this one is for you!

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LIST OF ABBREVIATIONS

AHP	Analytic Hierarchy Process
ARIMA	Auto Regressive Integrated Moving Average
BBN	Bayesian Belief Network
CMMI	Capability Maturity Model Integration
DCMA	Defense Contractor Management Agency
FAA	Federal Aviation Administration
FMEA	Failure Mode & Effect Analysis
JIT	Just-in-Time
KPI	Key Performance Indicator
NTSB	National Transportation Safety Board
OCAI	Organizational Cultural Assessment Instrument
PEMM	Process & Enterprise Maturity Model
PQA	Predictive Quality Analytics
RPN	Risk Priority Number
TPS	Toyota Production System
TQC	Total Quality Control
TQM	Total Quality Management

ABSTRACT

Quality drives customer satisfaction, improved business performance, and safer products. Reducing waste and variation is critical to the financial success of organizations. Today, it is common to see Lean and Six Sigma used as the two main strategies in improving Quality. As advancements in information technologies enable the use of big data, defect reduction and continuous improvement philosophies will benefit and even prosper. Predictive Quality Analytics (PQA) is a framework where risk assessment and Machine Learning technology can help detect anomalies in the entire ecosystem, and not just in the manufacturing facility. PQA serves as an early warning system that directs resources to where help and mitigation actions are most needed. In a world where limited resources are the norm, focused actions on the significant few defect drivers can be the difference between success and failure.

Key Words: Lean, Machine Learning, PQA, Quality, Risk Assessment, Six Sigma

CHAPTER 1. INTRODUCTION

The modern concept of Quality is primarily a Japanese and American phenomenon. After World War II, Taiichi Ohno implemented a management strategy called Just-in-Time (JIT). Although JIT roots can be traced back to the Henry Ford production line, Toyota perfected the system by focusing on the right number of parts, at the right time, in the right place, and without any defects (UKessays, 2018). The concept has been a global success with the advent of Lean and the Toyota Production System (TPS). Taiichi Ohno, the father of JIT, recalls that the wonderful ideas of Quality strategies and management systems came from the United States. The techniques were based on basic Industrial Engineering and Total Quality Control (TQC) principles (Ohno, 1998).

The Japanese push for improving quality further enhanced their management philosophy, resulting in the Toyota Production System. The basis of the TPS was JIT, automation with a human touch, and an obsession for waste elimination. Quality in TPS was based on ensuring that no defects were received, generated, or passed on through the entire value stream. TPS is a proven business process with an embedded Quality Management System.

Leading quality pioneers in the United States have been instrumental in advancing the concept of quality for years. The term Total Quality Management (TQM) was initially coined by the Naval Air System Command in the early 1920s. The concept was based on driving defect elimination using data, economic theories, and process analysis (ASQ, 2020). A few decades later, by the 1950s, Joseph Juran, W. Edward Deming, Armand V. Feigenbaum, and Phillip Crosby started laying the foundation for what is known today as Quality Management Systems (LSS, 2019).

The concept of Six Sigma and the use of statistics in supply chain manufacturing were also developed in the United States starting in the 1920s. Walter Shewhart, a researcher at Western Electric, began using statistics and the concept of normal distribution to identify defects and process anomalies. Bill Smith, an Engineer with Motorola, took it to the next level in the 1980s when he convinced Bob Galvin, the CEO, to use statistical process controls as a business process to drive a desired state of 3.4 defects per million opportunities, which was equivalent to six standard deviations from the mean, assuming a 1.5 sigma shift, hence the term Six Sigma was born (LSS, 2019).

Quality methods, tools, and strategies highlighted above are all proven principles in driving the reduction of defects. The basic principle of all quality strategies is rooted in the following basic elements:

1) Adherence to prescribed processes and procedures
2) Effective problem solving
3) Compliance with legal and regulatory requirements
4) Focus on customer satisfaction

Effective problem solving and driving root cause identification at the point of occurrence can ensure that corrective actions are implemented at the right point in the ecosystem. A defect found at the manufacturing facility may have a causal origin upstream in the design office or in the human resource practices of an organization. Corrective actions that do not address the true root cause will only remedy the symptoms or address the secondary root causes but fail to permanently eliminate the problem.

1.1 Statement of the Problem

Improving the quality of delivered products or services is a top priority for every organization. Companies use Total Quality Management (TQM), Lean, Six Sigma, and other methods to improve their overall quality performance and positively impact the customer experience. Within these improvement initiatives, it is very common for organizations to use Key Performance Indicators (KPI) such as customer disruptions, line rejects, scrap, rework, and warranty to measure and monitor quality. However, these metrics are all lagging indicators and are the output of variables in the upstream environments. In other words, events have already happened and damage to reputation, cost, and performance have already occurred. A more proactive way of improving quality is to assess the probability of the occurrence of an undesired event and implement actions prior to any disruption to the normal flow throughout the ecosystem.

Assessing risk and probability of failure is a proactive method for improving quality. Some researchers in the probability field have used Bayesian Network, Fault Tree, and Event Tree analysis to predict and prevent failures (Pereira & Lima, 2014). Additionally, processing large amounts of data to understand the quality impact to products and processes is possible with various techniques in Machine Learning (Peres, Barata, Leitao, & Garcia, 2019).

As Machine Learning technology advances and becomes more readily available, the use of data-based risk assessment in fields such as Quality and Supply Chain Management can become a competitive advantage in all industries. This research is focused on predicting quality events using leading indicators and variables not normally considered in traditional quality improvement methods. Predictive Quality Analytics (PQA) is based on analyzing conditions in the entire ecosystem to determine the probability of quality events and mitigating them prior to the occurrence. This research will focus on quality risk identification related to culture, design robustness, shop floor practices, technical data, and other potential categories.

The PQA basic model, outlined in Figure 1, illustrates how the system is setup to capture risk in various categories, take appropriate actions, and finally monitor performance. The system works based on risk profile reduction that leads to quality performance improvement. Risk profile is not a mathematical process. It is based on employees and relevant experts taking specific actions to mitigate the identified deficiencies in the system. In this research, quality performance is measured in terms of nonconformities generated by the respective manufacturing facilities.

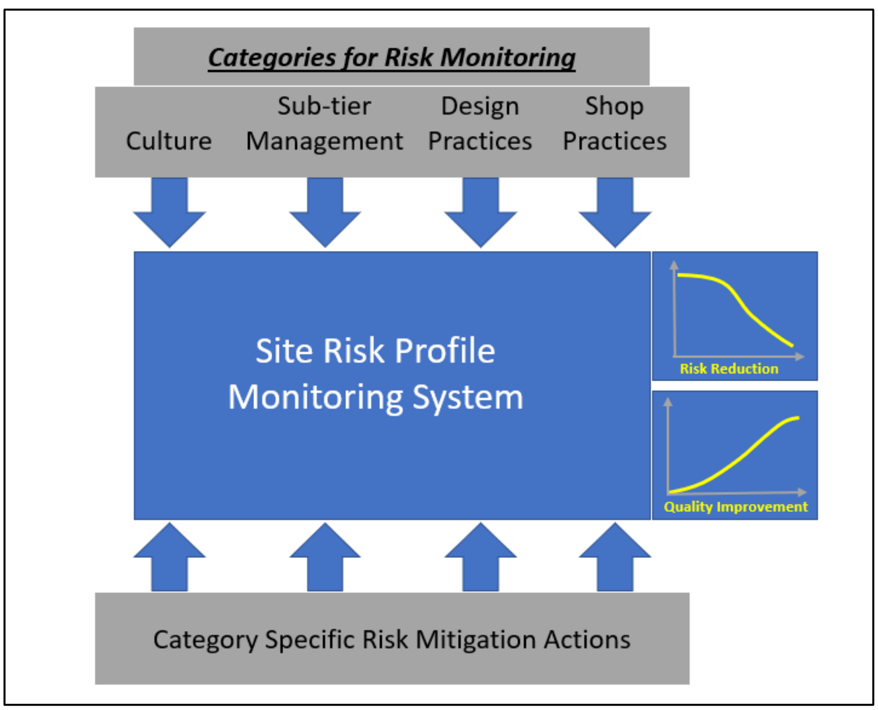


Figure 1 *Predictive Quality Analytics Basic Model*

This system should enable the prevention of nonconformities that lead to negative quality performance and customer dissatisfaction. The key part of the research is a broad look at direct and indirect quality related categories. This broad view should enable a more robust systemic approach to quality improvement activities.

1.2 Research Questions

The questions guiding this research are:

1. Is there evidence to suggest that subjective audit-based risk assessment of a broad range of categories such as; culture, design practices, shop floor activities, and sub-tier management can effectively identify the probability of a quality event?
2. How can Machine Learning be used in changing the subjective audit-based risk assessment into a predictive model than can alert users before the occurrence of a quality event?

1.3 Significance of the Problem

Reducing waste and variation is critical to the success of any organization. Lack of quality can lead to significant customer dissatisfaction and potential loss of business. Organizations throughout the world strive to improve the customer experience by providing products and services that not only meet cost targets but also perform to the specified requirements. Today, it is common to see Lean and Six Sigma used as the two main strategies for improving quality. The purpose of this research is to determine if risk assessment of site culture, design robustness, shop floor activities, technical data, and supplier management can accurately and proactively mitigate the occurrence of quality events. Based on the examination of the current body of knowledge, it is believed that risk assessment in manufacturing can be an effective method in improving quality performance.

Organizations can use the proactive approach to quality as a strategy and standard work to engage in high impact actions on specific elements of the ecosystem to mitigate risk and improve quality. The significance of this novel method is that it gives companies the ability to maximize resources by focusing on the most critical risk areas.

Industries such as Aviation, Automotive, and Health Care, may benefit from a proactive risk assessment strategy. The Federal Aviation Administration (FAA) and Defense Contractor Management Agency (DCMA), the two main US commercial and military regulating entities could conceivably mandate participation in such a network where PQA risk profiles can assist with more specific audits rather than the current spot check audit. In a study by the FAA (Dobbs, 2008), it was reported that there is a need to improve the risk-based oversight system for the commercial Aviation industry. Specifically, it was noted that the FAA does not perform enough audits to test how well manufacturers' quality assurance systems are working. The same report also found that the risk assessments that FAA inspectors use to evaluate a manufacturer's potential for producing substandard products exclude pertinent information that would aid in the evaluation of risks. Finally, the report determined that the FAA's inspections at supplier facilities were too focused on specific tasks rather than the overall quality system.

1.4 Purpose of the Study

Quality can have many definitions and descriptions. However, in its most basic form, Quality is meeting or exceeding customer expectations. Quality is one of the few things that can deliver sustained competitiveness that leads to financial prosperity for organizations (Saraiva, 2008). It is common knowledge that Quality is a byproduct of all of the functions in an organization; design, manufacturing, logistics, customer service, and many other functions either directly or indirectly impact the quality of a product.

Improving the customer experience depends on a few factors. Quality is among the top key elements in improving the voice of the customer. In order to drive continuous quality improvement, organizations must view quality as an integrated system (Conti, Kondo, & Watson, 2003). This study is focused on engaging the entire organization in problem-solving behavior to improve product quality. The purpose of this study is to prove that influencing leading indicators in a broad range of categories such as culture, design practices, shop floor activities, and sub-tier management can reduce the probability of quality events and therefore improve product quality and customer satisfaction.

1.5 Assumptions

There are several significant assumptions included in this study:

1. Categories selected of Site Culture, Design Robustness, Shop Floor Practices, Technical Data, and Sub-tier Management, are adequate in identifying the risk profile of a facility.
2. Selected questions in the audit-based risk assessment accurately represent the risk profile of a facility. In general, audits are subjective in nature. Subjectivity of an audit may skew the data based on the views and the expertise of the auditor.
3. There are no barriers to data flow for the analytical model due to cyber security, data confidentiality, or any other organizational policy or regulatory agency restrictions. These barriers are resolved and addressed with the relevant sources prior to establishing and utilizing the models.

To clarify the assumptions, a brief description of the categories used in the first assumption is outlined below. It should be noted that the researcher selected these categories based on the availability of data and subject matter expert opinion. Facilities interested in the implementation of PQA should conduct their own analysis. These analyses must include subject matter experts and technical resources familiar with the digital technology landscapes.

Site Culture:
Every site has a set of characteristics that are difficult to directly associate with quality or productivity. In this research, culture will be defined as characteristics that can be linked to quality. As an example, having a high number of ethics/compliance cases or having a high number of injury or illness reports would be indicative of a site with a culture that is not optimized for quality and lacks discipline.

Design Practices:
The term design practice is intended to capture how frequent and how thorough is the execution of the product related design changes. This is primarily focused on the design engineering functions. The goal would be to understand the influence of these types of practices to product

quality and the potential risk. As an example, a design that is undergoing frequent changes may have a lower level of quality as viewed by the customer.

Shop Floor Activities:

The category of shop floor activities is one of the most important aspects of quality control and is directly linked to the manufacturing processes and the associated operations. The elements of the shop floor category can be related to transportation, material handling methods, cleanliness of the shop floor, receiving and inspection work instructions, and calibration standards. The objective is to identify if there is a low-level or high-level risk associated with activities specific to the manufacturing facility and the related operations.

Sub-tier Management:

Most OEMs and tier 1 suppliers procure most of their manufacturing content and bill of material. A typical number could range from 60% to 70% of the total bill of material. Due to the significance of suppliers and sub-tiers, this research will have a dedicated category in sub-tier management. In this element, risk is assessed relative to how organizations flow down requirements to their sub-tiers and how their activities are monitored.

1.6 Limitations

There are three limiting factors in this study.

1. This study has been conducted based on studying manufacturing in the Aviation Industry. It may not apply to other sectors
2. The subjective element of the assessment is audit-based. As with any audit-based approach, results may vary based on the expertise and the subjectivity of the auditors. It is possible that auditor bias may influence the risk profile of selected elements in the model
3. The assessment process is static and representative of a point in time. Conditions may change faster than the periodic assessments. It is proposed to conduct monthly assessments to capture the ongoing state of quality in a system

4. The data analysis is based on the correlation of independent variables to nonconformities and quality events. Relative to quality events and nonconformities, it should be noted that correlation does not necessarily imply causation

1.7 Delimitations

Improving quality is a cross functional activity with many influencing factors. Quality may be impacted by factors other than the selected categories. This study will be limited in that it only focuses on five top level categories that impact quality:

1. Site Culture: Human resources data such as: employee turnover, training, health, and safety performance
2. Design Practices: Number of design changes and drawing specification errors
3. Shop Floor Activities: Gauge calibration, work instructions, and human factor errors
4. Technical Data: Initial launch data, process capability, and measurement system analysis
5. Sub-tier Management: Policy and specification flow down and management of change

1.8 Summary

This research is designed to predict quality events based on the risk profile of leading indicators. In this research, a quality Event is defined as any nonconformity identified either internally at the shop, or externally by the customer. This would include scrap and rework. The project consists of two different approaches in Analyzing proactive quality management system. The first model is based on audit-based risk evaluation in the areas of culture, design robustness, shop floor practices, technical data, and sub-tier management. Auditors will assess risk severity based on observations and the risk profile of elements associated with the five categories listed above. The second aspect of the research uses Machine Learning algorithms to predict correlation to quality events. Available data is set to be analyzed for statistical significance to nonconformities. The goal is to develop risk abatement action plans in response to the following:

1. Risk profile of the leading indicators during the subjective assessment process
2. Machine Learning model predicting trends that may lead to quality events

The novelty of this research project is the fact that the independent variables are selected from a wide range of elements beyond the immediate point of occurrence on the shop floor. The philosophy behind the broad selection of independent variables is that quality is a function of the entire ecosystem. The current published body of knowledge in the field of Predictive Quality is limited. This research study is focused on integrating the existing body of knowledge in quality with Machine Learning to develop a new methodology in Predictive Quality.

CHAPTER 2. REVIEW OF RELEVANT LITERATURE

The review of relevant literature involved a detailed examination of the body of knowledge in the fields of quality management, data analytics, conditional probability, machine learning, and audit-based qualitative assessment. Most of the work performed in the field of Quality is proactive with very little relevant literature of knowledge in the Predictive Quality field. Most of the material used in this dissertation has been researched using the Purdue Libraries. Purdue University Libraries and School of Information manage a vast number of resources and numerous databases.

Purdue University libraries and information systems contain nearly 700 databases that cover a wide range of topics. “The Purdue University Libraries and School of Information Studies (PULSIS) system on the West Lafayette campus includes six subject-oriented libraries, the Hicks Undergraduate Library, and the Virginia Kelly Karnes Archives and Special Collections Research Center. Staff total nearly 150, of which 81 are faculty and professionals. The campus library system includes 3,317,331 printed volumes and electronic books; 227,814 electronic and print journals; and government documents and microforms in excess of 400,000. To complement the online collections, PULSIS also houses more than 600,000 volumes in closed stacks that individuals can request for next-day delivery. In addition, any item held in the Big Ten Academic Alliance libraries can be requested directly and typically arrives within a few days” (Purdue University, 2021).

2.1 Methodology of Review

Information on Predictive Modeling and Quality was gathered primarily from papers written by researchers and authors in the fields of quality, statistical probability, and machine learning. In general, the topic of quality is well researched with a substantial body of knowledge in the areas of Lean, Six Sigma, Total Quality Management, and other Quality Management philosophies. Experts in the field have viewed these concepts as proactive quality. Predictive Analytics literature is generally rooted in Artificial Intelligence and Probability Modeling. A rich body of knowledge is available on both concepts, but little is available when both aspects are combined in the area of manufacturing.

2.2 Concept of Quality

The modern concept of Quality is primarily a Japanese and American phenomenon. After World War II, Taiichi Ohno implemented a management strategy called Just-in-Time (JIT). Although JIT roots can be traced back to the Henry Ford production line, Toyota perfected the system by focusing on the right number of parts, at the right time, in the right place, and without any defects. The concept has been a global success with the advent of Lean and the Toyota Production System (TPS). Taiichi Ohno, the father of JIT, recalls that the wonderful ideas of quality strategies and management systems came from the United States of America.

The techniques employed by Ohno and Toyota were based on basic Industrial Engineering discipline and Total Quality Control (TQC) principles (Ohno, 1998). Leading quality pioneers in the United States have been instrumental in advancing the concept of quality for years. The term Total Quality Management (TQM) was initially coined by the Naval Air System Command early in the 1920s (Semssar, 2020). According to Semssar, “The concept of TQM was to drive defect elimination based on data, economic theories, and process analysis” (Semssar, 2020). Six Sigma and the use of statistics in supply chains and manufacturing organizations were developed in the United States in the early 1920s.

Walter Shewhart, a researcher at Western Electric, started using statistics and the concept of the normal distribution to identify defects and process anomalies. During the 1980s, Bill Smith, an Engineer with Motorola, convinced Bob Galvin, the CEO, to use statistical process controls as a business process and to drive a desired state of 3.4 defects per million opportunities, which was equivalent to six standard deviations from the mean, hence the term Six Sigma was born” (Semssar, 2020).

The concepts of Six Sigma, Total Quality Management, Lean, and other problem-solving methodologies, are the foundation of today’s quality improvement philosophies. Organizations in every industry use these philosophies or various permutations of them to gain a competitive advantage in the market. World class quality enhances an organization standing, improves customer perception, and ultimately delivers better financial results. Degraded quality performances in the past have cost organizations significant loss of market share, trust of the customers, and penalties from the regulatory agencies. In 2021, Quality and compliance issues at Boeing, after the unfortunate 737 tragic events, led to significant fines by the Federal Aviation Administration (FAA, 2021).

2.3 Enterprise-Wide Improvement

Predictive Quality Analytics advocates for a system-wide view in improving quality. Organizations often approach quality from a pure functional responsibility, rather than an enterprise-wide lens. According to Saraiva and Sampaio, "In order for quality to be assumed through all of the levels of any given organization, it must be assimilated into the entire business or community system" (Sampaio & Saraiva, 2016). The Process and Enterprise Maturity Model (PEMM), proposed by Michael Hammer in 2007, is an outstanding framework in the support of enterprise-wide quality philosophy.

Carnegie Mellon's Capability Maturity Model Integration (CMMI) framework is similar in approach where a capability maturity assessment process is used to improve the overall capability of a group. CMMI has been primarily used in the software development processes (CMMI, 2005). Unlike the broad PEMM approach, CMMI is more specific to unique processes.

