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A Framework for Mitigating Obsolescence in Military Based Systems

Ryan Rust
University of Central Florida

A FRAMEWORK FOR MITIGATING OBSOLESCENCE IN MILITARY BASED SYSTEMS

By:

RYAN RUST
B.S. Industrial Engineering, University of Central Florida, 2014
M.S. Industrial Engineering, University of Central Florida, 2016

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Major Professor: Ahmad Elshennawy

ABSTRACT

Obsolescence is an unavoidable reality in manufacturing systems and supply chain environments as systems are needed to be sustained for longer and longer periods of time. These extended life cycle products include airplanes, ships, industrial equipment, medical equipment, and military systems. The United States military has coined this issue as Diminishing Manufacturing Sources and Material Shortages (DMSMS). Research shows that the main areas of concern for obsolescence are cost optimization, obsolescence management, system life cycle, design/system refresh planning, architecture/open systems, and end-of-life (EOL) predictions. This effort suggests a need for a more effective management approach to tackling obsolescence with an emphasis on proactive management. The goal of this research was to create an obsolescence management framework for the purpose of managing obsolescence issues with military based systems. This research shows the potential for using machine learning as a life cycle forecasting tool over traditional data mining tools. The results for this small-scale case study show promising results for a larger scale experiment. Another powerful proactive strategy using machine learning is building technology refresh cycles into a system based on obsolescence risk levels. Some key areas of focus for a strong framework are funding for a robust DMSMS team, a robust supply chain, system design that factors in obsolescence risk, and consistent communication with all parties involved. It is imperative to develop an effective and data-driven approach to communicating obsolescence impacts to leadership to ensure successful mitigation of obsolescence issues. Some post-case tools and strategies include utilizing sustainment, production, and technology refresh roadmaps, along with employing data driven metrics to provide key information to leadership and demonstrate value to the customer. This study demonstrates opportunities and challenges for entities dealing with component obsolescence, methods for minimizing the issues that go along with it, and identifies best practices for obsolescence management.

Keywords: Mitigating obsolescence; obsolescence; Diminishing Manufacturing Sources and Material Shortages (DMSMS); design refresh; component; system life cycle; life cycle forecasting; obsolescence management framework; machine learning.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Networks
ARC	Automation Research Corporation
BOM	Bill of Materials
CMA	Critical Material Analysis
COTS	Commercial-Off-The-Shelf
CVI	Content Validity Index
DLL	Dynamic Link Library
DMSMS	Diminishing Manufacturing Sources and Material Shortages
DMT	DMSMS Management Team
DoD	Depart of Defense
DRMS	Defense Reutilization and Marketing Service
ECD	Engineering Completion Date
EOL	End-of-Life
FM	Flash Memory
FPGA	Field Programmable Gate Array
GIDEP	Government-Industry Data Exchange Program
HOSE	House of Systems Engineering
IC	Integrated Circuit
IPT	Integrated Product Team
LCML	Life Cycle Forecasting
LOTE	Life of Type Evaluation
LRM	Line Replaceable Module
LRU	Line Replaceable Unit
LTB	Last-Time-Buy
MDRB	Max Distributed RAM Bits
MHz	Megahertz
MMCM	Mixed-Mode Clock Manager
MSE	Mean Square Error
MTBI	Mean Time Between Instances
NDIA	National Defense Industrial Association
NHA	Next-Higher Assembly
OEM	Original Equipment Manufacturer
OMT	Obsolescence Management Team
OOB	Out-of-Bag
ORML	Obsolescence Risk Forecasting
ORS	Obsolescence Revision Sequence
OWG	Obsolescence Working Group
PDN	Product Discontinuation Notice
PLL	Phase-Locked Loop

RAM	Random Access Memory
RF	Random Forest
SELCC	System Element Life Cycle Cost
SVM	Support Vector Machines
TAT	Turnaround-Time
TR	Technology Refresh
USN	US Navy
V	Volt
YTEOL	Years to End of Life

CHAPTER 1: INTRODUCTION

1.1 Introduction

Obsolescence is an area of product sustainment that has the greatest impact on technologies with long system life cycles. The United States military refers to this issue as Diminishing Manufacturing Sources and Material Shortages (DMSMS). Technologies that have long sustainment life cycles are typically the most impacted by obsolescence. These include airplanes, ships, industrial equipment, medical equipment, and military systems which are slow in the implementation of new technology and leading-edge technology often because of the expenses and length of time that accompanies the development of a new product (Sandborn P. , 2011).

The type of obsolescence that this dissertation focuses on will be based on natural market drivers and how machine learning can be used in forecasting tools. The goal is to discuss the current practices in DMSMS, future research in component obsolescence involving machine learning, and creating a best practices framework for mitigating obsolescence in military-based systems. Significantly more research needs to be done in proactively managing obsolescence to reduce the impact it has on a system. The more obsolescence is understood by companies, the longer a product can be sustained, thus bringing overall costs down and keeping the customer satisfied.

1.2 Obsolescence Background

Current research shows that most of obsolescence management today is reactive based, meaning that problems are managed once they occur using a set of mitigation tactics that include last-time-buy (LTB), aftermarket sources, substitute parts, emulated parts, salvaged parts, and thermal uprating (Sandborn P. , 2011). Most companies have a DMSMS team that handles the entire obsolescence process from product discontinuation notice (PDN) to the final resolution. However, once the part is obsolete the main solutions are to find a substitute or to perform an LTB. There is no more opportunity for being proactive, which is what this research places emphasis on. You must be purely reactive, but even that is an artform to be appreciated and having an extremely efficient reactive obsolescence mitigation process will always be crucial to the success of a company's product.

A big factor in your decision making depends on the life cycle stage of the product a company has developed for the customer. Your final solutions are going to be tailored differently for a product that is either still in the design phase, is in production, or is purely in its sustainment phase. Typically, the product is in the production and/or sustainment phases, which is where obsolesce has the greatest impact. Figure 1 depicts a basic current process for obsolescence management. Once the team identifies a component as obsolete, the best mitigation approaches are brought forth and ultimately executed through management.

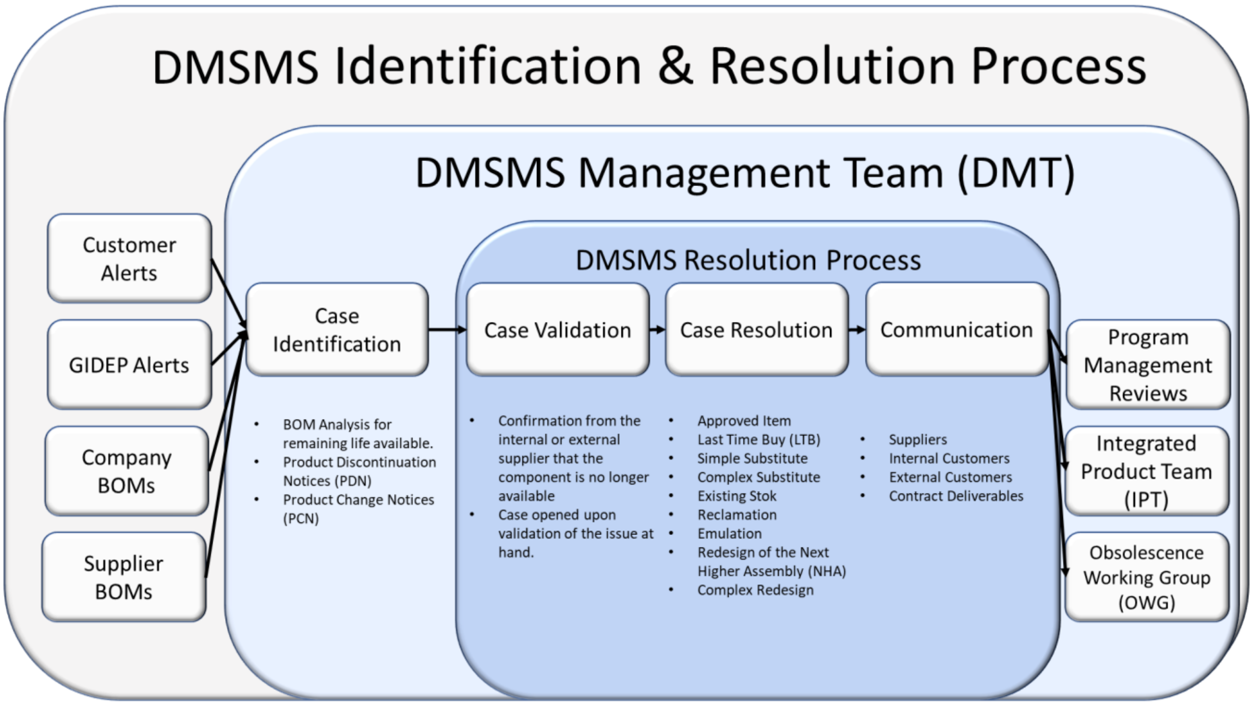

Figure 1: A Typical Obsolescence Management Process

When key obsolescence metrics are conveyed in an effective manner, leadership can make informed decisions and have a timeline for what steps need to be taken to avoid an obsolescence impact. Therefore, understanding the data early is vitally important for full risk mitigation of an obsolescence issue. Typically, you need leadership buy-in after you have collected and analyzed all of your data and you are down to three options: pay for a redesign now because there are enough parts on the shelf, perform a LTB with enough parts to last until a redesign, or perform a LTB with enough parts to last until your system's out-of-service date.

It is imperative to develop an effective and data-driven approach to communicating obsolescence impacts to leadership to ensure successful mitigation of obsolescence issues. Leadership needs to see their options in a quick, clear, and concise manner, that has the data analytics to back it up. Information is only valuable when it permits communication between those involved in decision making so constructive action can take place. More information is not necessarily better communication, so converting the information into a format that reduces its bulk and targets only the key aspect of an issue is important (Sanderlin, 1982). Leadership does not have time for their DMSMS team to explain every detail in its most raw form, nor are they going to understand it. However, the team must be able to back up their answers and be able to model out new solutions on the fly based on management's needs.

Figure 2 shows all the parties impacted by obsolescence and the strong relationships needed between the DMSMS team and all those groups. If an individual sector is not on board, things can fall through the cracks and timelines can be missed, resulting in a missed LTB date. All parties are equally important, but properly communicating needs with suppliers is often overlooked and is sometimes the easiest path forward to resolving a company's obsolescence issue.

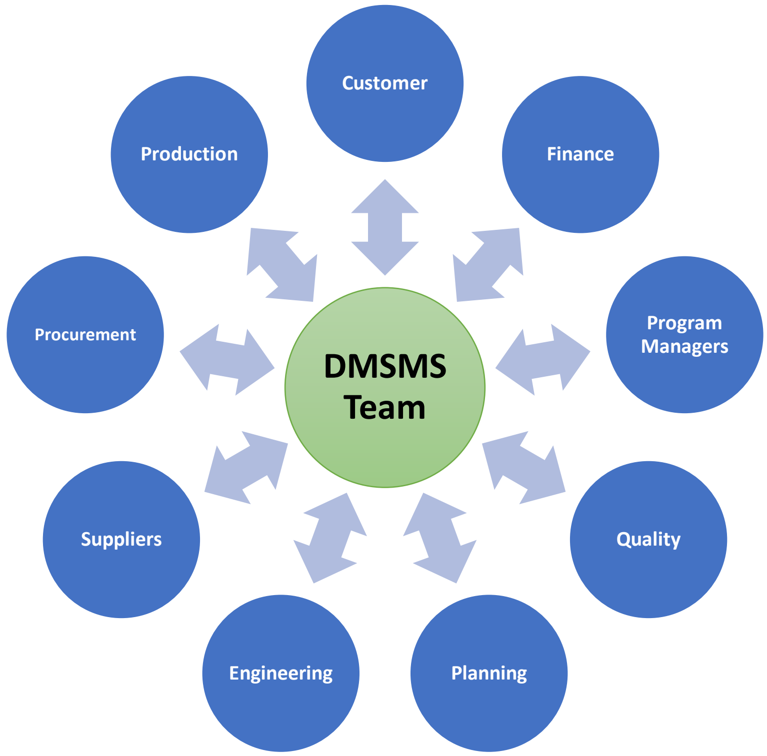

Figure 2: Parties impacted by obsolescence

The defense industry does not have market share majority over the supply chain for commercial-off-the-shelf (COTS) electronic components. COTS are becoming obsolete at an increasingly fast pace due to rapid changes in technology. Therefore, it is desirable to make partnering agreements with suppliers to ensure the continuous support and provision of critical components (Rojo, 2010). Achieving long term system availability that leverages COTS technology requires having efficacious relationships within the supply chain. It is essential that you work closely with suppliers to develop life cycle management plans to keep your systems up to date with active components, instead of waiting for obsolescence events to happen (Instruments, 2011).

On a component level, partnering agreements between two companies rarely exist, unless it makes financial sense for the manufacturer to continue building and selling a specific component to just a few companies. Is their purchasing volume going to be enough to even keep that product line profitable? Most likely not. However, it is still important to have a strong relationship with your suppliers, because often, especially if enough business in done with them in general, they may offer a company what is known as a lifeboat agreement. These are agreements that say the manufacturer will continue to produce a component for a specified extended amount of time until your company can develop a redesign or secure funding to perform an LTB. Figure 3 depicts many different obsolescence mitigation strategies, many of which are of the non-modeling type.

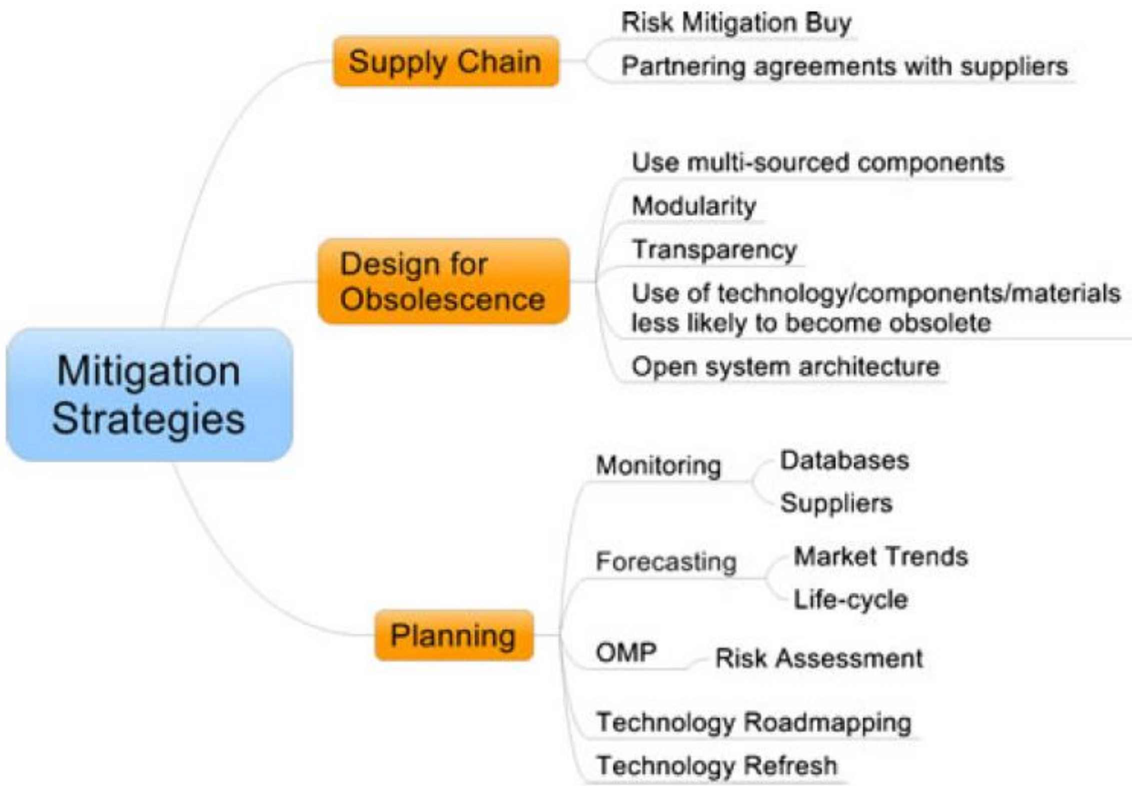

Figure 3: Obsolescence mitigation strategies (Rojo, 2010)

Technology refreshes are a useful way to help mitigate obsolescence issues by building in design refreshes to a system's lifecycle as a form of obsolescence management. According to Zheng (2015) there are a variety of ways to replace components at design refreshes. A component that is projected to be obsolete at a future time can be proactively substituted at any possible design refresh before it is obsolete, or it can be reactively replaced at the earliest design refresh once it is already obsolete (Zheng, Terpenny, & Sandborn, 2015). Figure 4 shows the optimal design refresh plan for components with projected obsolescence dates. The chart shows that even though planned designed refreshes can be put in place, reactive approaches will still be necessary when a component becomes obsolete between a refresh cycle.

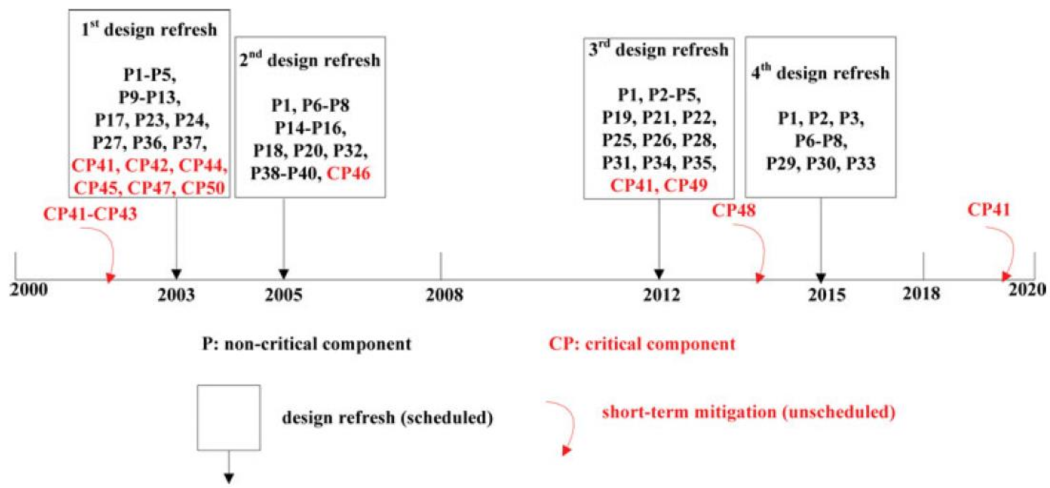

Figure 4: Optimal design refresh plan (Zheng, Terpenny, & Sandborn, 2015)

Having an open system architecture is one of the ways to break the dependence of systems on specific COTS technologies through "loose" coupling between applications and the underlying infrastructure of the platform (D.J.Jibb & J.B.Walker, 2000). The military is the largest holder of long-term assets. Being the sector that is affected the most by obsolescence issues, they are the ones who have named this issue the DMSMS problem (Feng, 2007). Much of the defense industry produces systems or parts that have strict requirements and are proprietary to the company itself or classified by the government, making open system architectures difficult to accomplish. Even though the United States Department of Defense has begun using open system architecture in limited cases, more research is needed to protect against security concerns using strict interface definition and control (Tokar, 2017).

1.3 Machine Learning Overview

The term artificial intelligence originates from the Dartmouth Conferences in 1956 when a group of computer scientists first defined the term and was the catalyst to propel the hypothetical concept into reality (Ongsulee, 2017). According to Bini (2018), artificial intelligence is the study of intelligent agents, which are devices that observe their environment and make decisions to maximize their chance of success at some goal. Some examples of artificial intelligence that we see in our everyday lives are, Apple's Siri, Amazon's Alexa, and natural language processing technology used to translate languages in Google Translate (Bini, 2018). Artificial intelligence makes use of the availability of graphics processing units that use efficient parallel processing of large amounts of data from various sources ranging from images, video, audio, text, transactions, and geospatial data (Ongsulee, 2017). Figure 5 shows a pictographic timeline of the invention time periods for artificial intelligence, machine learning, and deep learning.

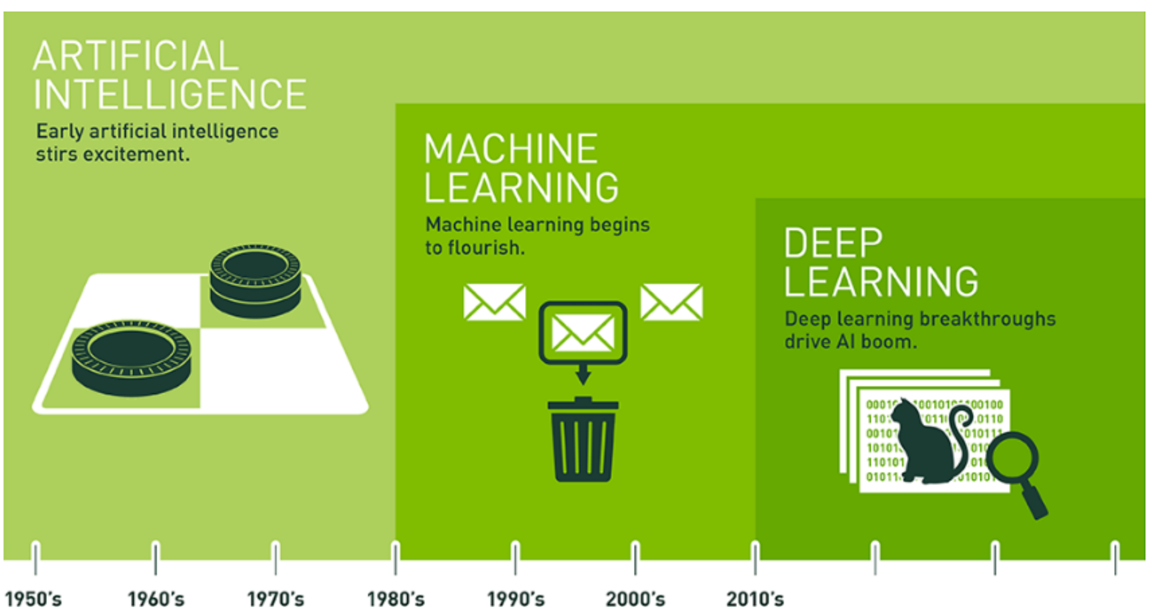

Figure 5: Timeline of Artificial Intelligence, Machine Learning, and Deep Learning (M, 2018)

Artificial intelligence is a broader concept than machine learning, which addresses the use of computers to mimic the cognitive functions of humans. (M, 2018). Machine learning is a subset of artificial intelligence and is a method of training algorithms so that they learn how to make decisions (Garbade, 2018). It is a scientific discipline that addresses how systems can be programmed to automatically learn and to improve with experience. To make this happen, the algorithms are developed to discover knowledge from specific data and experience, using statistical and computational principles (Intelligence, 2011). Ongsullee (2017) states that machine learning is related to and often compared to computational statistics, which also focuses on prediction-making using computers. It utilizes mathematical optimization, which delivers methods, theory, and application domains to the field (Ongsulee, 2017).

The three forms of machine learning are supervised, unsupervised, and semi-supervised. Brownlee (2016) states that with supervised learning, all data is labeled, and the algorithms learn and make their output predictions from the input data. Unsupervised learning is unlabeled, and the algorithms learn to categorize from the input data. With semi-supervised learning, some data is labeled but the majority is not, and it contains a combination of supervised and unsupervised techniques (Brownlee, 2016). Figure 6 shows a flowchart for the supervised machine learning process. Supervised learning is the method that will be used in this research as the data being used for the regression and classification analytics will be labeled.

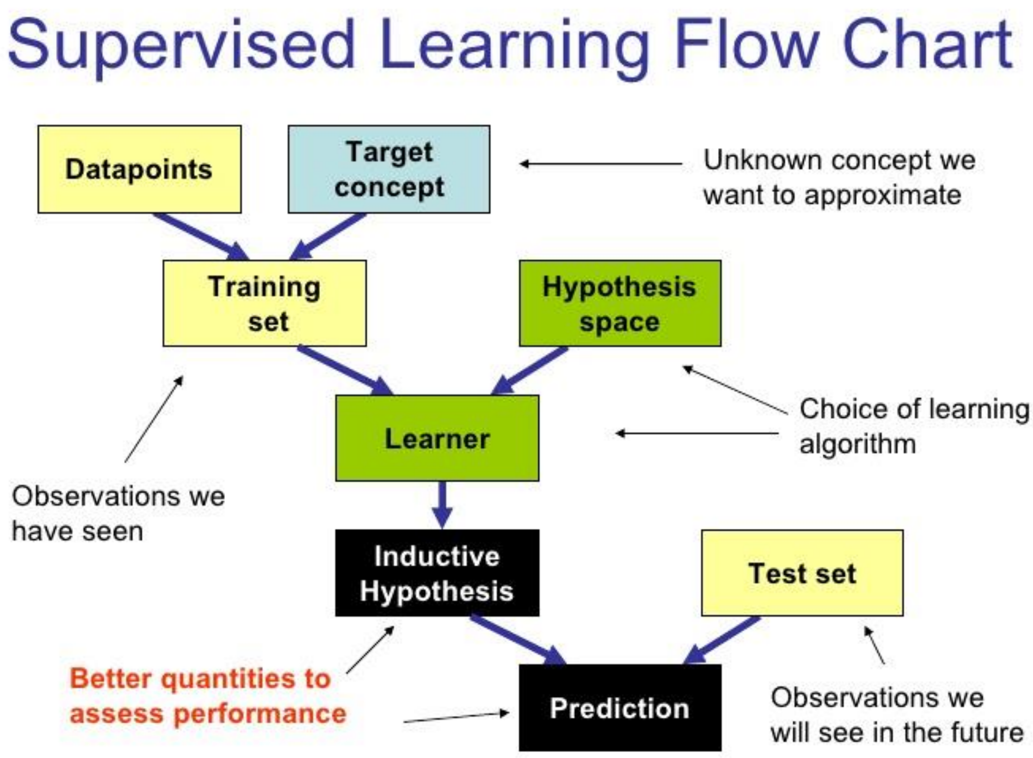

Figure 6: Supervised Machine Learning flowchart (Butest, 2010)

The model must first be trained to learn the mapping function using known information. These input attributes of a training data set have a known expected output value. This is essentially giving the model the questions and the answers to begin with. Once the model is trained, the mapping function should be able to calculate at such a high level that when you input new data with unknown outcomes, you can predict the output value for that data. Machine learning has gained popularity in many application fields because it can process large data sets with many applications from creating better recommendation systems on Netflix, facial recognition in pictures, and even cancer prediction and prognosis (Jennings, 2016). The entire field of artificial intelligence, encompassing machine and deep learning, will continue to grow and evolve as the demand for big data analytics continues to increase year after year.

There are a large variety of algorithms, and they all have their own special characteristics. Some are linear, some are nonlinear, and some can be a combination of both. Linear algorithms include logistic and linear regression. Support vector machines are unique in the sense that they can use what is known as a kernel to use a linear classifier to solve a non-linear problem. It involves converting linearly inseparable data to linearly separable ones. The kernel function removes the need to define large amounts of features and instead defines a single kernel function to compute similarity between prediction possibilities (Afonja, 2017).

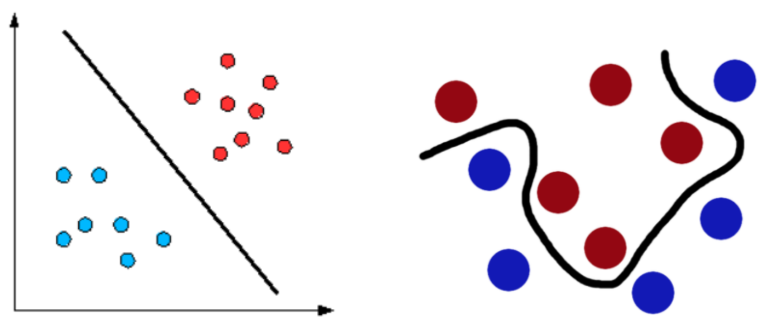

Figure 7: Linear vs Nonlinear problems (Afonja, 2017)

Figure 7 above shows a visual difference between trying to solve a linear problem on the left and a nonlinear problem on the right. According to Auret & Aldrich (2012), nonlinear models include artificial neural networks and random forests and they do not have the basic type of influence analysis as with linear models. Interactions and transformations of variables are accounted for and when variables change, the response will not necessarily change at a proportionate rate, for all possible values of all other variables. These unique correlations and interactions of variables can make interpretation of influence more difficult (Auret & Aldrich, 2012).

In machine learning, variables are called features and are the measurable characteristics or factors of an object being studied. Feature selection methods are used to identify and remove irrelevant and redundant variables from data that do not contribute to the accuracy of a predictive model or could decrease the accuracy of the model (Brownlee, An Introduction to Feature Selection, 2014). There are many feature selection techniques, but some common ones are filter methods, wrapper methods and embedded methods. Filter methods compare the relationship between features and the output to compute the importance of features, wrapper methods generate models with subsets of features and calculate their performances, and embedded methods utilize the insights provided by various machine learning models such as linear regression and random forest (Asaithambi, 2018). Figure 8 shows the basic feature selection flow chart for forward selection, which is a wrapper method algorithm that uses cross-validation for estimating the accuracy of a feature subset until the optimal subset is chosen (Hall, 1999).

