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Electronic Warfare Receiver Resource Management and Optimization

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This is to certify that the doctoral dissertation by

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Walden University
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Abstract

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MA, University of Nebraska, Omaha, 2002

BS, United States Air Force Academy, 1997

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

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Abstract

Optimization of electronic warfare (EW) receiver scan strategies is critical to improving the probability of surviving military missions in hostile environments. The problem is that the limited understanding of how dynamic variations in radar and EW receiver characteristics has influenced the response time to detect enemy threats. The dependent variable was the EW receiver response time and the 4 independent variables were EW receiver revisit interval, EW receiver dwell time, radar scan time, and radar illumination time. Previous researchers have not explained how dynamic variations of independent variables affected response time. The purpose of this experimental study was to develop a model to understand how dynamic variations of the independent variables influenced response time. Queuing theory provided the theoretical foundation for the study using Little's formula to determine the ideal EW receiver revisit interval as it states the mathematical relationship among the variables. Findings from a simulation that produced 17,000 data points indicated that Little's formula was valid for use in EW receivers. Findings also demonstrated that variation of the independent variables had a small but statistically significant effect on the average response time. The most significant finding was the sensitivity in the variance of response time given minor differences of the test conditions, which can lead to unexpectedly long response times. Military users and designers of EW systems benefit most from this study by optimizing system response time, thus improving survivability. Additionally, this research demonstrated a method that may improve EW product development times and reduce the cost to taxpayers through more efficient test and evaluation techniques.

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Dedication

I would like to take this opportunity to extend my deepest gratitude to my wife, Nanette, for supporting me in this effort. It has been long road and one that I certainly would not have been able to finish without her unwavering love and support. Along those lines, I have to thank my children. There have been several times when we would have preferred to play, but instead did our homework. Finally, I have to acknowledge my parents. Sadly, they passed away 20 years ago; they instilled in me the value of education. That passion for education and knowledge inspired me to pursue education in every aspect of my life, and I try to pass that passion on to my children.

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Chapter 1: Introduction to the Study

The focus of this study was to characterize and understand how the variables relating to the functions of an electronic warfare (EW) receiver affect response time. The basis of this study was a simulation designed specifically to evaluate the effects of the independent variables on the dependent variable: response time. In order to understand the concepts involving EW receiver response time, it vitally important to understand the background, foundation, and research leading up to the experiment.

In Chapter 1, I introduce the problem and the purpose of the study. I also present the research questions and theoretical foundation. Additionally, I cover key definitions, assumptions, and limitations. Finally, I describe the significance of the study, including the impact on theory, practice, and social change.

Background of the Study

Electronic warfare is an ever-evolving technical field that is dedicated to the protection aircraft. EW involves the detection, location, identification, and suppression of enemy radars. The concept of electronic warfare has existed for as long as radars have operated. As early as World War II, both the Allied and Axis powers developed and employed radars designed to detect incoming aircraft (Guerci, 2015). In response, aircraft began dropping small metal strips of foil with the intention of deceiving the enemy. Early on, engineers realized that when metal strips were cut in increments of the wavelength use by the radar, they reflected the energy in a manner that made the detection of aircraft impossible. This material is referred to as chaff. Eventually, engineers improved the ability of radars to operate in a chaff environment. In response, equipment used by aircraft to defend against radars had to be improved as well.

This equipment generally falls into three categories: electronic support, electronic protection, and electronic attack (Swassing, 2013). Equipment that operates within the three domains collectively improves the aircraft's ability to survive in a hostile environment. They may work independently of one another or in a cooperative manner as required by the situation. Regardless of the operation performed, timeliness is a critical factor in all electronic warfare operations. Adversarial radars seek to detect aircraft early and maintain tracks throughout the duration of their coverage. This gives them the opportunity to respond and react as necessary. Ultimately, if weapons are employed, early and accurate detection is necessary. Furthermore, if detection is suppressed or delayed, the probability of survival and success is increased (Pace, 2004). Given the inherent advantage ground systems have in the detection, tracking, and engagement of aircraft, survivability in hostile environments is highly dependent upon the successful use of systems that detect, locate, identify, and degrade adversarial sensors.