PEMM proposes that systemic transformation is possible when the entire enterprise is engaged. Hammer suggests that for transformation to be successful, two elements are needed. The first element is the process enablers and the second is enterprise capabilities (Hammer, 2007). Process enablers are identified as: Design, Performers, Owners, Infrastructure, and Metrics. The enterprise capabilities are defined as Leadership, Culture, Expertise, and Governance (Hammer, 2007). A brief description of the PEMM process enablers that are key to a successful transformation is outlined in Table 1. Process enablers are critical in the design, ownership, execution, and the progress monitoring of the transformation process. Hammers also notes that for transformation to be successful, a proper infrastructure must be considered.

Table 1 *Process & Enterprise Maturity Model Enablers*

Process Enablers	Description
Design	The robustness of the specification of how the process to be executed
Performers	Skill and knowledge of the people who execute the process
Owners	Senior Executives responsible for results
Infrastructure	Information and management system supporting the process
Metrics	Process performance tracking

The second element of a successful systemic transformation is enterprise-wide capabilities. Enterprise-wide capabilities provide the catalyst to ensure that the ecosystem is prepared and receptive to transformation. Enterprise-wide capabilities address the broader ecosystem. Hammer notes that the overall maturity of a system is based on the lowest maturity of the sub elements. As an example, if culture ranks low on maturity, then the entire enterprise capabilities should be viewed at the same low maturity level. For a transformation to be successful, the weakest link in the maturity model must be addressed. The descriptions for the enterprise-wide capabilities are listed in Table 2.

Table 2 *Process & Enterprise Maturity Model Capabilities*

Enterprise-Wide Capability	Description
Leadership	Senior Executives who support the creation of the processes
Culture	Value of customer focused, teamwork, and personal accountability
Expertise	Skills and methodology for process re-design
Governance	Mechanism for managing complex projects and change initiatives

The cultural transformation outlined by Hammer, employs an audit process for each element to evaluate maturity and probability of success during transformation. While the concept is not the same as risk assessment, PEMM uses maturity levels in a similar fashion to identify strengths and weaknesses in the transformation processes (Hammer, 2007). PEMM is a process where deficiencies in the ecosystem are highlighted and the risk of failure is outlined. The transparency that this process brings to an organization, creates a platform where leaders can address and mitigate risk of failure.

PEMM uses a unique maturity assessment process to determine which elements need improvement. The maturity assessment scale in the PEMM is based on the strength of maturity in both enablers and capability categories. Michael Hammer uses four levels of strengths in the process enabler element denoted as P1, P2, P3, and P4. The lower numbers denote a low level of maturity, where higher numbers are an indication that the enablers are primed for maximum efficacy and a greater probability of success. Similar classification is used for the enterprise-wide capabilities (Hammer, 2007).

2.4 Bayesian Model & Risk Analysis

Bayes' Theorem is a conditional probability theory developed by Thomas Bayes, a British mathematician, philosopher, and a Presbyterian minister (Kotz & L Johnson, 1982). The theory states that the probability of an event is based on prior knowledge of conditions that might be related to that event. Bayes' Theory, outlined in Equation 1, states that the probability of event H given conditions of E is equal to the probability of E given conditions of H multiplied by the portability of H divided by the probability of E.

$$P\ (H|E) = \frac{P(E|H) \times P(H)}{P(E)} \tag{1}$$

Bayes' Theory has been extensively used in risk assessment and formulating the probability of certain risks given a set of conditions (Fenton & Neil, 2019). Risk Analysis researchers use Bayes' Theory to understand what the risks in their field of interest are, given prior knowledge and conditions that might be significant. Safety is a critical part of industries such as Aviation and Automotive. A safety risk that is not addressed or detected could lead a catastrophic failure and significant loss of life. The risks in these industries could be in human facto errors, maintenance practices, or training methods to name a few. A risk profile with a mitigation plan can be formulated based on subject matter expert opinion and prior knowledge. As an example, the subject matter experts can highlight prior cases of maintenance errors or gaps in training policies.

Bayesian Belief Network (BBN) facilitates the study of conditional probability of an adverse event based on a set of conditions. The foundation of Predictive Quality Analytics is based on detecting the probability of an event occurring. There is extensive literature on the Bayesian Network of Conditional Probability. Using Bayesian Belief Network, (Pereira & Lima, 2014) look at the probability of risk due to design, operation, and maintenance activities. Additionally, the Bayesian Network is used extensively in the fields of reliability, safety, and risk assessment.

The risk assessment associated with BBN is intended to identify potential failure modes and implement actions to prevent them prior to occurrence. Pereira and Lima used the basic BBN principle to focus on the following elements:

1. Concept of Probabilistic Risk Analysis
2. Description Fault Tree and BBN Systems
3. Application of Probabilistic Risk Analysis
4. Results, Discussions, & Conclusion of the Study

Causal Modeling using Bayesian Network with quantitative methodology, and an expert elicitation process is feasible and has a positive effect on the determination of engine failure in manufacturing situational operation in the Aviation repair and overall environment (Pereira & Lima, 2014). A similar research, conducted by Marais and Robichaud, highlights the importance of risk identification and probability of occurrence analysis. They note that in the field of Aviation accidents due to maintenance can be up to 6.5 times more fatal than that of other errors (Marais & Robichaud, 2012).

Marais and Robichaud conclude that the operations and maintenance errors pose the highest risk in aircraft safety as illustrated in Figure 2, which depicts the contributing factors in airline accidents from 1999 to 2008. The authors state that to reduce the probability of an accident, focus should be on errors related to human and environmental factors. They propose a probability model that is based on a risk score card with conditional probability (Marais &

Robichaud, 2012). This research was heavily influenced by the pilot pre-flight safety and the aircraft maintenance technician's checklists.

To ensure proactive quality, the methodology used in this study assumes certain risks associated with human factors and errors by individuals conducting the required operations. The framework then introduces mitigating actions by following a series of avoidance actions. The avoidance actions are based on previous data that highlights historical accident categories. Marais & Robichaud used the NTSB historical data, shown in Figure 2, to construct a pareto of root cause codes associated with reported errors and accidents. Data collected from 1999 to 2008 indicate that an overwhelming majority of the accidents were caused by operational and maintenance errors (Marais & Robichaud, 2012).

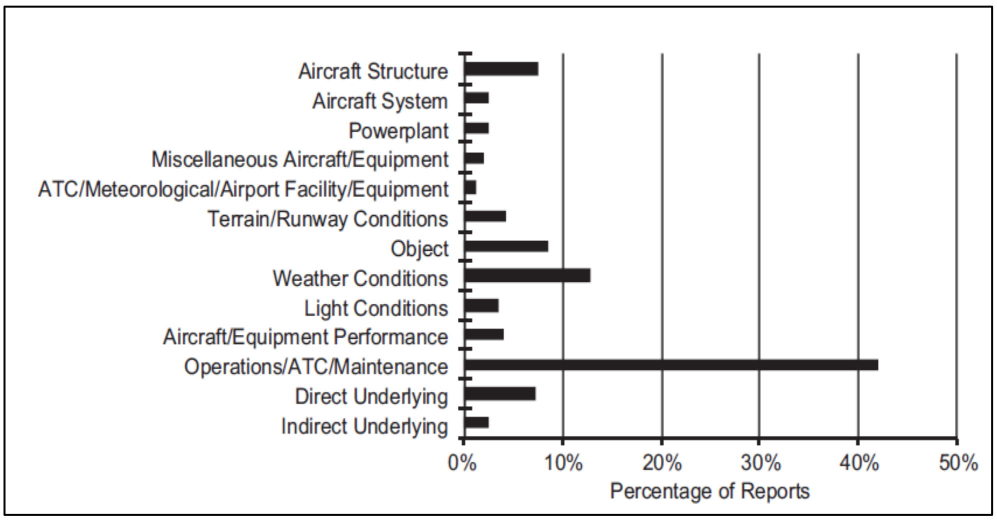


Figure 2 *Contributing Factors in Airline Accidents - from 1999 to 2008*

Note: Reprinted from Marais, K. & Robichaud, M. (2012). Analysis of trends in aviation maintenance risk: An empirical approach. *Reliability Engineering and System Safety*.

2.5 Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) is a structured technique for organizing and analyzing complex decision based on mathematics and psychology. The Analytical Hierarchy Process was developed by Thomas L. Saaty who partnered with Ernest Forman in the 1970s to develop this method. AHP uses subject matter experts to develop an analytical model for problem solving and risk assessment (Saaty, 1980). Most risk assessment processes in manufacturing are qualitative and are based on traditional qualitative methods because they are easier to implement and can operate independently and without the complexities of the quantitative methods (Pereira & Fragoso, 2016).

To evaluate risk using qualitative methods, Pereira, Fragoso, and Todorov use BBN in conjunction with Analytic Hierarchy Process (AHP). AHP is a multi-criterion, pairwise decision-making method where each criterion is associated with a factor signifying its importance. AHP divides complex problems into smaller sections where they are ranked hierarchically (Pereira & Fragoso, 2016). AHP is structured based on subject matter experts using a weighted scale to develop an impact score. In the case of risk assessment, Saaty's Model is formulated to evaluate the identified risk based on impact level as illustrated in Table 3.

A variation of this ranking will be used in the Predictive Quality Analytics. Some models such as the Process and Enterprise Maturity Model use percentile and ranges from mean to classify categories. The process used in the AHP is very similar to most ordinal scale scoring mechanisms. Most Aviation and Automotive suppliers use a demerit-based scoring system. Some suppliers and manufacturing sources use an increasing score based on the importance and significance of the events. In the demerit-based scoring systems, every entity and source start with a perfect score and based on negative events, points are taken off from the overall score. It is typical to have a score of 100 indicating a baseline and a starting point for a perfect quality facility.

Table 3 *AHP Impact Scores and Levels*

Impact Score	Impact Level
5	Very High
4	High
3	Moderate
2	Low
1	Very Low

2.6 Bowtie Method

The Bowtie (Papion) analysis is a qualitative risk assessment process that uses a graphical representation to illustrate the connection between causes or risk areas of an undesired event to potential consequences (Voicu, Panaitescu, Panaitescu, Dumitrescu, & Turof, 2018). Bowtie models are tools for integrating broad classes of cause-consequence models. In simple terms, Bowtie depicts the fault tree on the left and depicts the event tree and the consequence on the right. A Bowtie chart uses qualitative risk analysis that is linked to an event and the subsequent consequences (Pereira & Fragoso, 2016).

Figure 3 is a basic illustration of the Bowtie model (CGE, 2020). Bowtie methodology is very popular in most entities and is used where quantitative methods are not possible. Most experts in the field of Bowtie risk assessment operate on the basis of identifying risk, assessing impact and then implementation controls and mitigation actions to prevent hazard from impacting the operations.

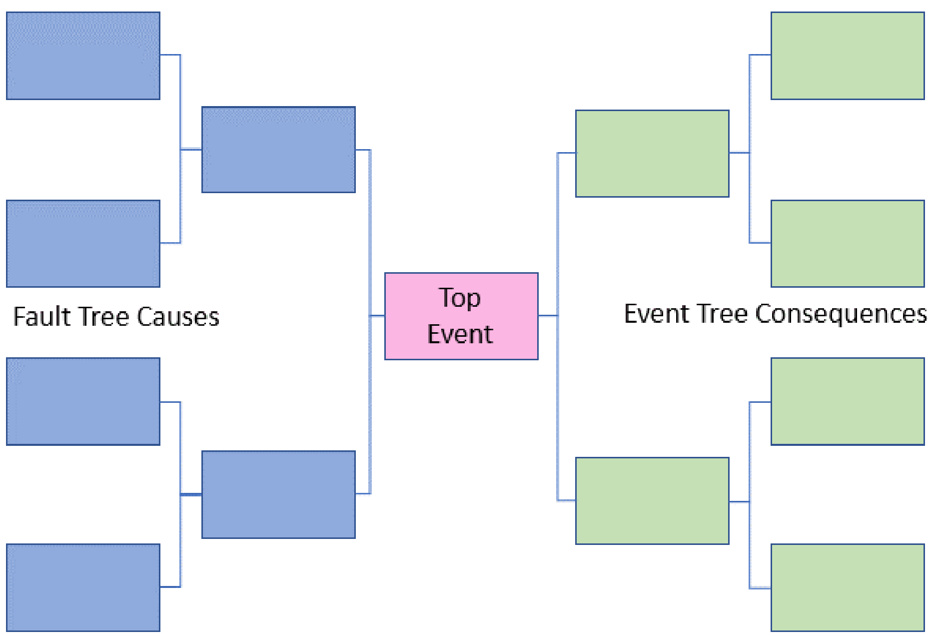


Figure 3 *Basic Illustration of a Bowtie Model*

Note: Adapted from BowtieXP Visual Risk Management Software (CGE, 2020)

Risk Management experts have developed many software systems where users can qualitatively list all potential causes (left side of the model), linked to specific outcomes (right side of the model). Bowtie methodology can then enable the user to insert risk mitigating actions for each potential cause to disrupt the connection to the event. Bowtie models are purely subjective and are based on what a group of experts determine to be risk areas (CGE, 2020). Bowtie methodology is extensively used in the aviation maintenance, overhaul and operation environments.

2.7 Failure Mode & Effect Analysis

Developed during the 1940s by the US Military, Failure Mode and Effect Analysis is a proactive risk assessment methodology (ASQ, 2020). The process is based on identifying potential failure modes and the corresponding effect. In principle, FMEA is similar to Bowtie methodology, where both methods work on linking failure modes to consequences. The FMEA process can be utilized a risk assessment tool in design or manufacturing environments.

The FMEA is widely used in the Automotive Industry, and it is the basis of process development and new product introduction. According to a paper published by Lund University, "The analysis starts with the lowest level components and proceeds up to the failure effect of the overall system. A failure effect at a lower level becomes a failure mode of the component at the next higher level. FMEA also measures severity, occurrence, and detection probability that are used to calculate risk priority numbers for the identified failure modes" (Sulaman, Beer, Felderer, & Host, 2017). The process of FMEA is set to evaluate risk at every operation or characteristic based on the probability of occurrence and detection. The FMEA also evaluates the severity of an event based on the failure impact of the product. The FMEA is a qualitative risk assessment process that develops a risk priority number based on the composite score of occurrence, detection, and severity. As noted in Equation 2, the unit of measurement of FMEA is called Risk Priority Number or RPN. Although there is not set RPN threshold in most published literature in the Automotive and Aviation fields, organizations tend to view RPNs above the range of 150-200 as undesirable and require mitigating action. It is not unusual to see threshold as low as 120 RPN in some industries that have a higher sensitivity towards safety and quality.

$$RPN = Severity \times Occurrence \times Detection \tag{2}$$

The Failure Mode and Effect Analysis uses a scale of 1 to 10 to rate the occurrence, detection, and the level of severity of failure modes. The lower the Risk Priority Number, the lower the probability of negative impact on the operations and the customers. Table 4 illustrates the ratings associated with the RPN generation in the FMEA process. Today, the FMEA tool is an integral part of the product and process development in many industries. The Automotive Industry requires performing separate FMEAs for design and process developments known as dFMEA and pFMEA respectively. The FMEA process is a requirement in the Advanced Product quality Planning standard work. In Aviation and Automotive, most customers require a joint FMEAs study to ensure all failure modes are captures. The benefit of a joint FMEA is the ability to see interactions between components and subassemblies in aircraft or vehicles.

Table 4 *FMEA Risk Priority Number Rating Scale*

Rating	Severity		Occurrence		Detection
	Criteria	Effect	Criteria	Odds	Description
10	Hazardous without Warning	Compromises Safety without Warning	Inevitable	1 in 2	Absolute Uncertainty
9	Hazardous with Warning	Compromises Safety with Warning	Almost Inevitable	1 in 3	Very Remote
8	Very High	Loss of Functionality	Very High	1 in 8	Remote
7	High	Reduced Functionality	High	1 in 20	Very Low
6	Moderate	Customer Experiences Discomfort	Moderate	1 in 80	Low
5	Low	Customer Experiences Some Discomfort	Low	1 in 400	Moderate
4	Very Low	Defect Noticed by Most Customers	Very Low	1 in 2000	Moderately High
3	Minor	Defect Noticed by Average Customer	Remote	1 in 15000	High
2	Very Minor	Defect Noticed by Discriminating Customer	Very Remote	1 in 150000	Very High
1	None	No Effect	Negligible	1 in 1500000	Almost Certain

Note: Sulaman, S. (2017). Comparison of the FMEA & STPA. *Software Quality Journal*.

2.8 Organizational Cultural Assessment Instrument

As mentioned earlier in this study, culture plays a role in quality. Improving quality performance has a cultural element that spans policies, procedures, leadership, operators, and technology. It is fair to assume that improvement strategies in any aspect of an organization should have a cultural element embedded in it. Organizational Cultural Assessment Instrument (OCAI) was developed by Kim Cameron and Robert Quinn of the University of Michigan and is a validated research method to assess organizational culture. The process is based on a Competing Value Framework assessment that rates competing values against each other (OCAI, 2021). The categories assessed in the OCAI framework are internal-external and stability-flexibility dimensions. The OCAI assessment rates the dimensions out of a possible 100-point scoring scale and suggests the type of the organization culture. OCAI bins the organizational culture into four categories.

1) Create Culture (Adhocracy Culture)
   This is in line with a dynamic and creative environment such as disruptive technology firms where the focus is purely on experimentation and innovation

2) Collaborative Culture (Clan Culture)
   This environment is friendly, and loyalty based. The focus is internally based on a sense of family critical. Most non-for-profit entities and hospitals tend to have this culture.

3) Control Culture (Hierarchy Culture)
   Unlike the previous culture, rules, policies, and procedure drive this culture. Leadership is focused on metrics and stability is critical. Military and regulatory agencies tend to fall in this category.

4) Compete Culture (Market Culture)
   Compete category is where most of the manufacturing sectors reside. In this culture metrics, delivery, competition are the main drivers. Financial results tend to drive leadership decision.

Organizational Cultural Assessment Instrument advocates for assessing the culture based on the framework and an evaluation of where the organization would like to be (Cameron & Quinn, 1999). A free sample of the assessment is variable online. The sample is based on a series of questions that define culture. A sample assessment was completed to show the OCAI process for the organization known to the researcher. The output is based on a four-category scoring system and a radar map. The scoring categories are shown in Figure 4. Researchers interested in understanding the cultural profile of their respective organizations can perform the assessment and view their categories relative to the preferred state.

	Current	Preferred
Clan	8.33	9.17
Adhocracy	10.00	10.00
Market	44.17	50.00
Hierarchy	37.50	30.83

Figure 4 *OCAI Score - Typical Manufacturing Sector*

Source: https://www.ocai-online.com/products/ocai-one

In addition to the assessment categories, OCAI provides a radar map of where the assessed categories are relative to the peer group. The radar map for the manufacturing sector and the results of the survey for the organization under study is outlined in Figure 5. The map is a graphical illustration of the current state of the culture in comparison the peer group in the same industry.

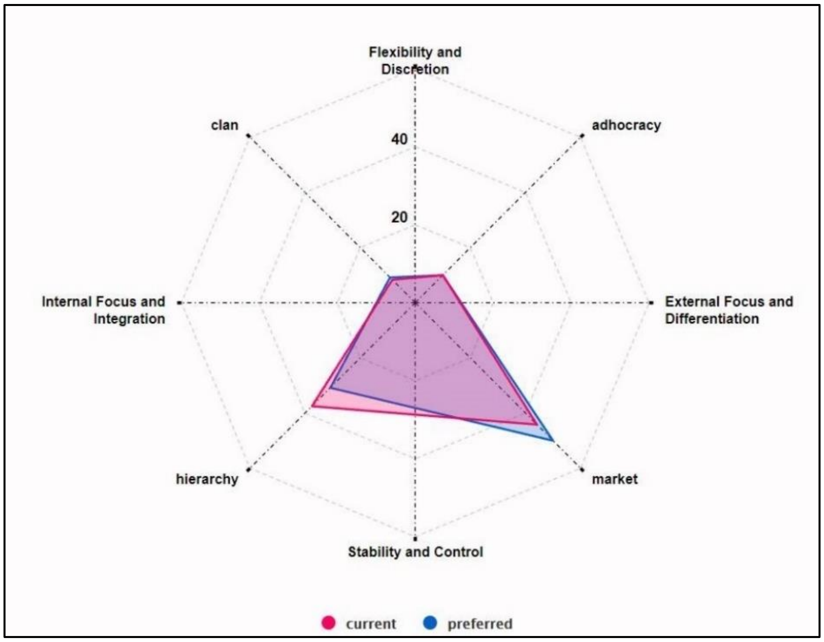


Figure 5 *OCAI Radar Map – Manufacturing Sector*

Source: https://www.ocai-online.com/products/ocai-one

2.9 Machine Learning

The term Machine Learning was coined by Arthur Samuel and was developed to play and learn the game of checkers. As the computer played more games, it became more proficient at the game by learning moves and optimizing the winning strategy (Samuel, 1959). Today, Machine Learning is broadly used in creating models that can predict the future performance of a given characteristic based on analyzing the past performance of related variables. Advances in computing power combined with data science has enabled the effective creation of models that can discern patterns and make predictions in almost every field. Machine Learning and data driven problem solving is becoming a common tool used in all industries. Applications range from email spam control, fraud detection, targeted advertising, to selecting the winners of a football game on any given Sunday.