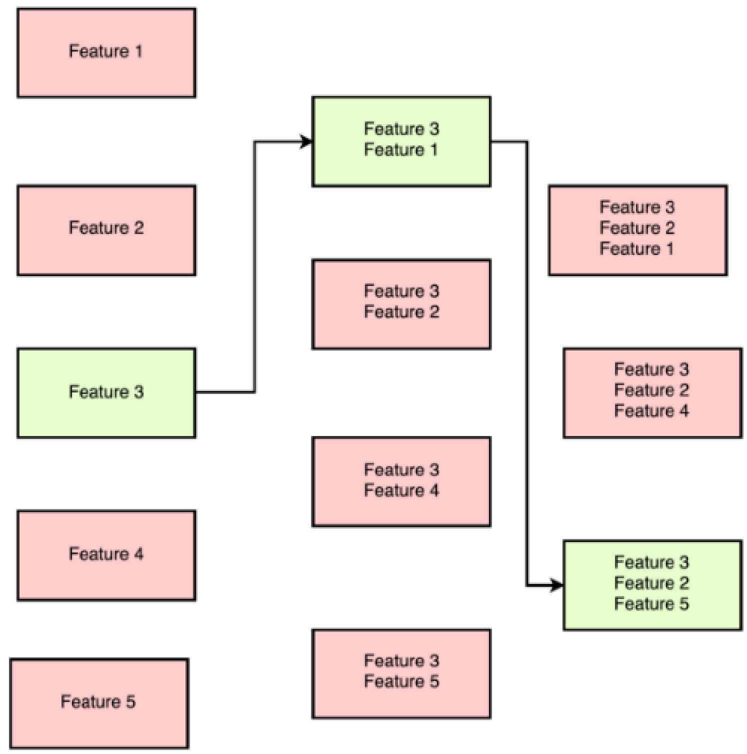

Figure 8: Forward selection decision flow chart example (Asaithambi, 2018)

The models primarily use heuristic approaches to evaluate the effects of individual features corresponding to each category to obtain an optimal feature subset (Cai, Luo, Wang, & Yang, 2018). Often it is unknown which variables in the data are going to be the most important, so using machine learning itself to help determine key attributes is extremely useful. The features in an original set can be placed into the four categories of completely irrelevant and noisy features, weakly relevant and redundant features, weakly relevant and non-redundant features, and strongly relevant features (Cai, Luo, Wang, & Yang, 2018).

One non-machine learning obsolescence study using linear regression found configurable logic blocks, maximum logic gates, logic cells, and maximum user input/out performance to be the most relevant model variables for Field Programmable Gate Array (FPGA) integrated circuits (Gao, Liu, & Wang, 2011). Using these approaches to classify features based on significance, therefore knowing what the important component attributes to look for are, will make it easier to acquire additional data and process it through the models in an accurate and efficient manner.

1.4 Common Machine Learning Practices

Machine learning is a tool that has already been used in a wide variety of industrial engineering studies. One study by (Candanedo, Feldheim, & Deramaix, 2018) was able to use the linear regression and random forest algorithms to predict missing data. Two regression models were trained to predict the average indoor temperature of a home using different sample sizes for the training set to detect differences in the error of the training and testing sets and how they respond as the sample size increases. The predictor variables, or features, for the models were outdoor temperature, humidity, windspeed, visibility pressure, temperature dew point, and total electricity use. The study determined the optimal sample size for the trained linear regression model was about 15,300 and random forest was about 27,300, with random forest having a smaller root mean square error. If the study were done using different models, the learning curves would display similar behavior and have specific optimal sample sizes of their own (Candanedo, Feldheim, & Deramaix, 2018).

When it comes to this research, there too may be instances of missing or incomplete data. Machine learning can help accurately fill in those gaps. Figure 9 shows how random forest regression models were able to reconstruct indoor temperate data with high accuracy.

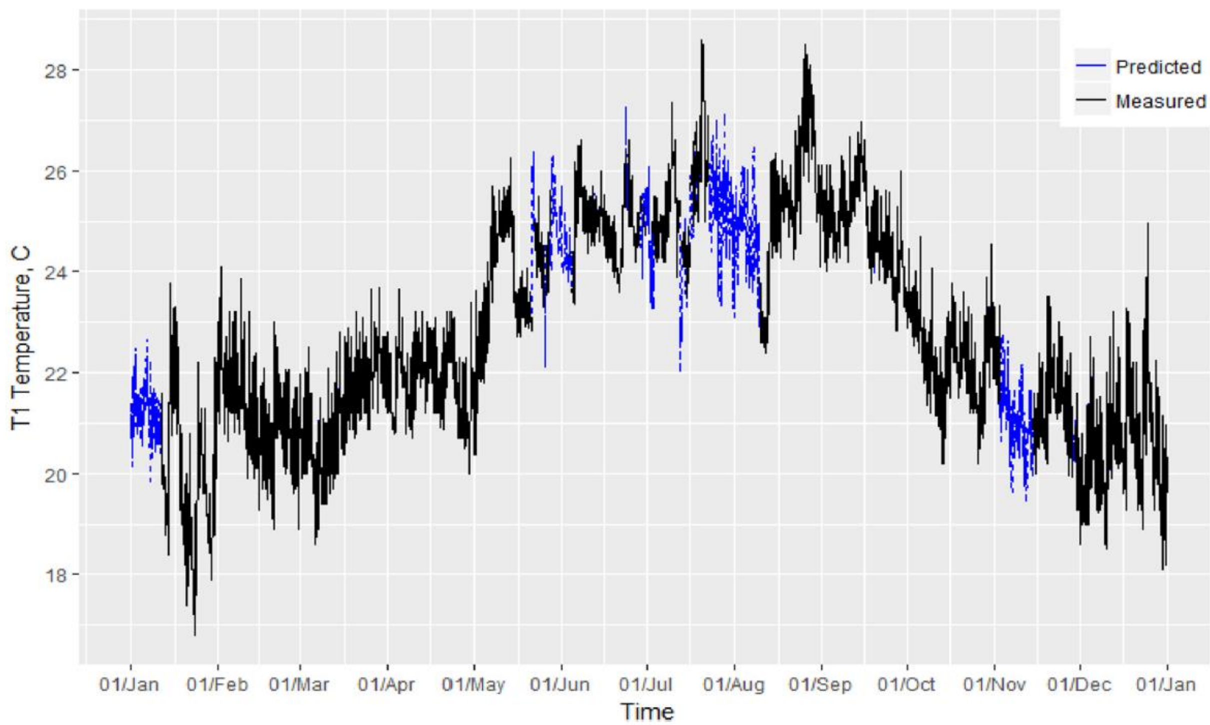

Figure 9: Machine Learning reconstructing missing data (Candanedo, Feldheim, & Deramaix, 2018)

Studies have been performed using deep learning, a specialized subset of machine learning, for prevalent topics in processing traffic data including transportation network representation, forecasting for traffic flow, traffic signal control, automatic vehicle detection, traffic incident processing, forecasting travel demands, autonomous driving and driver behaviors (Nguyen, Kieu, Wen, & Cai, 2018). At present, according to Gao & Sun (2018), a series of traffic flow forecasting methods have been proposed and applied, such as time series-based algorithms, nonparametric methods, local regression models and so on. Although these methods do improve the prediction performance to some extent, most of them only predict one link's unidirectional traffic flow at a time. This study was able to use neural networks to take the relevance of adjacent links into account and found out that 21 out of 31 road links had multilink predictions outperform single-link predictions resulting in improvements in short-term traffic flow forecasting (Gao & Sun, 2010).

A case study by Priorea et al. (2018) was done on job sequencing and job routing for flexible manufacturing systems using Support Vector Machines, Inductive Learning, Backpropagation Neural Networks, and Case-Based Reasoning using ensemble methods of Boosting, Bagging, and Stacking methods. Ensemble methods are procedures that combine multiple different models to improve results. Figure 10 shows a conceptual evolution of modeling methods for scheduling these systems. The models looked at arrival of parts, the relative workload, the due date, along with other features to calculate the best dispatching rule for each state (Priorea, Ponteb, Puentea, & Gómez, 2018).

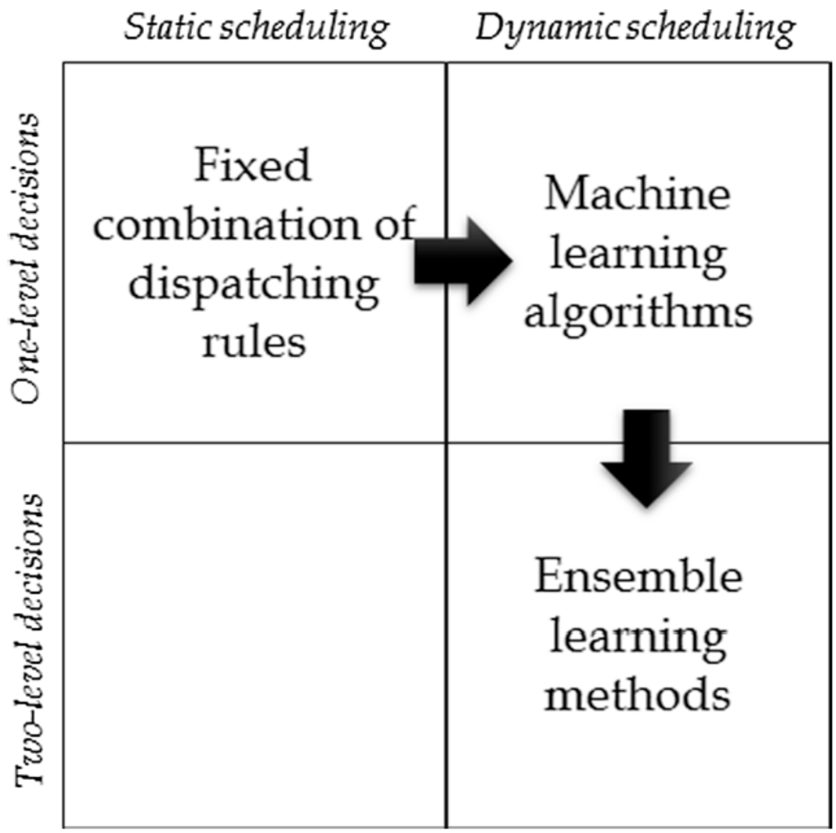

Figure 10: Approaches for scheduling of flexible manufacturing systems (Priorea, Ponteb, Puentea, & Gómez, 2018)

Machine learning has been used in various other applications with concepts that can be used for predicting obsolescence. A study by Kilham et al. (2018) used Logistic Regression, Classification and Regression Trees, and Random Forest algorithms to project large-scale forest growth and timber inventory estimates. In this study, the Logistic Regression models achieved higher overall classification accuracies, but tended to underestimate or overestimate the number of harvest shares for several subsets of the data. The Classification and Regression Trees models did a better job at estimating the harvest shares based on actual data from the National Forest Inventory (Kilham, Kändler, Hartebrodt, Stelzer, & Schraml, 2018). Table 1 and Figure 11 show the results for the classification accuracy and the number of harvest shares, respectively.

Table 1: Algorithm classification accuracy. Adapted and modified from (Kilham, Kändler, Hartebrodt, Stelzer, & Schraml, 2018)

Method	Classification Accuracy	Precision	Sensitivity	Specificity	Cohen's Kappa
Logistic Regression (MK)	0.670	0.737	0.747	0.536	0.280
Logistic Regression (YI)	0.642	0.773	0.618	0.684	0.280
CART and Random Forest	0.639	0.719	0.709	0.516	0.220
CART and random prediction	0.586	0.676	0.667	0.444	0.110
CART: Classification and Regression Trees; MK: Max Kappa; YI: Youden Index					

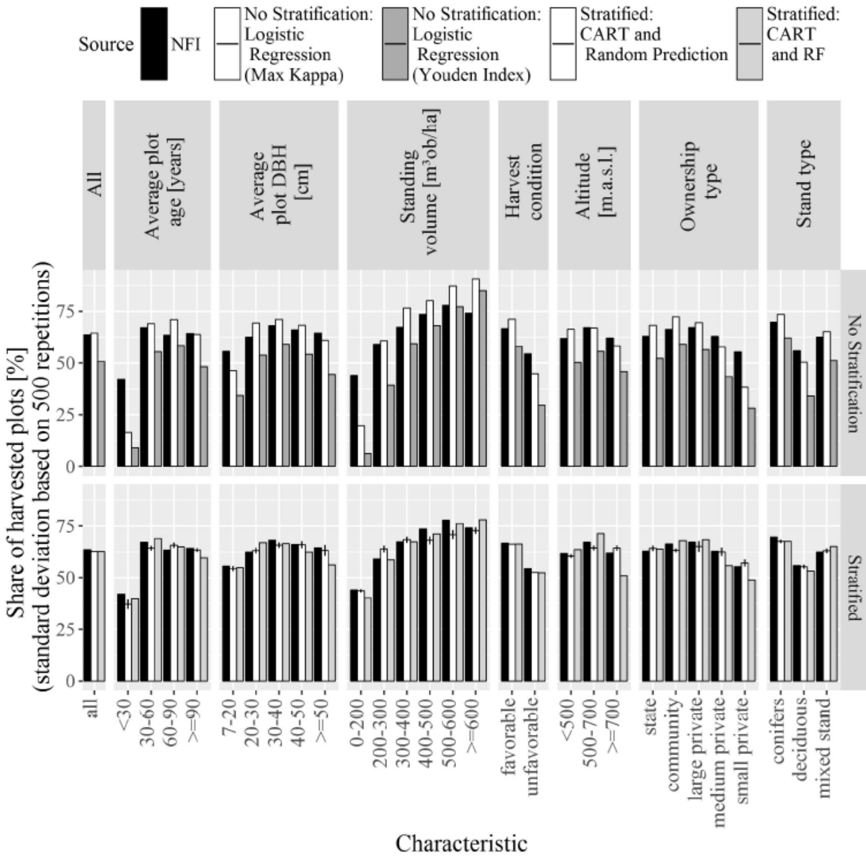

Figure 11: Shares of harvest plots algorithm accuracy (Kilham, Kändler, Hartebrodt, Stelzer, & Schraml, 2018)

Another study by Curtis et al. (2017) was conducted to predict waiting times for nonscheduled patients and delayed times for scheduled patients for various services at a radiology facility. The ten machine learning algorithms used were Neural Network, Random Forest, Support Vector Machine, Elastic Net, Multivariate Adaptive Regression Splines, K-th Nearest Neighbor, Gradient Boosting Machine, Bagging, Classification and Regression Tree, and Linear Regression. The two models that consistently performed the best and had the lowest root mean square error and highest R^2 were Gradient Boosting Machine and Elastic Net as depicted in Figure 12 (Curtis, Liu, Bollerman, & Pianykh, 2017).

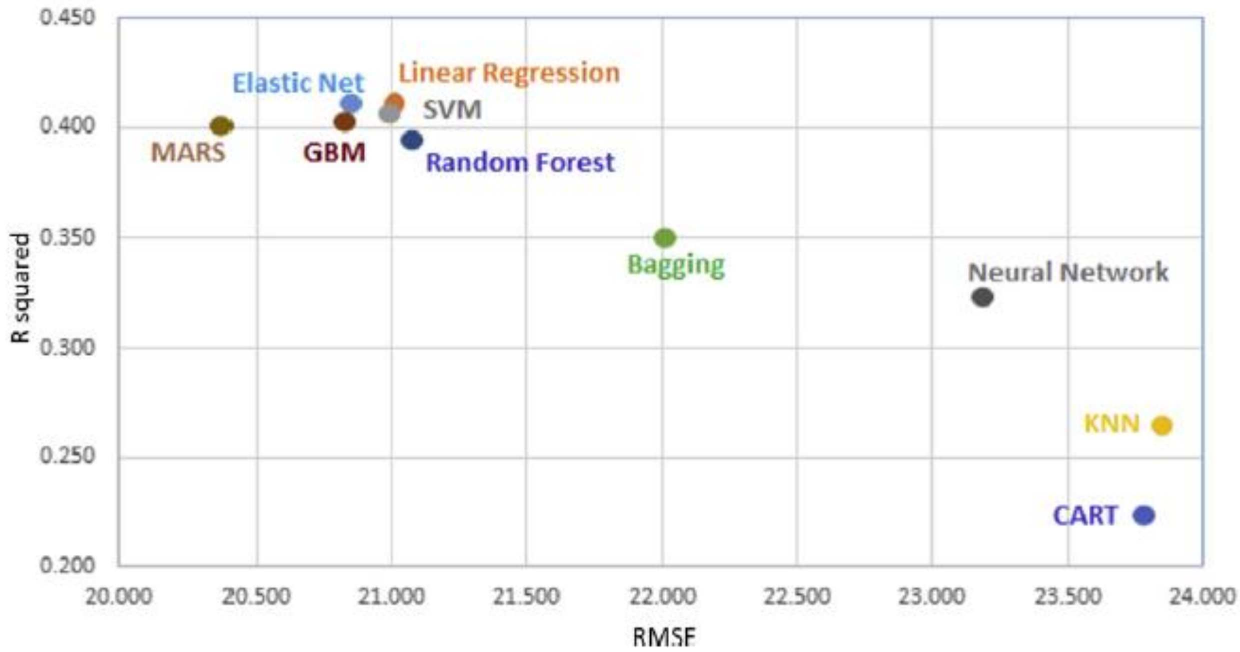

Figure 12: Lowest Root Mean Square Error and highest R^2 (Curtis, Liu, Bollerman, & Pianykh, 2017)

The above examples are all ways that industrial engineers and others alike are already performing research using machine learning approaches and should continue to do so in the future. Not only does machine learning show promise for predicting product discontinuation dates and creating obsolescence risk profiles, but it has also shown great use for interpreting missing data, traffic pattern and flow forecasting, and manufacturing job sequencing and routing. This research will be of value to anyone who is studying any sort of classification or predictive regression methods. An ancillary goal to this doctoral study is to help educate the industrial engineering research communities on various machine learning algorithms, performing in a multitude of big data situations, that can be beneficial and useful in their research endeavors.

This research shows great promise that machine learning can be used as a prediction tool, based on various input variables. Tailoring the inputs specifically to electrical components should be possible to predict a product discontinuation date with high accuracy, even with the human factor of a manufacturer deciding to discontinue a part for any reason at any time. It is important to note that most studies use a wide variety of algorithms for testing purposes. When conducting the experimental side for future research, the plan is to do the same as you do not know which model will be the most accurate until you test it.

1.5 Problem Statement

Research suggests a need for an effective managerial framework to tackling obsolescence. When it comes to forecasting obsolescence, today's best tools use traditional algorithms that analyze inputs using defined logic but are only as good as the logic provided.

1.6 Goal Statement

The aim of this research is to determine if machine learning predictive algorithms can accurately predict the product discontinuation date and availability status by a manufacturer and provide a framework for obsolescence management in military systems driven by best practices.

1.7 Research Questions

- Can machine learning algorithms be used to accurately forecast electrical component obsolescence?
- If the question above is true, which variables carry the most influence?
- What tools and strategies can be implemented to create an effective obsolescence management framework?

1.8 Potential Contributions to the Body of Knowledge

This goal of this research is to create an obsolescence management framework for anyone in the field of managing obsolescence issues with military based systems. This research could show the potential for using machine learning as a life cycle forecasting tool over traditional data mining tools. Machine learning could prove to be useful in the selection of components for system designs and creating BOM risk profiles. Another contribution the framework could provide is a clear path on how to find a solution to problems as the occur and how to manage these newly mitigated obsolescence issues.

1.9 Document Distribution

1. Chapter 1 is the introduction of this dissertation and covers a background on obsolescence, machine learning, the problem statement, the goal statement, research questions, and the potential contribution to the body of knowledge.

2. Chapter 2 is the Literature Review and covers obsolescence consequences, current practices, future practices, and the knowledge gap.
3. Chapter 3 is the methodology and covers the aims, data collection, framework development, algorithm selection, feature selection, Random Forest model validation, and framework validation.
4. Chapter 4 is the Initial Experiments and includes the case study and the related code for the Random Forest model.
5. Chapter 5 is the Results and Discussion and examines the classification and regression results from the Random Forest model.
6. Chapter 6 is the Best Practices Framework and discusses the pre-case, open case, post-case, and best practices portions of the obsolescence management framework. This framework also includes the benefits of using machine learning for DMSMS forecasting.
7. Chapter 7 is the Concluding Remarks and includes the dissertation conclusion, contributions to the body of knowledge, and the challenges, limitations, and future research possibilities.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

The UCF library electronic database was the source for researching background information on the topic of forecasting obsolescence. The searches resulted in 24,692 titles initially identified, 91 abstracts being read, 71 full text articles read for review, and 55 articles used in the Literature Review. Figure 13 below depicts an overview of the article selection process. It should be noted that there is not an abundant amount of scholarly information available on the topic of component obsolescence as it is still an area of product sustainment that is working to gain traction in industry.

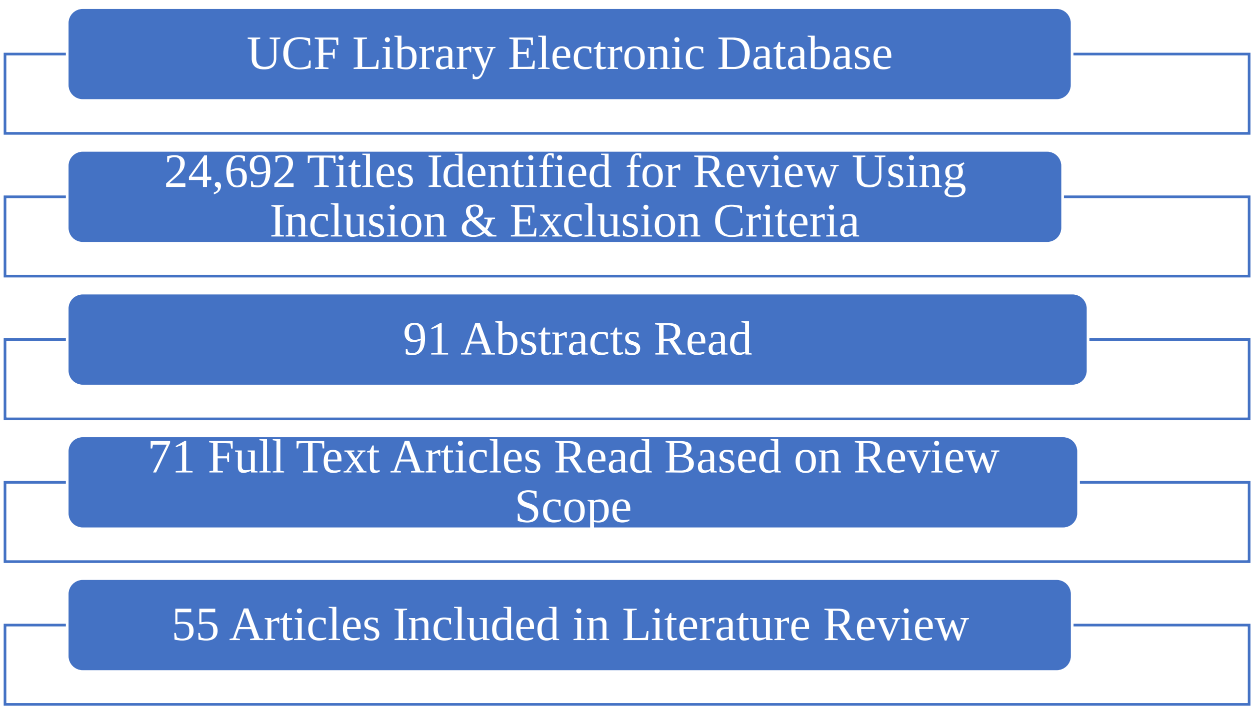

Figure 13: Literature Review article selection process overview

The aim of this research is to conduct an all-inclusive investigation on past studies of DMSMS, the issues involved, and tactics for mitigation. One of the toughest obstacles that face the supply chain industry today, stated by Amankwah-Amoah (2017), is the ability to procure obsolete components and the process for managing obsolescence while dealing with an evolving competitive environment. This issue is inflated when parts or components with short life cycles are employed in products with long life cycles such as capital-intensive military and electronic equipment (Amankwah-Amoah, 2017).

According to Underwood (2011), since the 1970's, the ever-expanding commercial markets surpassed the needs of the military and companies were no longer manufacturing military specific components. This has forced the military to utilize Commercial-off-the-Shelf (COTS) parts and thus be at the mercy of the demand of the electronics market (Underwood, 2011). In 1975 the military controlled approximately 17% of the electrical component market share and by 1995 it controlled less than 1% (Bell, 1998).

This research is exploring the various consequences, mitigation strategies, management techniques, and possible future areas of research in the field of obsolescence. A deep dive into the literature, as depicted in Figure 14 below, shows that the main areas of concern for obsolescence are cost optimization, obsolescence management, system life cycle, design/system refresh planning, architecture/open systems, and end-of-life predictions. It should be noted that in the End-of-Life (EOL) predictions category, of the six articles, there was only one article that proposed the idea of machine learning.

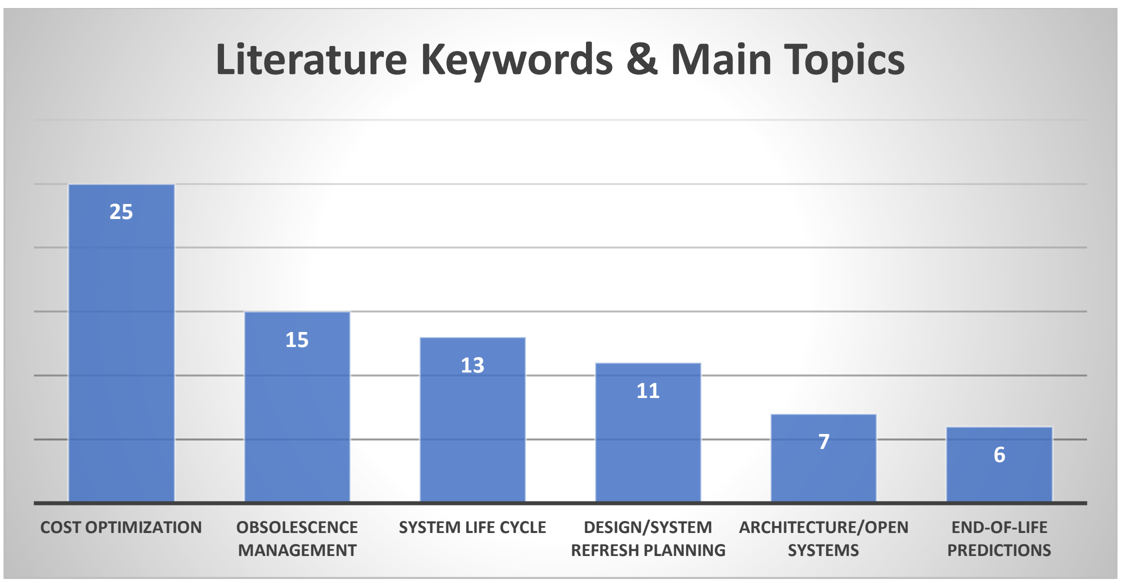

Figure 14: Literature Keywords & Main Topics

Of the 55 articles reviewed, 45% came from the academia sector, 35% from the industry sector, and 20% were from government sources. While most articles from all three sectors placed emphasis on life cycle or obsolescence management and minimizing costs, the academic sector had many articles focusing on forecasting techniques and looking towards future improvements. Some of these topics included forecasting design refresh points and predicting obsolescence dates. Figure 15 below depicts the sector of literature reviewed by count.

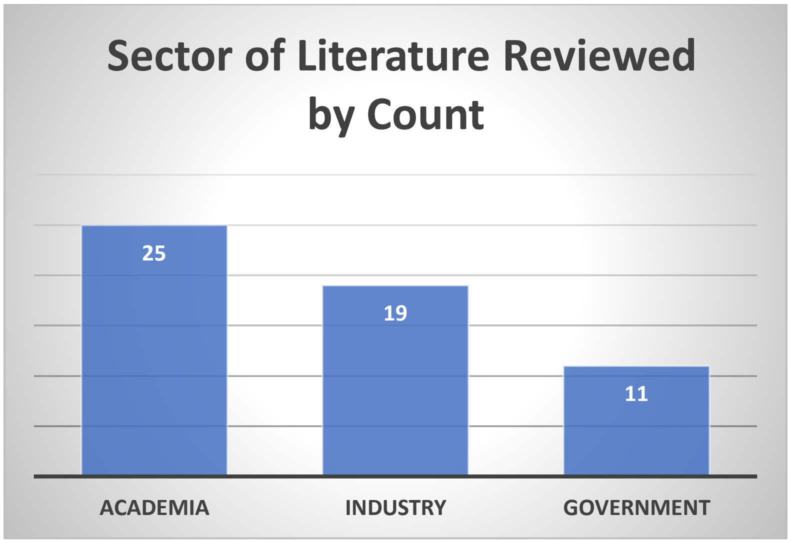

Figure 15: Sector of literature reviewed by count

Obsolescence studies are largely research areas for of citations, bibliometrics, scientometrics and infometrics (Mulla, 2013). DMSMS management is important because it guards programs from issues that can be caused by low-volume market demand, changing science or technology, deviations to detection limits, toxicity values, or chemical and material regulation changes, which can greatly affect the Depart of Defense’s (DoD) supply chain (Office D. S., 2016).

Since 2003, the Government-Industry Data Exchange Program built by the United States Department of Defense has been releasing information about DMSMS once a week rather than once a month, which shows that this issue is becoming more and more important for cost effective sustainment (Meng, Thörnberg, & Olsson, 2014). A key concern that the Navy has is being left behind as manufacturers introduce new products based on new technology and discontinue production and support of older items included in the initial designs of the various electronics systems (Office U. S., 2010). A greater emphasis on taking a proactive approach to the issue needs to take place rather than waiting for the problem to occur and then acting.

Systemic obsolescence is intentionally making a product obsolete by making it too difficult to continue using it, and programmed obsolescence is the intentional restriction of the use a product that requires the consumer to acquire a replacement (Shaffer, 2015). There are various assessments of product obsolescence that influence the decision of the manufacturer and the issue can be interpreted from an instrumental and consequentialist standpoint (Echegaray, 2016).

The components of the sustainment dominated systems typically go through the six life cycle phases of introduction, growth, maturity, decline, phaseout and discontinuance (Rojo, 2010). Once a part is discontinued by a manufacturer, your product is no longer functional, and it is up to a company's DMSMS team to take a proactive approach to try and catch issues ahead of time before a component's EOL reaches. Typically, a manufacturer will do this due to lack of market demand for that product line or the company may be having issues finding raw material to build the component. The customers are then given a defined window of time to perform what is known as an LTB. Customers will then internally decide if they would like to try and find a different supplier or determine if an alternate part that still performs to all their customer's requirements. If neither of those options are available, then they must perform a last-time-buy and purchase enough parts until they can perform a redesign of their product. Figure 16 below depicts a product's life cycle curve used for forecasting.