I examined the functions of an EW receiver and variables that affect its operation. More specifically, I examined how four variables affect the response time of an electronic support receiver. The term EW receiver is broad, and it is intended to be. It includes categories of electronic support equipment such as (a) radar warning receivers that specialize in detecting a small subset of threat signals that represent significant threats to the aircraft, (b) traditional reconnaissance receivers that scan for all emitters, and (c) hybrid variations that perform most of the functions of the traditional receiver at speeds similar to radar warning receivers (Gupta et al., 2011). Regardless of the case, each of these receivers scans the frequency spectrum in search radars that could be of interest. In doing so, the EW receiver must tune to a radio frequency (RF) for short period of time and then switch. Ideally, the receiver will optimize the dwell time and revisit interval to enable the acquisition of the signal of interest within a specified period (Hero & Cochran, 2011).

The purpose of this study was to predict how the variations of the radar signals and the variations of the dwell cycles mix to influence the probability of detection. More specifically, the dependent variable was defined as the time it takes the EW receiver to detect the radar signal from the moment the radar signals are first detectable. This variable was referred to as response time. The concept of a response time was important because it reflected one of the most critical elements to self-defense: timeliness. The aircraft is already in a disadvantaged position. Late detection and response further puts that aircraft in a vulnerable position, thus limiting options and decreasing the probability of surviving the encounter. I sought to quantitatively describe how the independent variables of radar illumination time, radar revisit time, receiver dwell time, and receiver revisit interval affect the dependent variable of response time.

Problem Statement

The problem was the lack of quantification of how variations among the independent variables can influence the performance of the EW receiver. A central focus of the sensor-scheduling problem was optimizing the method to detect the signal of interest. Clarkson (2003) recognized that the inadvertent synchronization of receiver scan period and radar scan period has a high likelihood of delaying detection and presents a strong possibility of no detection at all. This problem is referred to as the problem of scan-on-scan. Overall, the problem is complex and has several facets.

The study addressed the quantitative effect that the natural variations of the independent variables have on the average response time. Clarkson (2011) noted that “the tuning and retuning of the center frequencies constitute a search strategy or sensor-scheduling problem for the receiver” (p. 1770). Richards (1948) first addressed the complexity of this problem in 1948 by describing the problem in a mathematical sense regarding search windows. As evidenced by much of the research to date, more study is required on this challenging issue to ensure rapid and reliable detection of signals of interests.

Purpose of the Study

The purpose of this quantitative experimental study was to fill gaps in the literature to help users and designers of EW receivers understand how the main factors influence the performance of the system. The current body of literature focuses on the question of optimization in a static environment. Some literature addresses the issues associated with the dynamic environment, but in a limited way. More importantly, researchers have not translated the results into quantitative results that address the single measure of performance most critical to the operators: response time.

The time it takes an EW receiver to detect an emitter is critical. In the case of a targeted aircraft, it is a question of surviving the engagement. For aircraft not targeted, a quick response time can help prevent the engagement or result in supporting action such as jamming. The prediction of response time is inherently stochastic and relies heavily upon sampling. The use of a simulation provided for sufficient statistical analysis to yield reliable results. Ideally, engineers and EW system operators can use these results for large-scale performance prediction that allows operators to adjust systems settings as able and modify tactics to improve survivability.