The concept of Machine Learning is based on data mining and finding patterns in a dataset to predict trends and future outcomes. Machine Learning uses statistical principles and data mining to facilitate the construction of predictive models. The process of data mining is based on segmenting the dataset into categories that can be easily ingested into various models. The main categories of the data mining segmentations are supervised and unsupervised learning.

Supervised learning is where data is labeled and contains the correct answers. Regression, Decision Trees, and Bayes Classifiers are all forms of supervised learning. In this type of analytics, the independent variables and the dependent variables are known with the correct answers. In other words, the relationship between the independent variable and the dependent variable for the given dataset is known (Provost & Fawcett, 2013).

It is not unusual for researchers to analyze a dataset without knowing the structure or order of that dataset. Anomalies may exist but labels and answers are not clear to the analyst. In this case the analysis is said to be unsupervised. In unsupervised learning the data is neither classified nor labeled. In this method the machine is set to cluster or group the unsorted data in patterns, similarities, or differences without any prior knowledge. The unsupervised learning methodology employs clustering or establishing associations between the datasets and various categories (Provost & Fawcett, 2013). This research study will be using supervised learning as the dataset is labeled, organized, and well structured. It should also be noted that this study will be using a clear dependent variable of nonconformities throughout the risk identification learning.

Programming languages such as Python and R have transformed Machine Learning by enabling users to create sophisticated predictive models with little to no upfront cost. R is a programming language created by the R Foundation, a not-for-profit organization, utilizing statistical computing. Python is an interpreted, high-level, and general-purpose programming language. Created by Guido van Rossum and first released in 1991, Python is a user friendly programing language that is broadly used in Machine Leaning (Kuhlman, 2012). The data analytics part of this research project was conducted using Python programming language and Jupytor Notebook Anaconda 3 Software. The statistical aspect of the research was completed using Minitab software.

2.10 Modeling Algorithms

Statistical algorithms are the foundation of model creation using R, Python, or any other programing language. Selection of the algorithm depends on the problem statement and what is being studied. Algorithms selected based on the dataset and the problem statement, facilitate accurate and effective design of the model. "Despite the large number of data mining algorithms developed over the years, there are only a handful of fundamentally different type of tasks these algorithms address" (Provost & Fawcett, 2013). The two main algorithms used in Machine Learning are regression and classification.

Two factors are critical in the design and selection of these models. First is the usage of effective statistical model in capturing data dependencies, and second is the scalable learning system that can learn as the data set increases (Chen & Guestrin, 2016). Regression analysis in predictive models describe how an independent variable is numerically related to the dependent variable. "Simple regression analysis is used in situation where one independent variable is hypothesized to effect on dependent variable" (Sekaran & Bougie, 2016). Some of the commonly used algorithms in the field of Machine Learning are: Random Forest, XGBoost, and Auto Regressive Integrated Moving Average (ARIMA). This research study will use ARIMA to conduct the analysis. ARIMA is a powerful algorithm where time series and past performance can play a significant role in the predictive model. Quality is a time series variable and is monitored in the same manner. According to Prabhakan "ARIMA is actually a class of models that explains a given time series based on its own past values, that is, its own lags and the lagged forecast errors, so that equation can be used to forecast future values" (Prabhakan, 2019).

CHAPTER 3. METHODS

3.1 Introduction

The field of Quality is mature and well researched. Concepts such as Lean, Six Sigma, and TQM have been used in almost every industry. Similarly, the field of Machine Learning is increasingly integrated and changing every aspect of science and technology. This research study is designed to integrate both fields in order to develop a new and novel method in improving quality. Predictive Quality Analytics is designed to develop action plans prior to a quality event occurring. This research project is designed to answer the following questions:

1. Is there evidence to suggest that subjective audit-based risk assessment of a broad range of categories such as culture, design practices, shop floor activities, and sub-tier management can effectively identify the probability of a quality event?
2. How can Machine Learning be used in changing the subjective audit-based assessment into a predictive model that can alert users before the occurrence of a quality event?

Both questions are designed to gain a better understanding of the leading indicators that impact quality and to develop mitigating actions to reduce risk. Most quality methodologies work based on the identification of root causes and the development of corrective actions. PQA is intended to optimize the problem solving in a proactive manner. This research project is designed to objectively broaden the impact of quality and problem solving in organization. Quality is often viewed as a well-defined organization with a set of strategies. This research project takes the conversional quality viewpoint to a more enterprise-wide philosophy.
Using leading indicators and a proactive approach to quality in the entire ecosystem, organizations can implement more systemic corrective actions when dealing with deficiencies and failure modes. The methodology in this type of research requires a well-balanced approach that considers qualitative as well as quantitative methods. Qualitative viewpoints can leverage subject matter expert opinions in analyzing conditions that may not have direct associated data connectivity. Quantitative methods can complement and enhance the methodology by augmenting objective data in the research study.

3.2 Research Design

This is an exploratory mixed method research project that is designed to use actual performance of a manufacturing facility to predict future quality events. Quantitative research is based on obtaining and analyzing data that is countable. This type of research facilitates the use of statistics in determining trends, cause and effect, and validating hypothesis to understand a phenomenon of interest to the researcher (World Atlas, 2017). According to Chelaa, “There are various methods used by quantitative research to collect data from the field. These methods are the use of a questionnaire, pre/post designs, pre-existing data, and pilot study.” (World Atlas, 2017).

Exploratory research focuses on a problem that has not been clearly defined and requires other methods to establish connectivity between various factors of the research topic. This methodology is often used when there is little body of knowledge of the topic (Form Plus, 2007). Unlike explanatory research where the focus is on a problem that explains the phenomena under study and is designed to test hypothesis by measuring the relationship between variables, exploratory research is focused on better understanding of the existing problems. In explanatory research, the data is analyzed using statistical methods (Maxwell & Mittapalli, 2008). It should be noted that this study is based on the Causal Modeling of the manufacturing ecosystem to understand the significance of each element in the quality performance.

Two distinct strategies are used to understand the cause-and-effect relationship between selected categories and quality performance. The first method is an audit-based assessment of risk as related to quality. This method consists of a series of questions to evaluate the probability of a quality event based on an ordinal scale. The audit-based strategy is design to leverage subject matter expert opinion and systemic weaknesses to design a develop a risk mitigation plan. This method will use a demerit-based scoring system where the baseline is aet at 100 points. The second method is designed to ingest data from various categories and develop a Machine Learning model to understand the significance of each element as related to quality, predict future performance of the selected variables, and drive the organization to develop corrective actions to change the trajectory of the predicted outcome. The Machine Learning model repeats the analysis process every month and generates a predicted number that is either acceptable or requires an action by the leadership team.

3.3 Data Collection – Audit Based

Data collection in this research project is based on the research questions. There are two different data collection methods. The first part is addressing the audit-based question of this research project. In this section, the researcher has developed an assessment questionnaire that trained assessors use to evaluate risk in the following categories: culture, design robustness, sub-tier management, and shop floor activities. Each category has sub elements that aid to objectively define the associated risks. The assessors are trained by the researcher to minimize variation.

The researcher used the help of a group of experts in the field of Quality to develop the audit-based assessment. The five individuals selected for this task had a minimum of 10 years of quality management experience. Each subcategory contained a series of questions that would highlight the associated risk profile based on an ordinal scale. The scoring methodology was based on the assessed risk. Table 5 highlights the scoring and the associated language clarifying the level of risk to be considered by the relevant parties.

Table 5 *Assessment Demerit Point System*

Risk Description	Demerit Points
Potential Product Impact or Systemic	-5
Noncompliance or High Risk	-3
Risk Identified	-2
Not Applicable (N/A)	0
Pass	0
Best Practice	0

Questionnaire was developed based on the categories of outlined earlier. As an example, questions selected to highlighted cultural issues were focused on resourcing, training, communication, compliance, and accountability elements. The type of questions used in PQA are intended to gain insight as to how the organization manages systemic issues. These systemic issues are needed to ensure an enterprise-wide approach to risk assessment and problem solving. Predictive Quality Analytics is based on investigating latent causes and not just point of occurrence and active causes. The demerit point system can serve as an escalation mechanism that highlight importance based on severity of the consequences. The culture section is highlighted in table 6. A complete list of question, scoring mechanism, and categories are available in appendix A.

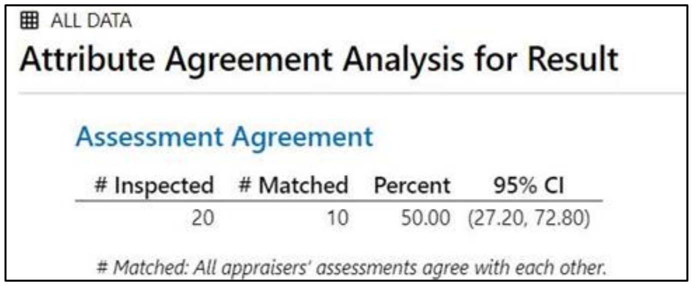
Table 6 *Culture Related Questions*

Element	Question
Resources	Does the site have an effective process for ensuring all new hires meet the minimum qualifications required to perform the essential responsibilities of their role?
Training	Does that site have an effective onboarding process for new employees?
Training	Does the site have an effective process for delivering and tracking established training requirements?
Training	Is the site up to date on required QEP training?
Resources	Does the site have an effective process for hiring and training contractors?
Compliance	Does the site have a process for raising a quality or compliance concerns?
Resources	Does the site have programs in place to reduce employee turnover and retain key knowledge?
Compliance	Does the site have compensation, benefits, bonus, or rewards programs that have the potential to influence an employee's ability and willingness to report a compliance or quality concern?
Accountability	Does the site have policies that discipline employees for making quality errors?
Communication	What is the communication rhythm and interaction with Quality and Operations?
Resources	Is Quality support adequate at the site?

To minimize variation and ensure accuracy, an Inter-rater reliability study was completed. The Inter-rater reliability study compared assessments of a minimum of two assessors as compared to the scores noted by the subject matter expert. In the Inter-rater reliability process, the subject matter expert score was considered as the reference. Additional validation by the researcher ensured that the assessments are valid and meet the intent of the risk assessment process. The Inter-rater reliability was found to be 50%, meaning that the raters agreed on 10 of the 20 questions. Based on this result, the researcher along with the subject matter experts decided to establish guidance for every question.

A thorough review of the questionnaire resulted in a set of guidance and examples to reduce variation and disagreement between raters. As manufacturing facilities conduct more

Predictive Quality Assessments, and more individuals participate in the assessment, the raters will gain a better and deeper understanding as to the level of risk, scoring principles, and the spirit of what the questionnaire is intending.


ALL DATA

Attribute Agreement Analysis for Result

Assessment Agreement

# Inspected	# Matched	Percent	95% CI
20	10	50.00	(27.20, 72.80)

 # Matched: All appraisers' assessments agree with each other.

Figure 6 *Inter-Rater Reliability – Pre-Training*

To reduce variation between raters, it was decided to add additional guidance for each question. The complete guidance section is available in the questionnaire. Table 7 is an example of the guidance in the resource element.

Table 7 *Guidance to Reduce Variation*

Element	Question	Guidance
Resources	Does the site have an effective process for ensuring all new hires meet the minimum qualifications required to perform the essential responsibilities of their role?	● A random selection of at least 2 job descriptions from roles posted within the last 12 months. ● Resumes/CVs of selected candidates (anonymized, w/o any personally identifiable information (e.g., names, addresses, contact information). ● Interview with at least 1 manager who has hired a new employee within the last year (if applicable) (for suppliers, ensure a supplier representative is present during the interview). ● Interview with at least 1 employee who has < 1 YOS (if applicable) (for suppliers, ensure a supplier representative is present during the interview).

To validate the efficacy of the guidance a second Attribute Agreement analysis was conducted, and the inter-rater agreement improved to 65%. The 15% improvement was due to the new established guidance in the questionnaire. The researcher and the team of subject matter experts agreed that a 65% inter-rater agreement is sufficient for the subjective risk assessment element of the PQA.

Attribute Agreement Analysis for Result

Between Appraisers

Assessment Agreement

# Inspected	# Matched	Percent	95% CI
20	13	65.00	(40.78, 84.61)

 # Matched: All appraisers' assessments agree with each other.

Figure 7 *Inter-Rater Reliability Post-Training*

3.4 Data Collection – Analytics

The second part of the research is focused on data ingestion from the various data sources associated with each facility and monitoring them for abnormal conditions. Researcher determined early in the process that data availability and integrity was limited to a few sub elements in the categories of culture, design robustness, and shop floor activities. Data collection was transformed and accepted by Python Machine Learning programming software and Jupytor Notebook Anaconda 3 code Software. It should be noted that the initial dataset was extracted from the digital portals and the data lakes in the form of Excel spread sheets. The Excel spread sheets were post processed to enable ingestion in the Machine Learning software. Minitab Statistical software was used to conduct the hypothesis testing of the research study. The data from the five manufacturing facilities were used as a single group for the correlation study and as induvial subgroups in the predictive modeling section.

The analytical section of the research was divided into two parts. The first part was the determination of what data was available in digital form. The second part was the validation process to determine significance of the independent variables to the dependent variable which was the number of nonconformities produced by the manufacturing site. The independent variables were selected from various data sources to represent the sub elements that provide the data stream. The independent variables used will be based on the availability of digital data in the data lakes of each facility. The independent variables will increase as the data sources improve in accuracy and availability. Data collection element in the Predictive Quality Analytics is fundamental to the success of the research study.

3.5 Sample

The sample for this research study was data from 5 different manufacturing facilities involved in component manufacturing. The facilities selected were all in the United States. The audit-based assessment included sub elements that add a better understanding to the high-level categories. For example, the number of unplanned maintenance work orders was used to determine the stability of the manufacturing assets. In this research study, manufacturing assets are machinery such as grinders, milling machines, broach stations, and welding equipment. Monitoring maintenance activities was determined to be critical in manufacturing environment stability by subject matter experts and data analytics.

The culture category included sub elements such as employee turnover, absenteeism, open positions, compliance cases, and training delinquencies. The same strategy was used for the remaining categories. It should be noted that the selection of the sub elements must be reviewed with the subject matter expert to ensure a well-rounded view of the quality landscape. This step is critical in the PQA strategy to ensure latent and active causes are investigated. In this context latent causes may be related to organizational factors away from the defect point of generation. The researcher encountered significant challenges in acquiring Human Resources related data. Variables such as absenteeism, turnover, and injury and illness rates are highly confidential and require significant filtering and masking to ensure privacy. Close coordination with the compliance team and Human Resources professionals enabled an effective data transfer in this highly sensitive area.

In the statistical analysis, larger data sample sizes are preferred to facilitate an optimized understanding and full impact of the variables. Larger sample sizes enable the researcher to better understand average values and avoid errors and outliers from the dataset (Zamboni, 2018). For the Machine Learning section of the study, 3 years of data was used to construct the model. In Machine Learning projects, it is common to use 2/3 of the data to train the model and 1/3 of the data to test. For this research project, 3 years of data was used to develop the model and approximately one year was used to conduct testing and validation. The large data set was used to determine the significance factor of the selected independent variables. This data set did not include the 2020 Covid-19 downturns. The analytical section used data from June of 2020 to September 2021. The ARIMA model selected for this research study was not capable of analyzing data that included Black Swan event of Covid-19 Pandemic.

3.6 Research Instruments

Research instrument is any tool used to collect, obtain, and analyze the data in the research project. In quantitative studies, research instruments may consist of questionnaires, surveys, and sample variable data. Validity and reliability of the research instrument is critical because invalid data may lead to erroneous research conclusions (Biddix, 2009). To ensure validity and reliability of the assessors, a rigorous guidance module was added to the assessment. The questionnaire, designed to capture the risk profile of the facility, leveraged subject matter expertise from a cross functional group. This cross functional group possessed significant experience in quality systems and customer defect monitoring. The questionnaire is currently Excel based with manual entry in the global PQA portal. The global PQA portal resides in the main quality homepage that is fully visible to all employees. This instrument is designed to track actions with detailed information. The information of the action tracking mechanism contains facility name, employee name, start date of the action, and completion date. Additionally, the portal is linked to the calendar that shows the status of on target versus behind schedule actions.

The instrument used for the analytical section of this research project was Python programming software. Data was structured for ingestion by Python 3.9.0 version. Jupytor Notebook Anaconda 3 coding Software was used to develop ARIMA model. Data was ingested from Excel spreadsheets where independent and dependent variables were clearly identified. This was the first step to validate that the selected independent variables are strongly correlated to nonconformities. The actual model was selected to predict future values of these independent variables in a time series architecture. The researcher used regression type algorithms for data analysis. After many trials, Auto Regressive Integrated Moving Average (ARIMA) was used as the preferred algorithm in this analysis. This algorithm is suitable for analyzing data with time series significance. The data for this research is available monthly from the various data sources in the organization’s data lake.

Although Python is capable of performing statistical analysis, the researcher opted to use the Minitab Statistical software to conduct the relevant statistical analysis of this research study. Paired T-Test was used to compare quality performance of the manufacturing facilities before and after the implementation of PQA. The quality performance in the hypothesis testing was number of nonconformities of the 5 facilities in the Audit based section and monthly performance of the data analytics of the single manufacturing facility denoted as Plant R.

3.7 Data Analysis

The researcher used two methods in the data gathering and analysis. For the audit-based assessment, the researcher used a simple linear transfer function to identify the overall risk profile of a facility as denoted in Equation 3. The audit-based model was a risk category and a demerit-based scoring system. The basic equation was set up to estimate a cumulative risk number for each facility:

$$f(x) = \Sigma(Ax_1 + Bx_2 + Cx_3 + Dx_4) \qquad (3)$$

Where $f(x)$ is nonconformities generated by a facility and the elements of the model are defined as; A is site culture, B is design elements, C is supply base variables, and D is shop floor practices. In this equation, x1, x2, x3, and x4 represent the summation of risk levels for category and each sub element. The value of risk profile of a facility, which is a number on a scale of 0 to 100, will then be correlated to the actual number of nonconformities. In this scoring system 0 would signify an extremely high-risk facility and 100 would be a perfect and risk-free environment. As noted earlier, PQA is a demerit-based scoring system with a 100-point maximum structure. A facility with no risk would score a maximum 100 point. As assessors identify risk and record the severity of the identified hazards, the total PQA score will be reduced. Frequent and monthly tracking of risk profiles and the resulting score would ensure that the PQA tracking system can identify risks without significant delays.

The second method of the data analysis will incorporate a regressive model to determine the significance of each category to nonconformities. This study will use Python programming software with a regressive algorithm ARIMA to determine the significance level of each category and the relevant sub elements. The ARIMA prediction was used in concert with a Pre-

Control Chart to notify management teams of an impending shift in the leading indicator that could ultimately impact quality. Control Charts are graphical representations of process change over time. Originally developed by Walter Shewhart, Control Charts present the process variation relative to Mean, Upper Control Limit, Lower Control Limit, and Specifications. Control Charts are part of the Statistical Process Control (SPC) that is broadly used today in controlling processes, preventing defects, and thereby improving quality (ASQ, 2021).