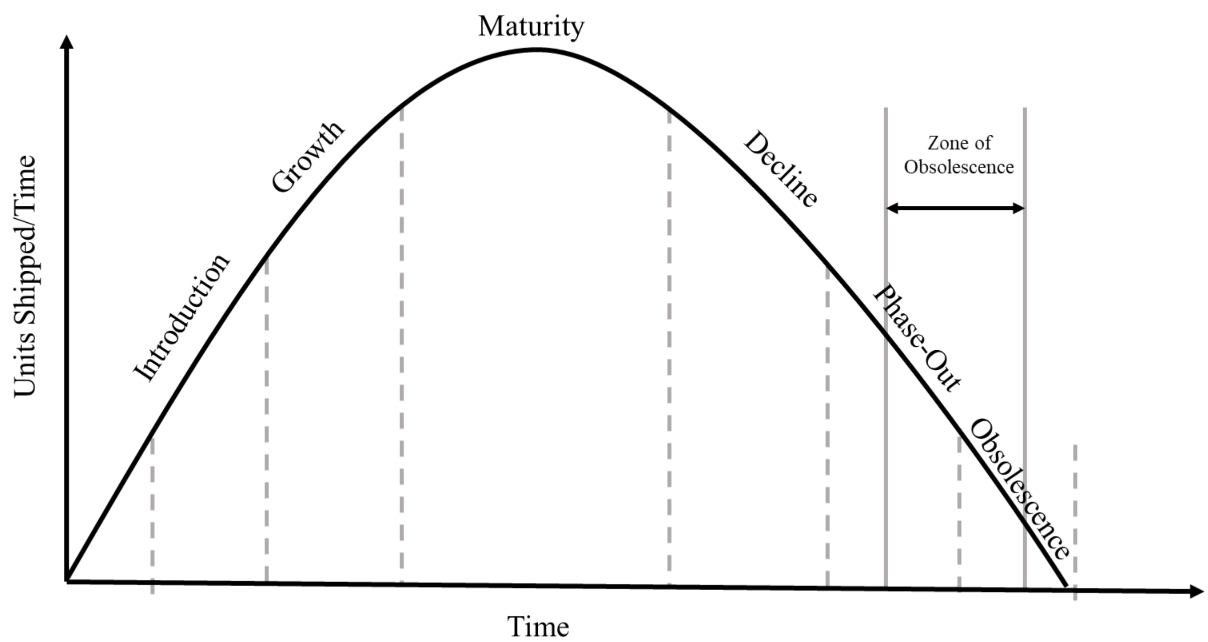

Figure 16: Life cycle forecast using Gaussian trend curve. Adapted and modified from (Soloman, 2000)

Soloman (2000) states that the introduction stage of a product's life cycle usually experiences high production costs that are created from costly designs, poor yield, constant modifications, everchanging rates in production, and improper production equipment. The growth stage shows an increase in sales that may validate the need to develop dedicated production equipment, which progresses the rate of production. Maturity of the part life cycle is represented by large amounts of sales. Decline shows slowing of demand and normally decreasing profit margin. The phase-out stage is when the manufacturer sets a production discontinuation date for a component. The obsolescence phase is when the manufacturer completely stops production of the component. It is possible that the component may still be available for procurement if the production line has excess components remain at an aftermarket source (Soloman, 2000).

As indicated by Sait (2016), a survey was directed via Automation Research Corporation (ARC) Advisory Group to analyze the best practices of the automation industry for managing the life cycle of process automation systems from start to finish. At the conclusion of the study, it was determined that the best practice for reducing the risk of automation obsolescence is to not through the procurement of proprietary solution but rather by incorporating multioperation COTS, open source, or technologies with more than one supplier into the system (Sait, 2016).

According to Fossum (1986), three major deficiencies exist in the study of skills obsolescence. The imprecision in its definition, there is no guiding model to suggest important variables and potential processes in its development, and a failure to use a multidisciplinary approach in explaining its development (Fossum, 1986). “The very pace of the evolution of these technologies creates a novel dilemma: what should I purchase, and when should I purchase it, given that I know that a better product, with more—and more powerful—features, will be coming out in just a few months?” (Sparrow, 2015, p. 232). Supporting and maintaining the machinery that contains end of life components often is difficult and expensive, which influences the reliability and safety of the product (Gao, Liu, & Wang, 2011). With that said, any type of mechanism that allows companies to upgrade their capabilities and counter obsolescence is considered valuable (Jain, 2015).

2.2 Obsolescence Consequences

Electronic component obsolescence is one of the largest technical risks a system can face regarding their operational uptime and maintainability (A. Meyer, 2003). Various mitigation techniques can be implemented, but they all affect reliability, maintainability, and cost of a system (Tomczykowski, 2003). When selecting new components for design, their reliability and maintainability must be taken into consideration. When left unchecked, obsolescence can put entire product lines out of commission due to an inability to manufacture new products or repair existing ones which has an excessive impact on business continuity (Nishant Verma, 2015). The following examples paint a picture of the financial risk and impact of component obsolescence on various sectors in the military and related environments:

- “Obsolescence is also very expensive, costing the US Navy (USN) hundreds of millions of dollars each year” (A. Meyer, 2003).

- “The Deputy Under Secretary of Defense for Logistics (USA) indicates that the average cost to redesign a (single) circuit card to eliminate obsolete components is $250,000” (A. Meyer, 2003).

- “The (USA) Air Force is reprogramming $81 million for the F-22 program to purchase obsolete or soon-to-be out-of-production parts and to redesign assemblies to accept commercial parts” (A. Meyer, 2003).

- “An avionics manufacturer for the commercial airlines spent $600,000 to replace an obsolete Intel chip” (A. Meyer, 2003).

- “The F-16 program has spent $500 million to redesign an obsolete radar” (A. Meyer, 2003).

Not every one of these situations could have been avoided but overlooking DMSMS issues for too long only makes the problem worse. On any program, one of the main goals is to minimize costs. This is where having a robust obsolescence management team in place can be used to avoid these extra expenses.

Complicating the issue even more is that most military based systems require the use of 5-volt logic devices while the commercial industry is quickly moving away from 5-volt logic and towards 3.3 volts and lower (Glum, 2000). According to Tomczykowski, as technology continues to advance, digital designers can create higher densities at faster speeds with lower voltages. The main benefits include lower operating temperatures, speed, and size in low power commercial products, but this movement will catalyze a further increase in obsolescence for the DoD, airlines, and others alike (Tomczykowski, 2003). Before the year 1999, the procurement life for these components was decreasing as industry was shifting to 3.3 volts and lower components. However, as seen in Figure 17 below, 5 volt components introduced to the market after 1999 have been seeing slight increases in procurement life as manufacturers of these parts are seeking out platforms that are either slowly transitioning or not at all moving towards applications that utilize lower voltages (Sandborn P. , 2011).

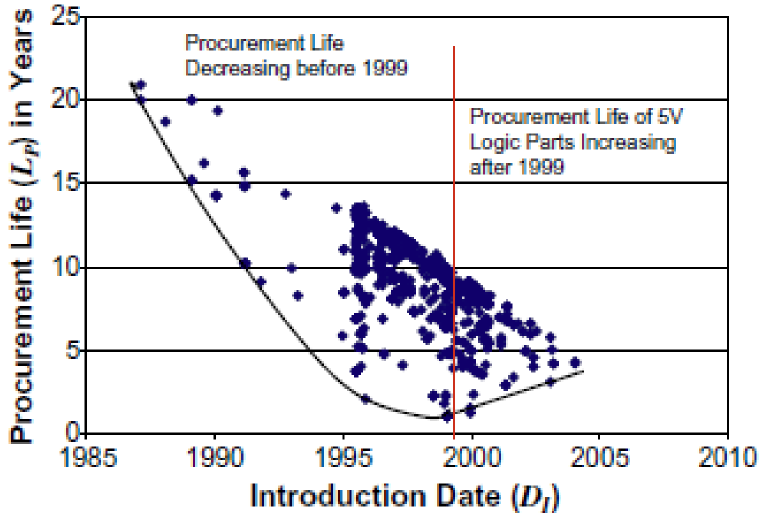

Figure 17: 5V Bias Logic Parts (Sandborn P. , 2011)

Obsolesce can also pose an impact to the reliability and maintainability of a system. The Government-Industry Data Exchange Program (GIDEP) is a voluntary data exchange agreement between the US government and industries that provides critical DMSMS information which has impacts on system reliability life cycle cost (Underwood, 2011). Tomczykowski (2003) states that if not proactively managed, DMSMS could lead to higher operational downtime and decreased reliability if certain mitigation solutions are not thoroughly investigated. The solutions that require the highest reliability and maintainability considerations include reclamation, aftermarket, and emulation due to potential defects or variations in manufacturing processes (Tomczykowski, 2003).

2.3 Current Practices

Most of DMSMS management today is reactive based which means that the management process starts once discontinuance occurs using various mitigation techniques such as: last-time-buy, aftermarket sources, substitute parts, emulated parts, salvaged parts, and thermal uprating (Sandborn P. , 2011). Conventionally speaking, according to Zheng (2015), efforts to mitigate the effects of DMSMS have been reactive in nature. This reactive DMSMS management method brings forth faster, but more expensive, solution paths with desirable short-term wins to avoid having an irreparable or producible system, but it overlooks the long-term solution paths that could reduce or prevent future DMSMS issues (Zheng, Terpenny, & Sandborn, 2015).

However, merely replacing obsolete components with updated components is not always feasible because of high re-engineering costs and system requalification and recertification costs (Zheng, Terpenny, & Sandborn, 2015). Strong long-term management of DMSMS in systems required the problem to be addressed on reactive, proactive, and strategic levels of management. (Zheng, Terpenny, & Sandborn, 2015). Reactive mitigation approaches involve the use of alternate or substitute parts, aftermarket sources, lifetime buys, thermal uprating of parts, and emulated parts (Konoza, 2014). On the other hand, proactive management involves part criticality analysis, critical spare part stocking, maintenance planning, and strategic solutions include planning design refreshes based on forecasted part obsolescence (Konoza, 2014). A strategic proactive obsolescence approach consists of an LTB quantity, timeframes for redesigning, and determining which components should be replaced during the redesign periods (Meng, Thörnberg, & Olsson, 2014).

According to Solomon (2000), "Uprating is becoming a common mitigation approach because the obsolete part is often the "MIL-SPEC" part while the commercial version of the part continues to exist. In some cases, the best obsolescence mitigation approach for OEMs who need a broader environmental range part (often automotive, avionics, and military) is to "uprate" the commercial version of the part" (Soloman, 2000).

Using a component with a higher industry wide demand such as a commercial grade piece may help with EOL issues, but government and system requirements may call for higher specifications that only industrial or military grade components may have. Even with that said, the defense industry has less control over the supply chain for commercial off-the-shelf electronic components. These components are being discontinued at a progressively fast rate. Hence, it is worthwhile to create strong relationships with suppliers to increase the time of support and provision of critical components (Rojo, 2010).

2.3.1 Reactive Measures

A strong obsolesce management program is going to consist of both reactive and proactive measures. These measures include decisions made after the part is obsolete and actions taken prior to minimize risk or get ahead of the issue altogether. Many mitigation solutions can be used in conjunction with one another and fall into the reactive category.

2.3.1.1 Existing Stock

When there are already enough parts in stock to last the remainder of a system's life, no further action is required to mitigate the obsolescence problem. If the amount of existing stock will only partially fulfill the required needs, an additional mitigation will be needed such as a substitute part or LTB.

2.3.1.2 Reclamation

This is the use of a component from non-repairable systems or subassemblies also known as cannibalization. This option is not recommended by the Defense Reutilization and Marketing Service (DRMS) and should be used as a last resort due to potential reliability impacts from the reuse of components (Tomczykowski, 2003).

2.3.1.3 Alternate or Simple Substitute

This is the use of a different component that has the same form, fit, and function of the existing component. It can meet or exceed the requirements of the existing component in use that has gone obsolete. These components can also come from an aftermarket source where manufacturers are authorized by the original equipment manufacturer (OEM) to reproduce obsolete components using existing wafer and die (Tomczykowski, 2003).

2.3.1.4 Complex Substitute

This is the replacement of the obsolete component with one that has different specifications but does not require modification of the source product or the next-higher assembly (NHA) (Office D. S., 2016). These components can also come through emulation where the component is replaced with another that emulates it. (Tomczykowski, 2003). This type of substitute must be thoroughly tested.

2.3.1.5 Last-Time-Buy and Bridge Buy

An LTB consists of procuring enough components to last until a system is no longer in service. A bridge buy is purchasing enough components until a redesign can take place. With both solutions, the production and sustainment usage demand for the component must be taken into consideration to properly calculate the needed quantity.

2.3.1.6 Circuit Board Redesign – Next Higher Assembly (NHA)

When no substitute components exist, or a new component cannot be used unless the circuit card is redesigned, an NHA redesign may be used. In this scenario, only the NHA is affected, and the new design will not result in any changes above this level (Office D. S., 2016). A bridge buy is usually necessary to have enough inventory to last until the NHA redesign is complete.

2.3.1.7 Complex/System Redesign

This redesign involves multiple changes to various parts of the system beyond the NHA of the obsolete component. This is the costliest mitigation option, and a bridge buy is usually necessary to have enough inventory to last until the system redesign is complete.

2.3.2 Cost Avoidance

Each of the mitigation techniques mentioned above has an associated cost upon implementation. One of the principal metrics that an Obsolescence Management Team (OMT), also known as a DMSMS Team (DMT), tracks is cost avoidance. The cost avoidance of a solution relates to the cost difference between the solution being implemented and the next most feasible solution (Office D. S., 2016). An example of this would be if a simple substitute and complex redesign were determined to be the only two solutions, then the cost avoidance for that case would be \$10,473,148 - \$12,805 = \$10,460,343. Table 2 below shows the average cost associated with each resolution option. The data comes from a 2014 Department of Commerce survey of government and commercial DMSMS programs (Office D. S., 2016).

Table 2: Average cost associated with implementing each DMSMS resolution option (Office D. S., 2016)

Resolution option	Average[85]
Approved item	$1,047
Life-of-need buy	$5,328
Simple substitute	$12,805
Complex substitute	$25,867
Extension of production or support	$25,930
Repair, refurbishment, or reclamation	$66,185[86]
Development of a new item or source	$667,209
Redesign–NHA	$1,112,528
Redesign–complex/system replacement	$10,473,148

2.3.3 Proactive Measures

There is not one catch all solution that will proactively manage a system's obsolescence issues. Key areas to focus on include having a robust supply chain, designing your system with obsolescence in mind, and planning for mitigating issues before they occur. It is essential that your supply chain has multiple sources and strong supplier relationships. Also, an open system architecture allows for easier replacement of components as old ones are discontinued. Having an OMT that constantly tracks obsolescence cases is imperative for catching DMSMS issues. They monitor current and past cases to make sure part shortages do not occur.

The latest research in DMSMS consists of various models for forecasting the discontinuance for proactive management. Figure 18 below shows multiple forecasting methods provided through different researchers that will be shown throughout this paper.

LIST OF ALL METHODOLOGIES AND SCALABILITY FACTORS

Methods	Life-Cycle Forecasting	Obsolescence Risk Forecasting	Sales Data Required	Human Inputs	Multi-Feature Capable
ORML	-	✓	-	-	✓
LCML	✓	-	-	-	✓
Solomon et al. (2000)	✓	▪	✓	✓	✓
Sandborn (2005)**	✓	▪	✓	▪	▪
Josias (2009)	▪	✓	▪	✓	✓
van Jaarsveld et al. (2010)	▪	✓	✓	✓*	✓
Sandborn (2011)**	✓	▪	▪	▪	✓
Rojo et al. (2012)	-	✓	-	✓*	✓
Zheng (2012)	✓	-	✓	✓	✓

Notes:

*Human bias due to manually filtering the BOM

**Sandborn 2005 & 2011 are different methods but the same creator

Figure 18: List of various forecasting methods (Jennings, 2016)

Proactive management entails forecasting and tracking obsolescence risk for the system's components (Meng, Thörnberg, & Olsson, 2014). It includes part criticality analysis, spare stock posture, and planning for maintenance (Konoza, 2014). Figure 19 below depicts how early and proactive engagement will result in fewer obsolete components in a system over time.

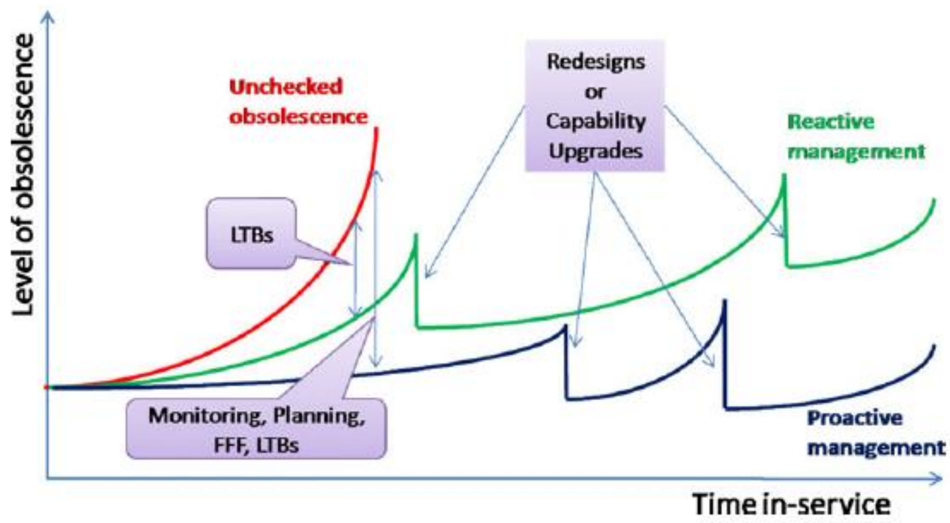

Figure 19: Levels of obsolescence based on the type of management (Rojo, 2010)

Building in design refreshes to a system's lifecycle is a form of proactive obsolescence management. According to Zheng (2015) there are a variety of ways to replace components at design refreshes. A component that is projected to be obsolete at a future time can be proactively substituted at any possible design refresh before it is obsolete, or it can be reactively replaced at the earliest design refresh once it is already obsolete (Zheng, Terpenny, & Sandborn, 2015). Issues arise though with high costs and timely redesigns. High costs and initial investments often mean that they will only realize a return on investment if they are able to operate for a long time, sometimes 20 or more years, thereby sometimes making is more desirable to keeping working with older technology (Amankwah-Amoah, 2017).

The highest form of obsolescence mitigation is called strategic management and involves planned technological refreshes to keep the newest components with the freshest life cycles in the system. Much of the latest DMSMS research today falls into the proactive or strategic categories. According to Sandborn (2011), “Proactive management means identifying and prioritizing selected non-obsolete parts that are at risk of obsolescence and identifying resolutions for them before they are discontinued. Design refreshes ultimately occur as other mitigation options are exhausted and functionality upgrades becomes necessary. Strategic management is done in addition to proactive and reactive management and involves the determination of the optimum mix of mitigation approaches and design refreshes” (Sandborn P. , 2011).

One mitigation method is to perform a risk/cost benefit analysis on designing for obsolescence for the purpose of long-term sustainment. The benefit of this design approach is you can potentially increase the life of your product by using electrical components that have had fewer years in the marketplace. The downside is engineers are having to design with components with limited real-world test data which can lead to other complications down the road if appropriate measures are not taken. These material shortages, because of obsolescence of instruments for both research and instruction, have brought alarm to engineers in academia and industry about whether institutions can keep their capacity to provide quality products (National Science Foundation, 1981). Another approach is modernization through known synchronous revision frequency and throughout a system life cycle (Herald, 2012). With this approach, built in technological refreshes keep the components within the system up to date and are less likely to become discontinued by a manufacturer while your system is still in use.

According to Zheng, ontology is a clear formal requirement of the terms and their relations for sharing data in a domain. In product design and development, an assembly design ontology has been established for cooperative product development. Ontology has also been practical to provision product conceptual design. Defined ontologies can be reused, even though there has not been a specific ontology to be defined for the problem of obsolescence. The obsolescence forecasting technique characterized with ontology fits the sales data to acquire the product life cycle curve and calculates years to EOL and life cycle steps created on the life cycle curve (Zheng, 2013).

Pobiak (2011) states that the House of Systems Engineering (HOSE) is a system engineering architecture framework and was introduced in 2010. The framework shows the holistic view of systems engineering rather than an isolated style. This system engineering architecture framework can be used to build successful obsolescence management systems, can support educational organizations in teaching system engineering principles, and will be a valuable instrument for systems engineers from an all-inclusive viewpoint (Pobiak, 2013).

According to Rio (2014), many studies have shown that the implementation of any type of new technology is expensive. Increases in obsolescence expenditures, reduces investment in the short run which causes a time of low productivity. Rio's simulations show that increases in the obsolescence costs, caused by the acceleration of equipment–specific technical development, shows the slowing in productivity. Since 1974, there has been a large slowdown in productivity in the United States, and a lot of it can be attributed to these technological changes (Rio, 2014).

Lawlor (2015) states that arguments suggesting that the people should not be so focused on planning for obsolescence, which is already characterized as being inevitable. It can be argued that focusing on the fact that obsolescence is inevitable diverts attention from the fact that changing when a component goes end of life can have a substantial impact in terms of reducing waste. With that said, these views have been criticized for being too conservative. It is being suggested that obsolescence should not solely be planned for, but it should also be trying to be delayed (Lawlor, 2015).

According to Herald (2012), a study led by the National Defense Industrial Association (NDIA) shows that "rapid evolutionary advances in information technology are expected to continue unabated - (resulting in) continued short technology life spans." Two models were used called the system element life cycle cost (SELCC) and the obsolescence revision sequences. Both models essentially showed that having multiple vendors and have multiple insertion points for technology refreshes are required for best obsolescence management practices (Herald, 2012). In addition to utilizing the latest information to update technologies, there is a need for companies be more aware of equipment and components as a way of recognizing and responding to indicators of obsolescence as shown in Figure 20 below (Amankwah-Amoah, 2017).

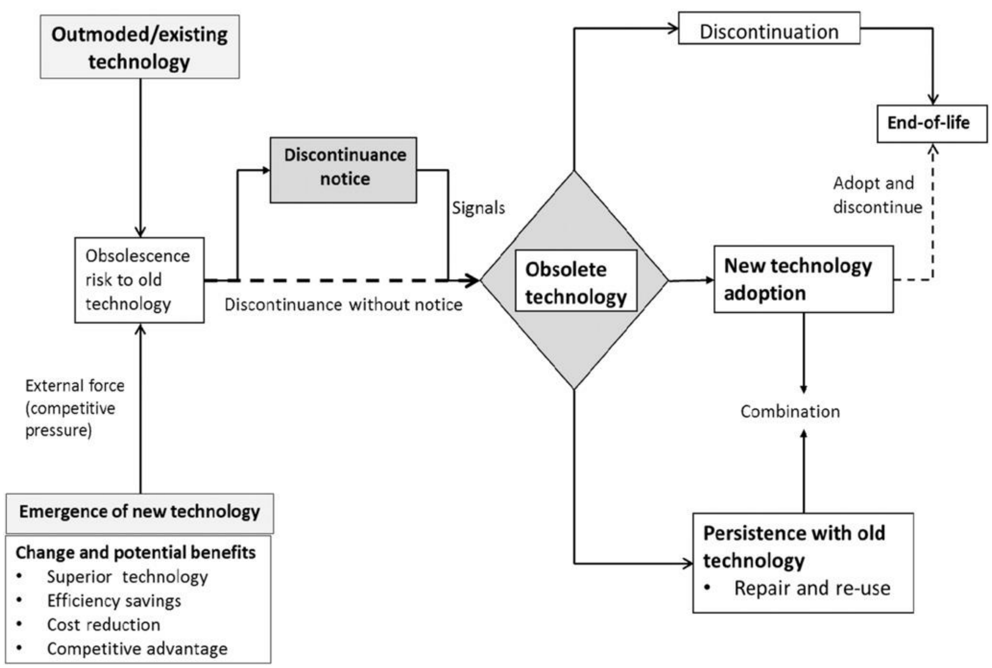

Figure 20: Intersections of technology change and technology persistence (Amankwah-Amoah, 2017)

Furthermore, Figure 21 shows the defined cost be the expected cost for the remainder of an obsolescence cycle as the inventory runs out over time (Emsermann, 2007). Whatever extra profits are expected on upgrading technology need to uphold existing capacity of production to help edge off any production reduction (Patriarca, 2009).

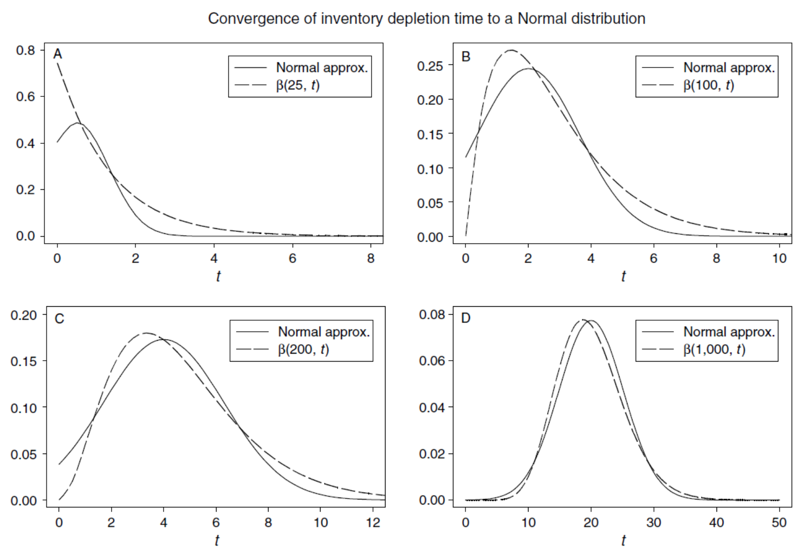

Figure 21: Inventory depletion over time (Emsermann, 2007)

Research performed by Sandborn (2007) shows an obsolescence forecasting approach using life cycle curve forecasting methodology created by curve fitting sales data for an electrical component. Historically, most techniques involved some sort of ordinal scale or data mining approach with linear regression that usually only performs well when the true obsolescence date is near. Figure 22 shows a data mining trend equation of historical and forecasted sales data for monolithic flash memory being used to try and forecast future chip discontinuation dates.

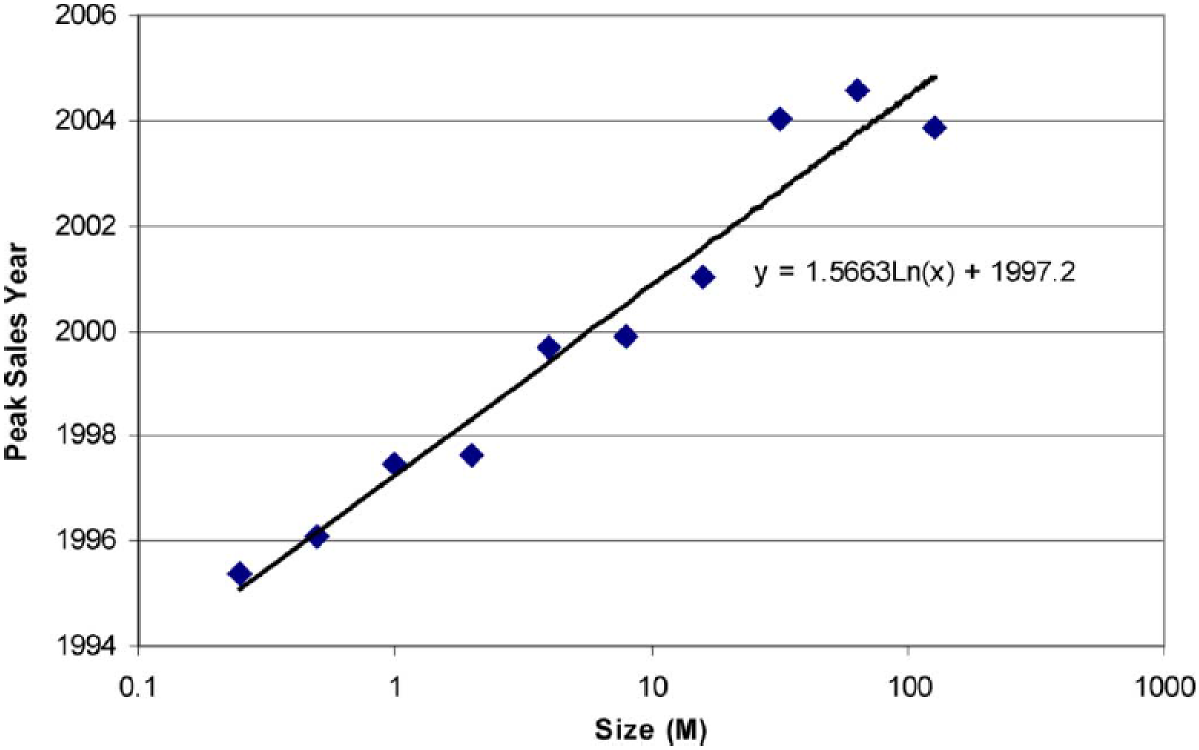

Figure 22: Trend equation for peak sales year for flash memory (Sandborn P. A., 2007)

The characteristics of the curve fits are graphed, and functions based on the trends are determined to calculate the life cycle curve of that component. The first technique offers a way to make the life cycle curve for component family with memory size being its primary attribute. The second method is a determination of electrical component obsolescence using vendor-specific windows from data mining historical last-order or last-ship dates. The combination of the life cycle curve trends and vendor-specific windows substantially improved the accuracy of the algorithm for forecasting flash memory obsolescence dates compared to the original algorithm of a fixed window as shown in Figure 23 (Sandborn P. A., 2007).