Research Question(s) and Hypotheses

The focus of this study was EW receiver response time (dependent variable). Many factors directly affect response time, and they were translated into four independent variables in this study: EW receiver dwell time, EW receiver revisit interval, radar scan time, and radar illumination time. The following research questions were the focus of this study:

- How does the application of the 16-test conditions affect mean (μ) response times compared to the control sample?
    - H_0: The application of the 16-test conditions does not affect mean (μ) response times compared to the control sample ($\mu 0 = \mu 1 \ldots = \mu 16$).
    - H_1: The application of the 16-test conditions does affect mean (μ) response times compared to the control sample ($\mu 0 \neq \mu 1 \ldots \neq \mu 16$).
- How do the mean response times from each treatment compare to each other?
    - H_0: The mean (μ) response times that receive treatment are not different from each other (H_0: $\mu_2 = \mu_{3\ldots} = \mu_{17}$).
    - H_1: The mean (μ) response times that receive treatment are different from each other (Not all $\mu_i (i = 2, \ldots, 17)$ are equal).

- How does the variation (σ^2) among the response times from each treatment compare to each other?
  - H_0: The variation (σ^2) among response times that receive treatment are not different from each other (H_0: $\sigma^2{}_1 = \sigma^2{}_{2\ldots} = \sigma^2{}_{17}$).
  - H_1: The variation (σ^2) among response times that receive treatment are different from each other (H_1: Not all $\sigma^2{}_i$ ($i = 1,\ldots.,17$) are equal).
- Is there a relationship (β) between the variables that can reliably predict the response time of an EW receiver given the independent variables?
  - H_0: The relationship (β) between the variables can reliably predict the response time of an EW receiver given the independent variables (H_0: $\beta_1 = \beta_2 = \ldots = \beta_j = 0$).
  - H_1: The relationship (β) between the variables can reliably predict the response time of an EW receiver given the independent variables (H_1: $\beta_1 \neq 0$ for at least one j).

The independent variables were set using minimum and maximum values determined to be operationally representative of those factors. With respect to the last research question, the intent was to identify which factors and factorial interactions affect the independent variable. Additional researchers can use the results of this study to further map the detailed effects of any interactions between the minimum and maximum values.

Theoretical Foundation

The theoretical base for this study was the use of a research approach called design of experiment (DOE). DOE is a broad topic that covers several methods of conducting research. DOE techniques are designed to test and evaluate factorial interactions. The 2^K (where K is the number of factors) factorial design was employed in this study for several reasons. The primary reason for using 2^K factorial design was that it is a version of a true experimental design. An experimental design consists of meaningful changes of the input factors to a process for the purpose of observing the resultant changes in the responses. The 2^K factorial design exemplifies this concept by using two predetermined levels for each factor that are mixed in an exhaustive manner. With the extremities defined, the relationship between the main factors and interactions among the factors become observable. The identification of the relationship between the factors was critical to understanding how they influence the system. Upon identification of the relationship, further studies can more accurately address the degree of the effect for predictive purposes. Generally, this knowledge is required to optimize system performance by reducing noise that negatively impacts performance and amplifying desired effects that are necessary for better products.

There were key elements to the 2^K factorial design that made it preferable to the one-factor-at-a-time method that is the basis of the true experimental design. The first benefit was that the 2^K factorial design only uses two settings that translated into coded variables; normally 1 and -1 distinguish a high setting a low setting. This simplified the problem, which is beneficial studying a new concept. Montgomery (2005) observed that “the 2^K design is particularly useful in the early stages of experimental work, when many factors are likely to be investigated” (p. 203). As indicated by various researchers including Clarkson (2001, 2003, 2007) and Kelly, Noone, and Perkins (1996), the effects of variation of these variables are believed to have an effect on the response time, but the effects have not been quantified. Given the early stage of research into these effects, the 2^K factorial design was an efficient method to examine the possible effect of the individual factors and their interaction.

Ultimately, the efficiency of this design is what made it attractive. The simulated environment enabled the controlled manipulation of several variables required in a structured and efficient approach to identify which factors and interactions had a significant effect. Montgomery (2005) described this approach as more efficient, accurate, and in-depth. This study primarily focused on quantifying the effect of the four factors on the response time. Previous researchers acknowledged the complexity of this study because it required an experiment specifically designed to evaluate the interaction of these factors. These researchers primarily examined methods to optimize sensor-scan strategies (Clarkson, 2003; Clarkson 2011; Clarkson & Pollington, 2007; Clarkson, Perkins, & Marcels, 1996). As a result, possible effects were noted, but were beyond the scope of previous studies.