Although practitioners can use SPC in the PQA implementation, this study uses a much simpler approach. PQA strategy is based on using Pre-Control Charts. Pre-Control Chart is a simple yet effective method of process monitoring that does not require large data sets and statistical calculations. A Pre-Control Chart operates based on dividing the tolerance zones into three segments. These segments signify Green, Yellow, and Red zones. (Urdhwareshe, 2002). Pre-Control Charts in this study is based on the zones identified in Figure 8. The Andon system mentioned earlier in this report will be activated based on values denoted in a Pre-Control Chart. The Pre-Control limit selection is up to the team and subject matter experts. Based on conversations with the maintenance team, it was determined to set the target at 5% below historical performance mean. The historical mean is this target setting was chosen to be the 2021 previous 9-month data. The yellow zones were set as 15% greater than the green zone. Values above the 15% limit were set to be in the Red zone and require immediate action.

The zones selected in the pre-control chart may vary based on category and elements. The researcher in this study changed the zones every month. The latest zone values were based on data from January to August of 2021 time frame. As the model matures and organization gain a better understand of the independent variable trends, subject matter experts can adjust these targets and zones for maximum efficacy of quality improvements and stability in the manufacturing environment.

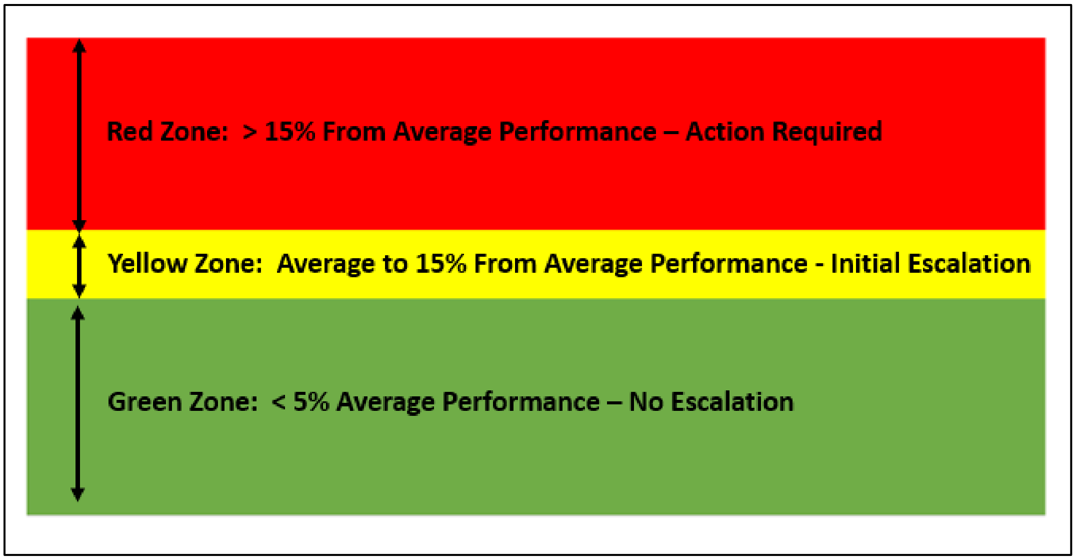


Figure 8 *Pre-Control Chart Description*

It should be noted that individual facilities can set these targets based on values that make the most operational sense to them. Also, each variable may have a different target and pre-control chart limit. The researcher developed a dashboard where each category and sub elements were listed with an Andon system that would indicate an increased risk level as related to quality performance. Categories and their relevant sub elements use the Andon system to highlight Red, Yellow, or Green, depending on risk profile and alert the facility of an impending quality event. Andon is a Toyota Production System tool that refers to a mechanism of automated or operator activated notification system. Andon is designed to notify the manufacturing personnel and management of an anomaly in operations (Liker, 2004).

3.8 Paired Sample T-Test

The results from pre and post Predictive Quality Analytics in the selected facilities were compared using the paired sample t-test. This statistical method of hypothesis testing uses two related samples to understand the relationship between a before and after design procedure (Statistics, 2004). The paired sample t-test is structured to determine the differences in population means in two dependent groups. In this research study the dependent groups were selected to the be the same manufacturing facility, before and after the implementation of PQA.

The paired t-test requires that the outcome condition be at continuous level, have two compared in the study, and the two groups under study be independent (Mowery, 2011).

The Paired sample t-test or the matched t-test is a useful tool to investigate if the action taken on the subject has changed or remained the same. In other words, each facility in this study is considered as a matched pair. In the PQA analysis, samples of defects before and after the implementation of the audit-based risk assessment were compared. Minitab statistical software was used to determine if the change of the number of defects, prior to and after the implementation of PQA was significant. Equation 4 sets up the hypothesis testing that notes that there are no differences between defects in a facility prior to and after the implementation of the Predictive Quality Assessments. The calculation for the paired t-test is based on determining the mean differences between defects in each facility. In this analysis the assumption is that null hypothesis of H_o would remain unchanged and unaffected by the implementation of PQA. To conduct the paired sample t-test and to determine if the differences between the pre and post PQA values were zero, equation 6 was used to calculate and determine the “t” value in the above-mentioned analysis. Researchers can use the “t” Tables to determine the significance of the hypothesis. Statistical software such as Minitab, complete the full analysis without the need to resort to the “t” Tables. In the calculation of “t” values, the μ_{diff} is set to zero denoting that there are no differences between the before and after quality performance.

$$H_0: \mu_{Post} - \mu_{post} = \mu_{diff=0} \qquad (4)$$

$$\bar{d} = \Sigma \frac{di}{n} \qquad (5)$$

where $\bar{d}$ = Mean difference of defects before and after PQA and n = number of sample size (5 paired facilities)

utilizing the above, the t-statics can be calculated using the following equation.

$$\mathrm{t} = \frac{\bar{d} - \mu_{diff}}{\frac{Std.Error}{\sqrt{n}}} \qquad (6)$$

where:

$Std.\ Error = \frac{Std.\ Dev.}{\sqrt{n}}$

Using T-Statistics Standard tables, P values can be determined. In this research $P < 0.05$ is used to determine significance. The paired sample T-Test was conducted for both sections of the research. The assumption is made that a single facility is viewed as a matched pair. Individual manufacturing facilities as tested as a single entity with a before and after event. The event is this case is the implementation of the Predictive Quality Analytics and the impact it has on nonconformities.

CHAPTER 4. RESULTS

4.1 Analysis of Findings by Research Question

The findings for both questions were addressed separately in this chapter. The research study consisted of two sections. The first section consisted of a qualitative method in risk assessment. This section was based on a questionnaire and subject matter expert opinion of the quality landscape. The second section was a quantitatively based method that was constructed to ingestion data, generating a predictive model, and notify stakeholder of any unusual trends. Based on the research questions, each section will be discussed separately.

4.1.1 Question 1 – Audit Based

Is there evidence to suggest that subjective audit-based risk assessment of a broad range of categories; such as culture, design practices, shop floor activities, and sub-tier management can effectively identify the probability of a quality event?

The Audit Based PQA was implemented in 5 Manufacturing Facilitates in the United States. These facilities were: Facility B, Facility G, Facility H, Facility M, and Facility W. The percent of change of nonconformities from these Manufacturing Facilities was compared to the same data set prior to the implementation of PQA. This analysis was completed using a paired sample t-test. To compare a matched pair, data from 2020 was from January to September. The data for 2021 was the same and included January 021 to September of 2021. This equalization ensured that the analysis was using similar time segment in both populations. Table 8 outlines the actual values and the percentage of change in the subject facilities in the same time period (January to September).

Table 8 *Nonconformities in PQA Facilties*

Manufacturing Facility	2020 (January to September)	2021 (January to September)	Variance	% Change
Plant B	2183	1497	-686	31%
Plant M	404	1043	639	-158%
Plant H	705	802	97	-14%
Plant G	1450	486	-964	66%
Plant W	1639	1389	-250	15%

Nonconformities did not improve in two of the manufacturing facilities. As noted in Table 8, Plant M showed a significant degradation of 158% and Plant H exhibited a 14% degradation in quality performance. The remaining three facilities showed improvements of 15%, 31%, and 66%. The manufacturing facilities with degraded performance had a significant number of leadership changes, labor relation issues with the workforce, and a high amount of attrition due to Covid-19 business downturns. The researcher acknowledges the data from Facility M and Facility H and will review the causes in the discussion chapter. Nonetheless, Facility M and Facility H were included in the calculation.

The net improvement in the 5 facilities as compared to the entire enterprise is outlined in table 9. Despite the significant degradation in Plan M, the overall nonconformities in the subject facilities were reduced by 18% as shown in Table 9 below. The rest of the enterprise showed an improvement of 8% in nonconformities from 2020 to 2021. To keep the consistency with the comparison and ensure matched pair validity, throughout this research, 2020 annual data was from January to September and the 2021 annual data followed the same logic of January to September. At the time of the completion of this report data from October is 2021 was not fully available and therefore not included in this study.

Table 9 *Overall Comparison of Defect Percentage of Change – 5 Manufacturing Plants*

All 5 Plants	2020 (Jan-Sep)	2021 (Jan-Sep)	Variance	% Change
Total	6381	5217	-1164	18%

A paired sample t-test was performed on the 5 facilities to determine if the reduction of nonconformities due to the implementation of PQA was significant or not. The initial box plot of pre and post defect counts is illustrated in Figure 9. The box plots showed overall reduction of the mean and a reduced variation. Minitab Statistical software was used in the pair t-test analysis. Although not part of this analysis, the two degraded facilities showed similar performances in scrap, rework, productivity, and direct labor performance. These key performance indicators were not part of this study. This study only focused on the number of nonconformities as the single indicator of quality performance.

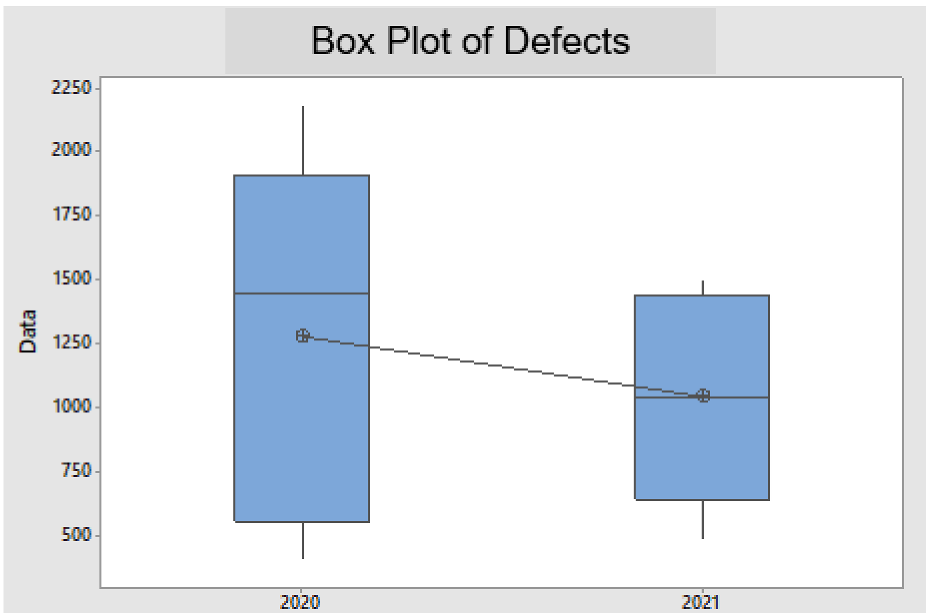


Figure 9 *Box Plot of Defects 2020 to 2021 (Septembers)*

The individual facility defect performance is outlined in Figure 10. As noted earlier, Plant M and Plant H exhibited degradation of performance despite conducting an audit-based PQA. The two facilities with degraded performances had special causes associated with their negative performance that will be discussed later.

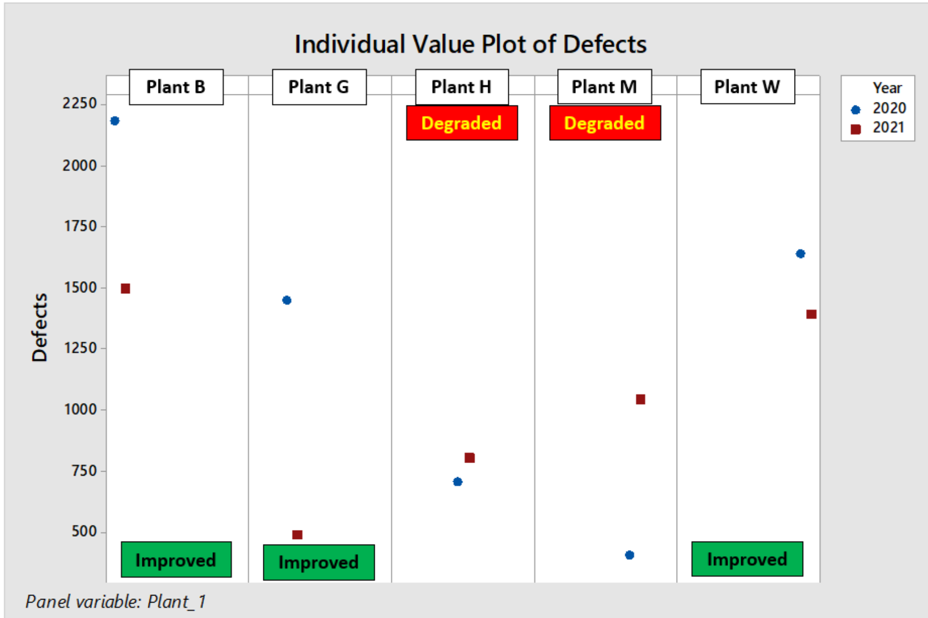


Figure 10 *Individual Plant Defect Performance 2020 to 2021 (January to September)*

4.1.1.1 Question 1 – Audit Based Paired Sample T-Test

Minitab Statistical software was used to conduct the paired t-test for the 5 subject manufacturing facilities. Paired sample t-test compared the nonconformities in the 5 manufacturing facilities during 2020 and 2021 years. To ensure a comparative performance, the data from January to September of 2020 was compared to the data from January to September of 2021. The standard deviation of 2021 was significantly less than the standard deviation of 2020 as shown in Figure 11.

Paired T-Test and CI: 2020, 2021

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
2020	5	1276	720	322
2021	5	1043	417	186

Figure 11 *Paired T-Test Descriptive Statistics*

The paired sample t-test analysis resulted in a P value greater than 0.05. This indicates that the null hypothesis is not rejected, and the quality performance of 2020 is similar to 2021. This means that there was no significant difference between the performance of the 5 manufacturing facilities in 2020 and 2021. At the surface, the result would indicate that the implementation of PQA did not improve quality. As outlined in Figure 12, the P value of the paired sample t-test was 0.458 which is higher than the threshold of 0.05 for this statistical hypothesis test.

Test

Null hypothesis	H_0: μ_difference = 0
Alternative hypothesis	H_1: μ_difference ≠ 0

T-Value	P-Value
0.82	0.458

Figure 12 *Final Test Results Audit Based Paired t-test*

Based on observed Quality improvement and the percent net reduction of Quality nonconformities, it is the researcher's assessment that the significant improvements seen in the facilities are due to the incorporation of the Predictive Quality Assessment. Relative to the specific research question, PQA cannot predict the probability of a negative quality event. However, objective evidence suggests that quality will improve as a result of a systemic analysis of leading indicators that are perceived to impact quality. PQA, on its own, cannot improve quality. Predictive quality methodology can highlight risk areas. Quality is improved if effective risk mitigation plans are incorporated in the manufacturing facilities' standard work.

4.1.2 Question 2 – Machine Learning

How can Machine Learning be used in changing the subjective audit-based risk assessment into a predictive model than can alert users before the occurrence of a quality event?

This research project has shown that Machine Learning can be leveraged to highlight risk, identify abnormal trends, drive corrective actions, and improve quality. Data set studied was provided by an unnamed manufacturing facility in the United States. This study refers to that manufacturing facility as Plant R. The dataset analyzed in this study was unplanned maintenance (reactive) work orders. The initial data set period was from March 2018 to September 2021. Having said that, due to Covid-19 related lockdowns and the significant impact on the industry, pre-Covid data was excluded. The final data set in the model was from June of 2020 to September of 2021. Advanced models may be able to optimize and account for the Covid-19 factors. Deep learning field is investigating the possibility of predicting such events. Covid-19 type events are known as Black Swan events. Black Swan event was originally coined by Nassim Taleb, a Professor of Finance and Probability, as a rare event, near impossible to predict, and with far reaching consequences (Khan, 2019). The ARIMA model of PQA does not have the ability to account for such catastrophic anomalies. As a result, the ARIMA model was constructed to include data from June of 2020 to September of 2021. Pre Covid-19 lock down data was excluded. The dataset was prepared to index by month and year for the model ingestion. Table 10 shows the format used for the ARIMA model.

Table 10 *Dataset Python Stratified Format*

Out[14]:

SE1	year	month	Type R	Year-Month
0	2018	4	800	2018-4
1	2018	5	798	2018-5
2	2018	6	750	2018-6
3	2018	7	692	2018-7
4	2018	8	951	2018-8
5	2018	9	812	2018-9
6	2018	10	1007	2018-10
7	2018	11	773	2018-11
8	2018	12	672	2018-12

4.1.3 Factor of Importance

The goal of this analysis was to evaluate the strength of the correlation of the selected independent variables to nonconformities. Note that this step is not necessary but might reveal variables not normally obvious to the team. Once the impact of a certain variable is proven significant, the corresponding real-time monitoring mechanism can be established. Several regression models were used to quantify the significance of the selected variables. Table 11 outlines the correlation factor for the selected variables. The factors were represented in terms of Pearson Correlation Coefficient. Based on the factor of importance, a series of variables were selected. All of the regressive models showed a high correlation between the selected independent variables and nonconformities. The process of adding independent variables should be n ongoing project. Subject matter experts should add additional variables if they believe it could broaden the scope of Predictive quality Analytics.

Table 11 *Pearson Correlation Coefficient*

Model	Test Set R^2
Linear Regression	0.86
Random Forest	0.80
XGBoost	0.90

The measure used in the correlation study was the Pearson Correlation Coefficient. The square of the Pearson Correlation Coefficient is also known as R-Squared. The R-Squared is often used to quantify the linearity of two random variables and the strength of their relationship. For example, a value of 1 denotes the strongest relationship which indicates that as one variable increases so will the other. The inverse of that denotes a strong negative relationship between the observed values (Wang & Jiang, 2017). The final analysis tool used in the correlation study was XGBoost. The Factor of Importance of XGBoost is very simple and can be obtained from open-source portals like ‘mljar website’ (Ptonski, 2021). The researcher promotes the maximum use of data streams even if the correlation may appear to be weak. Figure 13 shows the initial data set for the factor of importance.

The factor of importance analysis utilized a substantial amount of data. The researcher was able to obtain data for the selected elements from 2017, 2018, and 2019. This large data set gave the researcher high confidence that the categories and their relevant sub elements can serve as a reliable baseline for the predictive model. The researcher however did not use this data set for the ARIMA predictive modeling. Due to the Boeing 737 Max grounding and the Covid-19 Pandemic, the researcher opted to use data from June of 2020 to September of 2021 in the development and construction of the ARIMA analysis. It was assumed that by selecting data after June of 2020, the model would not be adversely impacted by the significant reduction in production volumes observed during the Boeing 737 grounding and the Covid-19 pandemic.