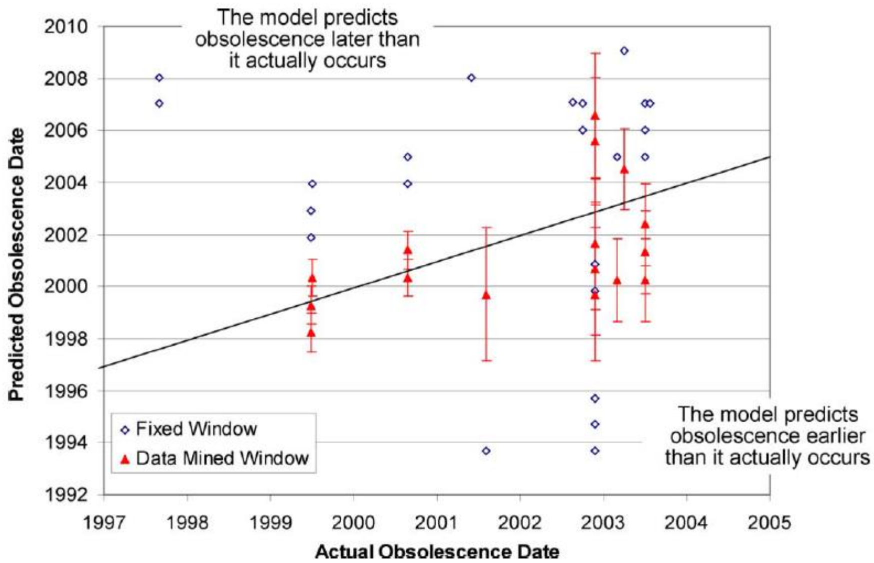

Figure 23: Obsolescence Date Comparison of Old and New Algorithms (Sandborn P. A., 2007)

2.3.3.1 Design for Obsolescence & Cost Optimization

Designing for obsolescence can include designing the physical architecture of a product to have multiple component replacement options and the overall management plan for combatting component discontinuance. These physical strategies include implementing open architecture, functional partitioning, and technology insertion which need to be addressed during system engineering, detailed design, production, and product support (Young, 2001). One method is to divide the hardware into distinct partitions using modularity that is afforded by open architecture to functionally split the system into multiple platforms (Young, 2001). Many companies use the terminology of Line Replaceable Module (LRM) or Line Replaceable Unit (LRU). Often performance constraints supersede any obsolescence management concerns to use functional partitioning when designing a system, which can make this an unusable solution (Sandborn P. , 2007).

A study done by Feng (2007) also looks at cost minimization from an LTB perspective. He developed a tool called the Life of Type Evaluation (LOTE) tool to optimize LTB quantities. This tool looked at and compared demand distributions, holding costs, system downtime or unavailability penalties from the customer, and excess component disposal costs. The study determined that some companies may be placing more emphasis on their contractual penalties for system unavailability and not enough on the procurement, holding, and disposal costs of conducting LTBs. As a result, they may be purchasing more components than necessary (Feng, 2007). However, this is completely dependent on the language of the contact and for some situations, especially military systems, downtime is not an option. This means having too many parts outweighs to consequences having too few.

Herald (2012) also proposes two different models for system refreshes that focus on optimizing the cost of the system during its lifetime. The two models are the System Element Life Cycle Cost (SELCC) and Obsolescence Revision Sequence (ORS). Figure 24 below depicts the S-curve associated with the acquisition cost of a specific system element.

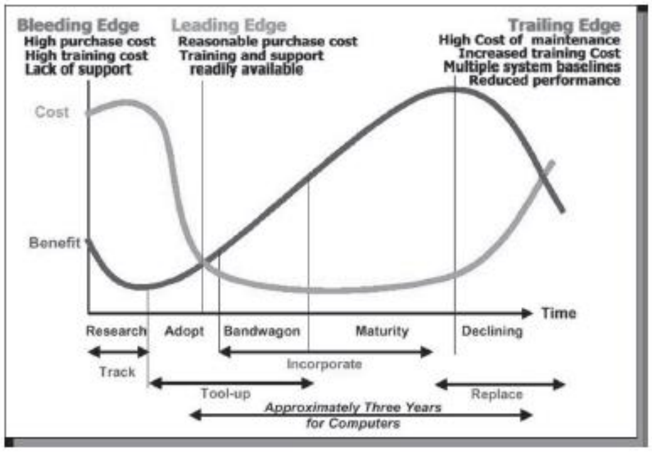

Figure 24: Market sales benefit S-curve vs. support cost (Herald, 2012)

The bathtub type curve shows high costs at the bleeding edge and the lowest cost during the maturity phase of the component. There is a benefit to cost ratio intersection where a component should be purchased called the leading-edge point and then another point towards the end of the maturity phase where the component should be replaced to minimize total cost. The ORS model uses the inputs from the SELCC model and provides a mathematical representation for optimizing the rate and sequence of system element revisions (Herald, 2012).

2.3.3.2 Management & Tools

According to Sandborn (2007), designing your management plan for obsolescence focuses on the problem of minimizing the life cycle cost of sustaining the system. Figure 25 below shows a hierarchy of design for involuntary obsolescence activities that can be implemented to help manage this issue (Sandborn P. , 2007).

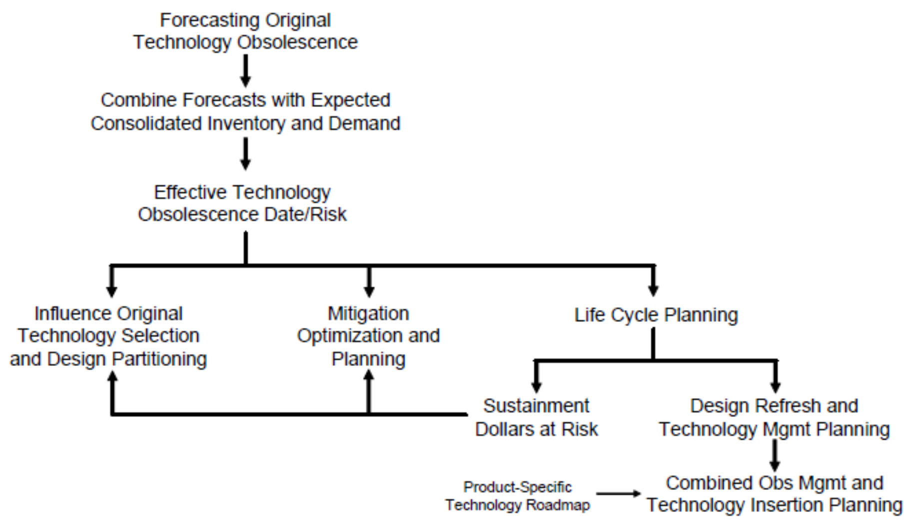

Figure 25: Hierarchy of design for involuntary obsolescence activities (Sandborn P. , 2007)

The management process for selecting new components in a design and the development of a system is complex and should be done with an iterative process. According Lebron (2000), this process can be broken into the three stages of operational requirement analysis, COTS solutions for these requirements, and a COTS assessment. During the COTS assessment, the components are reviewed for performance, reliability, cost, and obsolescence risk. A system designed with open architecture is beneficial when a component goes obsolete because systems designed under completely closed and proprietary architecture typically require complex redesigns or new interfaces to incorporate new components (Ruben A. Lebron Jr., 2000). Figure 26 below shows the iterative decision analysis process that occurs when there is need for a new design. Other management considerations that go into the component selection process should include Critical Material Analysis (CMA), to check for hazardous materials and potential material shortages for a component selection and contracting language that proactively sets customer money aside to resolve obsolescence issues that may occur in the future (Office D. S., 2016).

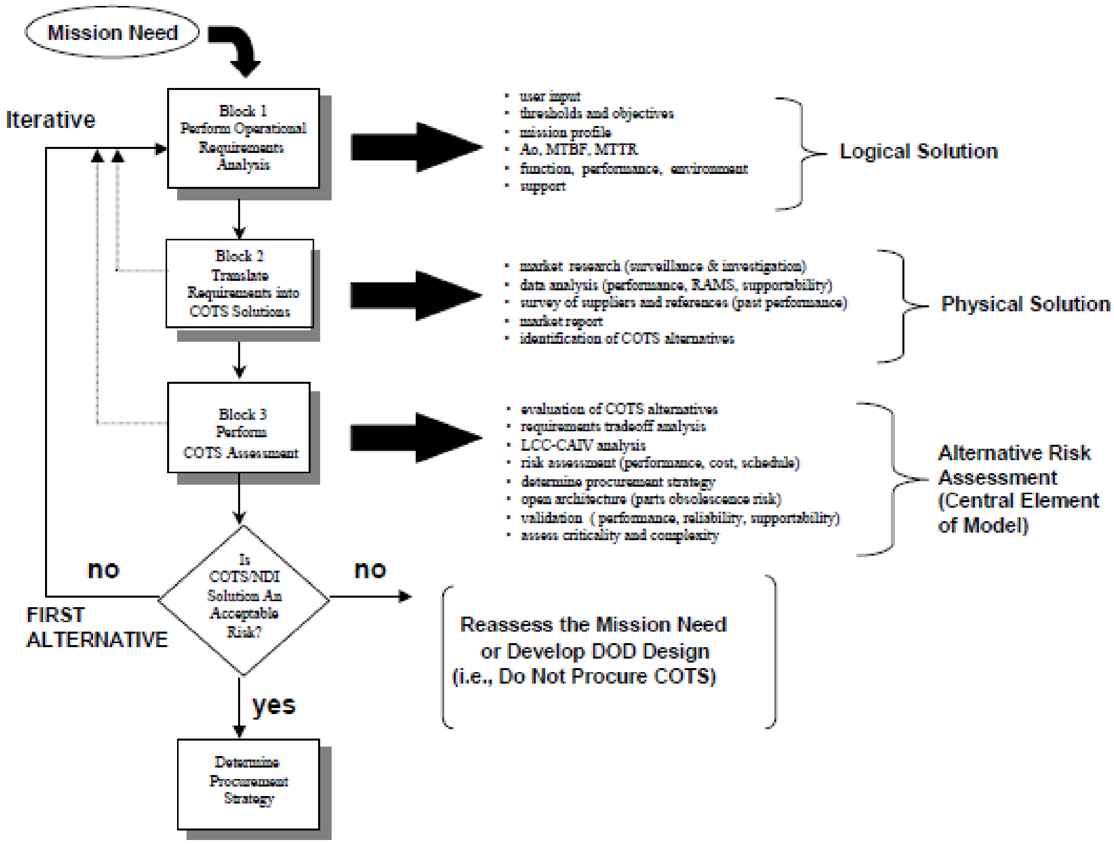

Figure 26: Iterative Decision Analysis Process (Ruben A. Lebron Jr., 2000)

Rojo (2010) reviews the three different approaches of forecasting, monitoring, and identifying alternative components, and mitigation strategy development. Some of these software tools include Q-Star, MOCA, Obsolescence Manager, Parts Plus, CAPS BOM Manager, and a few others. Most of these tools are focused on BOM management and alternative component identification, but the MOCA tool is unique regarding the fact that it attempts to predict the optimum technology insertion points to minimize obsolescence impacts to the system (Rojo, 2010).

2.4 Future Practices

Machine learning is a systematic process that determines how systems can be programmed to learn and improve automatically over multiple iterations. To make this happen, machine learning applications use statistical and computational principles to develop self-learning algorithms that find information from datasets and experience. The model must first be trained to learn the mapping function using known information with a known expected output value. Once the model is trained, test data is put into the newly developed model to predict the output value for that data. Figure 27 shows an algorithm training execution steps for a supervised machine learning process.

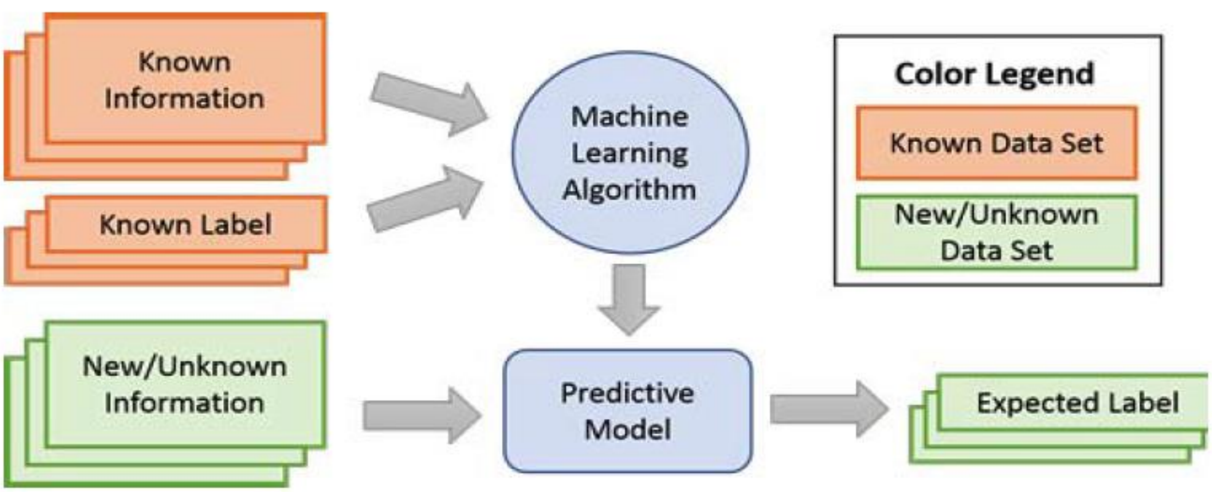

Figure 27: Supervised Machine Learning Process (Jennings, 2016)

A case study by Connor Jennings (2016) revealed that machine learning can process large sets of obsolescence data with multiple variables and provide recommendations based on its results. Two forecasting methods were used applying machine learning to increase accuracy and long-term usability over current forecasting methods. The first was Obsolescence Risk Forecasting (ORML) where the output was the risk associated with a component being obsolete. The second method was Life Cycle Forecasting (LCML) where a component discontinuation date was estimated. In this research, the case study was performed using more than 7000 unique cell phone models with knowledge of the obsolescence status, release year and quarter, and other technical specifications such as screen size, weight, and camera resolution (Jennings, 2016).

The study by Jennings used the three machine learning algorithms of Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF). RF resulted as the most suitable algorithm for ORML earning a rank of first in ¾ of the categories. When setting the RF model's training set to 100%, the algorithm correctly identified 98.3% of the cellphones as active or discontinued and had a test accuracy of 94.3% when the training size was set to 90% (Jennings, 2016). Table 3 below show the average accuracy of each algorithm based on varying training sizes from 50% to 100%.

Table 3: Average Accuracy of Predictions by Training Size for ORML (Jennings, 2016)

AVERAGE ACCURACY OF PREDICTIONS BY TRAINING SIZE FOR ORML

Training Size (%)	Random Forest			Neural Network			Support Vector Machine		
	Training (%)	Testing (%)	Overall (%)	Training (%)	Testing (%)	Overall (%)	Training (%)	Testing (%)	Overall (%)
50	98.8	92.2	95.5	91.8	91.2	91.5	90.9	91.7	91.3
60	98.5	92.5	96.1	91.4	91.7	91.5	91.0	92.2	91.4
70	98.5	92.9	96.8	91.5	91.9	91.6	91.3	92.3	91.6
80	98.2	93.3	97.2	91.7	91.1	91.6	91.6	91.7	91.6
90	98.2	94.3	97.8	91.7	91.2	91.6	91.7	91.2	91.6
100	-	-	98.3	-	-	91.1	-	-	91.6

For LCML, SVM was determined to be the best forecasting algorithm for discontinuation dates of each cell phone in the dataset. Although RF received the highest rating for both nonperformance-based characteristics, SVM achieved higher on accuracy and speed, thus earning a better overall score (Jennings, 2016). Table 4 below shows to average Mean Square Error (MSE) for each algorithm where average prediction error is calculated by taking the square root of the MSE. The average life cycle of the cell phone was less than 2 years, so MSE values of less than 1 are desired.

Table 4: Average MSE of Predictions by Training Size for LCML (Jennings, 2016)

AVERAGE MSE OF PREDICTIONS BY TRAINING SIZE FOR LCML

Training Size (%)	Random Forest			Neural Network			Support Vector Machine		
	Training	Testing	Overall	Training	Testing	Overall	Training	Testing	Overall
50	0.47	2.00	1.27	4.71	5.73	5.10	0.36	0.88	0.56
60	0.41	1.81	1.01	4.75	5.67	5.10	0.33	1.41	0.74
70	0.40	1.22	0.68	4.70	5.89	5.15	0.34	1.02	0.60
80	0.39	0.74	0.48	4.80	5.65	5.12	0.39	0.92	0.59
90	0.33	1.09	0.44	4.87	5.75	5.21	0.32	1.34	0.71
100	-	-	0.36	-	-	5.21	-	-	0.60

2.5 Knowledge Gap

This literature review has presented the various opportunities and challenges that exist for those fighting DMSMS. It is an unavoidable reality in manufacturing systems and supply chain environments as many systems, especially in the defense industry, are needed to be sustained for multiple decades. There are various proactive/strategic approaches to mitigating obsolescence and tools to help track and forecast cases. Newer research shows an interesting shift from system life cycle management towards future proactive improvements of forecasting techniques with EOL predictions and system design refreshes. One of the key findings in this study was that of the 55 articles reviewed, there was only one that proposed the idea of using machine learning for forecasting purposes. This research effort suggests a need for an improved framework for managing obsolescence that places emphasis on proactiveness using the latest technology.

Throughout the research there are attempts to manage obsolescence from many different angles, but current frameworks do not encompass some of the latest ideas in DMSMS management. While there are tools currently available to forecast obsolescence, they do not explore the area of machine learning. Machine learning has the potential for creating BOM obsolescence risk profiles and improving component selection for design. Neither of these subjects have much discussion in current research. Research also lacks information on the most cost efficient and cost-effective path to tackle an obsolescence case from start to finish.

Table 5 below depicts some areas of obsolescence research that are well understood, understood but could be improved, or have little to no research on them at all. A case refers to an occurrence of an obsolescence issue.

Table 5: DMSMS Research Gaps

Pre-Case	Open Case	Post-Case
BOM Scrubbing with GIDEP, Vendor, and Third Part Component data sources	Information on various mitigation solution types	Monitoring implemented solution
Regular Technology Insertion Points	Clear cost-effective path to choosing mitigation solution	Communication strategies
Open Architecture	Component Demand Analysis	Details on how to create tracking tools
BOM Scrubbing using Machine Learning		Details on the importance of metrics
Machine Learning for Component Selection		
Machine Learning for BOM Risk Profiles		

Color Legend
Well Researched
Partially Researched
Minimal Research

All aspects of pre-case, open case, and post-case topics are areas of study that need more research and will be explored in this dissertation. The main benefit of having a strong understanding of obsolescence is that systems can be sustained for extended periods at reduced system life cycle costs and downtime.

CHAPTER 3 METHODOLOGY

3.1 Aims

Research suggested a need for an effective managerial framework to tackling obsolescence. When it comes to forecasting obsolescence, today's best tools use traditional algorithms that analyze inputs using defined logic but are only as good as the logic provided. The aim of this research is to determine if machine learning predictive algorithms can accurately predict the product discontinuation date and availability status of an electrical component by a manufacturer and provide a framework for obsolescence management in military systems driven by best practices. This framework consists of mitigation practices from pre-case, open case, and post-case situations. However, the main improvements to current mitigation methods will come in the form of proactive management using machine learning technology. A case study was performed using the Random Forest classification and regression algorithms predict the product discontinuation date and availability status of a set of electrical components.

3.2 Data Collection

The machine learning aspect of the framework consisted of collecting component data from Xilinx component datasheets. These datasheets contain all the necessary info for selecting the desired variables for testing in the algorithms. Data collection for validation of the overall framework from pre-case, open case, and to post-case was done using a questionnaire with a 5-point Likert scale response. There were 13 questions sent out to 11 experts in the field of machine learning, military systems, or DMSMS. Their responses were used to determine the level of benefit a DMSMS team would receive by implementing parts or all the proposed management framework.

3.2.1 Raw Data

Table 6: List of 92 Xilinx Memory Chips used when testing in R

Part	Family	Intro Year	Slices	Logic Cells	Max. Distributed RAM Bits	DLL	PLL/MMCM	Max I/O	5V Tolerent	MHz	Status
XC2S50E	SPARTAN-IIE	2001	768	1728	24000	1	0	182	0	200	12
XC2S100E	SPARTAN-IIE	2001	1200	2700	37000	1	0	202	0	200	12
XC2S150E	SPARTAN-IIE	2001	1728	3888	54000	1	0	265	0	200	12
XC2S200E	SPARTAN-IIE	2001	2352	5292	73000	1	0	289	0	200	12
XC2S300E	SPARTAN-IIE	2001	3072	6912	96000	1	0	329	0	200	12
XC2S400E	SPARTAN-IIE	2001	4800	10800	15000	1	0	410	0	200	12
XC2S600E	SPARTAN-IIE	2001	6912	15552	216000	1	0	514	0	200	12
XC2V40	VIRTEX-II	2001	256	576	8	1	0	88	0	200	13
XC2V80	VIRTEX-II	2001	512	1152	16	1	0	120	0	200	13
XC2V250	VIRTEX-II	2001	1536	3456	48	1	0	200	0	200	13
XC2V500	VIRTEX-II	2001	3072	6912	96	1	0	264	0	200	13
XC2V1000	VIRTEX-II	2001	5120	11520	160	1	0	432	0	200	13
XC2V1500	VIRTEX-II	2001	7680	17280	240	1	0	528	0	200	13
XC2V2000	VIRTEX-II	2001	10752	24192	336	1	0	624	0	200	13
XC2V3000	VIRTEX-II	2001	14336	32256	448	1	0	720	0	200	13
XC2V4000	VIRTEX-II	2001	23040	51840	720	1	0	912	0	200	13
XC2V6000	VIRTEX-II	2001	33792	76032	1056	1	0	1104	0	200	13
XC2V8000	VIRTEX-II	2001	46592	104882	1456	1	0	1108	0	200	13
XCS05XL	SPARTAN XL	2002	100	238	3100	1	0	77	1	80	8
XCS10XL	SPARTAN XL	2002	196	466	6100	1	0	112	1	80	8
XCS20XL	SPARTAN XL	2002	400	950	12500	1	0	160	1	80	8
XCS30XL	SPARTAN XL	2002	576	1368	18000	1	0	192	1	80	8
XCS40XL	SPARTAN XL	2002	784	1862	24500	1	0	205	1	80	8
XCV50E	VIRTEX-E	2000	768	1728	24576	1	0	176	0	240	14
XCV100E	VIRTEX-E	2000	1200	2700	38400	1	0	196	0	240	14
XCV200E	VIRTEX-E	2000	2352	5292	75264	1	0	284	0	240	14
XCV300E	VIRTEX-E	2000	3072	6912	98304	1	0	316	0	240	14
XCV400E	VIRTEX-E	2000	4800	10800	153600	1	0	404	0	240	14
XCV600E	VIRTEX-E	2000	6912	15552	221184	1	0	512	0	240	14
XCV1000E	VIRTEX-E	2000	12288	27648	393216	1	0	660	0	240	14
XCV1600E	VIRTEX-E	2000	15552	34992	497664	1	0	724	0	240	14
XCV2000E	VIRTEX-E	2000	19200	43200	614400	1	0	804	0	240	14
XCV2600E	VIRTEX-E	2000	25392	57132	812544	1	0	804	0	240	14
XCV3200E	VIRTEX-E	2000	32448	73008	1038336	1	0	804	0	240	14
XCV50	VIRTEX	1998	768	1,728	24576	1	0	180	0	200	15
XCV100	VIRTEX	1998	1200	2,700	38400	1	0	180	0	200	15
XCV150	VIRTEX	1998	1728	3888	55296	1	0	260	0	200	15
XCV200	VIRTEX	1998	2352	5292	75264	1	0	284	0	200	15
XCV300	VIRTEX	1998	3072	6912	98304	1	0	316	0	200	15
XCV400	VIRTEX	1998	4800	10800	153600	1	0	404	0	200	15
XCV600	VIRTEX	1998	6912	15552	221184	1	0	512	0	200	15
XCV800	VIRTEX	1998	9408	21168	301056	1	0	512	0	200	15
XCV1000	VIRTEX	1998	12288	27648	393216	1	0	512	0	200	15
XC2VP2	VIRTEX-II PRO	2003	1408	3168	44	0	1	204	0	300	17
XC2VP4	VIRTEX-II PRO	2003	3008	6768	94	0	1	348	0	300	17
XC2VP7	VIRTEX-II PRO	2003	4928	11088	154	0	1	396	0	300	17
XC2VP20	VIRTEX-II PRO	2003	9280	20880	290	0	1	564	0	300	17
XC2VP30	VIRTEX-II PRO	2003	13696	30816	428	0	1	644	0	300	17
XC2VP40	VIRTEX-II PRO	2003	19392	43632	606	0	1	804	0	300	17
XC2VP50	VIRTEX-II PRO	2003	23616	53136	738	0	1	852	0	300	17
XC2VP70	VIRTEX-II PRO	2003	33088	74448	1034	0	1	996	0	300	17
XC2VP100	VIRTEX-II PRO	2003	44096	99216	1378	0	1	1164	0	300	17
XC2VPX20	VIRTEX-II PRO	2003	9792	22032	306	0	1	552	0	300	17
XC2S15	SPARTAN-II	2000	192	432	6000	1	0	86	1	200	20
XC2S30	SPARTAN-II	2000	432	972	13500	1	0	92	1	200	20
XC2S50	SPARTAN-II	2000	768	1728	24000	1	0	176	1	200	20
XC2S100	SPARTAN-II	2000	1200	2700	37500	1	0	176	1	200	20
XC2S150	SPARTAN-II	2000	1728	3888	54000	1	0	260	1	200	20
XC2S200	SPARTAN-II	2000	2352	5292	73500	1	0	284	1	200	20
XC3S50	SPARTAN-3	2003	768	1728	12000	1	0	124	0	300	17
XC3S200	SPARTAN-3	2003	1920	4320	30000	1	0	173	0	300	17
XC3S400	SPARTAN-3	2003	3584	8064	56000	1	0	264	0	300	17
XC3S1000	SPARTAN-3	2003	7680	17280	120000	1	0	391	0	300	17
XC3S1500	SPARTAN-3	2003	13312	29952	208000	1	0	487	0	300	17
XC3S2000	SPARTAN-3	2003	20480	46080	320000	1	0	565	0	300	17
XC3S4000	SPARTAN-3	2003	27648	62208	432000	1	0	712	0	300	17
XC3S5000	SPARTAN-3	2003	33280	74880	520000	1	0	784	0	300	17
XC3S100E	SPARTAN-3E	2005	960	2160	15000	1	0	108	0	300	15
XC3S250E	SPARTAN-3E	2005	2448	5508	38000	1	0	172	0	300	15
XC3S500E	SPARTAN-3E	2005	4656	10476	73000	1	0	232	0	300	15
XC3S1200E	SPARTAN-3E	2005	8672	19512	136000	1	0	304	0	300	15
XC3S1600E	SPARTAN-3E	2005	14752	33192	231000	1	0	376	0	300	15
XC5VLX30	VIRTEX-5	2007	4800	30720	320	0	1	200	0	550	13
XC5VLX50	VIRTEX-5	2007	7200	46080	480	0	1	280	0	550	13
XC5VLX85	VIRTEX-5	2007	12960	82944	840	0	1	280	0	550	13
XC5VLX110	VIRTEX-5	2007	17280	110592	1120	0	1	400	0	550	13
XC5VLX220	VIRTEX-5	2007	34560	221184	2280	0	1	400	0	550	13
XC5VLX330	VIRTEX-5	2007	51840	331776	3420	0	1	600	0	550	13
XC6VLX75T	VIRTEX-6	2009	11640	74496	5616	0	1	360	0	600	11
XC6VLX130T	VIRTEX-6	2009	20000	128000	9504	0	1	600	0	600	11
XC6VLX195T	VIRTEX-6	2009	31200	199680	12384	0	1	600	0	600	11
XC6VLX240T	VIRTEX-6	2009	37680	241152	14976	0	1	720	0	600	11
XC6VLX365T	VIRTEX-6	2009	56880	364032	14976	0	1	720	0	600	11
XC6VLX550T	VIRTEX-6	2009	85920	549888	22752	0	1	1200	0	600	11
XC6VLX760	VIRTEX-6	2009	118560	758784	25920	0	1	1200	0	600	11
XC6VSX315T	VIRTEX-6	2009	49200	314880	25344	0	1	720	0	600	11
XC6VSX475T	VIRTEX-6	2009	74400	476160	38304	0	1	840	0	600	11
XC6VHX250T	VIRTEX-6	2009	39360	251904	18144	0	1	320	0	600	11
XC6VHX255T	VIRTEX-6	2009	39600	253440	18576	0	1	480	0	600	11
XC6VHX380T	VIRTEX-6	2009	59760	382464	27648	0	1	720	0	600	11
XC6VHX565T	VIRTEX-6	2009	88560	566784	32832	0	1	720	0	600	11

Table 6 above depicts the 11 Xilinx Part Families consisting of 92 FPGA chips used in this case study. There were 54 obsolete components used that are indicated with red in the Status column, and there were 38 active components used. The component marketplace introduction dates range from the years 1998 – 2009.

3.3 Obsolescence Management Framework Development

The obsolescence management framework was developed using personal experience in the field of DMSMS and through research of peer reviewed articles on current management practices. The main area of focus was on proactive management, thus the reason for the case study on machine learning, but the framework also consists of open case and post-case processes. The framework was built by searching for articles in the University of Central Florida library using the keywords of mitigating obsolescence, obsolescence, Diminishing Manufacturing Sources and Material Shortages (DMSMS), design refresh, component, system life cycle, life cycle forecasting. and obsolescence management framework. Various aspects of obsolescence management were taken from multiple articles and were combined with personal experience to create a full framework. There were not any frameworks that incorporated machine learning, design refresh, in-depth component demand analysis, and post mitigation strategies all in one. This framework was built using today's best obsolescence management practices.

Quantitative methods were used in both the analysis of the Random Forest algorithm results and the expert validation of the questionnaire. The regression analysis looked at the difference between the numerical average of the components actual or the Q-STAR forecasted discontinuation date and the model's predicted discontinuation date. Q-STAR is a commercial database that helps companies with component life cycle management. The classification analysis determined the accuracy of its predictions of a component being available in the marketplace or discontinued. This information was then taken and placed into the pre-case framework to aide in component selection for design and helping determine technology refresh cycles.

3.3.1 Algorithm Selection

There are several machine learning algorithms to choose from for making predictions. Some of the most common ones that have good speed, accuracy, and interpretability include RF, SVM, ANN, and Naïve Bayes. The fastest and most accurate classification and regression algorithms include SVM, RF, ANN, Gradient Boosting Tree, and Naïve Bayes, Decision Tree, Linear Regression, and Logistic Regression (Li, 2017). The RF algorithm was selected for this study due to its well-rounded capabilities. Both the regression and classification RF algorithms were used.