Nature of the Study

Studies on EW are commonly performed in a simulated environment. The nature of EW necessitates the use of simulation at several levels. The design element progresses in a pyramid form. The early phases of conceptual design and analysis begin in software and mathematical modeling. The next level is a higher fidelity model that involves limited hardware and software, eventually progressing to a scenario with more hardware in the loop. Only after extensive modeling and simulation does actual testing occur.

Nearly all research in the field of EW takes place before actual flight-testing. The cost of flight-testing precludes the possibility of performing significant research without simulation. Within the field of EW, some elements are deterministic and more amenable to less simulation. For example, many EW systems rely on symbology to convey information. In this scenario, engineers do not require a high degree simulation before flight-testing because they do not have a high degree of variation. Essentially, this level of simulation is designed to ensure proper logic and coding within the system. The type of simulation represents a level of analysis more consistent with risk reduction designed to ensure basic levels of operation during the low-cost phase of development.

Analyses of concepts involving stochastic processes require extensive levels of study. Progression from one phase to another is dependent upon meeting evaluation criteria. In the case of this study, a simulation was the most effective method to evaluate performance. The dependent variable, response time, was based on a stochastic process that had a high degree of variation. Furthermore, the basis of this study was the effects of variation upon the independent variables had on EW receiver response time. The 2^K factorial design of experiment method was ideal for evaluating the effects of the independent variables. The principle benefit of this design was the ability to produce a high number of samples within the boundaries of a valid intercept.

Definitions

The following definitions are essential to understanding the research conducted.

Beam pattern: A collection of radar measurements that describe how the radar beam is transmitted (Guerci, 2015). These measurements collectively describe the beam width, level of the sidelobes compared to the main beam, position of the sidelobes relative to the main beam, and the level of the back lobe relative to the main beam. A beam pattern is used to describe the entirety of the transmission in both azimuth and elevation.

Dwell/Switch: Dwell and switch pulse repetition interval patterns describe a series of pulses that dwell for several iterations before switching (Vaccaro, 1993). The number of dwells that define it as a dwell and switch is ill defined. However, somewhere between four and eight pulses before a switch is used to distinguish a dwell and switch from a traditional stagger. Doppler processing methods use dwell and switch modulation types in addition to time-based range resolution to detect targets.

Effective radiated power (ERP): The ERP of a radar is the amount of energy in decibels that is emitted out of the antenna (Stimson, 1998). A radar's power is measured in multiple places, but the effect of the antenna is the most important and its effect is reflected by the ERP. A high gain antenna is able to focus a small amount of transmitter power into a high ERP. However, this is done by making a small, pencil-like beam. Likewise, a radar with a cosecant squared pattern will disperse a high transmitter power into a relatively low amount of ERP with a large beam pattern.

Jitter: A jitter pulse repetition interval modulation pattern does not repeat within a discernible time period (Vaccaro, 1993). There are different types of jitter patterns such as sinusoidal, saw-tooth, triangle, and complete random. Radar typically uses jitter PRI patterns to resolve range and reduce the effects of jamming.

Probability of intercept: The probability that a signal will be detected within a given period of time (Clarkson & Pollington, 2007).

Pulse repetition interval (PRI): The amount of time between two pulses emitted from a radar. Often, this is a complex pattern and is described with various terms such as stagger, jitter, and dwell/switch (Barshan & Eravci, 2012).

Pulse width (PW): The pulse width is the amount of time a radar radiates a single pulse (Barshan & Eravci, 2012). This term is synonymous with the term *pulse duration*. Technically, pulse duration is more accurate because it refers to time, and the pulse width implies a measurement of distance. However, in practice, the terms are used interchangeably in units of microseconds. Most radars use PWs between .25 μs to 5 μs. Longer range radars use much longer pulses, but have to modulate the pulse in either frequency or phase to retain range resolution.