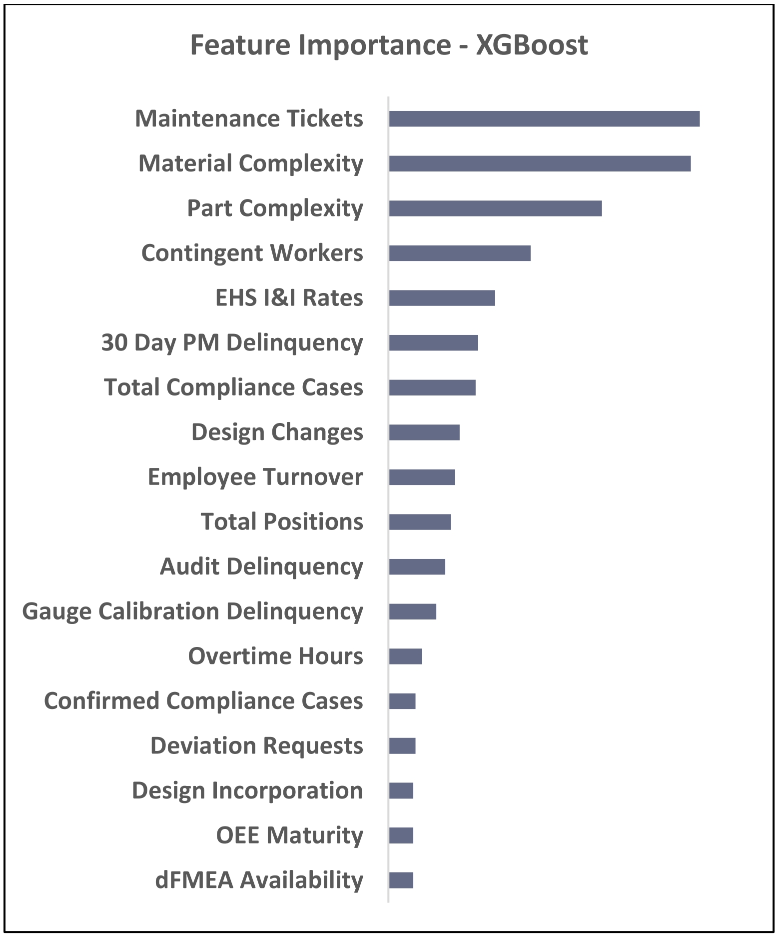


Figure 13 *Factor of Importance - Selected Categories*

Note that categories and elements will differ between organizations and industries. The categories used for this study should only serve as an example. In this study the data streams outlined in Figure 13 were selected as the independent variables. It is important to note that the correlation study should be used to include elements rather than exclude nonsignificant elements.

The categories and elements will vary from one organization to the next. The dependent variables may be customer returns, rework, scrap, warranty, or any other negative quality metric. Knowing what variable correlates to quality nonconformities is important, however, PQA can be optimized by analyzing as many data streams as possible to capture a broad range of potential quality impacting variables.

4.1.4 ARIMA Model Results

Two factors are critical in the design and selection of the models. First is the usage of an effective statistical model to capture data dependencies, and second is the scalable learning system that can learn as the data set increases (Chen & Guestrin, 2016). Some of the commonly used algorithms in the field of Machine Learning are: Random Forest, XGBoost, and Auto Regressive Integrated Moving Average (ARIMA). This research study uses ARIMA to conduct the predictive analysis. ARIMA is a powerful algorithm where time series and past performance can play a significant role in the predictive model. Quality is a time series variable. ARIMA operates based on time series data by using past performance to predict future values (Prabhakan, 2019). The ARIMA was processed for each of the selected elements. ARIMA is a time series model that uses auto regression, integrated, and moving averages to predict future values of a variable based on past performance. The algorithm consists of model identification, parameter estimation, model recognition and finally forecasting (Faruk, 2010). The ARIMA python code section is outlined in Figure 14. The complete code is available in Appendix B.

```
In [17]: # fit model
model = ARIMA(new1['Type R'], order=(1,2,1))
model_fit = model.fit(disp=0)
print(model_fit.summary())
# plot residual errors
residuals = pd.DataFrame(model_fit.resid)
residuals.plot()
plt.show()
residuals.plot(kind='kde')
plt.show()
print(residuals.describe())
model_fit.plot_predict(dynamic=False)
plt.grid()
plt.show()
```

Figure 14 *ARIMA Model Python Code*

ARIMA models have three key terms that are critical in developing the forecasting model. These three terms are p, d, and q. The first term, p, is the autoregressive element. To enable better predictions, the preceding numbers are added or subtracted in the model. Having a p value of 1 means a single preceding value is subtracted from the next value. The term d identifies the number of times the data have to be differenced to produce a stationary signal. Having a d value of 0 means that the data does not tend to increase or decline over times. When d is equal to zero, the actual analysis is ARMA which means that in the long term, the trends are not increasing or decreasing. The term q represents the number of preceding or lagged values for the error which captures the moving average (Abugaber, 2021). Figure 15 shows the ARIMA model results. While the model can be further enhanced, the values obtained from this iteration can serve as a starting point in the analysis. The model utilized a (1,2,1) analysis format.

```
                             ARIMA Model Results
==============================================================================
Dep. Variable:               D2.Type R   No. Observations:                   12
Model:                 ARIMA(1, 2, 1)   Log Likelihood                 -75.557
Method:                       css-mle   S.D. of innovations            114.796
Date:                Sun, 31 Oct 2021   AIC                            159.115
Time:                        12:15:08   BIC                            161.054
Sample:                             2   HQIC                           158.397

===================================================================================
                      coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------
const               8.7052      6.794      1.281      0.232      -4.611      22.022
ar.L1.D2.Type R    -0.3359      0.285     -1.177      0.270      -0.895       0.224
ma.L1.D2.Type R    -1.0000      0.228     -4.388      0.002      -1.447      -0.553
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1           -2.9770           +0.0000j            2.9770            0.5000
MA.1            1.0000           +0.0000j            1.0000            0.0000
-----------------------------------------------------------------------------
```

Figure 15 *ARIMA Model Results*

While most of the output variables are not necessarily interpreted, the final results indicate a model sufficient for utilization in the field of quality improvement. The key variables in Figure 15 are values of AIC and BIC. These values indicate the strength of the model. The researcher used various ARIMA inputs (p,d,q) until the lowest AIC and BIC was achieved.

AIC is Akaike's Information Criterion and BIC stands for Bayesian Information Criterion. The lower these values, the better the fit and the strength of the predictive model. The AIC, BIC and Standard Deviation of the model are:

AIC = 159.115

BIC = 161.054

S.D. of Innovations = 114.796

This would entail that approximately 72% of the predictions are within 1 standard deviation or said a different way, 114 units from what was observed. The other elements of the model that are interpreted are outlined below. The constant element is not interpreted, however the Autoregressive (AR) and Moving Average (MA) are interpreted. The AR and MA variables that are < 0.05 indicate significance which is preferred in optimum models.

Table 12 *ARIMA Output Values and Interpretation*

Variable	P > |z|	Decision
Constant	0.232	Uninterpreted
AR (Autoregressive)	0.270	Not Significant
MA (Moving Average)	0.002	Significant

The data outlined in Table 12 indicates that autoregressive (AR) element of the model was not significant. That would mean that lag values would have a statistically significant relationship with the future values. In simple terms, this significance would indicate the strength of data in determining the future value based on the previous month. The moving average (MA), which was 0.002 and significant, signifies that the forecast error from prior time is informative in predicting current values. In summary, the ARIMA model developed to predict the unplanned maintenance work orders is valid and sufficient to drive actions based on trends and consequently drive quality improvements. Figure 16 shows the June 2020 to September 2021 actual work orders (Type R) and the corresponding predictive model output (Forecast).

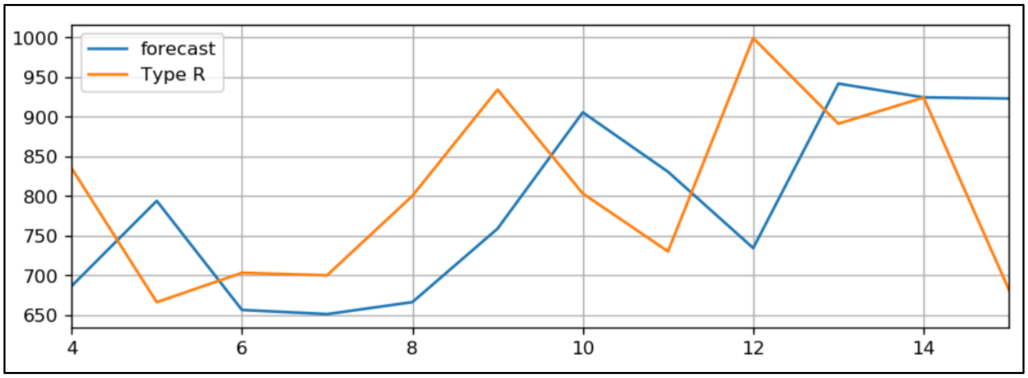


Figure 16 *ARIMA Model Results*

4.1.5 Pre-Control Chart

The Unplanned reactive maintenance work orders from June of 2020 until September of 2021 were ingested into the model. Figure 16 shows the forecast and the actual data from the above stated period. The Pre-Control Chart was populated with the monthly work orders and the predicted values in August and Septembers of 2021. The Andon system was established based on previously determined thresholds to drive escalation and corrective actions.

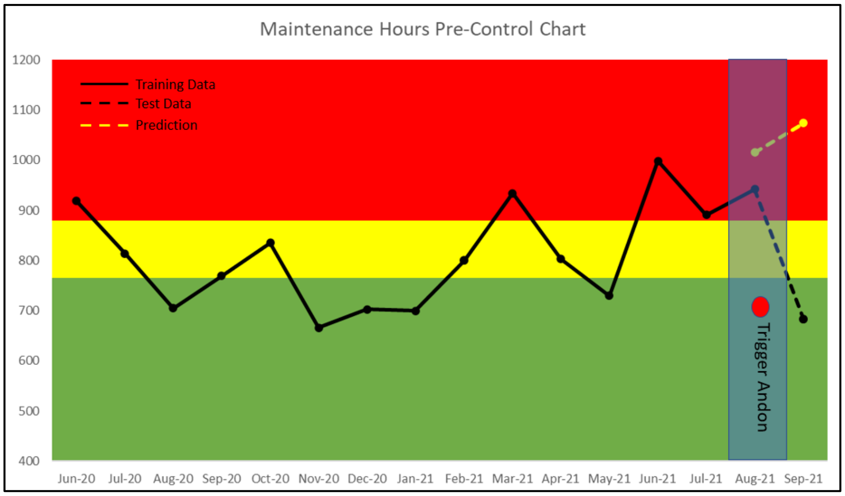


Figure 17 *Unplanned Maintenance Work Orders Andon System*

Figure 17 shows the unplanned maintenance work orders from June of 2020 to August of 2021 in a Pre-Control Chart environment. In this setup August of 2021 was projected to have a value in the Red Zone. Based on the predictive values in August of 2021, the Andon system was activated. Subsequently the maintenance department in the facility performed a series of preventative maintenance actions to reduce the unplanned down time. The data in Figure 13 shows that the September 2021 actual number of work orders was significantly reduced due to the mitigation activities. Objective evidence and data suggest that due to the Andon system highlighting the issues, management put special focus on the unplanned maintenance work orders as a metric, hence driving the significant reduction in the unplanned work orders.

The heightened sense of urgency and the drive to actions is in fact the very essence of PQA. The activation of the Andon and the subsequent actions is the primary reason for reduction of unplanned maintenance work orders. The ARIMA model had predicted the unplanned maintenance work orders to continue increasing if not addressed. The activation of the Andon system and the subsequent management corrective actions significantly reduced the actual values of the unplanned maintenance hours in September of 2021. The PQA model is set up to index every month and repeat this process on a monthly basis. This would mean that every month a new actual value replaces the previously predicted month. Subsequently the upcoming month would be an output by the ARIMA predictive model. This concept is outlined in Figure 18 which depicts the basic PQA Machine Learning framework.

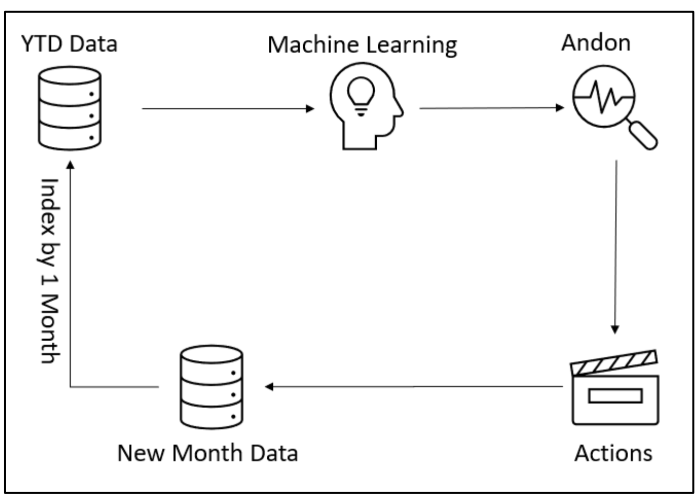


Figure 18 *The Machine Learning PQA Model Framework*

4.1.6 Machine Learning Paired T- Test

The monthly values of the nonconformities of Plant R were analyzed using a Paired T-Test. The paired sample t-test used data from January to September of 2020 as compared to the same period in 2021. Table 13 shows the monthly performance of defects. Paired T-Test hypothesis testing using Minitab Statistical software showed significant reduction in mean and standard deviation in defects. Data showed that the 2021 performance was significantly better than 2020. This assessment will be validated by using a form of hypothesis testing that is known as the Paired T-Test.

Table 13 *Monthly Defects Performance Data - Plant R (2020 - 2021)*

Months	2020 Defects	2021 Defects
January	188	160
February	173	68
March	112	92
April	43	62
May	103	108
June	212	150
July	159	28
August	56	57
September	123	72

Figure 19, an output of the Minitab Statistical software, shows that the mean of defects in 2020 was 129.9 and the mean of defects for 2021 was 88.6. The quality performance in terms of nonconformities was reduced by nearly 32% in Plant R. The standard deviation was equally reduced from 58.0 in 2020 to 43.8 in 2021. The reduction of standard deviation indicated a more predictable environment and smaller range of variation. The standard deviation in 2021 was reduced by approximately 25%. Overall, Plant R exhibited a reduction of nonconformities with a reduced monthly variation as indicated by the calculated standard deviation. Although the sample population was only 9 months, a normality check was performed to ensure that data was normally distributed. A normally distributed data is a requirement for paired sample hypothesis testing. As more data becomes available, the researcher will continue monitoring efficacy of the corrective actions. Recall that the implementation of PQA is only an information tool and only actual problem solving and corrective actions can only improve the quality metrics.

Paired T-Test and CI: 2020, 2021

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean
2020	9	129.9	58.0	19.3
2021	9	88.6	43.8	14.6

Figure 19 *Mean & Standard Deviation Analysis of Plant R (2020-2021)*

The result of the paired sample t-test is outlined in Figure 20. Based on the P = 0.041 and the Significance test set as $P < 0.05$, it is determined that the values of defects in 2021 are significantly different than the same values in 2020. This would entail that the Predictive Quality Analytics implementation and more importantly the resulting actions has had a positive impact on the quality performance. This positive impact is manifested in the reduced number of nonconformities in 2021. Based on this data, we can objectively answer the research question that Machine Learning can be used in changing the subjective audit-based risk assessment into a predictive model than can alert users before the occurrence of a quality event. We can further enhance that statement by noting that quality event is measured in term of actual quality performance which in this research study is number of nonconformities.

Test

Null hypothesis	H_0: μ_difference = 0
Alternative hypothesis	H_1: μ_difference ≠ 0

T-Value	P-Value
2.43	0.041

Figure 20 *Paired Sample T-Test Plant R - Machine Learning Data*

CHAPTER 5. DISCUSSION & CONCLUSION

5.1 Audit Based PQA Discussion

As noted in the previous chapter, the paired sample T-Test failed to show that there was a significant improvement of the quality performance in the 5 facilities after the implementation of PQA. This was mainly due to the two facilities (Plant M & Plant H) failing to show improvements in 2021. The two facilities were Plant M and Plant H. The facilities that showed improvements were Plant B, Plant G, and Plant W. As part of the implementation of PQA, as a quality improvement strategy, the researcher implemented a digital portal where all facilities can compile their risk profiles and the associated corrective actions. This digital portal is accessible to all employees and part of the main quality organization's homepage. The Predictive Quality Analytics is set as a proactive framework strategy and the PQA risk profiles can be accessed through the Quality Insight Dashboard.

Figure 21 *PQA Portal and the Quality Homepage*

5.1.1 Plants with Improving Performance

The facilities that showed improvements under the audit-based PQA, had an average of 15 risks identified and an average of 10 risk mitigation actions during 2021. Figure 22 illustrates the risk profile and a monthly evaluation of that profile. These facilities had systemic corrective actions associated with the identified risk. Note the number of risks identified in the profile outlined in the image. This facility was part of the audit-based population and showed the highest gain in quality improvement. The number of nonconformities in Plant G was reduced by 66%. The other two facilities with improvements in nonconformities were Plant B which had a 33% reduction and Plant W had a 15% reduction in nonconformities.

The common factors in the three facilities that showed improvement in quality were: continuous monitoring of risk through the year, continuous follow up on actions, adherence to closure rate, and assigned personnel to the actions. These facilities also had the same leadership in the last three years and no changes in either Plant Manager or Plant Quality Leader roles. These facilities also had an established monthly quality improvement rhythm where PQA, actions, and closure rates were part of the standard work. It is important to note that all three facilities had a cultural transformation where PQA was used as part of the management monthly review. It is also important to note that the PQA profile in Figure 22 was shared with the hourly associates in the overall plant communication boards on the shop floor.

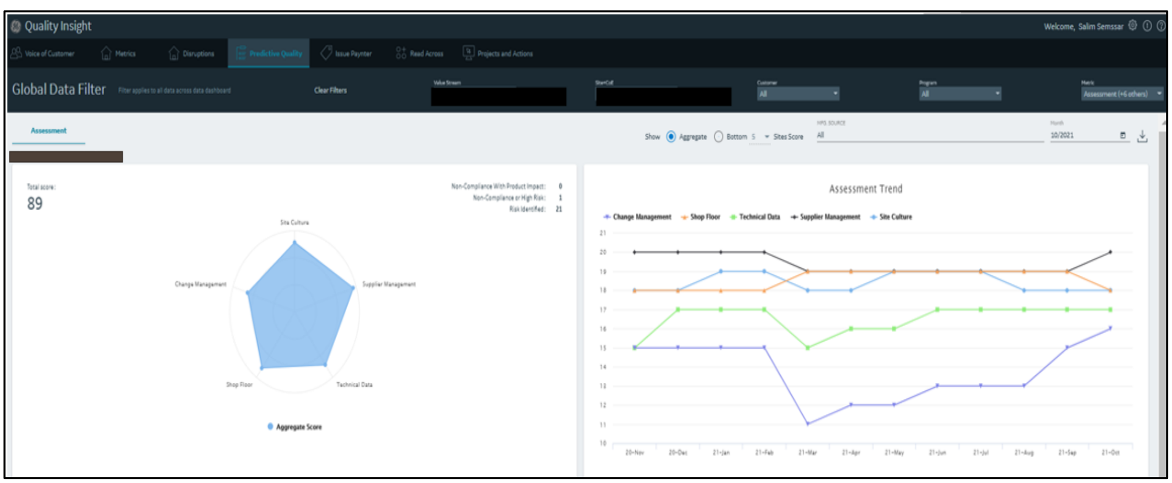


Figure 22 *PQA Profile of Plant G*

As part of the PQA implementation, the researcher assisted the organization with the development a category and element visualization portal. The category and element visualization from the portal are outlined in Figure 22 and Figure 23. Note the number of actions associated with each category. This visualization is critical to ensure transparency and accountability. Transparency of risk can heighten the awareness of the manufacturing personnel. The increased awareness and transparency will drive accountability in the ecosystem. The assigned personnel and the status of the tasks are visible to the entire employee population. The actions are interactive and accessible by anyone in the portal. As an example, Figure 24 illustrates one of the actions associated with a cultural risk of training identified in Plant G. This tracker outlines the action, names (Blacked Out), start date, and finish date. Note the green status indicating that actions are on target to completion.