3.3.1.1 Random Forest

Random Forest is a supervised algorithm that combines multiple sets of decision trees to derive an accurate result. One of the useful features of the Random Forest algorithm is that is can be used for both regression and classification analysis. The model works by expanding the number of trees and selecting the best feature from a random subset of features. The large number of uncorrelated models working together will outperform a general decision tree model that just looks for the most important feature at each node split (Yiu, 2019). Another benefit to Random Forest is these random subsets of features is help reduce the chance of overfitting which is when the mapping function is too closely related to a few datapoints. A final large benefit of using Random Forest is it does not require scaling to normalize data and it is affected very little by multicollinearity due to its use of bootstrap and feature sampling. This is again referring to the selection of different random subsets of features each time the model is run and having each decision tree train off a random sample of datapoints. A liner model summary, Pearson's Chi-squared test, residuals vs fitted plots, Q-Q plots, scale-location plots, and residuals vs leverage plots were looked at to test for collinearity and normalization of the data and is discussed further in Appendix A.

3.3.2 Feature Selection

Feature selection is referred to the algorithmic process of obtaining a subset from an original set of features to select the relevant features of the dataset (Cai, Luo, Wang, & Yang, 2018). Figure 28 shows the framework for the feature selection process.

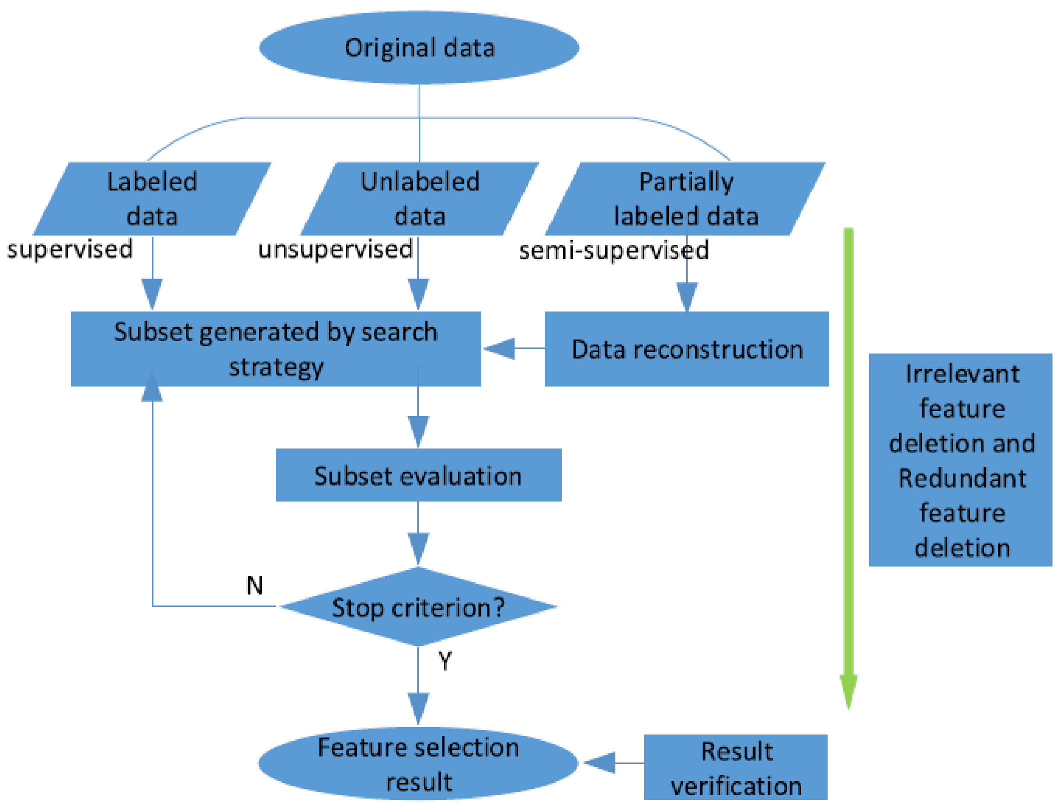

Figure 28: Feature selection framework (Cai, Luo, Wang, & Yang, 2018)

The main reasons for feature selection are for faster algorithm training times, reduced model complexity, improved model accuracy, and reduced overfitting (Kaushik, 2016). Selecting features will be a combination of previous studies, personal knowledge, and the algorithms mathematically selecting them on their own based on relevance. Data will initially be gathered from publicly available datasheets such as the one from Xilinx in Table 7 below.

The top portion of the table contains information such as System Gates, CLB Array, Number of Slices, Logic Cells, and so on, that can be used as possible obsolescence predictors. Not every data sheet for every part family or manufacturer contains the same information. This makes the initial feature selection process difficult and time consuming. However, once the features are selected and the model is trained, the model can be modified to use only what it determines to be the most important variables to improve its accuracy and speed.

Table 7: XILINX VIRTEX-II Series FPGAs Datasheet (Xilinx)

XILINX®
The Programmable Logic Company℠

XILINX VIRTEX-II SERIES FPGAs

http://www.xilinx.com/products/platform/

Platform FPGAs

		CLB Resources				Memory Resources			DSP	Clock Resources		I/O Features				Speed							
	System Gates (see note 1)	CLB Array (Row X Col)	Number of Slices	Logic Cells (see note 2)	CLB Flip-Flops	Max. Distributed RAM Bits(kbits)	# 18 kbits Block RAM	Total Block RAM (kbits)	# 18x18 Dedicated Multipliers	DCM Frequency (min/max)	# DCM Blocks (see note 3)	Digitally Controlled Impedance	Maximum Differential I/O Pairs	Max. I/O	I/O Standards	Commercial Speed Grades (slowest to fastest)	Industrial Speed Grades (slowest to fastest)	Serial PROM Family	System ACE	Config. Memory (Bits)	RocketIO™ Transceiver Blocks	PowerPC Processor Blocks	Virtex-II Series EasyPath Solution (see note 4)
Virtex-II Pro Family — 1.5 Volt																**.13um Nine Layer Copper Process**							
XC2VP2	*	16 x 22	1,408	3,168	2,816	44	12	216	12	24/420	4	YES	100	204	LDT-25, LVDS-25, LVDSEXT-25,	-5 -6 -7	-5 -6			1.31M	4	0	
XC2VP4	*	40 x 22	3,008	6,768	6,016	94	28	504	28	24/420	4	YES	172	348	BLVDS-25, ULVDS-25, LVPECL-25,	-5 -6 -7	-5 -6			3.01M	4	1	
XC2VP7	*	40 x 34	4,928	11,088	9,856	154	44	792	44	24/420	4	YES	196	396	LVCMOS25, LVCMOS18,	-5 -6 -7	-5 -6			4.49M	8	1	
XC2VP20	*	56 x 46	9,280	20,880	18,560	290	88	1,584	88	24/420	8	YES	276	564	LVCMOS15, PCI33, LVTTL,	-5 -6 -7	-5 -6			8.21M	8	2	
XC2VP30	*	80 x 46	13,696	30,816	27,392	428	136	2,448	136	24/420	8	YES	372	644	LVCMOS33, PCI-X, PCI66, GTL,	-5 -6 -7	-5 -6	ISP/OTP	ISP	11.36M	8	2	✔
XC2VP40	*	88 x 58	19,392	43,632	38,784	606	192	3,456	192	24/420	8	YES	396	804	GTL+, HSTL I (1.5V,1.8V),	-5 -6 -7	-5 -6			15.56M	0** or 12	2	✔
XC2VP50	*	88 x 70	23,616	53,136	47,232	738	232	4,176	232	24/420	8	YES	420	852	HSTL II (1.5V,1.8V),	-5 -6 -7	-5 -6			19.02M	0** or 16	2	✔
XC2VP70	*	104 x 82	33,088	74,448	66,176	1,034	328	5,904	328	24/420	8	YES	492	996	HSTL III (1.5V,1.8V),	-5 -6 -7	-5 -6			25.60M	16 or 20	2	✔
XC2VP100	*	120 x 94	44,096	99,216	88,192	1,378	444	7,992	444	24/420	12	YES	572	1,164	HSTL IV (1.5V,1.8V), SSTL2I,	-5 -6 -7	-5 -6			33.65M	0** or 20	2	✔
XC2VP125	*	136 x 106	55,616	125,136	111,232	1,738	556	10,008	556	24/420	12	YES	644	1,200	SSTL2II, SSTL18 I, SSTL18 II	-5 -6 -7	-5 -6			42.78M	0**20, or 24	4	✔
Virtex-II Family — 1.5 Volt																**.15um Eight Layer Metal Process**							
XC2V40	40K	8 x 8	256	576	512	8	4	72	4	24/420	4	YES	44	88	LDT-25, LVPECL-33,	-4 -5 -6	-4 -5			0.4M			
XC2V80	80K	16 x8	512	1,152	1,024	16	8	144	8	24/420	4	YES	60	120	LVDS-33, LVDS-25,	-4 -5 -6	-4 -5			0.6M			
XC2V250	250K	24 x16	1,536	3,456	3,072	48	24	432	24	24/420	8	YES	100	200	LVDSEXT-33, LVDSEXT-25,	-4 -5 -6	-4 -5			1.7M			
XC2V500	500K	32 x 24	3,072	6,912	6,144	96	32	576	32	24/420	8	YES	132	264	BLVDS-25, ULVDS-25,	-4 -5 -6	-4 -5			2.8M			
XC2V1000	1M	40 x 32	5,120	11,520	10,240	160	40	720	40	24/420	8	YES	216	432	LVTTL, LVCMOS33,	-4 -5 -6	-4 -5			4.1M			
XC2V1500	1.5M	48 x 40	7,680	17,280	15,360	240	48	864	48	24/420	8	YES	264	528	LVCMOS25, LVCMOS18,	-4 -5 -6	-4 -5	ISP/OTP	ISP	5.7M			
XC2V2000	2M	56 x 48	10,752	24,192	21,504	336	56	1,008	56	24/420	8	YES	312	624	LVCMOS15, PCI33, PCI66,	-4 -5 -6	-4 -5			7.5M			
XC2V3000	3M	64 x 56	14,336	32,256	28,672	448	96	1,728	96	24/420	12	YES	360	720	PCI-X, GTL, GTL+, HSTL I,	-4 -5 -6	-4 -5			10.5M			✔
XC2V4000	4M	80 x 72	23,040	51,840	46,080	720	120	2,160	120	24/420	12	YES	456	912	HSTL II, HSTL III, HSTL IV,	-4 -5 -6	-4 -5			15.7M			✔
XC2V6000	6M	96 x 88	33,792	76,032	67,584	1,056	144	2,592	144	24/420	12	YES	552	1,104	SSTL2I, SSTL2II, SSTL3 I,	-4 -5 -6	-4 -5			21.9M			✔
XC2V8000	8M	112 x 104	46,592	104,832	93,184	1,456	168	3,024	168	24/420	12	YES	554	1,108	SSTL3 II, AGP, AGP-2X	-4 -5				29.1M			✔

Note: 1. System Gates include 20-30% of CLBs used as RAM
2. Logic cell = (1) 4 Input (LUT) Look Up Table + Flip Flop + Carry Logic.
3. DCM – Digital Clock Management
4. Virtex-II Series EasyPath solution available to provide a no risk, no effort cost reduction path for volume production.
* System gate count not meaningful for Virtex-II Pro devices with immersed special blocks such as PowerPC processors and multi-gigabit transceivers.
** The FF1148 and FF1696 packages support higher number of user I/O and zero RocketIO multi-gigabit transceivers.
Important: Verify all Data with Device Data Sheet (http://www.xilinx.com/partinfo/databook.htm)

3.4 Random Forest Model Validation

There are five ways that the model's accuracy can be validated. This study will be able to use four of those five methods.

1. Classification – Comparing a prediction of Obsolete to known information on whether the component is active or obsolete.
2. Classification – Comparing a prediction of Active to known information on whether the component is active or obsolete.
3. Regression – Comparing the model's discontinuation date to a component's actual discontinuation date on an obsolete component.
4. Regression – Comparing the model's discontinuation date to a component's predicted discontinuation date on an active component. The accuracy of these Machine Learning algorithmic models can be compared to a traditional data mining solution such as Q-STAR for current EOL predictions.
5. Regression – Comparing the model's discontinuation date to a component's predicted discontinuation date on an obsolete component. The accuracy of these Machine Learning algorithmic models *cannot* be compared to a traditional model such as Q-STAR for historical EOL predictions. Information is not available on historical predictions for an already obsolete component.

Validation methods 1-3 are those most important because they compare the Machine Learning results to known information. Methods 4 and 5 are less important because they are comparing one prediction tool to another when neither may be correct. Further data validation is detailed in the appendix of this paper.

3.5 Obsolescence Management Framework Validation

The overall management framework was validated through expert consensus on a 13 question, 5-point Likert scale questionnaire. The 13 questions were as follows:

1. The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.
2. Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.
3. Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.
4. Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.
5. Machine Learning can aid in early detection of BOMs at high obsolescence risk.
6. The Open Case Framework demonstrates a strong process for implementing obsolescence mitigation solutions.
7. The Open Case Framework follows a logical path to a final solution.

8. The Post-Case Framework demonstrates a beneficial technique for managing mitigated obsolescence issues.
9. Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.
10. Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.
11. Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.
12. Implementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.
13. Implementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.

The participants were also asked to provide their degree, current work position, and professional background. They were given a PowerPoint with three slides each depicting the three sub-frameworks of pre-case, open case, and post-case. They were also provided a Word document that provided more details on each part of the framework. These details are listed in the Appendix of this document. The participants were asked to fill out and email back the Excel document that contained the questionnaire by answering each question with a number 1,2,3,4, or 5. 1 represented Strongly Disagree, 2 represented Disagree, 3 represented Neutral, 4 represented Agree, and 5 represented Strongly Agree. These results will then be used to validate or invalidate the proposed framework. Chapter 4 will introduce the initial machine learning experiments and how they were conducted. The results will be discussed in chapter 5 to justify the use of machine learning as a forecasting tool in the obsolescence management framework is laid out in chapter 6.

CHAPTER 4 INITIAL RANDOM FOREST EXPERIMENTS

4.1 Introduction

This experimentation used the Random Forest classification and regression algorithms to complete a small-scale case study using a sample size of 92 Xilinx FPGA chips. R statistical computing and graphics software was used to conduct this experiment. The goal was to see how accurately the algorithm classified each chip as “Active” or “Obsolete” and how closely it can predict a product discontinuation date. The features selected for the algorithms to use were Slices, Logic Cells, Max Distributed RAM Bits (MDRB), Dynamic Link Library (DLL), Phase-Locked Loop/Mixed-Mode Clock Manager (PLL/MMCM), Max Input/Output (IO), 5V Tolerant, and Megahertz (MHz). The result of this case study could lead to the next step in future research. The next step would involve using a larger sample size with multiple algorithms and variable training sizes for comparison.

4.2 Case Study

A case study was performed using the Random Forest classification and regression algorithms with a sample size of 92 Xilinx FPGA chips. R statistical computing and graphics software was used to run these algorithms comparing the selected features of Slices, Logic Cells, MDRB, DLL, PLL/MMCM, Max IO, 5V Tolerant, and MHz.

4.2.1 Classification Code

Below is code used for classifying a component as Active or Obsolete. The importance of this code's output is that it allows for the creation of an obsolescence risk model to show the probability that a part is obsolete or not. A component may still be available in the marketplace, but based on the machine learning model, there may be a high risk that it will be obsolete soon and is therefore not desirable for future designs.

The R coding packages of cowplot and RF were used for classification. The training and testing sizes were both set to 50% with the decision tree level set to 500.

```
library(cowplot)
library(ggpolt2)
library(randomForest)

my_data <- read.csv(file.choose())
set.seed(12343)
trainIndex= sample(nrow(my_data), 0.5*nrow(my_data), replace = FALSE)
head(trainIndex)
train=my_data[trainIndex, ]
test=my_data[-trainIndex, ]

model1 <- randomForest(Status ~ ., data = train, ntree=500, importance = TRUE)
model1
model2 <- randomForest(Status ~ ., data = test, ntree=500, importance = TRUE)
model2

print(table(my_data$Status))
print(table(train$Status))

oob.error.data <- data.frame(
Trees=rep(1:nrow(model2$err.rate), times=3),
Type=rep(c("OOB", "ACTIVE", "OBSOLETE"), each=nrow(model2$err.rate)),
Error=c(model2$err.rate[,"OOB"],
        model2$err.rate[,"ACTIVE"],
        model2$err.rate[,"OBSOLETE"]))
```

4.2.2 Regression Code

Below is the regression code used for predicting the EOL date of a component. The importance of this code is that its output gives design engineers a timeframe for when the part is expected to be discontinued. This information not only provides designers a useful way of predicting the amount of time needed to complete a redesign or find an alternative part, but this timeframe assists in maximizing the number of high-risk components that can be removed from the current product or redesign (Jennings, 2016).

The RF library was used, and the decision tree level was set to 500. Obsolescence predictions were compared to actual discontinuation dates and active components were compared to Q-STAR predictions. Having results comparable to an already available commercial data source helps validate the accuracy of the machine learning algorithms and their efficacy in predicting obsolescence.

```
library(randomForest)
dataset <- read.csv(file.choose())
dataset = dataset[1:9]
set.seed(1234)
regressor = randomForest(x = dataset[1:8],
                    y = dataset$Status,
                    ntree = 500)


y_pred = predict(regressor, data.frame(ï..A=14752, B=33192 ,C=231000, D=1, E=0, F=376,
G=0, H=220))
```

4.2.3 Error Rate Plot Code

The error rate code uses the ggplot2 package to create the decision tree chart down in Chapter 4 Results and Discussion section of this paper. The importance of this chart is it shows how many decision trees are needed for the algorithm to perform with the lowest error rate. Too few trees will result in a larger rate of errors. A model with more trees than needed will not hurt the results, but the model will perform slower.

```
library(ggpolt2)
ggplot(data=oob.error.data, aes(x=Trees, y=Error)) +
geom_line(aes(color=Type))
```

4.2.4 Feature Importance Code

The code below was used for determining feature importance and the statistical significance of each of the selected features. This shows us what weight the algorithm is placing on each variable along with the associated p-values.

```
library(randomForest)
require(randomForest)
fit=randomForest(Status~., data=my_data)
(VI_F=importance(fit))
Rfpermute(Status ~ . , data = test, ntree = 500, na.action = na.omit, nrep = 50)$pval
```

CHAPTER 5 RESULTS AND DISCUSSION

5.1 Introduction

As previously stated, a case study was performed using the Random Forest classification and regression algorithms with a sample size of 92 Xilinx Field Programmable Gate Array (FPGA) chips. R statistical computing and graphics software was used to run these algorithms comparing the selected features of Slices, Logic Cells, MDRB, DLL, PLL/MMCM, Max IO, 5V Tolerant, and MHz. The results are discussed below and are used to justify the use of machine learning as an integral part to the proposed obsolescence management framework in chapter 6.

5.2 Results

Both the training data and the test data had an OOB error rate of 10.87% using 500 trees. The training set was 50% of the population and the test set was the remaining 50%. Higher training sets resulted in lower OOB training error rates but did not improve testing results due to small sample sizes. The regression analysis shows that the Random Forest algorithm was able to predict an obsolescence date of an Obsolete component on average 0.75 years after the actual discontinuation of the component. On average the algorithm estimated the obsolescence date of an Active component 1.08 years early when compared to Q-STAR predictions. Q-STAR is a commercial database that helps companies with component life cycle management. Detailed findings are discussed below.

5.2.1 Classification Results

The OOB error rate for the 50% training set was 10.87%. From the sample size of 46, the Random Forest classification algorithm correctly guessed 14 components as Active and 27 Obsolete. The algorithm incorrectly guessed 4 components at Active when they were Obsolete and incorrectly guessed 1 component as Obsolete when it was Active. Figure 29 below depicts the training classification confusion matrix results from R.

```
Call:
 randomForest(formula = Status ~ ., data = test, ntree = 500,      importance = TRUE)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 2

        OOB estimate of  error rate: 10.87%
Confusion matrix:
         ACTIVE OBSOLETE class.error
ACTIVE       14        4  0.22222222
OBSOLETE      1       27  0.03571429
```

Figure 29: Random Forest Training Data Results

The OOB error rate for the 50% testing set was 10.87%. From the sample size of 46, the Random Forest classification algorithm correctly guessed 17 components as Active and 24 as Obsolete. The algorithm incorrectly guessed 3 components at Active when they were Obsolete and incorrectly guessed 2 components as Obsolete when they were Active. Figure 30 below depicts the testing classification confusion matrix results from R.

```
Call:
 randomForest(formula = Status ~ ., data = train, ntree = 500,      importance = TRUE)
               Type of random forest: classification
                     Number of trees: 500
No. of variables tried at each split: 2

        OOB estimate of  error rate: 10.87%
Confusion matrix:
         ACTIVE OBSOLETE class.error
ACTIVE       17        3  0.15000000
OBSOLETE      2       24  0.07692308
```

Figure 30 Random Forest Testing Data Results

5.2.2 Regression Results

The regression analysis shows that the RF algorithm was able to predict an obsolescence date of an obsolete component on average 0.75 years after the actual discontinuation of the component. On average the algorithm estimated the obsolescence date of an active component 1.08 years early when compared to Q-STAR predictions. It is important to note that actual discontinuation dates were used for obsolete components and Q-STAR data was used for active components. Q-STAR was used as a comparison tool because there is no way of knowing how well the Random Forest algorithm predicted the years until EOL without comparing it to another widely used software tool in industry today. Overall, the algorithm predicted the EOL date on average 0.08 years early which is a margin of error of less than 1% as shown in Table 7 below.

Table 8: Random Forest Regression Results

Status	RF Prediction (Years)	Actual or Q-STAR Prediction (Years)*	Difference in Years	Percentage Difference	Over/Under
Obsolete	13.92	13.17	0.75	5.70%	OVERESTIMATED
Active	16.92	18.00	-1.08	6.00%	UNDERESTIMATED
ALL	15.28	15.36	-0.08	0.53%	UNDERESTIMATED

**Actual discontinuation dates were used for obsolete components and Q-STAR data was used for active components.*

5.2.3 Error Rates

Figure 31 shows the fluctuation in Active, Obsolete, OOB error rates for the RF algorithm as the number of decision trees are increased to 500. After about 200 trees, all the error rates flatten off indicating that 500 trees are enough for this analysis. Larger datasets may require more decision trees and therefore take longer for the model to run.

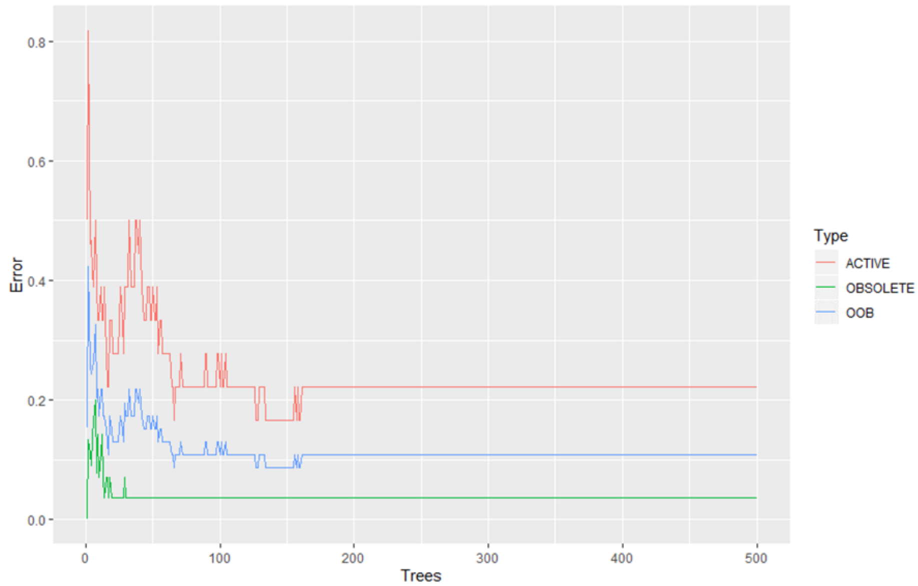

Figure 31: Error Rates Based on Number of Decision Trees

5.2.4 Feature Importance

The RF algorithm places a factor on each feature based on which attributes it determines to be the most important. Of the eight features selected for this study, MHz, the number of Logic Cells, and the number of MDRB in the FPGA chips were the top three most important attributes for predicting obsolescence status and EOL dates. Each feature has an associated P-value with MHz and Logic cells having statistically significant values of 0.02 and 0.05, respectfully. Table 9 below presents both the Importance Factor and P-Value for all eight features used in the model.

Table 9: Feature Importance and Statistical Significance

Feature	Importance Factor	P-Value
Slices	3.84	0.12
Logic Cells	5.87	0.05
Max Distributed RAM Bits	5.72	0.16
DLL	1.46	0.12
PLL.MMCM	1.42	0.09
Max IO	4.34	0.15
5V Tolerant	2.45	0.18
MHz	15.81	0.02

5.2.5 Discussion

The results from this small-scale case study provide some positive information regarding using machine learning as a tool for predicting obsolescence. The RF classification algorithm was able to predict the Active vs. Obsolete status in both the training data and the test data with an OOB error rate of 10.87% at a 50% training size and 500 decision trees. The training set was 50% of the population and the test set was the remaining 50%.

Higher training sets did result in lower OOB training error rates but did not improve testing results due to the small sample size. The sample size of 92 components was small, so increasing the training size too large leaves too few of samples in the testing set to allow for any sort of statistical significance. The reason why the data is split into training and testing sets to reduce the risk of model overfitting the data. The algorithm uses the training set to define the logic it wants to use for predictions and then uses that logic on the test set. The importance of this classification information it allows for the creation of an obsolescence risk profile for a design's Bill of Material (BOM). A company can look at the risk profile for a BOM and based on their risk tolerance, they can add or remove certain components as desired.

The RF regression algorithm was able to predict the years to EOL date 0.75 years after the actual discontinuation of obsolete components and 1.08 years early when compared to Q-STAR predictions for active components. This was an error of 5.7 % and 6.0 % for active and obsolete components, respectively. The overall error was 0.53%.

Although a larger sample size would reduce variance and provide more significant information, there are two very positive takeaways from this information. The first is with parts that have a status of Obsolete. A discontinuation date is known information and the algorithm was able to predict its discontinuation date within one year. The second is comparing the Active results with another commercially available piece of software called Q-STAR. The Random Forest algorithm and Q-STAR predictions were on average only 1.08 years apart. This provides some accuracy validity to the machine learning model given the fact that its results were comparable to another widely used and accepted software solution in the marketplace today.

CHAPTER 6: OBSOLESCENCE MANAGEMENT FRAMEWORK

An obsolescence management framework is a multiprong approach. There is not an exact path to every solution, but there are many methods that can help keep you ahead of the curve and help minimize the impact of each obsolescence case. The framework can be broken down into the three sections of pre-case, open casework, and post-case. Pre-case work is going to focus on efforts before a component goes obsolete while open case and post-case work will demonstrate measures for dealing with a newly obsolete component. The results in chapter 5 show that machine learning has the potential to be used in the pre-case framework and is discussed below. This framework was then validated through expert consensus using a 13 question Likert scale questionnaire. The flowcharts for each portion of the framework are placed in the Appendix section of this dissertation.

6.1 Pre-Case

Pre-case work is going to consist of scrubbing bills of materials (BOMs) for all subsystems within the system. Based on most military designs today, we are going to assume that systems are modular and contain LRMs. Scrubbing of BOMs can be done using third party obsolescence software such as QSTAR or through machine learning methods as detailed earlier on in this paper. This scrubbing process is mostly used to get an estimate of the years to end of life (YTEOL) of each component. Most component manufacturing companies send out a PDN when they are planning on discontinuing a product. This usually will provide their customers with 6-12 months of time to perform an LTB. The United States government usually provides similar information to any company subscribed to their GIDEP alerts.

During the scrubbing process, if a component is not found to be obsolete, the YTEOL should be recorded, and the component is then placed back into the BOM scrub cycle. It is recommended that each BOM is reviewed for obsolescence at a minimum of once a year, however, quarterly is preferred. The reason for this is because some component manufactures may only provide a few months to place an LTB with them. When recording the YTEOL, any components with an estimated life of under 5 years should be placed into a subsystem design review analysis.

Once the risk level reaches a certain threshold of components with YTEOL under 5 years, the LRM would then be placed into a Technology Refresh (TR) phase to redesign the subassembly without the aging components. The number of years can be raised or lowed based on risk tolerance. A conservative estimate of 10% could be used as a requirement for redesign. This means that if 10% or more of the critical components in a BOM have a YTEOL of 5 years or less, the LRM should be redesigned. Critical components are any component that is not easily replaceable like a resistor or capacitor would be.

This analysis should also be approached using machine learning classification algorithms to determine the obsolescence risk level of each BOM. These algorithms can output a weighted percentage for the probability that a component will be obsolete. This model can then be applied to the entire BOM to determine the overall obsolescence risk level. Once the level reaches a predetermined threshold, the LRM should be redesigned. Third party software or machine learning regression and classification algorithms can then again be used for the component selection process in the new design.