Radar illumination time: The amount of time energy from the radar of interest breaks the receiver detection threshold, thus making it detectable (Budge & German, 2015).

Radar scan period: The amount of time it takes a radar to complete a cycle (Budge & German, 2015).

Radio frequency (RF): Free space transmissions require the use of the radio frequency spectrum (Budge & German, 2015). Most radars operate between 1000 MHz and 16000 MHz.

Response time: The amount of time it takes for the coincidence of the radar scan period to sufficiently overlap in time with the receiver scan period (Clarkson, 2011).

Scan type: In order to detect targets, radars scan the environment in a periodic manner (Budge & German, 2015). The term scan type describes radar search pattern in general terms. There are several types of patterns employed based upon the specific function. The time in which a radar repeats a pattern is called the scan time. Air traffic control radars commonly use circular scans with scan periods of 5 to 10 seconds. However, target-tracking radars often use a conical scan to track an aircraft. More advanced radars that use tracking algorithms and agile beams, as opposed to mechanically driven beams, return to a target in an adaptive manner, meaning that the beam scans the environment based upon its own measurements and calculations predicting the future location.

Sidelobes: All energy radiation has a pattern. Directed energy has a beam that represents the primary radiated element. However, the reflecting antennas cannot be 100% efficient, and energy is radiated in alternate directions at lower power levels (Kulpa, 2013).

Stagger: A stagger PRI modulation type comprises a series of pulses that have different PRIs but have a repeating pattern (Vaccaro, 1993). For example, a radar with 3 PRIs of 1000 microseconds (μs), 1200 μs, and 1400 μs might radiate them in the following order: 1000, 1200, and 1400. This would be called a 3-element, 3-position stagger with an order of 1, 2, 3. However, variations of this 3-element, 3-position stagger could radiate the pulse sequence as 1200, 1000, and 1400, which would be described as 2, 1, 3 pattern. Taking this concept further, a radar could also repeat some PRIs more than others. Using the same PRIs from the 3-element, 3-position stagger, if the radar repeated one of the values twice, this pattern would be described as a 3-element, 4-position stagger. For example, the pattern might be 1000, 1000, 1400, and 1200. This pattern would be written as 1,1,3,2. A radar uses a stagger to improve range resolution. Radar calculates range based on the amount of time it takes for a pulse to return. However, using this method, range harmonics with a maximum ambiguous range of 40 nautical miles (NM) could reflect aircraft that are 80 NM away. By staggering the PRI, these ambiguities can be quickly resolved.

Revisit interval: The amount of time the receiver uses to revisit a frequency in an attempt to detect a radar (Richards, 1948). Revisit interval is measured in units of seconds.

Assumptions

Periodic search strategies

I assumed that the EW receiver would use determined periodic search strategies that followed a set of rules defined by an algorithm. This implies that the EW receiver would not have the capacity to dwell on a single frequency to the exclusion of others for a long period (Woon, Rehbock, & Loxton, 2010). Generally, EW receivers dwell in a frequency range only as long as necessary to gather a requisite number of pulses. Although it is possible for an EW receiver to dwell in a particular frequency range, it rules out the possibility of detecting any radar beyond that range. This is known and not necessary to research.

Normally distributed variation of independent variables

I assumed that the four independent variables had a normal distribution around a defined average. This is assumption was based on a similar principle explained in radar theory referred to as constant false alarm rate (CFAR). CFAR specifically assumes that radar returns have a Gaussian distribution and are used for the purpose of sorting good tracks from false tracks (Budge & German, 2015). The Gaussian assumption was based on a dynamic scenario of a moving target in association with a moving beam and ground effects. The EW receiver is perceiving a similar environment as the radar (Hao et al., 2012). Additionally, Clarkson (2011) described the similarity between the radar and EW receiver with respect to this problem, thus justifying the application of the Gaussian distribution to this study.