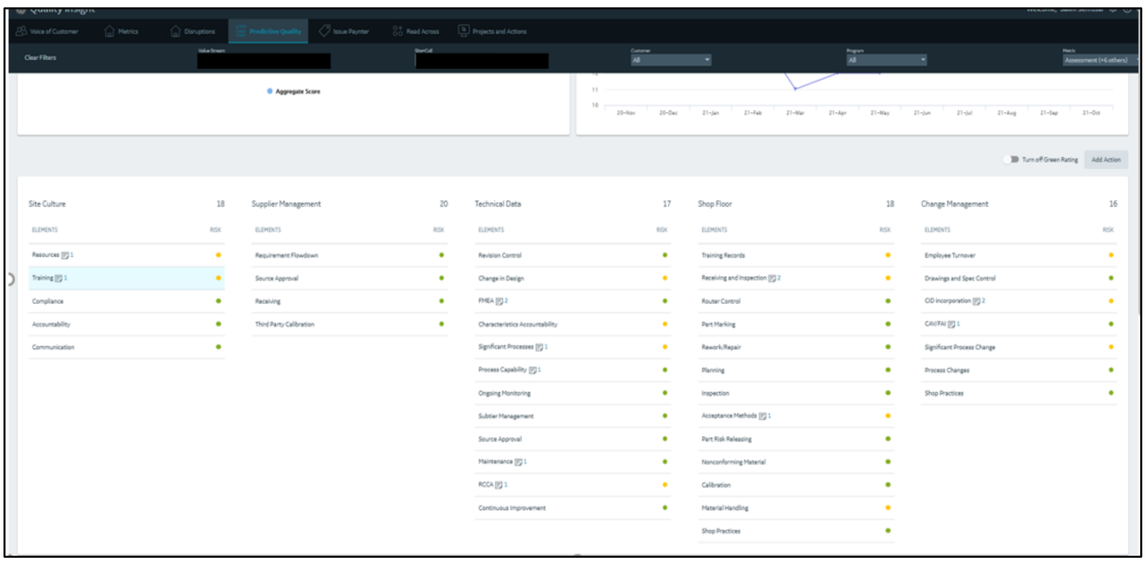


Figure 23 *PQA Category & Elements of Risk Profile – Plant G*

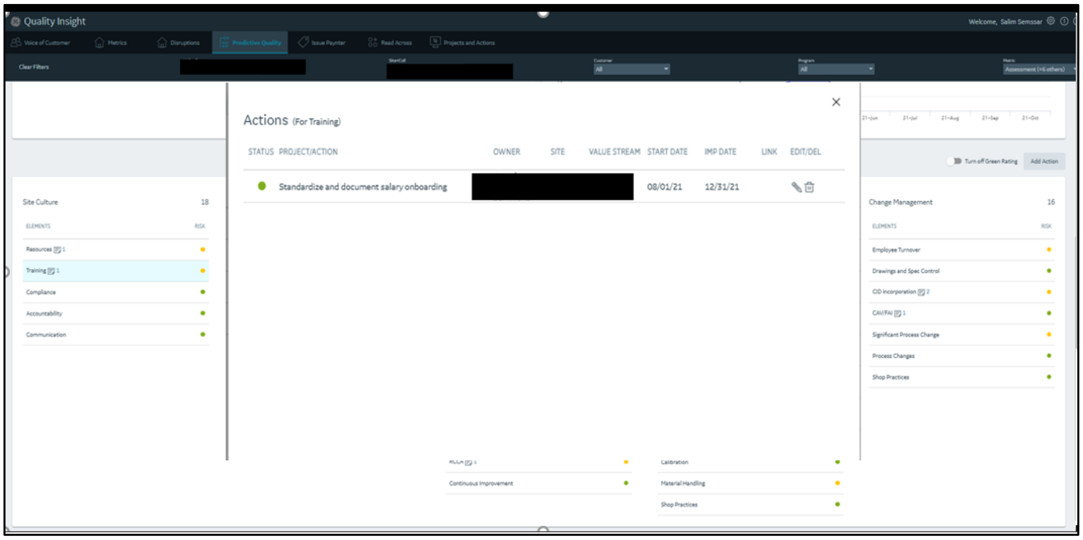


Figure 24 *Action Tracker - Training Risk – Plant G*

5.1.1 Plants with Degraded Performance

Two manufacturing facilities in the research study failed to show any improvement. In fact, these two manufacturing facilities exhibited a significant degradation in quality performance. Plant M had a significant degradation in quality. The researcher conducted a deeper analysis to gain insight into the causes of this degradation. The PQA risk profile of Plant M, illustrated in Figure 25, was extracted from the global quality portal. Note the highlighted noncompliance (2) and risk (9) in the portal. It is also important to note that there is no monthly monitoring or updates of the risk profile in this facility.

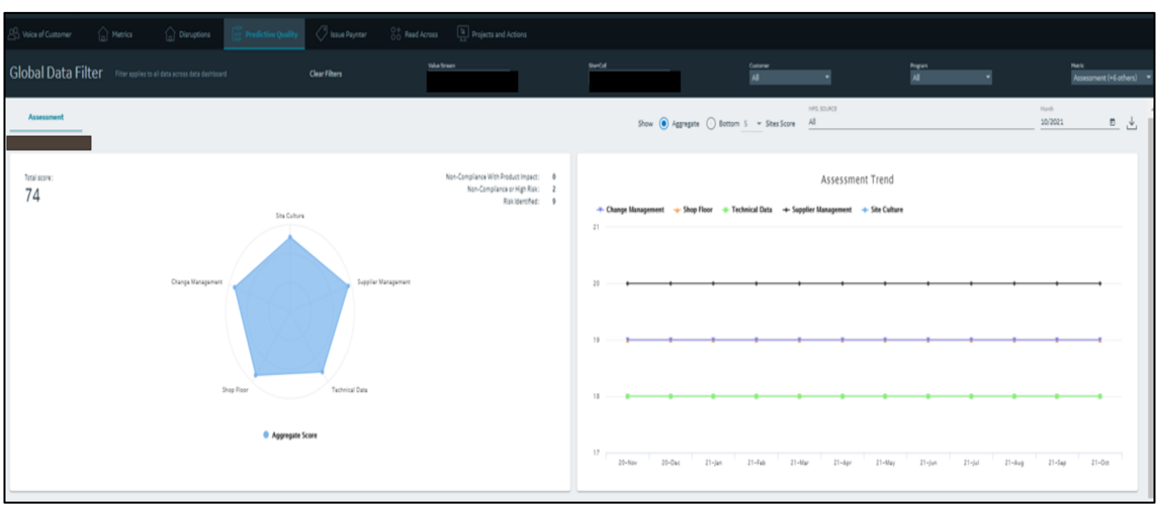


Figure 25 *Plant M PQA Risk Profile*

To further understand the causes behind the degradation, the researcher analyzed the category and element section of the PQA in Plant M. Note that there are no actions assigned to any of the highlighted risks in the initial risk assessment. Furthermore, the assessment was completed only once and there were no follow ups associated with the process.

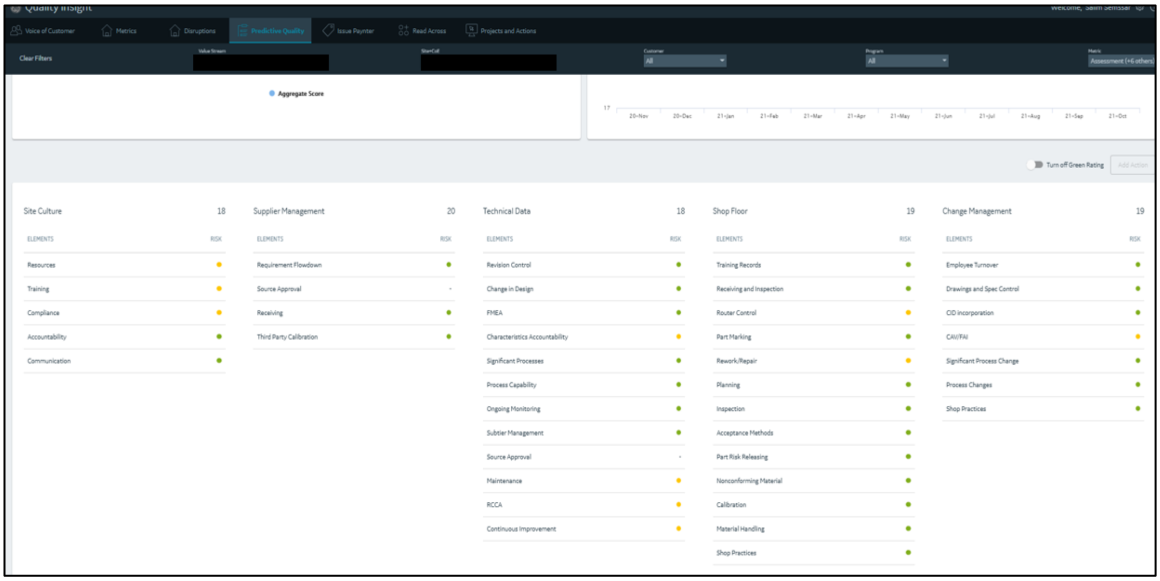


Figure 26 *PQA Category & Elements of Risk Profile – Plant M*

Additional discussion points about Plant M include the turnover of the plant management and quality leadership positions. This facility had a resignation of the Plant Manager and Quality Leader in 2020. Also, the Business Unit Quality Leader resigned after only 1 year on the job. The plant leadership position was open for 3 months during 2021 and Business Unit Production Manager was acting as the interim plant manager. The facility is a unionized facility with a significant adversarial relationship due to Covid-19 downturn, layoff, restrictions, masks, and Covid related policies. Resource allocation at various levels and departments were highlighted as a risk but, due to the lack of senior leadership presence and ownership, no actions were implemented. Plant H had a similar profile. Early in 2021 the Plant Leader had resigned, and the position was open for a significant amount of time. The PQA portal did not have any actions in Plant H despite the initial PQA highlighting risks in many areas. While the facilities with improved quality performance had assigned personnel to address the PQA risks, Plants M and H did not have a disciplined approach in addressing and mitigating risk.

5.2 Machine Learning PQA Discussion

The Predictive Quality Analytics (PQA) research is an intersection of quality methodologies and Machine Learning. In this research, Machine Learning ARIMA algorithm is utilized to assist the quality professionals in identifying potential risk based on past performance. Categories and elements are selected to serve as leading indicators and independent variables that impact quality. The research project is designed to investigate leading indicators, perform predictive modeling, and activate the Andon system if needed. If Andon system is activated, the responsible parties can execute on actions and change the trajectory of that variable.

This research is not design t focus on the most optimized Machine Learning algorithm. Advanced modeling and expert data scientists can significantly improve the fit and the strength of predictive models. Furthermore, the study is not intended to account for Black Swan events like the Covid-19 pandemic. Advanced modeling, specialized Artificial Intelligence, and Deep Learning methods can potentially enhance that capability. The exclusion of data prior and during the Covid-19 pandemic reduced the number of data points. Although this might have adversely affected the accuracy and the strength of prediction of the model, it is believed that the strategy behind Predictive Quality Analytics is sound and unaffected by these factors.

This study was based on a monthly review of the selected independent variables. Each month the model is executed to project the next predicted value. If the value is in the acceptable zone, then the team can maintain existing actions and focus on variables that require additional attention. The process is repeated every month for the entire selected independent variables. As noted earlier, the acceptable zones are determined by the subject matter experts. Note that the Pre-Control Chart was selected to determine the escalation zones.

The researcher used a 5% improvement on each value as the baseline. This baseline served as the target green zone for the Pre-Control Chart. The 5% improvement from previous actuals was an arbitrary target and was used to see how the initial process can work. Quality professionals can use any target that is appropriate for their independent variables. A cautionary note is that if targets are selected too aggressively, the Andon system would activate on too many variables and defeat the purpose of focus on the most critical variables. The researcher selected a 15% zone as the region that indicated an undesirable trend. The red zone was determined to be the action required zone which include values above the 15% region.

5.3 Conclusions & Next Steps

Predictive Quality Analytics is a new and novel way of improving quality. It drives a cross functional monitoring of independent variables that impact quality of an organization. The Andon system is critical in ensuring transparency of conditions and visibility of data trends that might lead to adverse quality performance. PQA is a powerful tool that can highlight risk in the entire enterprise. Audit Based quality assessment and Machine Learning Assisted methods serve as risk identification and trend monitoring systems. On its own, PQA is not going to improve the quality performance. Management teams and quality professionals must rely on robust problem-solving philosophies such as Lean, Six Sigma, TQM, and other proven quality improvement methodologies to improve quality. PQA is a transformational approach in directing resources to where help is needed the most. This study objectively proved that the execution of PQA and highlighting risk will not improve quality. PQA is an ongoing activity that must be followed up with specific, measurable actions. Only the execution of the actions improve quality. The five facilities that embarked on the execution of PQA had results spanning the entire spectrum of quality performance. Plants that executed on the risk mitigation delivered improvements as high as 66% and manufacturing facilities that failed to act on the identified risk demonstrated significant quality degradation. For PQA to help organizations improve quality, the overall strategy should include a highly visible portal that is accessible to a wide range of employees and more importantly is monitored on a regular basis. Transforming the culture to be proactive and monitoring of the leading indicators requires a shift away from firefighting to fire prevention. Firefighting is the daily work on quality defects and fire prevention is a more systemic approach to problem solving. In fire prevention latent causes are analyzed and systemic issues are addressed.

The PQA model in this research can be further enhanced if organizations deploy Machine Learning expertise and resources that are dedicated to model enhancement. This researcher used basic Machine Learning techniques to develop the model and there are significant opportunities for further optimization. The researcher excluded Covid-19 impact data for this research study. The data was restricted to June of 2020 through September 2021. The model selected for this study was not capable to account for the high variabilities of the Covid-19 related pandemic.

The intent of this study is to show the possibility and the method of using Machine Learning in quality and not how to develop analytical Python models. PQA has broad applicability to organizations regardless of industry. Mitigating risk with leading indicators is far more effective in driving permanent corrective actions than relying on lagging data. In this context, conventional quality metrics are line rejects, customer disruptions, deviation requests, warranty, scrap, and rework. PQA can be applied at a cell level and rolled out to include an entire facility. Dashboards, similar to Figure 24, can be part of a communication strategy on the shop floor. This is a common mode of communication in most manufacturing facilities and a well proven Lean communication strategy.

Industries such as Aviation may benefit from a global list of PQA profiles. Federal Aviation Administration (FAA) and Defense Contractor Management Agency (DCMA) could conceivably mandate participation in such a network where PQA risk profiles can assist with more specific audits rather than the current spot check audit. In a study by the FAA (Dobbs, 2008), it was reported that there is a need to improve the risk-based oversight system. It was noted that the FAA does not perform enough audits to test how well manufacturers' quality assurance systems are working. The same report also found that the risk assessments that FAA inspectors use to evaluate a manufacturer's potential for producing substandard products exclude pertinent information that would aid in the evaluation of risks. Finally, the report determined that the FAA's inspections at supplier facilities were too focused on specific tasks rather than the overall quality system.

A Global PQA portal can have risk profiles and mitigation actions visible hence driving companies to improve quality on a systemic level. Today, the International Aerospace Quality Group (IAQG) provides an online service, known as the OASIS, for the AS 9100 certification. Customers can view the certification and the accreditation status of the supply base (IAQG, 2020). eAuditNet is another web-based software, developed and maintained by the Performance Review Institute (PRI), that serves as a collaborative portal where customers can view the accreditation and certification of suppliers relative to special processes. "eAuditNet houses the online Qualified Manufacturers List (QML), which is a searchable database of accredited companies" (PRI, 2020). PQA could be the collaborative tool used by regulatory bodies and customers to drive improvement in a wide range of industries. The above examples are very high-level sources that only focus on certification and accreditation status.

There are no systems known to date that enable customers and suppliers to view risk profiles at an enterprise level. PQA can go far beyond the certification and accreditation status and highlight risk areas at an enterprise level. The methods would be used to drive systemic corrective actions.

There are significant challenges associated with implementing a PQA risk management system. Organizations throughout the world are working to enhance their data aggregation capabilities along with integrity and accuracy. Significant gaps still exist in standardized high integrity data. As organizational data management improves, so will the accuracy of PQA modeling. Another significant challenge to the PQA framework is the fact that some of the datasets used in the analytics are highly confidential. These datasets may contain human resource elements such as overtime, turnover, and injury rates. Due to the confidentiality measures, some organizations may be reluctant to share such information. High levels of encryption may reduce that concern level.

A cultural transformation in transparency and the desire to improve quality is needed to bypass the initial data confidentiality concerns. Cybersecurity is also a great concern in implementing a global PQA system. PQA portals will contain data that could be highly valuable to cybercriminals and hackers. High levels of data security must be implemented to ensure multi-level authentication and protection against potential data leaks. Supply chain data is highly sensitive and may expose competitive advantages of participating companies. Sophisticated encryption is required to ensure that the focus remains on risk profile rather than the data that is used to perform the analysis.

PQA drives an enterprise-wide look into quality. Effective problem solving may yield multiple root causes. Permanent corrective actions must address primary and secondary root causes. Predictive Quality Analytics addresses issues that correlate to quality defects that are not normally considered to be quality related. PQA is a new and novel method in identifying leading indicators to impact and change output metrics such as safety, quality, delivery, and cost. PQA is currently part of a global quality strategy of one of the biggest aviation companies in the world. The implementation of PQA has been showing promising results in changing how quality is managed throughout the world.

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APPENDIX A – AUDIT BASED QUESTIONNAIRES FILE

PQA
Checklist-Rev41_AUDI

Site Culture		Supplier Management		Production / MFG - Walk the process				Change Management	
				Technical Data		Shop Floor			
Resources	20	Requirement Flowdown	20	Revision Control	20	Training Records	20	Employee Turnover	20
Training	20	Source approval	20	Change in Design	20	Shipping and Receiving Inspections	20	Drawings and Specs Control	20
Compliance	20	Receiving	20	FMEA	20	Router Control	20	CID Incorporation	20
Accountability	20	Third Party Calibration	20	Characteristic Accountability	20	Part Marking	20	CAV/FAI	20
Communication	20			Significant Processes	20	Rework / Repair	20	Significant Process Change	20
				Process Capability	20	Planning	20	Process Changes	20
				Ongoing Monitoring	20	Inspection	20	Shop Practices	20
				Subtier Management	20	Acceptance Methods	20		
				Source approval	20	Part Risk Releasing	20		
				Maintenance	20	Nonconforming Material	20		
				RCCA	20	Calibration	20		
				Continuous Improvement	20	Material Handling	20		
						Shop Practices	20		
Site Culture	**20**	**Supplier Management**	**20**	**Technical Data**	**20**	**Shop Floor**	**20**	**MOC**	**20**

APPENDIX B – PYTHON CODE OF THE PQA

ARIMA MODELING

In [1]:
```
from __future__ import print_function import
statsmodels.api as sm from
statsmodels.tsa.arima_process import
arma_generate_sample from
statsmodels.graphics.tsaplots import plot_acf,
plot_pacf import pandas as pd import numpy as np
import matplotlib.pyplot as plt import warnings

from datetime import datetime
from statsmodels.tsa.arima_model
import ARIMA
warnings.filterwarnings('ignore')
```

Read Dataframe

```
In [2]: data_dir = 'C:\\Users\\Salim
Laptop\\Documents\\PQA\\Analytics\\'  file_dir = data_dir +
'SubElement1Shop1.csv' df = pd.read_csv(file_dir)
df.head(10)
```

Out[2]:

	user_mapped	site_description	location_description asset	reportdate	SE1	worktype	wonum
0	Yes	Shop 1	B-BAY NORTH ROOF	3/10/2021	Type R	CM	8770 3044
1	Yes	Shop 1	B-BAY NORTH ROOF	3/27/2020	Type R	CM	8370 6268

2	Yes	Shop 1	B-BAY NORTH ROOF	7/28/2019	Type R	CM	8115 3008
3	Yes	Shop 1	B-BAY NORTH ROOF	6/20/2019	Type R	CM	8081 8439
4	Yes	Shop 1	B-BAY NORTH ROOF	8/29/2018	Type R	CM	7844 4122
5	Yes	Shop 1	EAST ADDITION	3/4/2021	Type R	CM	8763 6518
6	Yes	Shop 1	EAST ADDITION	3/4/2021	Type R	CM	8763 6517
7	Yes	Shop 1	EAST ADDITION	4/23/2020	Type R	CM	8396 9570
8	Yes	Shop 1	EAST ADDITION	11/19/2019	Type R	CM	8227 7001
9	Yes	Shop 1	EAST ADDITION	8/19/2019	Type R	CM	8135 6508

In [3]:

```
df["Date"] = pd.to_datetime(df['reportdate']) #prepare the file for date
      stratificatio df['year'] = pd.DatetimeIndex(df['Date']).year
f['month']        pd.DatetimeIndex(df['Date']).month
df.head(10)
```

user_mapped	lescription	location_description	reportdate :1	vorktype	m	asset

Out[3]:

0	Yes	Shop 1	B-BAY NORTH ROOF	3/10/2021	Type R	CM	87703044
1	Yes	Shop 1	B-BAY NORTH ROOF	3/27/2020	Type R	CM	83706268
2	Yes	Shop 1	B-BAY NORTH ROOF	7/28/2019	Type R	CM	81153008
3	Yes	Shop 1	B-BAY NORTH ROOF	6/20/2019	Type R	CM	80818439
4	Yes	Shop 1	B-BAY NORTH ROOF	8/29/2018	Type R	CM	78444122
5	Yes	Shop 1	EAST ADDITION	3/4/2021	Type R	CM	87636518
6	Yes	Shop 1	EAST ADDITION	3/4/2021	Type R	CM	87636517
7	Yes	Shop 1	EAST ADDITION	4/23/2020	Type R	CM	83969570
8	Yes	Shop 1	EAST ADDITION	11/19/2019	Type R	CM	82277001

9	Yes	Shop 1	EAST ADDITION	8/19/2019	Type R	CM	81356508

In [4]:

```
dff = pd.pivot_table(df, values='wonum', index=['year','month'],
        columns='SE1',aggfunc= dff
```

Out[4]:

year	month	OTHER	Type P	Type R
2018	3	6	96	548
	4	6	166	800
	5	16	160	798
	6	25	190	750
	7	14	144	692
	8	11	159	951
	9	23	128	812
	10	21	121	1007
	11	25	154	773
	12	13	126	672
2019	1	37	151	930

SE1 year month	OTHER	Type P	Type R
2	55	211	884
3	44	133	987
4	59	181	1019
5	53	179	910
6	65	203	1002
7	106	151	1010
8	82	164	1148
9	87	143	1005

	10	92	130	1055
	11	94	167	888
	12	58	139	898
	1	61	177	1202
	2	74	203	1013
	3	35	158	964
	4	43	185	447
	5	51	164	825
	6	39	199	919
2020				
	7	64	143	814
	8	38	162	705
	9	53	148	769
	10	55	124	835
	11	47	152	666
	12	24	147	703
	1	28	175	700
	2	48	194	800
	3	54	109	934
	4	40	215	803
2021	5	53	149	730
	6	49	188	999
	7	65	137	891
	8	97	163	924
	9	66	122	682

In [5]:

```
shop_param_list=dff.columns.values.tolist()
shop_param_list
```

Out[5]: ['OTHER', 'Type P', 'Type R']

In [6]:

```
dff.reset_index(level =[0, 1],drop =False,inplace=True)
```

Adding a new column called Year-Month for best labeling

```
In [7]: dff['Year-Month']=dff['year'].astype(str)+"-"+
    dff['month'].astype(str) #combine year a dff
```

Out[7]:

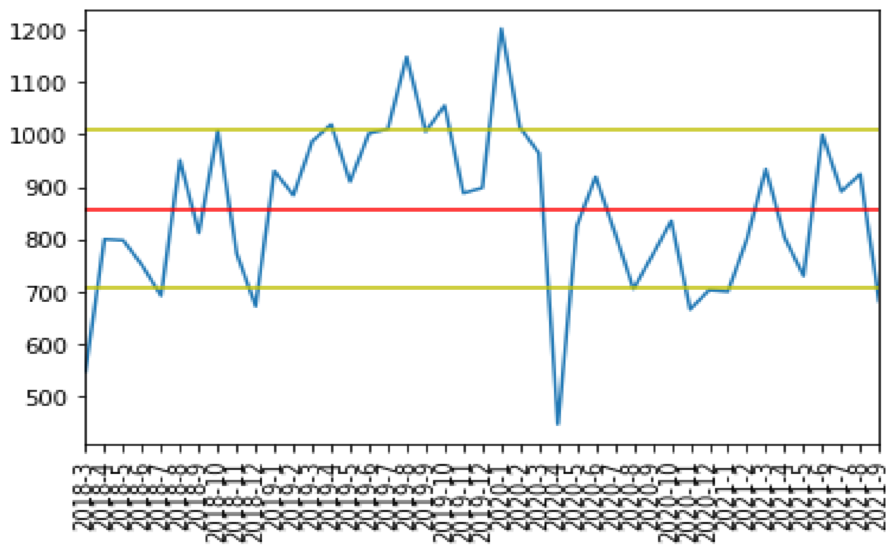
SE1	year	month	OTHER	Type P	Type R	Year-Month
0	2018	3	6	96	548	2018-3
1	2018	4	6	166	800	2018-4
2	2018	5	16	160	798	2018-5
3	2018	6	25	190	750	2018-6
4	2018	7	14	144	692	2018-7
5	2018	8	11	159	951	2018-8
6	2018	9	23	128	812	2018-9
7	2018	10	21	121	1007	2018-10
8	2018	11	25	154	773	2018-11
9	2018	12	13	126	672	2018-12
10	2019	1	37	151	930	2019-1
11	2019	2	55	211	884	2019-2
12	2019	3	44	133	987	2019-3
13	2019	4	59	181	1019	2019-4
14	2019	5	53	179	910	2019-5
15	2019	6	65	203	1002	2019-6
16	2019	7	106	151	1010	2019-7
17	2019	8	82	164	1148	2019-8
18	2019	9	87	143	1005	2019-9
19	2019	10	92	130	1055	2019-10
20	2019	11	94	167	888	2019-11
21	2019	12	58	139	898	2019-12
22	2020	1	61	177	1202	2020-1
23	2020	2	74	203	1013	2020-2
24	2020	3	35	158	964	2020-3

25	2020	4	43	185	447	2020-4
SE1	**year**	**month**	**OTHER**	**Type P**	**Type R**	**Year-Month**
26	2020	5	51	164	825	2020-5
27	2020	6	39	199	919	2020-6
28	2020	7	64	143	814	2020-7
29	2020	8	38	162	705	2020-8
30	2020	9	53	148	769	2020-9
31	2020	10	55	124	835	2020-10
32	2020	11	47	152	666	2020-11
33	2020	12	24	147	703	2020-12
34	2021	1	28	175	700	2021-1
35	2021	2	48	194	800	2021-2
36	2021	3	54	109	934	2021-3
37	2021	4	40	215	803	2021-4
38	2021	5	53	149	730	2021-5
39	2021	6	49	188	999	2021-6
40	2021	7	65	137	891	2021-7
41	2021	8	97	163	924	2021-8
42	2021	9	66	122	682	2021-9

Plot the Full Data

In [8]:

```
dff['Type R'].plot()
plt.xticks(np.arange(0,43), dff['Year-Month'],
rotation='vertical') plt.axhline(y=dff['Type
R'].mean(), color='r')
plt.axhline(y=dff['Type R'].mean()+np.std(dff['Type R']),
color='y') plt.axhline(y=dff['Type R'].mean()-
np.std(dff['Type R']), color='y') plt.show()
```



Output dff Data into CSV file

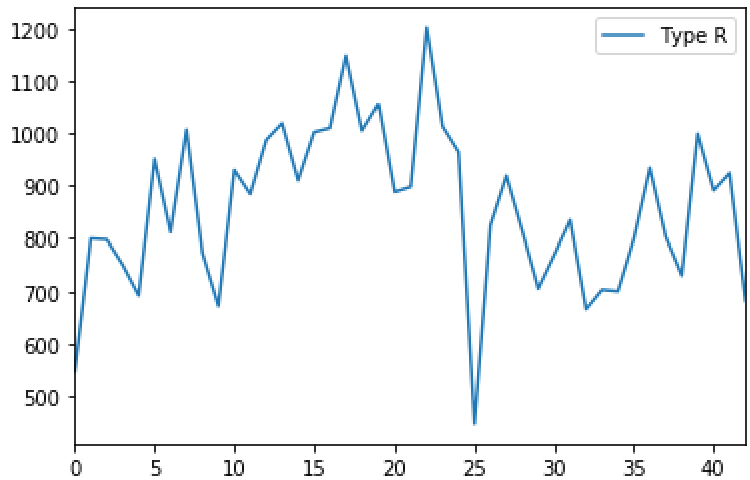
```
In [9]: dff.to_csv('dff.csv')
```

no-stationary or not? by Augmented Dickey-Fuller test

The null hypothesis of the ADF test is that the time series is non-stationary. So, if the p-value of the test is less than the significance level (0.05) then you reject the null hypothesis and infer that the time series is indeed stationary

p-value > 0.05: Fail to reject the null hypothesis (H0), the data has a unit root and is non-stationary. p-value <= 0.05: Reject the null hypothesis (H0), the data does not have a unit root and is stationary.

```
In
[10]:
     from statsmodels.tsa.stattools import
        adfuller from numpy import log

       series_train =
        dff['Type R']
   series_train.plot(label
   ='Type R') plt.legend()
         plt.show()

            result =
     adfuller(series_train)
   print('ADF Statistic: %f' %
    result[0]) print('p-value:
        %f' % result[1])
    print('Critical Values:')
        for key, value in
       result[4].items():
    print('\t%s: %.3f' % (key,
             value))
```




```
ADF Statistic: -
4.713467 p-value:
0.000079 Critical
     Values:
                          1%: -3.597
                          5%: -2.933
                          10%: -2.605
```

Since the p value is less than 0.05, Reject the null hypothesis (non-stationary). The data is stationary

Use partial data to check the stationary (Location 27 = June 2020 to Location 42 =

```
new1 = dff.loc[1:42, ] # This is to start from month 27
```

September 2021)

In [11]:

```
new1=new1.reset_index(leve
l=[0],drop=True)
new1['Type R'].plot(label
='Type R') plt.legend()
plt.show()

result =
adfuller(new1['Type
R']) print('ADF
Statistic: %f' %
result[0]) print('p-
value: %f' %
result[1])
print('Critical
Values:') for key,
value in
result[4].items():
print('\t%s: %.3f' %
(key, value))
```


```
ADF Statistic: -
4.318973 p-value:
0.000412 Critical
Values:
1%: -3.601
5%: -2.935
10%: -2.606
```

In [12]: new1.head()

Out[12]:

SE1	year	month	OTHER	Type P	Type R	Year-Month
0	2018	4	6	166	800	2018-4
1	2018	5	16	160	798	2018-5

2	2018	6	25	190	750	2018-6
3	2018	7	14	144	692	2018-7
4	2018	8	11	159	951	2018-8

D IS THE NUMBER OF DIFFERENCING REQUIRED TOMAKE THE TIME SERIES STATIONARY

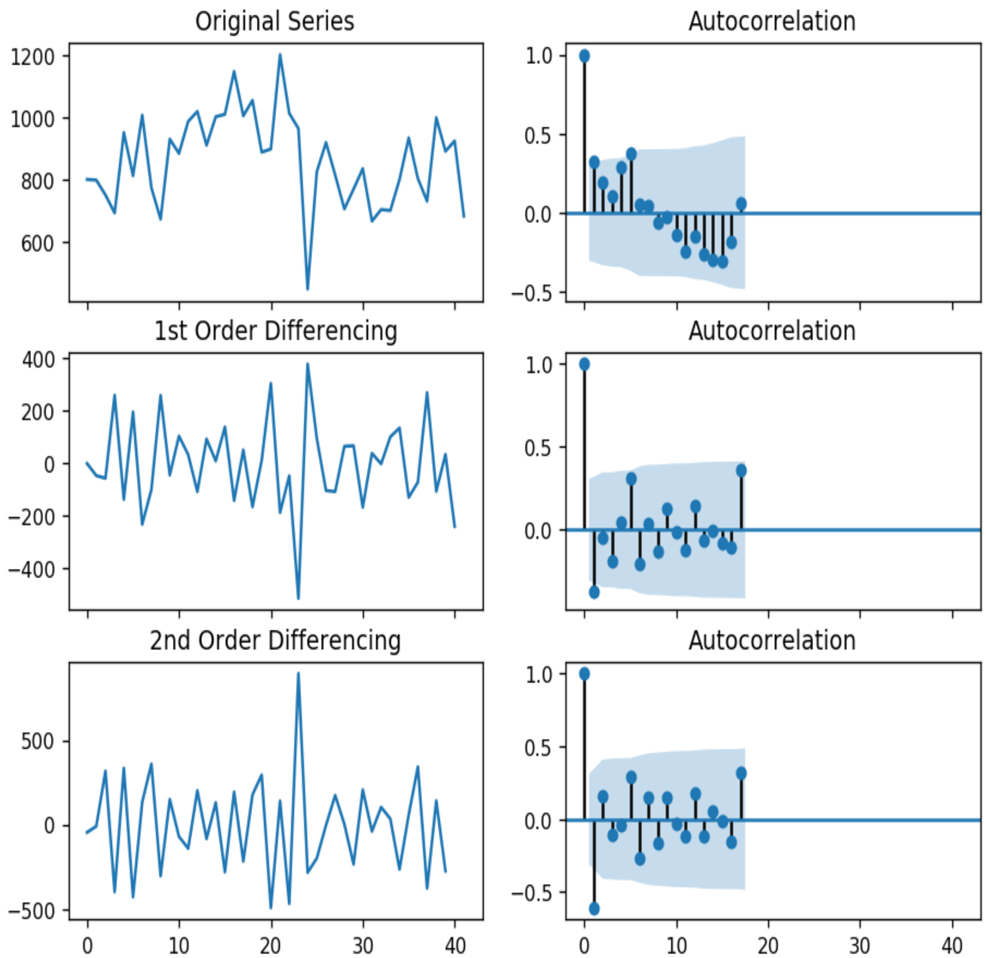
autocorrelaiton plots tell time series reaches stationarity with what order of differencing

In [13]:

```
import numpy as np, pandas as pd
from statsmodels.graphics.tsaplots import plot_acf,
    plot_pacf import matplotlib.pyplot as plt
  plt.rcParams.update({'figure.figsize':(9,7), 'figure.dpi':120})
```

```
result_table = pd.DataFrame(columns = ['param','ADF Statistic','p-value'])
param='Type R'
# for param in
shop_param_list:
series_train = new1[param]
result =
adfuller(series_train)
print('=============')
print('Parameter:','Type
R') print('ADF Statistic:
%f' % result[0]) print('p-
value: %f' % result[1])



# Original Series
fig, axes = plt.subplots(3, 2, sharex=True)
axes[0, 0].plot(series_train); axes[0, 0].set_title('Original Series')
plot_acf(series_train , ax=axes[0, 1])

# 1st Differencing
axes[1, 0].plot(np.diff(series_train.values)); axes[1, 0].set_title('1st
Order Differe plot_acf(np.diff(series_train.values), ax=axes[1, 1])



# 2nd Differencing
axes[2, 0].plot(np.diff(np.diff(series_train.values))); axes[2,
0].set_title('2nd Order plot_acf(np.diff(np.diff(series_train.values)),
ax=axes[2, 1]) result_table = result_table.append({
'param': param,
'ADF Statistic': result[0],
'p-value': result[1]}, ignore_index=True)
#paramname = param.replace("#", "")
paramname='Type R'
print(data_dir+'\\ACF\\'+paramname+'ACF.p
ng')
plt.savefig(data_dir+'\\ACF\\'+paramname+
'ACF.png')
#plt.show()
result_table.to_csv(data_dir+'ADFtest.csv',index=False)
```

```
=============
Parameter: Type R ADF
Statistic: -4.318973
p-value: 0.000412
C:\Users\Salim Laptop\Documents\PQA\Analytics\\ACF\Type RACF.png
```



In [14]: new1

Out[14]:

	SE1	year	month	OTHER	Type P	Type R	Year-Month
0	2018	4	6	166	800	2018-4	
1	2018	5	16	160	798	2018-5	
2	2018	6	25	190	750	2018-6	
3	2018	7	14	144	692	2018-7	
4	2018	8	11	159	951	2018-8	
5	2018	9	23	128	812	2018-9	
6	2018	10	21	121	1007	2018-10	

SE1	year	month	OTHER	Type P	Type R	Year-Month
7	2018	11	25	154	773	2018-11
8	2018	12	13	126	672	2018-12
9	2019	1	37	151	930	2019-1
10	2019	2	55	211	884	2019-2
11	2019	3	44	133	987	2019-3
12	2019	4	59	181	1019	2019-4
13	2019	5	53	179	910	2019-5
14	2019	6	65	203	1002	2019-6
15	2019	7	106	151	1010	2019-7
16	2019	8	82	164	1148	2019-8
17	2019	9	87	143	1005	2019-9
18	2019	10	92	130	1055	2019-10
19	2019	11	94	167	888	2019-11
20	2019	12	58	139	898	2019-12
21	2020	1	61	177	1202	2020-1
22	2020	2	74	203	1013	2020-2
23	2020	3	35	158	964	2020-3
24	2020	4	43	185	447	2020-4
25	2020	5	51	164	825	2020-5
26	2020	6	39	199	919	2020-6
27	2020	7	64	143	814	2020-7
28	2020	8	38	162	705	2020-8
29	2020	9	53	148	769	2020-9
30	2020	10	55	124	835	2020-10
31	2020	11	47	152	666	2020-11
32	2020	12	24	147	703	2020-12
33	2021	1	28	175	700	2021-1
34	2021	2	48	194	800	2021-2

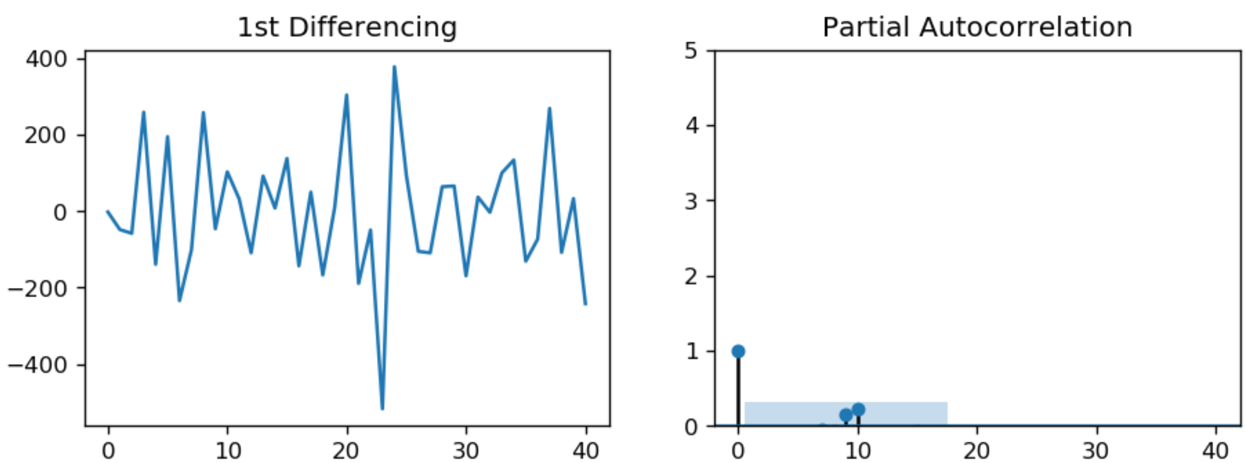
35	2021	3	54	109	934	2021-3
36	2021	4	40	215	803	2021-4
37	2021	5	53	149	730	2021-5
38	2021	6	49	188	999	2021-6
39	2021	7	65	137	891	2021-7
40	2021	8	97	163	924	2021-8
41	2021	9	66	122	682	2021-9

HOW TO FIND THE ORDER OF THE AR TERM (P)

Any autocorrelation in a stationarized series can be rectified by adding enough AR terms. So, we initially take the order of AR term to be equal to as many lags that crosses the significance limit in the PACF plot.