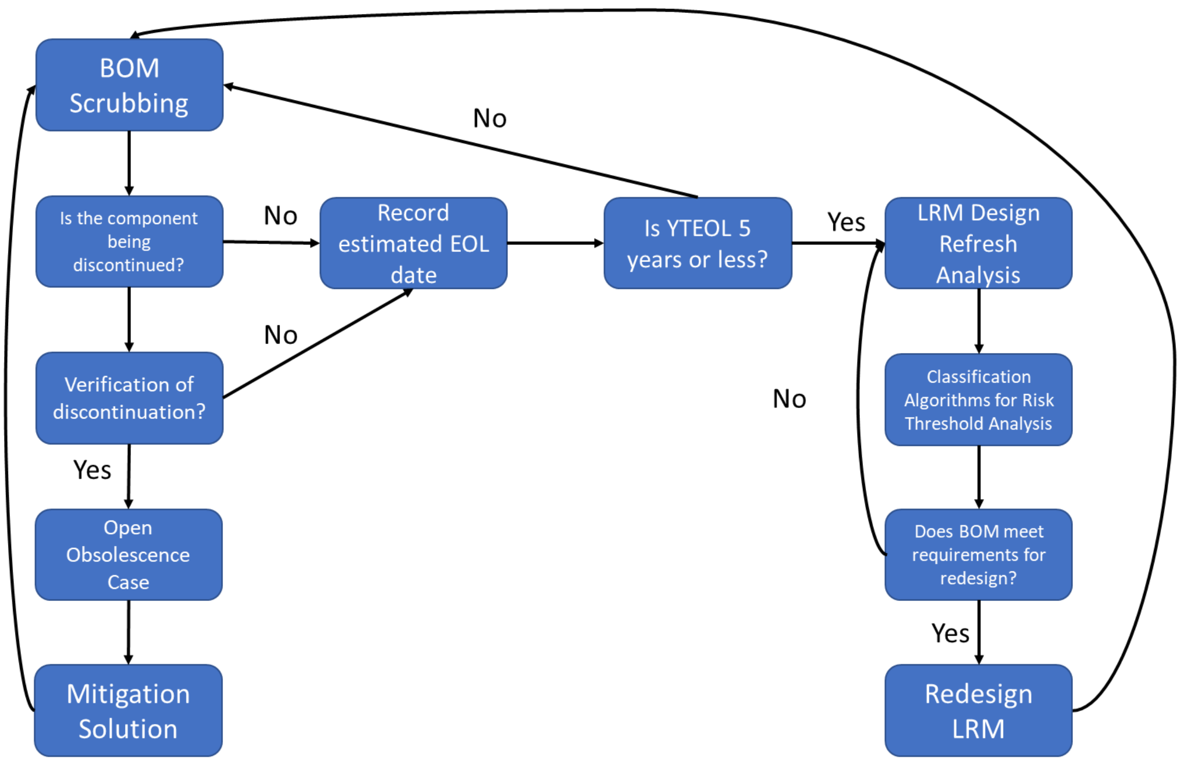

Figure 32: Pre-Case Process Flowchart

Figure 32 above shows the pre-case flowchart that management should follow for maximum proactiveness. Vendor alerts, GIDEP alerts, and EOL modeling should all be part of the initial BOM scrubbing process. If a component is identified and verified as discontinued, then an obsolescence case should be opened, and mitigation solutions should be investigated. If the component is not obsolete, then LRU design refresh analysis should take place. This analysis can consist of both the YTEOL machine learning regression approach and/or the machine learning classification risk threshold approach. Once the LRM has been redesigned, the new associated BOM goes back into the scrubbing cycle.

6.2 Open Casework

Once a component has been verified with the manufacturer for discontinuance, then an obsolescence case should be opened. Here all the different mitigation strategies such as existing stock, simple substitute, last-time-buy, etc, are contemplated until a solution is reached. Existing stock should be the first option looked at because there is no additional cost to implement this solution. Demand analysis will have to be conducted to determine if the number of components on hand will last the remaining life of the system. If the system is still in the production phase, then most likely existing stock will not be a viable solution.

The next three options to look at would be last-time-buy, simple substitute, and complex substitute. If the component is inexpensive or the quantity needed is minimal, then an LTB is typically preferred over a substitute component. The reason for this is because with an LTB, you do not have to worry about BOM updates, customer approvals, design requalification, and so on. However, if an LTB is very expensive and a substitute is available, the substitute solution should be selected.

To calculate the number of components you would need to purchase for an LTB, you will first need to look at historical usage. In the example below in Table 9, five years of historical demands, or usage, were used to forecast future needs. The average number of repairs per year was 10. The margin of error (MOE) using a critical value of 1.645 for a one-tailed 95% confidence level is 1.876. The total future needs for a system with 7 years of use left would be (10 + 1.876) * 7 = 84 components. The confidence level can be raised or lowered based on component cost, desired risk level, or customer requirements.

Table 10: Sustainment Forecast Model

Year	Usage
1	10
2	7
3	13
4	12
5	8
Average Yearly Repair Count (Usage)	10
Standard Deviation	2.550
System Life Remaining (Years)	7
Sample Size	5
Z Score (95% Confidence one-tailed)	1.645
Margin of Error	1.876
Total Needs	84

If components are also needed for systems still going through production, the calculation would be based off confirmed and/or potential future orders. A simple calculation based off confirmed production orders would be (Number of Confirmed Orders) * (Washout Rate) = Total Production Needs. The washout rate is a multiplier between 1 and 2 and is based off the percentage of components expected to fail, break, or be otherwise unusable during the assembly process. An example calculation for 1,000 confirmed orders with a washout rate of 2% would be (1,000) * (1.02) = 1,020 components needed for production. If potential future orders were wanted in the calculation also, the equation would be as follows:

((Number of Confirmed Orders) + ((Potential Future Orders) * (Percentage of Future Orders Expected to be Fulfilled))) * (Washout Rate) = Total Production Needs

The percentage of future orders expected to be fulfilled should be based off historical order fulfillment percentages and risk tolerance. The most risk averse multiplier would be 1 while the least risk averse (highest risk tolerance) multiplier would be 0. A Production Roadmap provides a clear picture on the number of components needed and is explained further down.

The next solution that should be look at is extension of production or support. This is also known as a lifeboat agreement. Having strong relationships with you suppliers is integral for this solution to work. Sometimes a manufacturer will continue producing a component that they have released a product discontinuation notice on past the LTB date. This will be done typically at a much higher price point and only for a short period of time. Agreements between suppliers and customers can be made to last a few years which is often enough time for a redesign to take place.

If the previously stated solutions are not feasible, repair, refurbishment, or reclamation can be investigated. This is rarely a final answer due to the limited number of non-operational systems available to salvage from and the difficulty of repairing an electrical component. For military systems, this solution is not recommended due to reliability impacts.

The final three mitigation solutions involve engineering redesign of the component, next higher assembly, or system itself. A development of a new item or source can be used if the component can be developed through emulation, reverse engineering, or a new item is created with the same form, fit, and function as the original. This can come from the original manufacturer or a new source. If the component cannot be recreated, then a design change at the NHA should be performed to allow for a substitute component to become compatible with the system. Beyond this, a complex or system redesign is generally the most expensive solution and requires changes within multiple areas of the system to make a substitute component compatible. If any of these final three solutions are chosen, an LTB must still be performed to bridge the demand gap between the discontinuation date and the redesign production date.

Table 11: Mitigation Solution Cost Elements (Office D. S., 2016)

	Existing material (logistics)				Substitute (engineering)		Redesign (engineering)		
Cost element	Approved item	Life-of-need buy	Repair, refurbish-ment, reclamation	Extension of pro-duction or support	Simple substitute	Complex substitute	Development of a new item or source	Redesign–complex/ system replacement	Redesign–NHA
Engineering, engineering data revision					X	X	X	X	X
Purchase of engineering, design, or technical data			X			X	X	X	X
Qualification of new items					X	X	X	X	X
Revision of test procedures			X			X	X	X	X
Software changes						X	X	X	X
Start-up costs (after-market, etc.)			X	X			X	X	X
Testing			X		X	X	X	X	X
Tooling, equipment, test equipment, or software			X			X	X	X	X
Computer programs/ documentation			X		X	X	X	X	X
Interim support							X	X	X
Supply/provisioning data					X	X	X	X	X
Support/test equipment			X			X	X	X	X
Technical manuals			X		X	X	X	X	X
Training/trainers			X			X	X	X	X
Item cost (optional)		X	X				X	X	X
Manpower (optional)			X						
Spares (optional)			X				X	X	X
Other (as required)	X	X	X	X	X	X			

Any solution that requires company or customer funding needs to be clearly communicated in a business case to management. Critical information includes the following:

1. Part Number
2. Part NHA
3. Parts on hand
4. Production/Sustainment Impact timeframe
5. Mitigation solutions with multiple scenarios based on risk tolerance
6. Cost

It is imperative to deliver this information to management as quickly as possible in a concise, but accurate, manner. It is not always appropriate to conduct an LTB modeled out to the remaining life of the system. Some electrical components are extremely expensive, and quantities needed can reach the thousands. This obsolete component may already be replaced in a new design five years down the road. The full LTB cost may be so high that management choses to do a partial LTB to last until a redesign is completed. No matter the decisions, it is important to relay the data to the decision makers as soon as possible. Funding could take time, especially if its customer funded, and time is often a limited commodity in the world of obsolescence.

6.3 Post-Case

Post-case work is going to consist of various tools and processes for properly managing component obsolescence along with metrics to track progress and provide updates to management and the customer.

6.3.1 Sustainment Roadmaps

Sustainment Roadmaps are an excellent tool for tracking component inventory levels to help ensure that parts on hand will last until a desired year. Accurate modeling beforehand is critical to make sure enough components are purchased in an LTB. In the roadmap below, there are two sets of years modeled for 2024 and 2035 based on historical component repair usage. In this example, some components will be phased out with a technology refresh. This tool allows you to track your obsolescence inventory as it is depleted and notifies you if you are consuming parts at rate faster than originally modeled for.

The roadmap below displays the following:

1. Component nomenclature
2. Quantity of components needed for future repairs
3. On-hand inventory
4. Next Higher Assembly nomenclature or Shop Replaceable Unit nomenclature
5. Quantity of the obsolete component in the Next Higher Assembly

6. The expected quantity of Next Higher Assembly washouts. A washout occurs when the Next Higher Assembly is beyond economical repair and a new subassembly is needed from production or sustainment stock.
7. Quantity of the obsolete component needed for Next Higher Assembly washout
8. Quantity of Next Higher Assembly units in stock or on order
9. Calculated component shortage or excess
10. The year being modeled out to
11. Approximate component depletion year
12. Line Replaceable Module/Line Replaceable Unit affected by the obsolete component
13. Mitigation notes
14. The model's assumptions. These assumptions can include the confidence level, contracted flight hours, the Mean Time Between Instances (MTBI), and any other factor that may be important.

Table 12: Sustainment Roadmap example

Customer								Current Year	Modeled to Year	Years Remaining	Tech Refresh Modeled to Year	Years Remaining	Updated: 1/1/2021
				SRU Washout Calculation				2021	2035	14	2024	3	
Obsolete Component	**Components Needed for Repairs**	**Component Stock**	**NHA SRU**	**Components Per SRU**	**SRUs Needs for Washout**	**Components Needed for SRU washout**	**SRU Stock**	**Component Shortage/Excess**	**Modeled to Year**	**Approx. Depletion Year**	**LRM/LRUs Affected**	**Mitigation Notes**	**Assumptions**
A	9	12	AA	1	13	13	11	1	2035	2035	AAA	Sufficient inventory to sustain repairs through 2035. NO ACTION REQUIRED BY CUSTOMER.	**Component:** 95% Confidence Contracted FH: 210,000 MTBI: 841,467 **SRU:** 50% Confidence Actual FH: 148,270 MTBI: 25,557
B	41	10	BB	1	5	5	19	-17	2024	2022	BBB	LTB of 31 components in progress. NO ACTION REQUIRED BY CUSTOMER.	**Component:** 95% Confidence Actual FH: 148,270 MTBI: 34,076 **SRU:** 50% Confidence Actual FH: 148,270 MTBI: 25,557
C	38	40	CC	1	13	13	11	0	2035	2035	CCC	Sufficient inventory to sustain repairs through 2035. NO ACTION REQUIRED BY CUSTOMER.	**Component:** 95% Confidence Contracted FH: 210,000 MTBI: 140,245 **SRU:** 50% Confidence Actual FH: 148,270 MTBI: 25,557
D	40	1330	DD	1	0	0	15	1305	2035	2035	DDD	Sufficient inventory to sustain repairs through 2035. NO ACTION REQUIRED BY CUSTOMER.	**Component:** 95% Confidence Contracted FH: 210,000 MTBI: 140,717 **SRU:** 50% Confidence Actual FH: 148,270 MTBI: 25,557
E	13	250	EE	1	0	0	165	402	2035	2035	EEE	Sufficient inventory to sustain repairs through 2035. NO ACTION REQUIRED BY CUSTOMER.	**Component:** 95% Confidence Contracted FH: 210,000 MTBI: 599,975 **SRU:** 50% Confidence Actual FH: 148,270 MTBI: 25,557
F	44	2	FF	1	0	0	165	123	2035	2035	FFF	Sufficient quantity of NHA FF. M-FFF available for any additional requirements. NO ACTION REQUIRED BY CUSTOMER.	**Component:** 95% Confidence Contracted FH: 210,000 MTBI:125,762 **SRU:** 50% Confidence Actual FH: 148,270 MTBI: 25,557
G	310	314	GG	1	0	0	0	4	2035	2035	GGG	Sufficient inventory to sustain repairs through 2035. NO ACTION REQUIRED BY CUSTOMER.	**Component:** 95% Confidence Contracted FH: 210,000 MTBI: 14,941 **SRU:** 50% Confidence Actual FH: 148,270 MTBI: 25,557
H	28	28	HH	2	4	8	9	1	2035	2035	HHH	Sufficient inventory to sustain repairs through 2035. Sufficient stock available/on-order to sustain fleet until M-HHH is available. NO ACTION REQUIRED BY CUSTOMER.	**Component:** 95% Confidence Contracted FH: 210,000 MTBI: 210,367 **SRU:** 50% Confidence Actual FH: 148,270 MTBI: 143,842

The calculation for the component shortage/excess is as follows:

(Component Stock – Components Needed for Repairs) – ((Components Per SRU * SRU Needs for Washout) – (SRU Stock))

For component A the calculation would be as follows:

(12-9) – ((1*13) - 11) = 3 - 2 = 1

Therefore, no further action is needed other than regular roadmap maintenance as components become consumed for repairs.

For component B, there is a shortage of 17 components. This would indicate a potential issue. However, the mitigation notes state that an LTB of 31 components is on order which surpasses the current shortage of 17. No further action is needed.

6.3.2 Production Roadmaps

The purpose of a Production Roadmap is the same as a sustainment roadmap which is to determine the number of components needed for an LTB and to track the depletion. Before an LTB is performed one must do the calculations for both repair and new hardware production. Production inventory levels must last until the next technology refresh point kicks in. To calculate the number of components needed for production, you would take the number of future production orders, multiply that number by the quantity of the obsolete component in that build, multiply that by a small scrap factor, and then multiply that by the order probability. The scrap factor would be based on historical yield rates to account for damaged components during assembly. In the example below, we will use a scrap rate of 10%. The order probability is the likelihood that the customer will follow through and pay for their order to be built.

In Table 13 below, component B is in type 1, 2, and 6 builds. There are 4 B components in each type 1 build, 15 in type 2 builds, and 4 in type 6 builds. Each build leading up to the technology refresh insertion point has a 100% build probability and a 10% scrap rate. Each individual build calculation is then also rounded up to the nearest whole number for an extra conservative value. The formula for component B would be as follows:

Round up (1 * 4 * 1.1 * 1) + Round up (23 * 15 * 1.1 * 1) + Round up (57 * 4 * 1.1 * 1) + Round up (14 * 4 * 1.1 * 1) + Round up (2 * 15 * 1.1 * 1) + Round up (14 * 15 * 1.1 * 1) + Round up (14 * 15 * 1.1 * 1) + Round up (55* 4 * 1.1 * 1) + Round up (50 * 4 * 1.1 * 1) + Round up (22 * 15 * 1.1 * 1) + Round up (31 * 4 * 1.1 * 1) + Round up (24 * 4 * 1.1 * 1) =

5 + 380 + 251 + 62 + 33 + 231 + 231 + 242 + 220 + 363 + 137 + 106 = 2,261

In Figure 12 below, component B would need an LTB purchase of quantity 2,261 to meet production needs until the technology refresh insertion date.

Component A has an on-hand quantity of 357. The burndown shows that an additional 585 components are needed to be purchased. Component C has an on-hand quantity of 410. This is more than enough to last until the new design kicks in. If certain obsolete components are no longer available for procurement, then discussions with the customer will have to take place about moving their order back in the schedule and providing them with the design refresh build.

Table 13: Production Roadmap example

Production Roadmap	Future Production Orders				Obsolete Component		
					A	B	C
					Current Inventory		
					357	0	410
	Order Probability	Build Date	Build Type	Build Needs	Burndown		
Current Design	100%	11/12/2016	1	1	355	-5	410
	100%	4/14/2017	2	23	203	-385	359
	100%	4/14/2017	3	28	203	-385	359
	100%	4/14/2017	4	16	203	-385	359
	100%	4/14/2017	3	9	203	-385	359
	100%	8/14/2017	1	57	140	-636	359
	100%	1/14/2018	3	42	140	-636	359
	100%	2/13/2018	1	14	124	-698	359
	100%	10/14/2018	2	2	110	-731	354
	100%	10/14/2018	2	14	17	-962	323
	100%	10/15/2018	2	14	-76	-1193	292
	100%	10/16/2018	3	50	-76	-1193	292
	100%	10/17/2018	3	55	-76	-1193	292
	100%	10/17/2018	1	55	-137	-1435	292
	100%	12/18/2018	1	50	-192	-1655	292
	100%	12/19/2018	2	22	-338	-2018	243
	100%	12/18/2018	1	31	-373	-2155	243
	100%	2/13/2019	6	24	-585	-2261	243
Technology Refresh	75%	5/16/2019	3	57	-585	-2261	243
	75%	7/14/2019	1	50	-585	-2261	243
	75%	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	75%	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	75%	1/14/2020	2	12	-585	-2261	243
	75%	1/14/2020	3	[illegible]	-585	-2261	243
	75%	1/14/2020	[illegible]	[illegible]	[illegible]	-2261	243
	50%	1/14/2020	3	33	-585	-2261	243
	50%	1/14/2020	1	30	-585	-2261	243
	75%	4/14/2020	2	36	-585	-2261	243
	75%	4/15/2020	1	23	-585	-2261	243
	75%	4/16/2020	1	24	-585	-2261	243

Technology Refresh Implementation Beyond This Point

6.3.3 Technology Refresh Roadmap

The purpose of a Technology Refresh Roadmap is to clearly display redesign timelines and obsolescence impacts to various LRUs. This tool is mainly geared towards the customer to provide them with quick and easy to read updates. Figure 33 below depicts five different Technology Refresh cycles and their various stages.

In the example below, the yellow bar represents the amount of time in years allotted for engineering to complete the redesign. The orange wedge represents the time expected for all fielded assets to be equipped with the new design. This can be done through attrition or scheduled refurbishments. The white triangle with green border represents the estimate Engineering Completion Date (ECD) for the redesign. This bar can be moved to the left or right as required due to accelerated progress or delays to the redesign. The solid green triangle represents the actual ECD. The solid black triangle signifies the production impact date. This date represents the latest possible date for the ECD before production can no longer produce the old LRU. The solid blue triangle depicts the sustainment impact date. This date represents the latest possible date for the ECD before fielded assets can no longer be repaired.

TR 1 denotes a scenario where engineering had five years from 2015 to 2020 to complete a redesign. Engineering took 6 years to complete and finished in 2021 just in time to meet the production impact date. There were no impacts to sustainment but planned fielding will have to be pushed back one year. In all five scenarios, the redesign timeframe and planned fielding are expected to take five years each. The production and sustainment impact date vary based on inventory levels of the obsolete components in each LRU. Smaller details can be laid out in the note’s section of the roadmap for the customer to understand specifically what may be driving certain timelines or impact dates.

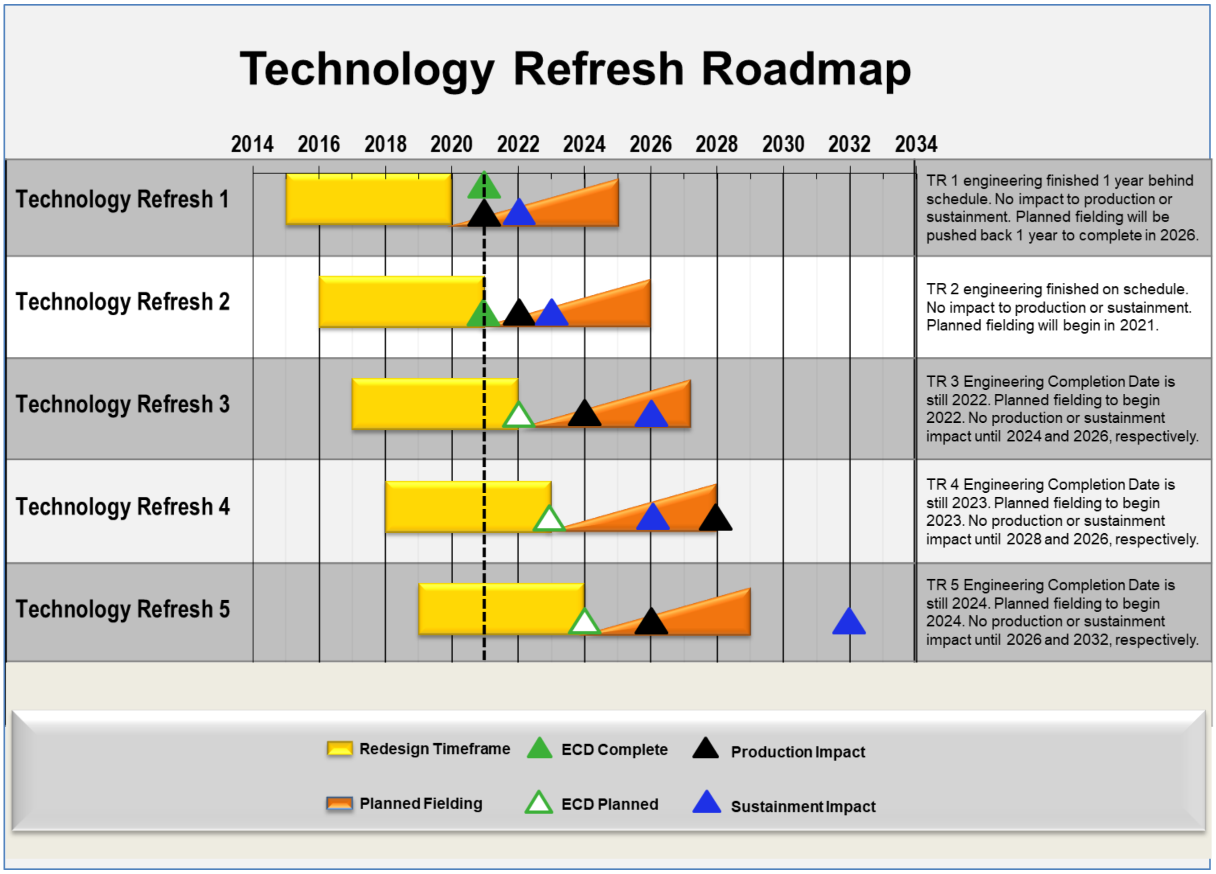

Figure 33: Technology Refresh Roadmap example

6.4 Metrics

Metrics are a great way for the DMT to track its progress and establish goals, while also being imperative to providing updates to the customer and demonstrate the value of the team. Some of the key metrics that will be discussed are cost avoidance, case resolution history, and annual case turnaround-time (TAT).

6.4.1 Case Resolutions

One of the main metrics to track for management and the customer is the overall case resolution counts for closed cases and the total number of cases opened each year. This provides a clear picture on what the main resolution types occurring are and the outlook for the expected future number of cases. Figure 34 below displays an example of the percentage of each resolution type that has resulted since 2010. The chart shows that 93% of all solutions result in a Simple Substitute or a Last-Time-Buy. This is valuable information because most solutions would result in a redesign if it were not for the work of the DMT.

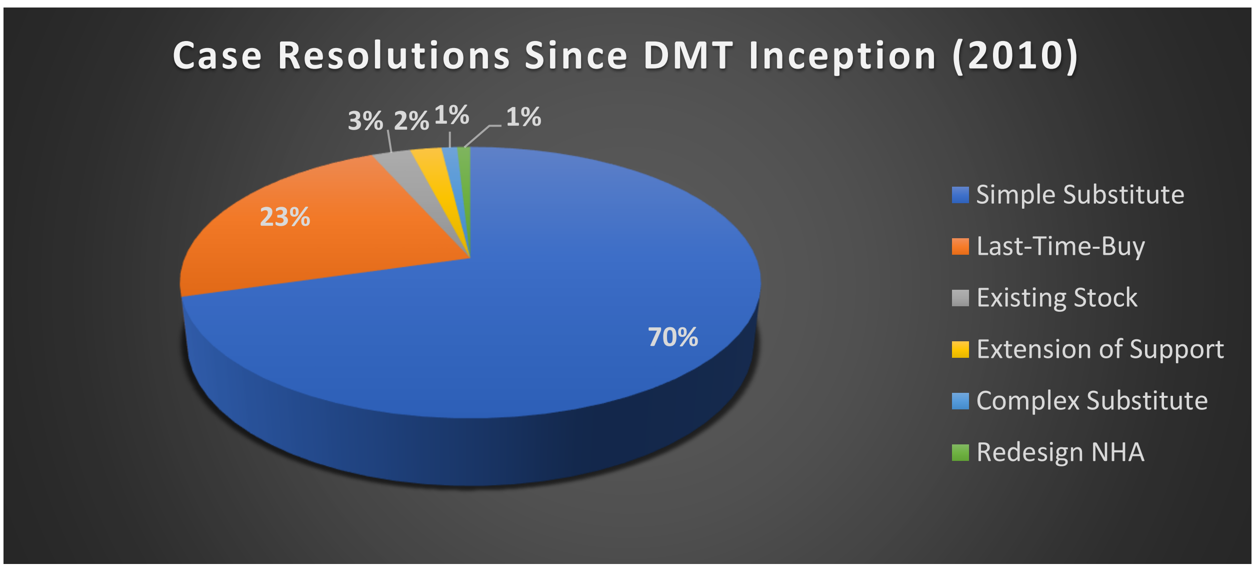

Figure 34: Case resolutions since inception by percentage example

Figure 35 shows the total number of open cases each year since 2010. The trend line indicates that over time, the number of cases is increasing. This is typical of an ageing system. This chart reinforces the need for a DMT by showing that each year the number of cases is only going to grow creating larger risk to the system. Without a DMT, the system would experience tremendous downtime.

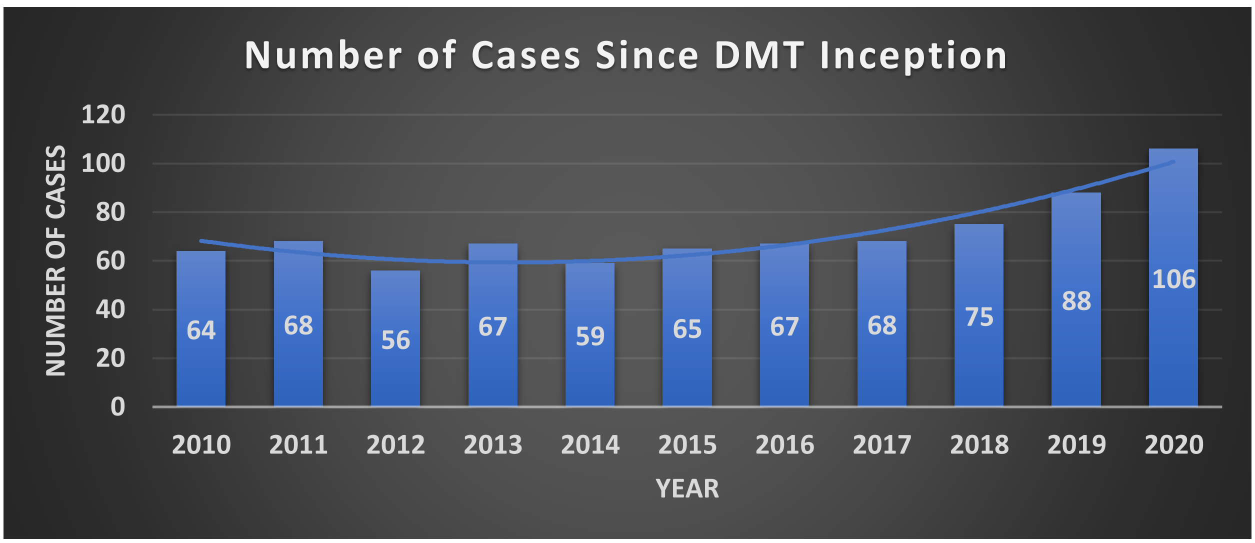

Figure 35: Number of cases since inception by count example

Figure 36 below is an example of case resolutions by percentage for the most current year. This information shows management and the customer the most up-to-date data and can be compared to historical data in Figure 34 above to see if there are any new emerging trends developing.

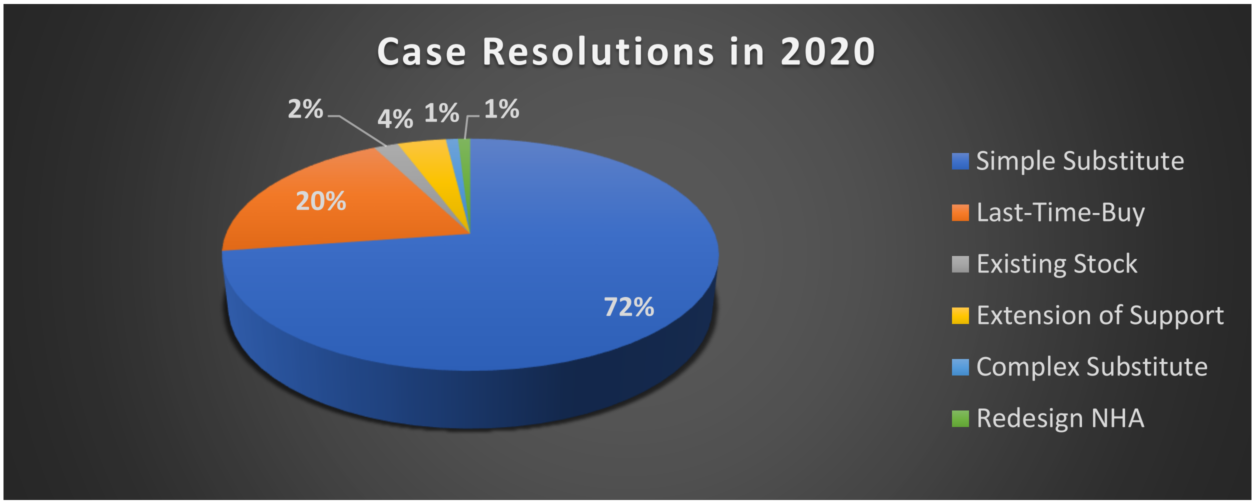

Figure 36: Case resolutions in 2020 by percentage example

Figure 37 consists of identical data from Figure 36 but displayed in a count format instead of a percentage. Providing information in multiple formats can paint a better picture for leadership and the customer. This helps them understand what they are looking at to make informed decisions.