The radar has a fixed frequency

Radars commonly change their operating frequency to decrease the probability of detection and decrease the effectiveness of jamming. The nature of this frequency agility can vary based on the radar. However, for the purpose of this study, I assumed frequency stability to assess the effects variation had on the dependent variable. Essentially, I assumed that a radar operates on a frequency for the minimum number of pulses required to generate a track.

Radar performance characteristics are known a priori

The exact operating parameters of a radar are irrelevant to this study. These parameters are assumed to be known in order to determine the optimal strategy in a static environment (Sarkhosh, Emami, & Mitchell, 2012). These values were used as the basis for establishing baseline points for the independent variables. Normal variation was applied to these values for the purpose of the simulation.

Radar field of view

A key assumption in this study was that while the radar is pointed in the direction of the EW receiver, it is not necessarily tracking the EW receiver.

100% pulse processing

I also assumed that the EW receiver successfully processed 100% of the available pulses.

Scope and Delimitations

The primary intent of this study was to characterize the effects that variation among the independent variables had upon EW receiver response time. This implied a narrow scope by defining elements that this study did not seek to address. In some cases, the scope was simply acknowledged and values were assumed. The topic of EW receiver scan strategy optimization is complex and is composed of many variables and cannot be thoroughly researched in a single study. However, this does not imply that further research in these areas cannot be performed to further increase knowledge in the field of EW. Concepts involved but beyond the scope of this research include radar identification algorithm optimization, radar location algorithm optimization, and EW receiver architecture.

Various methods in which EW receivers identify and detect radars were addressed in this study. However, description of these topics is only meant to shed light on the concepts involved. Algorithms used by EW receivers are highly specialized based upon the entire system they are integrated with. Several factors dictate variations in application that affect performance. There are many types of EW receiver systems that share many characteristics given the limitations of computer processing and physics, and those commonalities were relevant to the simulation used in this study. However, each system has unique characteristics that influence how that individual system performs (Ristic, Vo, & Clark, 2011). Specifically, radar identification and geolocation algorithms are highly proprietary in their implementation. A geolocation algorithm is the method by which an EW receiver determines the location of the radar it is detecting. An identification algorithm is the method by which the EW receiver determines the specific type of radar detected. Thus, although the algorithms can be classified into types of EW receivers, the algorithms employed are beyond the scope of this research.

Evaluating the effectiveness of types of algorithms regarding identification and geolocation would have to be performed on a system-by-system basis. This would require extensive access and cooperation with several types of systems to perform this analysis. Ultimately, this function is performed by the organizations tasked with testing and evaluating those systems based upon determined specifications. Realistically, systems are not compared to each other as much as they are compared to the specifications they were designed to address. If a specification is not stated, then it is generally not measured. As a result, there is not a standard algorithm for identification or geolocation. This directly affects response time as these criteria define the number of pulses required to identify and locate a radar. Given the various methods these functions can perform, I did not extensively consider the benefits or tradeoffs that may lead a program to choose an optimal method. Instead, I made assumptions about performance criteria that could be accounted for in the results. It is easier to use this data in a specific manner in future research as required if identification and geolocation algorithms are evaluated.

EW systems have similar characteristics of other complex engineering systems in that their designs have inherent strengths and weaknesses. There is no such thing as a perfect system because it depends on the object the system is being designed for. With respect to EW receiver scan strategy and the effect on response time, the architecture of the system was beyond the scope of this study. An aircraft that is primarily designed for the purpose of electronic warfare is likely to have an architecture in place that emphasizes characteristics that enhance response time. Likewise, a platform in which the primary objective is air-to-air combat, the EW subsystems are used to support the primary systems, which in this case would be the radar and missile system. Contrary to the reconnaissance aircraft that is optimized for signal detection, the fighter aircraft has limited space and computing power to accommodate a complex EW architecture that is necessary for optimal performance. The intent of this study was not to evaluate how the various architectures perform or how to improve their performance. Clearly, engineers design systems based upon a series of requirements, budgets, and constraints.