In [15]:

```
# PACF plot of 1st differenced series
plt.rcParams.update({'figure.figsize':(9,3),
'figure.dpi':120}) fig, axes = plt.subplots(1, 2,
sharex=True)
axes[0].plot(np.diff(series_train.values)); axes[0].set_title('1st
Differencing') axes[1].set(ylim=(0,5))
plot_pacf(np.diff(np.diff(series_train.values)),
ax=axes[1]) plt.show()
```

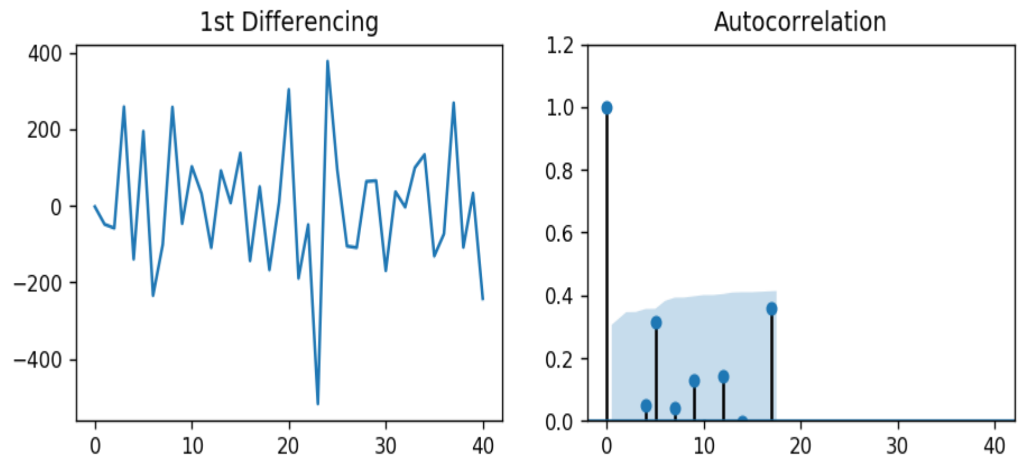


HOW TO FIND THE ORDER OF THE MA TERM (Q)

The ACF tells how many MA terms are required to remove any autocorrelation in the stationarized series.

In [16]:

```
plt.rcParams.update({'figure.figsize':(9,3),
'figure.dpi':120}) fig, axes = plt.subplots(1, 2, sharex=True)
axes[0].plot(np.diff(series_train.values));
axes[0].set_title('1st Differencing')
axes[1].set(ylim=(0,1.2))
plot_acf(np.diff(series_train.values),
ax=axes[1]) plt.show()
```



BUILD THE ARIMA MODEL USING ALL DATA

An ARIMA model is characterized by 3 terms: p, d, q where,

- p is the order of the AR term d is the number of differencing required
- to make the time series stationary q is the order of the MA term
- For example, ARIMAARIMA(1, 0, 12) means that it you are describing some response variable

(Y) by combining a 1st order Auto-Regressive model and a 12th order Moving Average model. A good way to think about it is (AR, I, MA). This makes your model look the following, in simple terms:

Y = (Auto-Regressive Parameters) + (Moving Average Parameters)

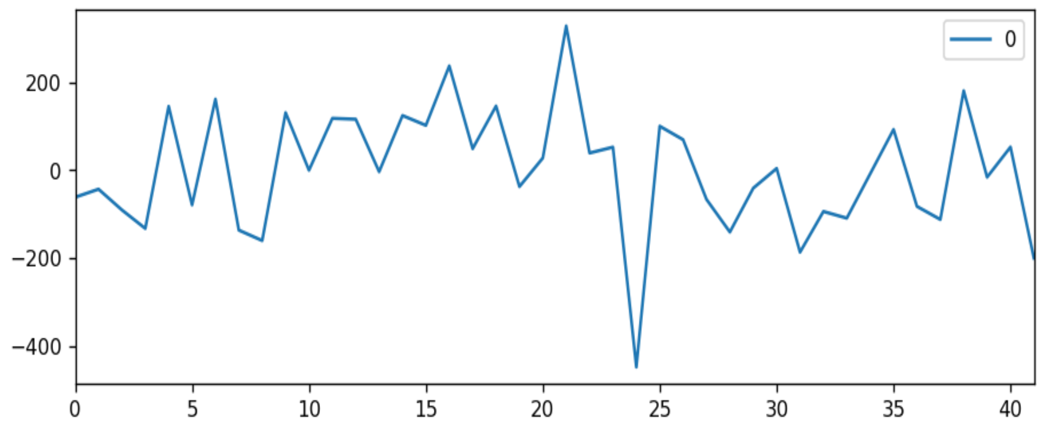
The 0 in the between the 1 and the 12 represents the 'I' part of the model (the Integrative part) and it signifies a model where you're taking the difference between response variable data this can be done with non-stationary data and it doesn't seem like you're dealing with that, so you can just ignore it.

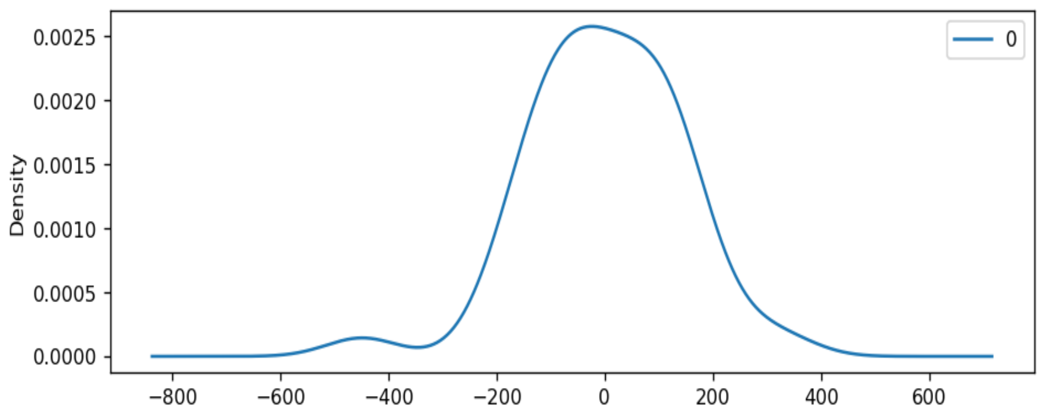
The link that DanTheMan posted shows a nice mix of models that could help you understand yours by comparing it to those.

In [17]:

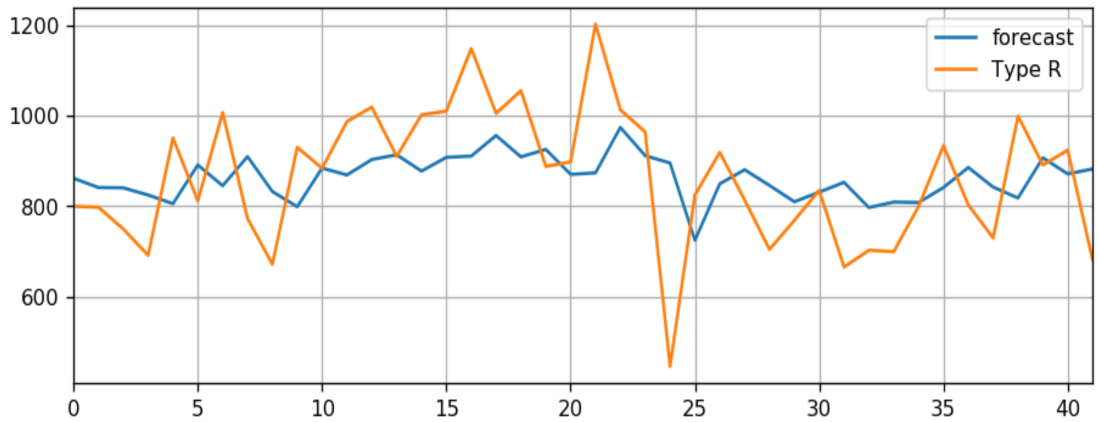
```
# fit model
model = ARIMA(new1['Type R'],
order=(1,0,0)) model_fit =
model.fit(disp=0)
print(model_fit.summary())
# plot residual errors
residuals =
pd.DataFrame(model_fi
t.resid)
residuals.plot()
plt.show()
residuals.plot(kind='
kde') plt.show()
print(residuals.d
escribe())
model_fit.plot_pr
edict(dynamic=Fal
se) plt.grid()
plt.show()
```

```
                              ARMA Model Results
==============================================================================
===
Dep. Variable:                    Type R   No. Observations:                  42
     Model:                      ARMA(1, 0)   Log Likelihood                  -
                                        266.478
           Method:                          css-mle   S.D. of innovations
                                        137.609
Date:                   Sun, 31 Oct 2021   AIC                           538.957
Time:                           07:40:17   BIC                           544.170
Sample:                                0   HQIC                          540.868


==============================================================================
=====                     coef    std err          z      P>|z|      [0.025
0.975] -----------------------------------------------------------------------
------------ const            861.8324     31.378     27.466      0.000
800.333      923.332 ar.L1.Type R      0.3299      0.147      2.250      0.030
         0.043       0.617                                              Roots
=============================================================================
              Real           Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1            3.0308          +0.0000j           3.0308
                                        0.0000
```






```
    0 count
42.000000 mean
 0.486364 std
139.312249 min
  -448.542495
   25%     -
    88.739215
   50%      -
 2.006960 75%
101.449876 max
   328.234145
```




```
In [18]: ModelResFit=pd.DataFrame({'Res': model_fit.resid, 'Type R': new1['Type
         R']}) ModelResFit.to_csv("ARIMA_allData1.csv")
```

FORCASTING

```
In [19]:
n_f = 2
train = new1['Type R'].iloc[:40]

test =new1['Type
R'].iloc[40:] train
```

```
Out[19]:
0
800 1
798
2     750
3     692
4     951
5     812
6     1007
7     773
8     672
9     930
10    884
11    987
12    1019
13    910
14    1002
15    1010
16    1148
17    1005
18    1055
```

```
19     888
20     898
21    1202
22    1013
23     964
24     447
25     825
26     919
27     814
28     705
29     769
30     835
31     666
32     703
33     700
34     800
35     934
36     803
37     730
38     999
39     891
Name: Type R, dtype: int64
```

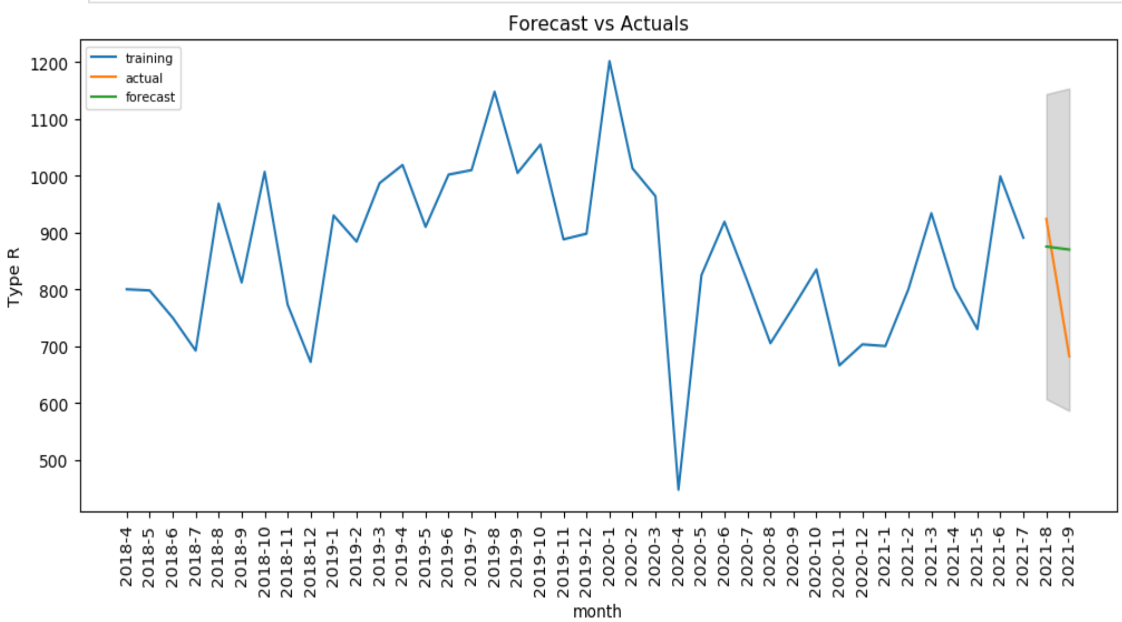
```
In [20]: model = ARIMA(train, order=(1, 0,
     0))   fitted = model.fit(disp=-1)
         print(fitted.summary())
```

```
                              ARMA Model Results
==============================================================================
Dep. Variable:                 Type R   No. Observations:                   40
Model:                     ARMA(1, 0)   Log Likelihood                -253.641
Method:                       css-mle   S.D. of innovations            137.078
Date:                Sun, 31 Oct 2021   AIC                            513.283
Time:                        07:40:17   BIC                            518.349
Sample:                             0   HQIC                           515.115


===============================================================================
    =                    coef    std err          z      P>|z|      [0.025
0.975] ----------------------------------------------------------------------
 -------- const          867.1876     32.489     26.692      0.000     803.510
 930.865 ar.L1.Type R      0.3413      0.146      2.332      0.025      0.054
              0.628                                        Roots
 =============================================================================
       Real          Imaginary           Modulus         Frequency

-----------------------------------------------------------------------------
                                      -
       AR.1           2.9298            +0.0000j           2.9298
                                    0.0000
  ---------------------------------------------------------------------------
```

```
In [21]: OutputData=pd.DataFrame({'Residual':fitted.resid,'Type R': train})
                   OutputData.to_csv("OutputData.csv")
```

```
In [22]:                    # Forecast
     fc, se, conf = fitted.forecast(n_f, alpha=0.05)  # 95% conf

              # Make as pandas series
     fc_series = pd.Series(fc,
   index=test.index) lower_series =
pd.Series(conf[:, 0], index=test.index)
  upper_series = pd.Series(conf[:, 1],
        index=test.index)
```

```
In [23]:            # Create Training and Test
                        # Build Model
                           # Plot
    plt.figure(figsize=(12,5),
     dpi=100) plt.plot(train,
       label='training')
  plt.plot(test, label='actual')
       plt.plot(fc_series,
       label='forecast')
      plt.fill_between(lower_series.index,
         lower_series, upper_series,
   color='k', alpha=.15) plt.title('Forecast vs
 Actuals') plt.xlabel('month') plt.ylabel(param)
            plt.legend(loc='upper left', fontsize=8)
plt.xticks(np.arange(0,42), new1['Year-Month'], rotation='vertical')
                  plt.show(param)
```




```
In [24]: fc_series
```

```
Out[24]:     40
          875.315320
              41
          869.961762
            dtype:
           float64
```

```
In [25]: test
```

```
Out[25]:     40    924
             41    682
           Name: Type R,
            dtype: int64
```

```
In [26]: train
```

```
Out[26]:      0     800
              1     798
              2     750
              3     692
              4     951
              5     812
              6    1007
              7     773
              8     672
              9     930
             10     884
             11     987
             12    1019
             13     910
             14    1002
             15    1010
             16    1148
             17    1005
             18    1055
             19     888
             20     898
             21    1202
             22    1013
             23     964
             24     447
             25     825
             26     919
             27     814
             28     705
             29     769
             30     835
             31     666
             32     703
             33     700
             34     800
             35     934
             36     803
             37     730
             38     999
             39     891
          Name: Type R, dtype:
                int64
```

VITA

CONTACT INFORMATION

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LinkedIn Profile

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EDUCATION

Purdue University

Doctorate of Technology

DTECH, Technology & Innovation, 2021

Indiana Institute of Technology; Indianapolis, Indiana

M.B.A., Business, Management and Marketing

Purdue University; Indianapolis, Indiana

B.Sc., Mechanical Engineering

Other Education

- (IKA) Vehicle Dynamics Certification; Aachen University; Aachen, North Rhine, Westphalia, Germany; 2001
- Crotonville MDC – July 2015
- Ceramic Matrix Composites Fundamentals
- Jet Engine Lite – June 2017

CAREER DETAILS

2018 to Present

GE Aviation

Head of Quality & Manufacturing Excellence – GE Aviation

General Manager / Senior Executive

Responsible for all GE Aviation Quality, Manufacturing Engineering, Continuous Improvement, and Quality Compliance activities - $31B Sales, 84 Global Facilities, and Approximately 1000 suppliers. Responsibilities include direct Customer Quality (Commercial & Military), Manufacturing Quality, and Supplier Quality. Responsible for Manufacturing Engineering of Special Processes, Advanced Inspection Modalities, and NPI. Responsibilities include Six Sigma, Operations Excellence, and Part Producibility activities.

2015 to 2018
GE Aviation
Executive Quality Leader – ATMRO Value Stream
Assembly, Test, Maintenance, Repaired & Overhaul

Responsive for all Quality, Integrity, and Compliance activities for 22 global facilities. Facilities range from Wholly owned, JVs, to minority ownership. ATMRO facilities are responsible for development, assembly, repair, overhaul, and on-wing support of GE Engines. Customers range from Air Framers (Boeing, Airbus, Bombardier, Embraer, etc.) to Airline Operators. Products cover complete range of Commercial & Military lines.

2014 to 2015
GE Aviation
Executive Quality Leader, Composites Value Stream

Responsible for Global Quality activities (9 Plants): North America (MRAS, Sterling, Newark, Asheville (Composite), Batesville, Ellisville, CFAN (JV with Safran, Hamble UK, and Dowty Prop UK.
Responsibilities include Escape management, control and reduction of losses, MRB's, and supplier quality. Implementation of GEAPS and overall reduction of process variations.

2012 to 2014 – International Assignment – Dusseldorf, Germany
TRW Automotive Holdings Corp
Global Director, Quality and Continuous Improvement

Responsible for Global Quality activities (25 Plants): United States (5 Plants), Mexico (1 Plant), AP (5 Plants), India (2 Plants), Europe (10 Plants), Brazil (2 Plants). Quality, Delivery, Cost, and Productivity metrics Champion for implementing Lean and Six Sigma initiatives.

Other responsibilities and accomplishments include:

- Quarterly Reviews with Chief Executive Officer, Chief Operating Officer, and Senior Executive team.
- Ensuring successful launch of new products.
- Customer communications across the globe (VW, Ford, GM, Fiat, Nissan, Chrysler, Mazda).

2007 to 2012
North American Director, Quality and Continuous Improvement

Responsible for all Quality and Continuous Improvement activities of 11 plants USA (5 Plants), Mexico (1 plant), China (2 plants), India (2 plants), Europe (1 plant). Quality, Delivery, Cost, and Productivity Metrics Champion for implementing Lean and Six Sigma initiatives.
Other responsibilities and accomplishments included:

- Quarterly Reviews with Chief Executive Officer, Chief Operating Officer, and Senior Executive team.
- Development of global annual budget, warranty targets and agreements, and personnel development and planning.

2002 to 2007
Automotive Components Holdings LLC (Visteon / Ford)
Plant Manager (Productions, Engineering, and Viability)

Lead successful $19 million launch of first ever high precision manual steering system. Managed manufacturing and process engineering of current and future models in a two million square feet facility with a staff five managers and over 30 engineers, three product lines (Rack and Pinion, Pump, and Integral Gear).

Other responsibilities and accomplishments included:

- Senior Manager responsible for all operational activities and CI

- Named Plant lead for divestiture and due diligence phase and strategic planning process.
- Member of the executive team in obtaining local UAW agreement.

1995 to 2002
Bishop Steering Technology
Engineering and Business Development Manager

Started as a process Engineer and was promoted to Global Engineering and Business development manager for North and South America, Asia Pacific, and Europe. Started the European operation in Langenfeld, Germany (including sales, application and design engineering, and maintenance)

Other responsibilities and accomplishments included:

- Sales and marketing activities for the steering division.
- Main author of the initial memorandum of understanding for a JV with Mercedes Benz Lenkungen (Steertec division).
- Responsible for bishop Steering related operational activities at Lamosa Steering Pant (Mexico) and wulfrath Steering facility (Wulfrath, Germany).

<u>Selected Accomplishments</u>

- Developed Proactive Quality Framework based on predictive machine learning models
- Reduced customer disruptions in 2018 by 18% and Material Review Board cases by 50% on LEAP NPI (Boeing 737 MAX and Airbus A320 NEO)
- Responsible for Quality metrics and activities of 84 Aviation Global Facilities and over 1000 Suppliers
- Reduced Customer disruption in overhaul shops by 45% from 16 to 17
- Reduced losses in ATMRO Value Stream by $10M in 2017
- Instrumental in setup of a new Quality System in GE Aviation based on Toyota Production Systems. Elements of the model is being leveraged by Airbus, Boeing, along with 3 World Class Airlines
- Established new Delivery Improvement System (eDIP Digital Tool) based on the simplifies model of constraint management
- Instrumental in commercializing Low Noise Steering Intellectual Property Achieved local UAW contractual agreement with record savings and labor classification reduction

Board Membership

- Performance Review Institute – PRI

  Member of the board of Directors

  PRI is the world leader in facilitating collaborative supply chain oversight programs, quality management systems approvals and professional development in industries where safety and quality are shared values.