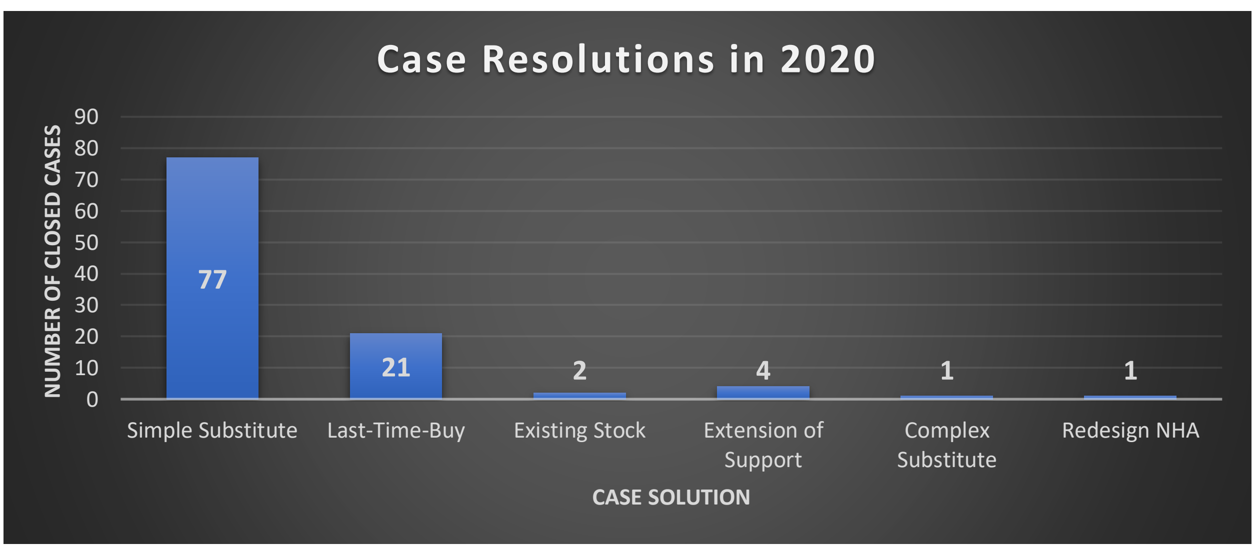

Figure 37: Case resolutions in 2020 by count example

6.4.2 Cost Avoidance & Cost of Service

Each of the mitigation techniques demonstrated in the table above has an associated cost upon implementation. As stated earlier, cost avoidance of a solution relates the difference in cost between the solution being implemented and the next most feasible solution (Office, 2016). In Figure 38 below, the chart depicts an example of a typical cost avoidance vs cost of service scenario. This is important information that management and the customer want to see.

The chart below demonstrates the value that the DMT is providing relative to the cost of the service. In 2020, the DMT's $4,000,000 service cost to the customer resulted in an avoidance of cost of over $46,000,000. Over the past eight years, the overall cost of service has decreased as the DMT has been able to provide the same or better service at less cost year over year, while the cost avoidance has continued to climb. The steady upward curve is often seen in aging systems, which makes this information even more valuable for both the company and the customer. When the customer can clearly see that not investing in a DMT would result in costs 5-10 times what they currently pay, they are likely to continue paying for a proactive obsolescence team.

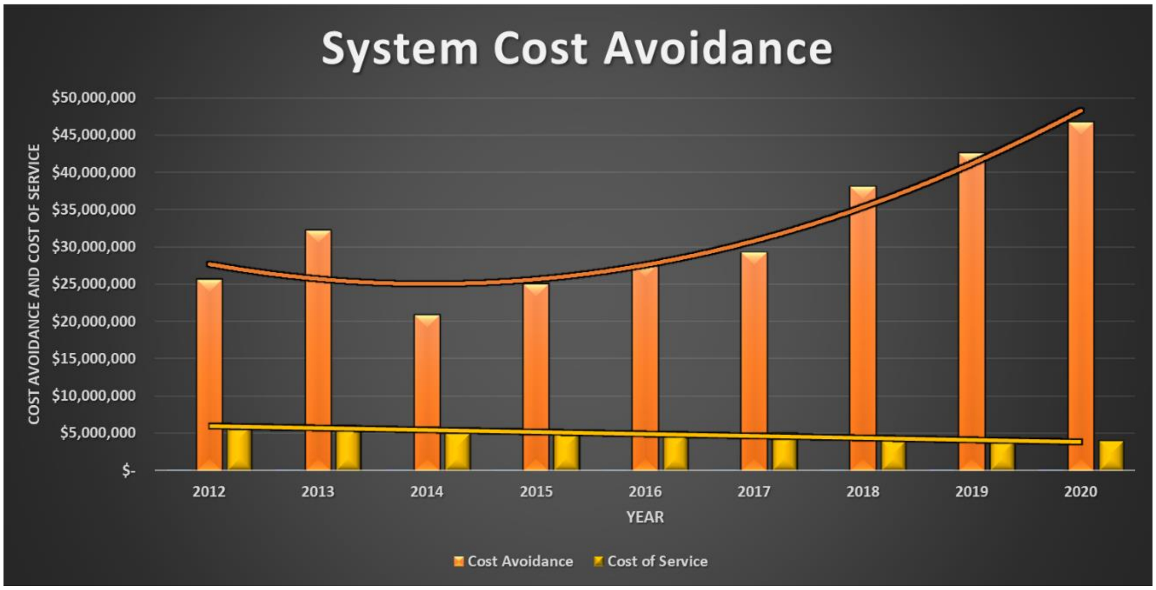

Figure 38: System Cost Avoidance example

6.4.3 Annual Case Turnaround Time

The purpose of tracking case TAT is to ensure that obsolescence cases are being worked in as quick of a manner as possible. The longer a case takes to complete, the higher the risk level to the system. Customers will often implement a contractual requirement for the DMT to not exceed a specified number of days from the date the case is opened to the date it is closed. This is usually done on a yearly collective basis for the average TAT for all cases each year. The example below depicted in Figure 39 shows a continual improvement in the yearly case closure TAT. This demonstrates to both the customer and leadership the value the DMT is providing to the program through consistent yearly obsolescence risk reduction.

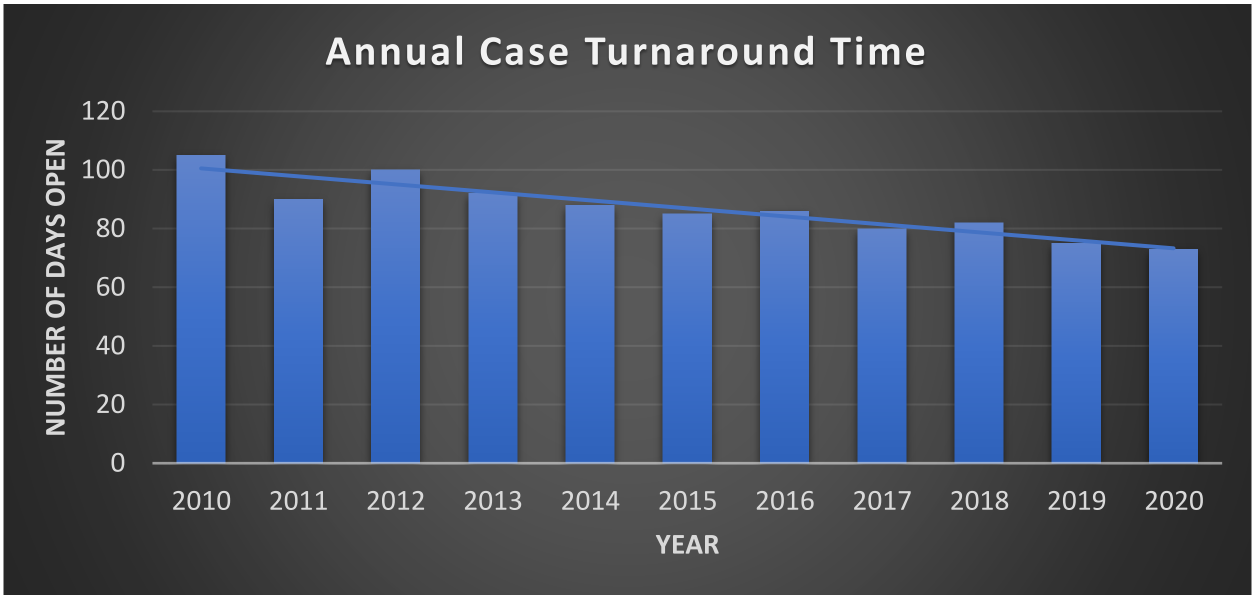

Figure 39: Annual case TAT example

6.5 Best Practices

1. Contractual funding for a DMT to promote proactive obsolescence management.
2. Pre-funded budget for mitigation solutions from customers. This saves time and resources for implementing a solution as there is no need to reach out to the customer for approval for most cases.
3. Machine learning models for initial design selection, component EOL tracking, and BOM obsolescence risk level evaluations.
4. Continuous technology refresh initiatives based on BOM obsolescence risk level evaluations.

5. Division of hardware into distinct partitions using modularity that is afforded by open architecture to functionally split the system into multiple segments known as LRMs or LRUs. Open architecture makes obsolescence easier to mitigate because systems designed under completely closed and proprietary architecture typically require complex redesigns or new interfaces to incorporate new components.
6. React quickly to high-risk situations and elevate information to management when necessary.
7. Implementation of the most cost-effective mitigation solutions through proper selection and accurate LTB modeling.
8. Require subcontractors to keep constant communication with the DMT and provide consistent and accurate information. This information includes up to date BOMs, solution implementation timelines, and remaining stock quantities.
9. Utilize multiple material sources and vendor locations, when possible, to reduce obsolescence risk.
10. Conduct regular obsolescence working group (OWG) and integrated product team (IPT) meetings with all internal and external customers including, but not limited to, the following: finance, program managers, quality, planning, engineering, suppliers, procurement, and production.
11. Monthly obsolescence reports to customers to keep a steady flow of communication.
12. Capture metrics such as cost avoidance, case outcomes, and long-range forecasting to demonstrate impacts and value to the customer.

13. Automate as many daily tasks as possible to reduce time collecting metrics and creating reports.
14. Keep all obsolescence case data in a central location that is easily accessible to all members of the team.
15. Keep thorough and well-organized documentation of work processes for knowledge transfer when training new team members. Critical historical information is often lost due to tribal knowledge that is not passed down when senior members leave the team.

6.6 Obsolescence Management Framework Validation

The obsolescence management framework was validated using a 13 question Likert scale questionnaire. The questionnaire was sent out to 11 industry experts all of which provided their responses. The average score for each question was as follows:

Table 14: Average Response Score

Question	Average Response Score
1	4.36
2	3.82
3	4.64
4	4.27
5	4.64
6	4.55
7	4.73
8	4.64
9	4.82
10	4.55
11	4.55
12	4.55
13	4.45
Overall	4.50

The question with the lowest overall score was question 2 with an average score of 3.82. This was mainly due to some of the experts not being certain whether machine learning is a new concept in DMSMS forecasting or not. Since the lowest score for question 2 was a 3, there were no responses disagreeing that it is a new concept in the field. The question with the highest overall score was on question 9 with an average score of 4.82. This question focused on the importance of roadmaps in managing mitigated cases. The overall score for the entire questionnaire was 4.50. This means that the overall expert consensus to the management framework was a mixture of agree to strongly agree. This provides strong justification to the legitimacy of the framework and provides validation that it would likely reduce obsolescence risk and downtime to a system whether in production or being sustained in the field.

A strong method to confirm the validity of the framework questionnaire is through a content validity index (CVI). The higher the CVI, the stronger the validation that the framework holds value. The table below discusses the acceptable minimum CVI values based on various quantities of experts.

Table 15: The number of experts and its implication of the acceptable cut-off score of CVI. Adapted and modified from (Yusoff, 2019)

Number of Experts	Acceptable CVI Values
2	At Least 0.8
3-5	Should be 1
6	At Least 0.83
6-8	At Least 0.83
9 or more	At Least 0.78

The questionnaire in this dissertation used 11 experts and therefore is aiming for a CVI value of 0.78 or higher. The Likert scale had a 5-point system. Any response score of 4 or 5 will count towards the CVI value, whereas any response score of 3, 2, or 1 will not. Table 16 below shows all 13 question responses from each of the 11 experts. The CVI looks at the number of experts in agreeance for each question. As an example, for question 1, there were 10 experts out of 11 who gave a response score of 4 or 5. The CVI for question 1 is 10/11 or 0.91. The overall CVI score for the entire questionnaire is 0.92 which surpasses the satisfactory level of content validity.

Table 16: CVI for Framework Questionnaire

	Content Validity Index (CVI)													
Questions	**Expert 1**	**Expert 2**	**Expert 3**	**Expert 4**	**Expert 5**	**Expert 6**	**Expert 7**	**Expert 8**	**Expert 9**	**Expert 10**	**Expert 11**		**Experts in Agreement**	**CVI**
Q 1	1	1	0	1	1	1	1	1	1	1	1		10	0.91
Q 2	1	0	0	0	1	1	1	0	1	1	0		6	0.55
Q 3	1	1	1	1	1	1	1	1	1	1	1		11	1.00
Q 4	1	1	1	1	1	1	1	1	1	1	0		10	0.91
Q 5	1	1	1	1	1	1	1	1	1	1	1		11	1.00
Q 6	1	1	1	1	1	0	1	1	1	1	1		10	0.91
Q 7	1	1	1	1	1	1	1	1	1	1	1		11	1.00
Q 8	1	1	1	1	1	1	1	0	1	1	1		10	0.91
Q 9	1	1	1	1	1	1	1	1	1	1	1		11	1.00
Q 10	1	1	1	0	1	1	1	1	1	1	1		10	0.91
Q 11	1	1	1	1	1	1	1	0	1	1	1		10	0.91
Q 12	1	1	1	1	1	1	1	1	1	1	1		11	1.00
Q 13	1	1	0	1	1	1	1	1	1	1	1		10	0.91
													CVI Average	0.92

Some overall comments provided by the experts were as follows:

1. Technology refreshes can be beneficial, but most programs tend to shy away from due to high initial costs unless they absolutely must.
2. While communication to all internal and external customers is important, not all contract types require customer notification of an obsolescence issue prior to a mitigation solution being implemented.
3. It is recommended to include in the framework the assumption that the systems are modularized.
4. It is recommended to include in the framework the assumption that the repair, refurbishment, or reclamation mitigation solution is not recommended for military systems.

CHAPTER 7 CONCLUDING REMARKS

7.1 Conclusion

To conclude, Diminishing Manufacturing Sources and Material Shortages is an inevitable reality in manufacturing systems and supply chain environments as systems are needed to be sustained for long timeframes. More emphasis needs to be put on proactive/strategic approaches to mitigating obsolescence, rather than just reactive. A proactive strategy comes in the form of obsolescence forecasting demonstrated by a case study by Connor Jennings. Using machine learning has validated the accuracy of the Life Cycle Forecasting framework by showing that obsolescence dates can be predicted within a few months of the actual discontinuation date. That case study demonstrated the strength of the Obsolescence Risk Forecasting by correctly identifying active and obsolete parts with high accuracy.

Today's best tools for forecasting obsolescence use traditional algorithms that analyze inputs using defined logic but are only as good as the logic provided. Machine Learning takes inputs and outputs to create its own logic and then uses this logic when analyzing new data. The results for this small-scale case study shows promising results for a larger scale experiment. The Random Forest algorithm was able to classify components as Active or Obsolete with an OOB error rate of 10.87% and predict actual obsolescence dates with less than a one-year margin of error. Future research in this area would require reperforming this experiment with a larger dataset, variable training sizes, optimized feature selection, and multiple algorithms such as Naive Bayes and Support-Vector Machines.

This research constructed an obsolescence management framework using personal experience in the field of DMSMS and through research of peer reviewed articles on current management practices. The main area of focus was on proactive management which is where the machine learning case study played a role. Expert consensus derived an average score of 4.50/5. This means that the expert agreed/strongly agreed that implementing the proposed framework likely reduce obsolescence risk, help mitigate issues, and reduce downtime to a system.

There are various proactive/strategic approaches to mitigating obsolescence and tools to help track and forecast cases. Some of these key areas of focus are funding for a robust DMSMS team, a strong supply chain, system design that factors in obsolescence risk, and strong communication with all parties involved. It is imperative to develop an effective and data-driven approach to communicating obsolescence impacts to leadership to ensure successful mitigation of obsolescence issues. Solution funding could take time, especially if its customer funded, and time is often a limited commodity in the world of obsolescence. Some post-case tools and strategies include utilizing sustainment, production, and technology refresh roadmaps, along with employing data driven metrics to provide key information to leadership and demonstrate value to the customer.

A powerful proactive strategy that this framework includes is built-in technology refresh cycles into a system that can be implemented using machine learning. A redesign can be implemented once a predetermined risk threshold is met. Afterwards, third party software or machine learning regression and classification algorithms can be used for the component selection process in the new design. Once a case is open, it is important to come to the most cost-effective mitigation solution. It is imperative to deliver this information to management as quickly and accurately as possible so a decision can be made.

7.2 Contributions to the Body of Knowledge

This framework provides a helpful guide to anyone in the field of managing obsolescence issues particularly with military-based systems. It demonstrates the potential for using machine learning as a life cycle forecasting tool in lieu of traditional models. This framework proposes the use of machine learning models to aide in the selection of components for system designs and creating obsolescence risk profiles for BOMs. It also provides a clear path on how to find a solution to problems as they occur and how to manage these newly mitigated obsolescence issues. This case study provides a path forward for future research using machine learning as a forecasting tool in the DMSMS field.

7.3 Challenges, Limitations & Future Research

One of the main challenges for completing future research with machine learning and obsolescence is collecting large amounts of complete of data. It is said that we are in the Information Age as take on projects of big data analytics and this era is moving towards more cognitive processing with machine learning and artificial intelligence capabilities that rely on the large amounts of data we collect and manage (Mullins, 2017). A model will always only be as good as the input information that it receives.

When it comes to machine learning, training data determines the performance of the model's outputs. According to Hale (2018), bad quality data will replicate itself as it flows through machine learning systems, generating flawed information. A quote from Thomas C. Redman, a well-known figure in the data quality management world, states, "Poor data quality is enemy number one to the widespread, profitable use of machine learning" (Hale, 2018). To overcome the enemy of bad data, a great deal of time must be spent analyzing data integrity to help safeguard against inaccurate and biased results.

Comparing component data is another challenge, but there are some online databases that can provide component obsolescence. Some of these databases include, but are not limited to, PartMiner, Q-Star, SiliconExpert, CAPS Universe and Total Parts Plus. Manufacturers also often have their component datasheets publicly available. It is important for the data to be as complete as possible, but as demonstrated in various studies, to a certain extent, machine learning models can make their own predictions to fill in gaps of missing or incomplete data.

Another challenge and possibly a limitation are fitting the models to make them work with data from all types of components. Different types of components include resistors, capacitors, microcontrollers, integrated circuits (IC), and so on. An FPGA is not going to have the same obsolescence trends as a diode. A digital IC may require different algorithm features than an analog IC for the predictive models to be accurate. Sometimes age can be used as a feature where other times primary attributes such as speed, size, logic gates, or logic cells can be used as inputs (Gao, Liu, & Wang, 2011). Figure 40 shows how age can be a primary driver on certain components such as an operational amplifier, but age does not have a strongly correlated effect on flash memory. This is an obstacle that may be hard to overcome in due to the complexity of having to set up different models for different types of components. This research focused on utilizing machine learning algorithms for predicting component obsolescence using Flash Memory (FM) chips. Future research can be done to branch out to other types of components since this dissertation study shows promise.

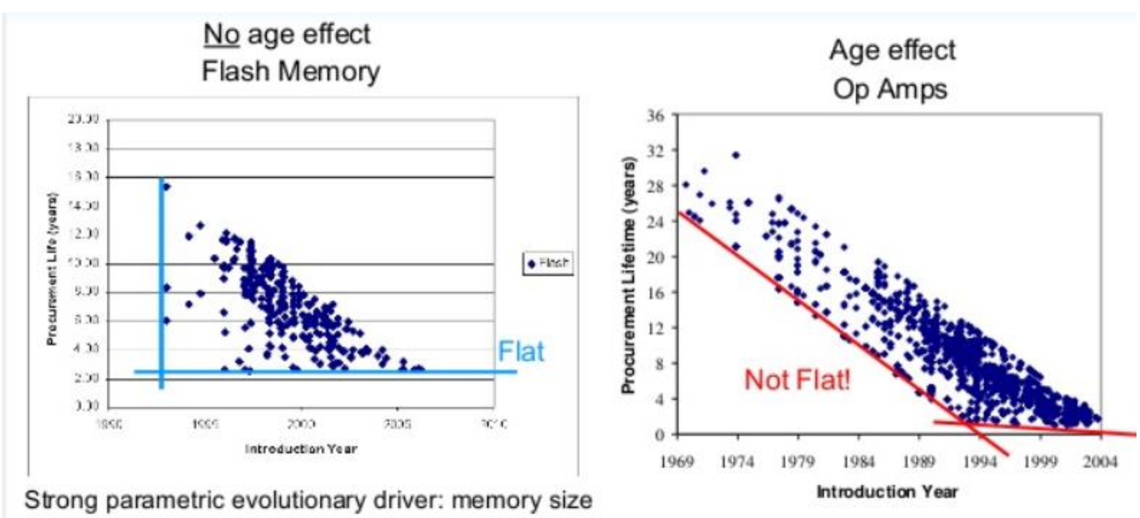

Figure 40: Age effect on Flash Memory vs. Op Amps (Technologies, 2015)

Making sure that the historical collected data still reflects current data is a third challenge. According to Jennings (2016), a machine learning or statistical obsolescence model in present day with past obsolescence data would not predict advancements and innovations in technology. This means that the obsolescence forecasting frameworks and all current machine learning models cannot predict unforeseen technological advancements, and therefore are better suited to track steady improvements in the electrical component industry (Jennings, 2016). This is an issue that is just the nature of the beast and cannot necessarily be completely erased, but it is important to be cognizant of this incidence. The main takeaway here is to remember that the goal is to improve upon the prediction accuracies of current models, of all types, and bring forward better obsolesce information to electrical design engineers than they are currently receiving. Nothing will ever be perfect, but everything can always be made better.

Another limitation to this study is there is not a way of comparing the accuracy of these machine learning algorithmic models to a traditional model such as Q-STAR for historical predictions. Access to historical predictions on an already obsolete component is not available. This does not mean the use of machine learning models for obsolescence predictions cannot be justified, as the case study results show promise. With all that said, and based on the positive preliminary results, I believe that continued research and experimentation using machine learning algorithms would provide great knowledge for the field of component obsolescence forecasting.

Future research within the realm of combining artificial intelligence and DMSMS would include the use of deep learning with larger datasets. As machine learning is a subset of artificial intelligence, deep learning is a subset of machine learning. The main difference between the two is machine learning makes informed decisions based on what it learns from the algorithm parsing data and deep learning layers algorithms to create an artificial neural network that can learn and make decisions on its own (Grossfeld, 2020). A classic example of deep learning in action is AlphaZero created by Google DeepMind. According to Silver et al., AlphaZero used deep neural networks to play millions of chess games against itself in a trial-and-error process called reinforcement learning. Over time the system learned the best moves by remembering strong moves and learning from mistakes on bad moves (Silver, Hubert, Schrittweiser, & Hassabis, 2018). This type of extreme machine learning could be explored for DMSMS forecasting in the future.

APPENDIX A: DATA VALIDATION

1. Variable Assumptions
    a. Multivariate Normality - Q-Q plot shows that the errors between observed and predicted values to be normally distributed. As variables are removed, the top of the line does begin to skew slightly.
    b. No Multicollinearity - Some exists but can be removed. Some variable reduction in future studies should not greatly negatively impact the model's accuracy.
    c. Homoscedasticity - The variance of error seems similar across the values of the independent variables. However, it is hard to definitively say because the data contains both numeric and ordinal data. This is creating negative sloped diagonal line clusters. This happens with mixed data and is not necessarily a reason for concern.
2. Fit Indices – R2 value ranges from 0.72-0.80 depending on variables used with the Chi-Squared test showing a p-value of less than 0.01. This means the model explains most of the variation within the data and is statistically significant.
3. Snapshot vs Longitudinal – This case study uses a small sample size and breaking the data down by years would result in very small testing and training groups.

The following data was pulled from R software using its multicollinearity tests, linear model summary, Pearson's Chi-squared test, residuals vs fitted plots, Q-Q plots, scale-location plots, and residuals vs leverage plots. The purpose of this information is to demonstrate the validity of the machine learning model outputs. Although this real-world data is not perfect, it does pass various validity tests. As some of the variables exhibiting collinearity were removed from the calculation for retesting, the outputs did not change dramatically. Some of the most important information from the validity testing is that the R2 values ranged from 0.72-0.80 in the Chi-Squared tests showing a p-value of less than 0.01. This shows that the model explains most of the variation within the data and is statistically significant. The initial multicollinearity test was with all seven variables with three of the variables showing some multicollinearity.

H0:the X's are orthogonal
H1:the X's are not orthogonal

All Individual Multicollinearity Diagnostics Result

	VIF	TOL	Wi	Fi	Leamer	CVIF	Klein
ï..A	4602313.5390	0.0000	4.679018e+07	5.706868e+07	0.0005	2470508.3127	1
B	4598253.3459	0.0000	4.674890e+07	5.701833e+07	0.0005	2468328.8130	1
C	1.5361	0.6510	5.450800e+00	6.648200e+00	0.8068	0.8246	0
D	2.3512	0.4253	1.373710e+01	1.675470e+01	0.6522	1.2621	0
F	11.3211	0.0883	1.049312e+02	1.279816e+02	0.2972	6.0771	1
G	2.0475	0.4884	1.064980e+01	1.298920e+01	0.6989	1.0991	0
H	3.5862	0.2788	2.629350e+01	3.206940e+01	0.5281	1.9251	0

1 --> COLLINEARITY is detected by the test
0 --> COLLINEARITY is not detected by the test

Linear Model Summary

```
Residuals:
    Min       1Q   Median       3Q      Max 
-0.30571 -0.06197 -0.01640  0.04870  0.20702 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.689e+00  1.425e-01  11.850  < 2e-16 ***
ï..A         1.084e-02  2.315e-03   4.680 1.68e-05 ***
B           -4.816e-03  1.029e-03  -4.682 1.67e-05 ***
C           -1.049e-07  7.705e-08  -1.362   0.1783    
D            1.160e-01  5.201e-02   2.230   0.0295 *  
F            1.140e-04  1.473e-04   0.774   0.4419    
G            3.442e-01  4.853e-02   7.092 1.74e-09 ***
H            3.628e-03  4.023e-04   9.019 9.16e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.103 on 60 degrees of freedom
Multiple R-squared:  0.8053,	Adjusted R-squared:  0.7826 
F-statistic: 35.46 on 7 and 60 DF,  p-value: < 2.2e-16
```

Pearson's Chi-squared test

```
data:  dataset

X-squared = 4787139, df = 335, p-value < 2.2e-16
```

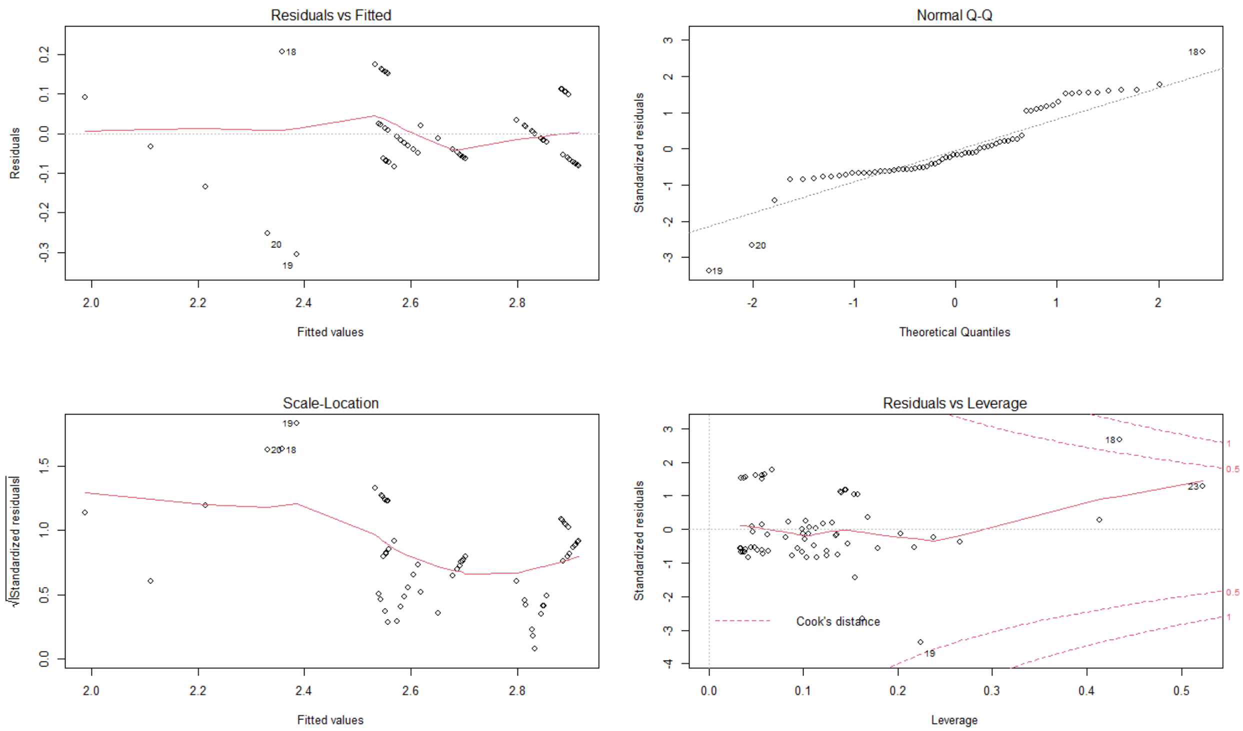

Figure 41: Residuals vs Fitted, Q-Q, Scale-Location, and Residuals vs Leverage plots for seven variables

Residual vs fitted plots are showing diagonal line clusters due to presence of both numeric and ordinal data.