Regardless of the various designs and algorithms involved, fielded EW systems are forced to operate in different environments that vary in many ways (Sylvester, Boudreau, & Jackson, 2013). These variations have the potential to alter the response time. I sought to demonstrate how the variations in the defined independent variables affected the response time. The factors that influenced the independent variables were estimated; however, a multitude of factors defined the actual independent variables. The effect of these factors can be applied to individual systems for future analysis to accommodate the specific system algorithms and architectures.

Limitations

The primary limitation of this study was the fidelity of the simulation. Simulation is a balance between accurately representing the key variables while excluding factors believed to be insignificant. Highly complex systems often include too many factors to accurately represent in a simulated environment, and they present too much noise for accurate experimentation. When possible, simulation enables the isolation of critical factors, thus permitting highly accurate and predictive results. However, a key element of any simulation is how well the code represents reality.

In this study, many of the minor variables that influence response time were blended into the primary independent variables. Accurate representation of all of the minor variables was impossible. Factors such as terrain, movement, weather, temperature, receiver tasking, receiver operational flight processor operations, and intelligence accuracy all affect response time. The exact effect of these factors is difficult to quantify. The inclusion of these factors fundamentally requires very specific scenario development that restricts the external validity of this type of study.

The uses of specific scenarios that explicitly define every minor detail significantly reduce the external validity of this study. Most of these variables are transient and constantly changing. Additionally, the exact method of how EW receivers scan the environment is specific to the particular model. Overall, the general effects are known and predictable. Response time is the result of EW receiver dwell time and revisit interval in concert with the amount of time the radar power rises above the receiver threshold and how often. In this study, these variables were approximated using normal variation. Previous studies on this topic acknowledged the presence of variation, but failed to account for the role that variation played in the response time. A key premise of this study was that the amount of variation is predictable based upon knowledge of the operating environment, but the variation is centered on known values. Depending on the results of this study, future studies can expand upon a more precise approximation of the variation given certain conditions. However, at this time, those values are beyond the scope of this study. Ultimately, this simulation sacrificed the fidelity of the lesser factors to evaluate the role of the major factors in a broad range of scenarios.

Significance of the Study

This study is significant because it may provide a method for EW system operators to predict their system performance. Most research focused on how to design algorithms to optimize performance. The objective of this study was to provide a method to understand how systems will perform given various combinations of high levels of variation or low levels of variation on critical factors. Ultimately, this was designed to be an iterative effort because EW system operators normally have the ability to alter their systems performance characteristics. Even if they do not, they will know how their system performs. Given this information, they will be able to make calculated decisions regarding the execution of their mission (Choi & Lee, 2011).

For example, their mission may take place in a high-density radar environment with several long-range missile threats. They would be able to determine that normal EW system operating modes have a response time that is beyond an acceptable threshold, and make a change to their system. Using this level of analysis, they could make accurate decisions regarding how to modify their mission system. During this process, they may find that the alterations necessary to get an acceptable response time for the threat systems in the region require very aggressive modifications. These modifications may not be suitable for the mission.

The fact that this level of analysis will provide guidance on the types of modifications necessary to produce the desired results is significant. The ideal settings are subjective based on the needs for a specific function. The assumption of the existence of a single optimal condition is unwise. Rather, the user of the system needs to have the modeling tools necessary to judge whether the condition of optimality has been met. This is done by allowing the operator to define the constraints regarding optimal performance. Using this information, the users have information regarding their survivability in a given scenario, and are now capable of making decisions to improve the odds of successfully completing their mission.

Significance to Theory

As the techniques of modern warfare progress, engineers are programming sensors to perform more functions. Furthermore, users of the electromagnetic spectrum are beginning to use it parsimoniously. Modern technology is progressing rapidly and requires significantly more sensor multitasking. The result is a complex set of multiplexed signal and receiver interactions. The added flexibility contributes to the overall mission effectiveness for both EW receiver and radar operations (Barshan & Eravci, 2012). However, the exact cost of this multitasking is not clear with respect to EW receiver response time. The significance to queuing theory and electronic warfare are significant to understanding how the variation placed upon the independent variables affects the most important aspect of EW receiver operation.