Six variables showed less collinearity.

```
All Individual Multicollinearity Diagnostics Result

      VIF    TOL       Wi       Fi Leamer   CVIF Klein   IND1   IND2
B  9.9335 0.1007 110.7754 140.7026 0.3173 6.6858     1 0.0081 1.4100
C  1.5347 0.6516   6.6298   8.4209 0.8072 1.0329     0 0.0525 0.5462
D  2.2202 0.4504  15.1300  19.2176 0.6711 1.4943     0 0.0363 0.8617
F 10.9267 0.0915 123.0916 156.3462 0.3025 7.3544     1 0.0074 1.4244
G  2.0112 0.4972  12.5391  15.9267 0.7051 1.3537     0 0.0401 0.7883
H  2.6198 0.3817  20.0855  25.5118 0.6178 1.7633     0 0.0308 0.9694

1 --> COLLINEARITY is detected by the test
0 --> COLLINEARITY is not detected by the test
```

Linear Model Summary

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.207830 -0.070689 -0.008673  0.061795  0.208599

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.389e+00  1.475e-01   9.417 1.68e-13 ***
B           -2.578e-06  1.752e-06  -1.472  0.14626
C           -9.374e-08  8.923e-08  -1.051  0.29761
D            1.734e-01  5.856e-02   2.961  0.00436 **
F            2.427e-04  1.677e-04   1.447  0.15294
G            3.140e-01  5.574e-02   5.633 4.79e-07 ***
H            4.606e-03  3.984e-04  11.560  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1193 on 61 degrees of freedom
Multiple R-squared:  0.7343,    Adjusted R-squared:  0.7081
F-statistic: 28.09 on 6 and 61 DF,  p-value: 7.865e-16
```

```
Pearson's Chi-squared test

data:  my_data
X-squared = 4613208, df = 402, p-value < 2.2e-16
```

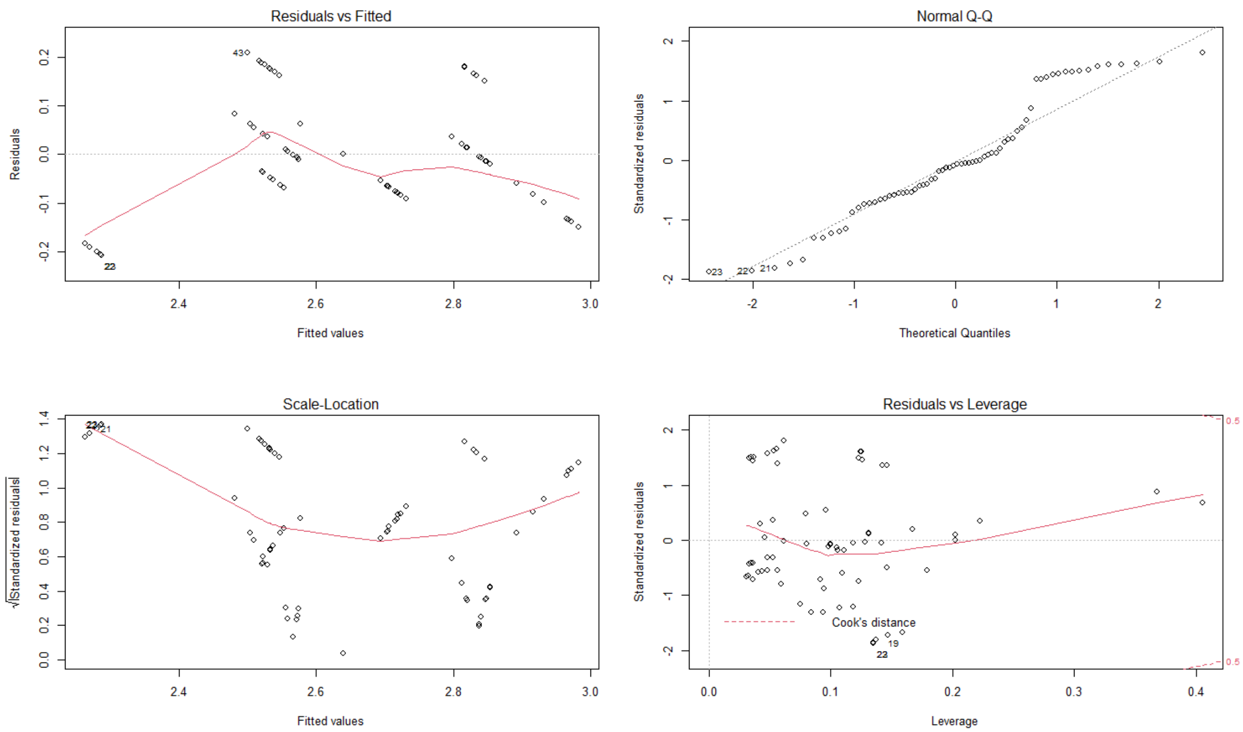

Figure 42: Residuals vs Fitted, Q-Q, Scale-Location, and Residuals vs Leverage plots for six variables

With five variables there was no more collinearity. However, the Q-Q chart begins to look a little worse. This is most likely due to the removal of numeric variables that were showing collinearity making the ratio of ordinal to numeric data larger. Although the Q-Q chart looks the worst out of the 3 sections here, on the residuals vs leverage chart none of data points show to be extreme outliers that would have a large impact on the overall results.

All Individual Multicollinearity Diagnostics Result

	VIF	TOL	Wi	Fi	Leamer	CVIF	Klein	IND1	IND2
B	1.5358	0.6511	8.4383	11.4297	0.8069	1.0193	0	0.0413	0.7977
C	1.5266	0.6551	8.2934	11.2334	0.8094	1.0132	0	0.0416	0.7888
D	2.0010	0.4998	15.7657	21.3546	0.7069	1.3281	0	0.0317	1.1439
G	1.6701	0.5988	10.5536	14.2949	0.7738	1.1085	0	0.0380	0.9175
H	2.4468	0.4087	22.7869	30.8649	0.6393	1.6240	0	0.0259	1.3521

1 --> COLLINEARITY is detected by the test
0 --> COLLINEARITY is not detected by the test

Linear Model Summary

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.21026 -0.06919 -0.00336  0.03514  0.20388

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.506e+00  1.244e-01  12.108  < 2e-16 ***
B           -2.469e-07  6.949e-07  -0.355   0.7235
C           -8.436e-08  8.978e-08  -0.940   0.3510
D            1.468e-01  5.608e-02   2.617   0.0111 *
G            2.807e-01  5.124e-02   5.479 8.28e-07 ***
H            4.457e-03  3.884e-04  11.476  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1204 on 62 degrees of freedom
Multiple R-squared:  0.7252,	Adjusted R-squared:  0.703
F-statistic: 32.72 on 5 and 62 DF,  p-value: 3.54e-16
```

Pearson's Chi-squared test

```
data:  my_data
X-squared = 4597051, df = 335, p-value < 2.2e-16
```

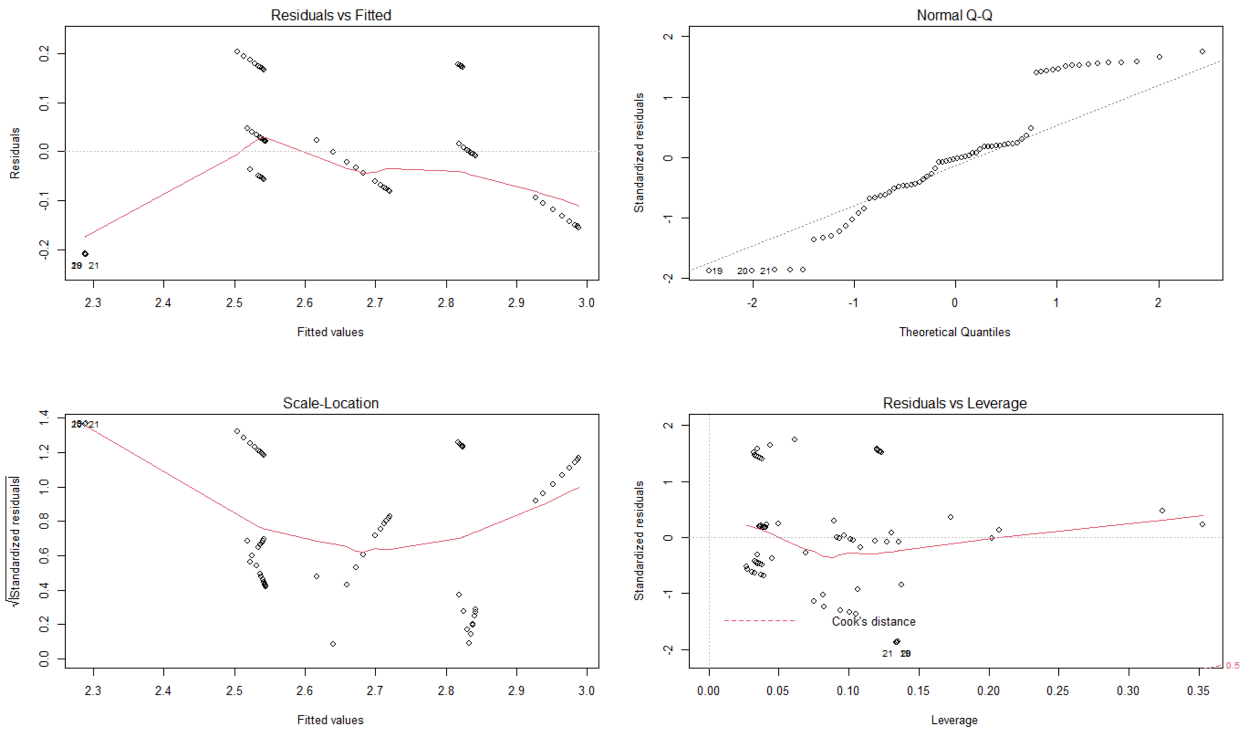

Figure 43: Residuals vs Fitted, Q-Q, Scale-Location, and Residuals vs Leverage plots for five variables

APPENDIX B: QUESTIONNAIRE FRAMEWORK

Pre-Case Framework provided for questionnaire.

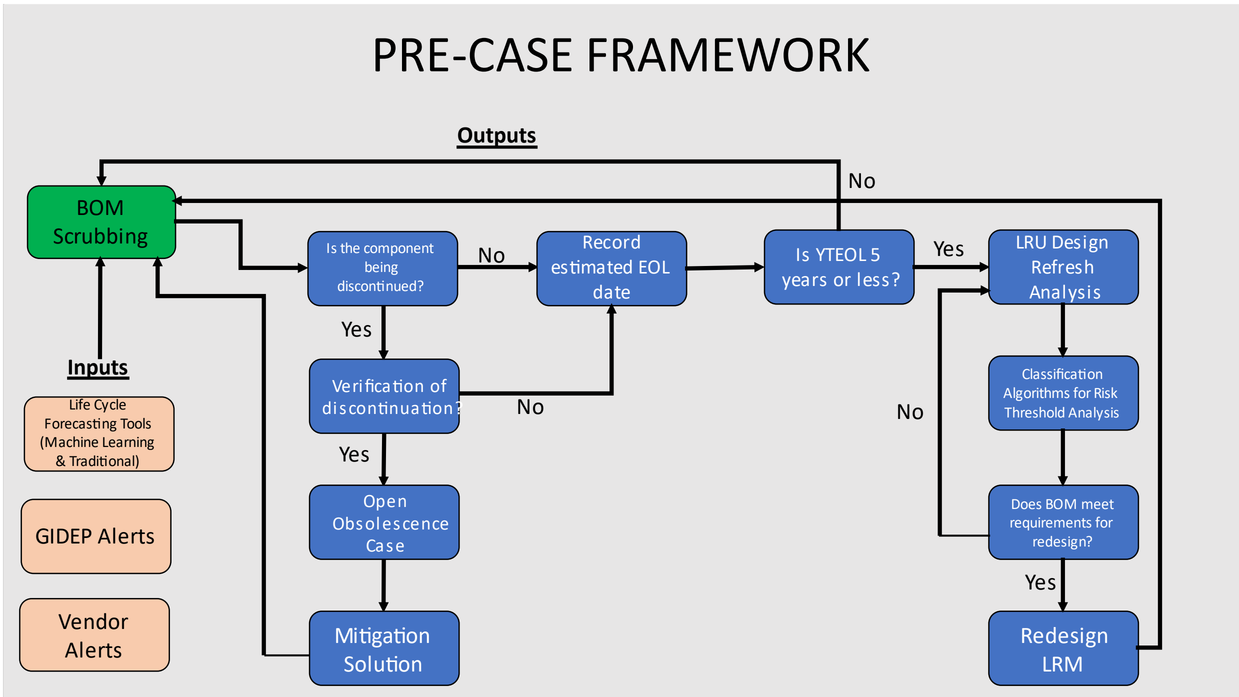

Figure 44: Pre-Case Framework

Open Case Framework provided for questionnaire.

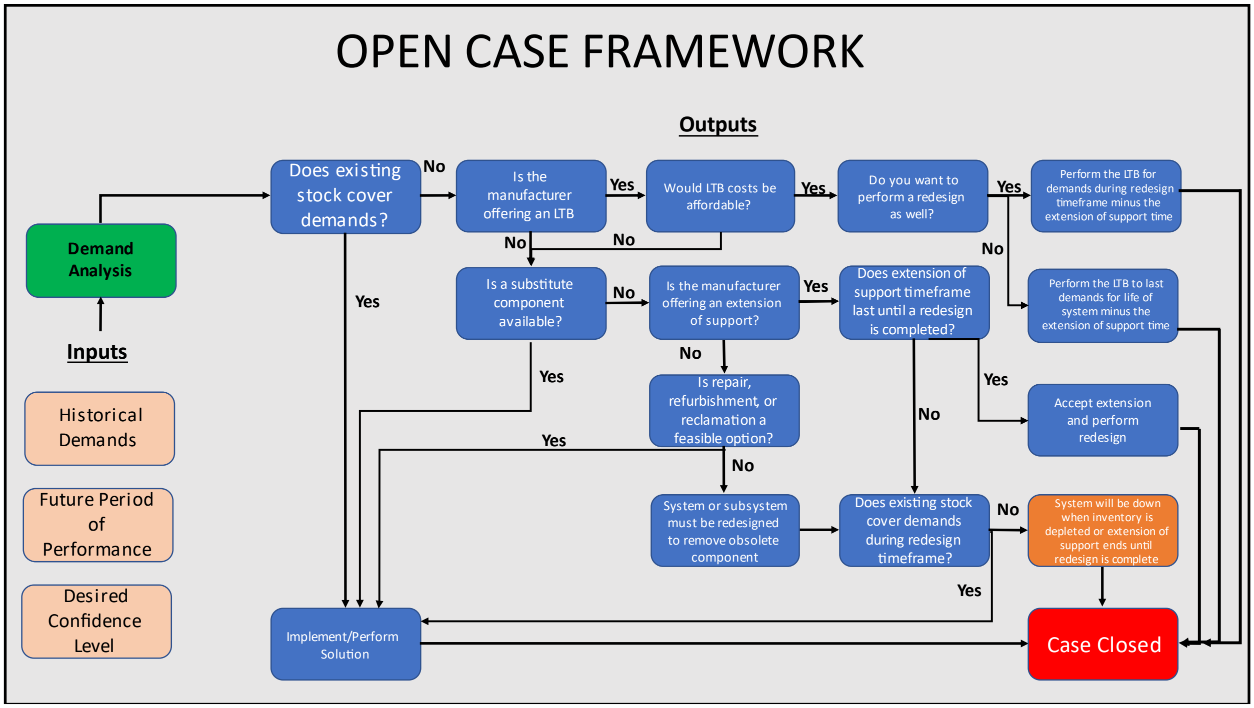

Figure 45: Open Case Framework

Post-Case Framework provided for questionnaire.

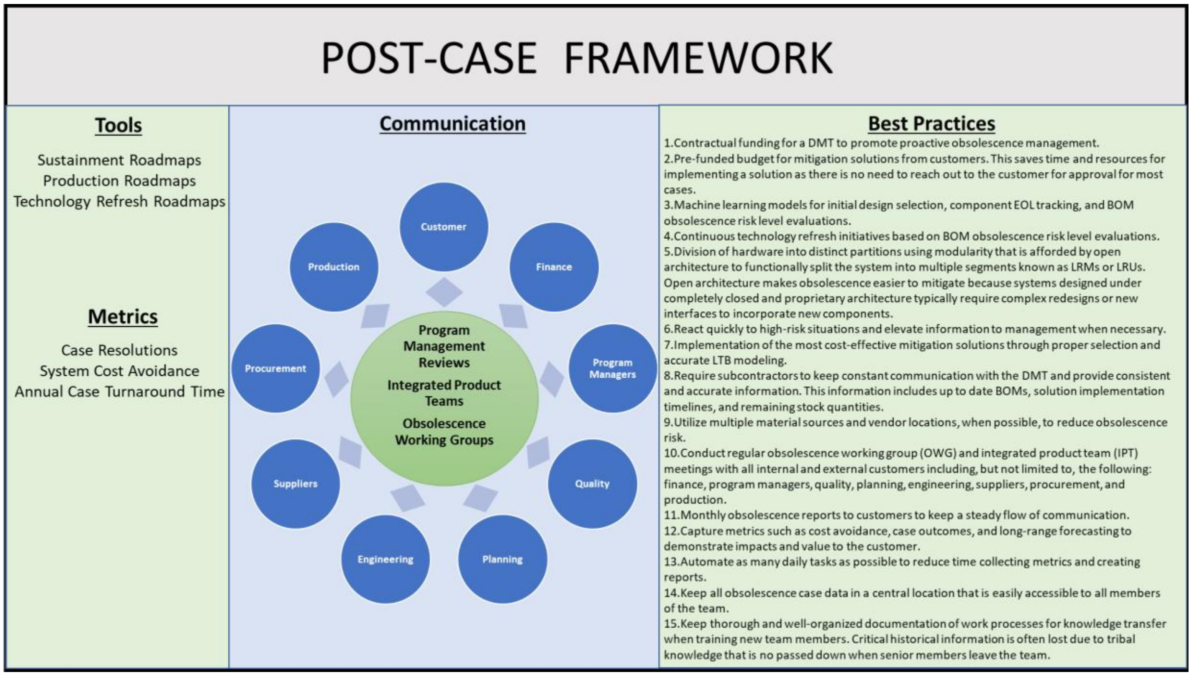

Figure 46: Post-Case Framework

APPENDIX C: QUESTIONNAIRE RESPONSES

Framework Questionnaire provided to experts.

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answer		Level	Meaning
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.			1	Strongly Disagree
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.			2	Disagree
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.			3	Neutral
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.			4	Agree
Machine Learning can aid in early detection of BOMs at high obsolescence risk.			5	Strongly Agree
The Open Case Framework demonstrates a strong process for implementing obsolescence mitigation solutions.				
The Open Case Framework follows a logical path to a final solution.				
The Post-Case Framework demonstrates a beneficial technique for managing mitigated obsolescence issues.				
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.				
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.				
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.				
Implementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.				
Implementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.				

Degree:
Current Work Position:
Professional Background (Anything applicable to Obsolescence, Military Systems, etc.):

Figure 47: Framework Questionnaire

Framework Questionnaire Responses.

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answer
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.	5
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.	5
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.	5
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.	5
Machine Learning can aid in early detection of BOMs at high obsolescence risk.	5
The Open Case Framework demonstrates a strong process for implementing obsolescence mitigation solutions.	5
The Open Case Framework follows a logical path to a final solution.	5
The Post-Case Framework demonstrates a beneficial techniques for managing mitigated obsolescence issues.	5
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.	5
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.	5
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.	5
Implementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.	5
Implementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.	5

Degree: PhD Industrial Engineering
Current Work Position: Engineering Project Manager (EPM)
Professional Background (Anything applicable to Obsolescence, Military Systems, etc.): Over 20 years of experience in system engineering. Working on DoD systems throughout the life cycle of a system (proposal, requirements, design, implementation, system integration and test, verification, logistics, deployment...).

Figure 48: Framework Response #1

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answer
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.	5
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.	3
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.	4
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.	5
Machine Learning can aid in early detection of BOMs at high obsolescence risk.	4
The Open Case Framework demonstrates a strong process for implementing obsolescence mitigation solutions.	5
The Open Case Framework follows a logical path to a final solution.	5
The Post-Case Framework demonstrates a beneficial techniques for managing mitigated obsolescence issues.	5
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.	5
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.	4
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.	5
Implementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.	5
Implementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.	5

Degree: PhD Ind Eng
Current Work Position: Causal Analyst
Professional Background (Anything applicable to Obsolescence, Military Systems, etc.): Systems Engineer and Program Manager for numerous military acquisition programs.

Figure 49: Framework Response #2

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answer
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.	3
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.	3
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.	5
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.	5
Machine Learning can aid in early detection of BOMs at high obsolescence risk.	5
The Open Case Framework demonstrates a strong process for implementing obsolescence mitigation solutions.	5
The Open Case Framework follows a logical path to a final solution.	5
The Post-Case Framework demonstrates a beneficial technique for managing mitigated obsolescence issues.	5
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.	5
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.	5
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.	5
Implementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.	5
Implementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.	3

Degree: Ph.D.
Current Work Position: Professor
Professional Background (Anything applicable to Obsolescence, Military Systems, etc.): Academic
Notes: The first and last questions are related to the implementation of the framework and that is something that I will not be able to answer as agree or disagree. Adding Machine Learning as Life Cycle Forecasting tool for a proactive obsolescence idea has been introduced before but may be not within a framework.

Figure 50: Framework Response #3

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answe
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.	5
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.	4
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.	5
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.	4
Machine Learning can aid in early detection of BOMs at high obsolescence risk.	5
The Open Case Framework demonstrates a strong process for implementing obsolescence mitigation solutions.	5
The Open Case Framework follows a logical path to a final solution.	5
The Post-Case Framework demonstrates a beneficial techniques for managing mitigated obsolescence issues.	5
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.	5
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.	5
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.	5
Implementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.	5
Implementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.	5

Degree: Bachelors of Science Business Administration
Current Work Position: Obsolescence Manager, Fixed Wing (LSE)
Professional Background (Anything applicable to Obsolescence, Military Systems, etc.):

Figure 51: Framework Response #4

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answer
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.	4
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.	3
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.	4
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.	4
Machine Learning can aid in early detection of BOMs at high obsolescence risk.	4
The Open Case Framework demonstrates a strong process for implementing obsolescence mitigation solutions.	4
The Open Case Framework follows a logical path to a final solution.	4
The Post-Case Framework demonstrates a beneficial techniques for managing mitigated obsolescence issues.	4
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.	4
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.	3
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.	4
Implementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.	4
Implementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.	4

Degree:
Current Work Position: Obsolescence Manager, Rotary System
Professional Background (Anything applicable to Obsolescence, Military Systems, etc.):

Figure 52: Framework Response #5

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answer
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.	4
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.	4
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.	4
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.	4
Machine Learning can aid in early detection of BOMs at high obsolescence risk.	5
The Open Case Framework demonstrates a stong process for implementing obsolescence mitigation solutions.	3
The Open Case Framework follows a logical path to a final solution.	4
The Post-Case Framework demonstrates a beneficial techiques for managing mitigated obsolescence issues.	4
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.	4
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.	5
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.	5
Impelementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.	5
Impelementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.	4

Degree:PhD
Current Work Position: Senior Expert engineer/ Program manager at Siemens-Energy
Professional Background (Anything applicable to Obsolescence, Military Systems, etc): Industrial Gas turbine repair

Figure 53: Framework Response #6

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answer
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.	5
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.	5
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.	5
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.	4
Machine Learning can aid in early detection of BOMs at high obsolescence risk.	5
The Open Case Framework demonstrates a stong process for implementing obsolescence mitigation solutions.	4
The Open Case Framework follows a logical path to a final solution.	5
The Post-Case Framework demonstrates a beneficial techiques for managing mitigated obsolescence issues.	5
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.	5
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.	4
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.	4
Impelementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.	4
Impelementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.	5

Degree: PhD
Current Work Position: Technical Fellow, Raytheon Technologies Research Center
Professional Background (Anything applicable to Obsolescence, Military Systems, etc):
Technical Fellow at RTRC with forty years of research experience in advanced manufacturing and materials. She has authored over forty patents in her field and has published over a 120 peer-reviewed journal articles and reports. She is responsible for: (i) identifying and creating new technology areas in materials and manufacturing with widespread impact across Raytheon Technologies; (ii) developing capabilities in the fields of advanced manufacturing and tribology; and (iii) guides technical project work in advanced manufacturing. She is an editor of the Journal of Applied Mathematics and editorial board member of the International Scholarly Research Network of Tribology. She is also a reviewer of multiple national and international journals in advanced manufacturing. She is a recipient of the 2015 Otis President Safety and multiple RTRC Outstanding Achievement Awards. She is a member of the Connecticut Academy of Science and Engineering, SME, ASME, SWE. Finally, she is an Adjunct Professor at University of Hartford and at the University of McMaster, Canada.

Figure 54: Framework Response #7

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answer
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.	4
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.	3
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.	4
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.	5
Machine Learning can aid in early detection of BOMs at high obsolescence risk.	4
The Open Case Framework demonstrates a strong process for implementing obsolescence mitigation solutions.	5
The Open Case Framework follows a logical path to a final solution.	4
The Post-Case Framework demonstrates a beneficial technique for managing mitigated obsolescence issues.	3
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.	5
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.	5
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.	3
Implementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.	4
Implementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.	5

Degree: Ph.D.
Current Work Position: Emeritus Professor, Founding& First President of E-JUST University
Professional 2Background (Anything applicable to Obsolescence, Military Systems, etc.): Supervised 2 Ph.D,s in line of obsolescence Studies, Advisor to the Military technical college, Cairo in research and systems optimization.

Figure 55: Framework Response #8

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answer
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.	4
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.	4
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.	5
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.	4
Machine Learning can aid in early detection of BOMs at high obsolescence risk.	4
The Open Case Framework demonstrates a strong process for implementing obsolescence mitigation solutions.	5
The Open Case Framework follows a logical path to a final solution.	5
The Post-Case Framework demonstrates a beneficial technique for managing mitigated obsolescence issues.	5
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.	5
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.	4
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.	4
Implementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.	4
Implementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.	4

Degree: BS Engineering Physics, MBA in Aviation, MS Systems Engineering
Current Work Position: Engineering Duty Officer, Mechanical Engineer, Strategic Systems Programs (SSP)
Professional Background (Anything applicable to Obsolescence, Military Systems, etc.): NAWCTSD (Naval Air Warfare Center Training Systems Division) August 2009 - July 2020: Systems Engineer for training system acquisition. SSP July 2020 - present: Mechanical Engineer. US Navy January 2014 - present: Engineering Duty Officer. All positions dealt with obsolescence.

Figure 56: Framework Response #9

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answer
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.	4
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.	5
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.	5
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.	4
Machine Learning can aid in early detection of BOMs at high obsolescence risk.	5
The Open Case Framework demonstrates a stong process for implementing obsolescence mitigation solutions.	4
The Open Case Framework follows a logical path to a final solution.	5
The Post-Case Framework demonstrates a beneficial techiques for managing mitigated obsolescence issues.	5
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.	5
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.	5
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.	5
Impelementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.	4
Impelementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.	4

Degree: BS Electronic Engineering Technology
Current Work Position: Project Engineering Associate Manager
Professional Background (Anything applicable to Obsolescence, Military Systems, etc): Obsolescence management for 4 years on Fixed Wing (primarily Sniper)

Figure 57: Framework Response #10

Please provide your response to the following statements by placing a number 1,2,3,4, or 5 in each cell in Column B.	Answer
The Pre-Case Framework demonstrates strong tools and processes for a proactive obsolescence management framework.	5
Adding in Machine Learning as a Life Cycle Forecasting tool is a new idea for a proactive obsolescence management framework.	3
Adding in Machine Learning as a Life Cycle Forecasting tool is a beneficial strategy for a proactive obsolescence management framework.	5
Regular Technology or Design Refreshes is a beneficial strategy for a proactive obsolescence management framework.	3
Machine Learning can aid in early detection of BOMs at high obsolescence risk.	5
The Open Case Framework demonstrates a strong process for implementing obsolescence mitigation solutions.	5
The Open Case Framework follows a logical path to a final solution.	5
The Post-Case Framework demonstrates a beneficial technique for managing mitigated obsolescence issues.	5
Sustainment, Production, and Technology Refresh Roadmaps are helpful tools for managing mitigated obsolescence issues.	5
Case Resolution, Cost Avoidance, and Case Turnaround Times are helpful metrics for managing mitigated obsolescence issues.	5
Communication to all internal and external customers is imperative and is clearly demonstrated in the Post-Case Framework.	5
Implementing the various Best Practices listed would aid in reduction of obsolescence risk/downtime to a system.	5
Implementing the entire framework (Pre, Open, and Post) would likely reduce obsolescence risk/downtime to a system.	5

Degree: B.S. in Business Management and A.S. in Electrical Engineering Technology
Current Work Position: Lead Logistics Management Specialist
Professional Background (Anything applicable to Obsolescence, Military Systems, etc.): Government DMSMS management team member for military ship and aircraft simulators.

Figure 58: Framework Response #11

APPENDIX D: IRB HUMAN SUBJECTS PERMISSION LETTER

UCF

UNIVERSITY OF CENTRAL FLORIDA

Institutional Review Board
FWA00000351
IRB00001138, IRB00012110
Office of Research
12201 Research Parkway
Orlando, FL 32826-3246

NOT HUMAN RESEARCH DETERMINATION

May 24, 2021

Dear Ryan Rust:

On 5/24/2021, the IRB reviewed the following protocol:

Type of Review:	Initial Study
Title of Study:	A Framework for Mitigating Obsolescence in Military Based Systems
Investigator:	Ryan Rust
IRB ID:	STUDY00003035
Funding:	None
Grant ID:	None
Documents Reviewed:	• Ryan Rust HRP-251 Form, Category: Faculty Research Approval; • HRP-250-FORM- Request for NHSR (96) - Ryan Rust.docx, Category: IRB Protocol; • Obsolescence Management Framework questions, Category: Survey / Questionnaire

The IRB determined that the proposed activity is not research involving human subjects as defined by DHHS and FDA regulations.

IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities are research involving human in which the organization is engaged, please submit a new request to the IRB for a determination. You can create a modification by clicking **Create Modification / CR** within the study.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Katie Kilgore

Katie Kilgore
Designated Reviewer

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