Regarding the significance to queuing theory, the fact that variation placed upon the independent factors will affect the dependent variable is predictable. The relevant point is characterizing how the change in these factors affects the dependent variable. The simulation implemented in this study was specifically designed to evaluate this effect. This study addressed shortfalls in previous studies that excluded the role of variation. Once the relationship of variations among the factors is evaluated, optimal settings in a dynamic environment can be determined.

Furthermore, this study is significant to the field of electronic warfare as the results are intended to be used by operators as well as engineers. Optimization is an attribute to be determined by the user of the system, suggesting a transient nature (Shi & Chen, 2013). Given the transient nature of the optimized state, the user of the system needs to be able to make adjustments to system settings to ensure mission effectiveness. Mission objectives change on a daily basis, and mission priorities can change constantly throughout a mission. The ability to predict system performance and manipulate settings is required for optimization to increase the ability of the operator to manage system resources for maximum situational awareness (Blasch, Breton, Valin, 2011).

Modern computing offers a substantial amount of predictive capability. As the electronic battlefield becomes increasingly complex, the use of predictive algorithms is necessary to truly optimize system performance. The ability to manipulate the demands placed upon the EW receiver in response the external environment relies on understanding the impact the primary factors have on the key performance parameter: EW receiver response time. The intent of this study was to characterize this relationship: thus adding to queuing theory and electronic warfare.

Significance to Practice

Initially, the professional application of this research was specifically designed to apply to a narrow set of military aircraft operators. The concept of predicting system performance for the purpose of optimization is not new to commercial or military application. Until recently, modeling and simulation tools were not used by the tactical operator, but instead confined to the operational planner. The complexity of the models and processing power required to use them limited the ability to field this software and train users on how to interpret this data. However, as processing power has become increasingly portable, the ability to perform limited modeling for the purpose of optimization has also risen (Jiang, Huang, Yang, Lin, & Wang, 2012).

Although this type of tactical optimization is not widely employed, the technology exists where it can be operationalized (Hoang & Vo, 2014). This would suggest that commercial application of multisensor optimization is foreseeable. Fundamentally, this study addressed a queuing problem that is based on a military application that directly affects the survivability of manned aircraft. However, queuing theory is encountered every day. The question is whether the system is optimized based on the desires of the individual (Aoki, Bagchi, Mandal, & Boers, 2011). As technology progresses, individuals have greater ability to apply technology in a manner more consistent with their values and desires. This means that operators will need to understand how the variations of the environment will affect them. The next step is to achieve a desired result based on that information.

The professional application of this research is the extension of the concept that system users will need to optimize their system based on their definition of optimal. Technology has enabled systems to have several diverse uses. However, determining the optimization of these functions is dependent on the desire of a particular user in a specific scenario. Enabling users to predict system performance and optimize based on those results within a queuing system is not only applicable to an air combat scenario, but also industrial and civilian scenarios.

Significance to Social Change

The central purpose of the study was to help aircrews predict the performance of their electronic support equipment with respect to response time. The expectation is that an increased ability to predict performance will enhance survivability. Military operations span a wide spectrum ranging from low intensity conflict in operations such as noncombatant evacuations to high intensity large force regional conflicts such as Operation Iraqi Freedom. In nearly every case, Allied forces use the broad range of reconnaissance and surveillance systems to support these operations (Dereszynski & Dietterich, 2012). In many cases, they operate in the environment where anti-aircraft weapons present a significant threat.

The study promotes positive social change in two ways. First, the optimization of electronic support equipment offers a significant opportunity to further enhance aircraft survivability in hostile regions. Second, the inherent survivability gained from optimization permits the more precise application of force. An unfortunate aspect of military intervention is civilian casualties. As weapon systems become more precise, civilian casualties decrease. Furthermore, as aircraft become more capable of operating in hostile environments, their ability to precisely engage their targets has the potential to significantly reduce the chances of civilian casualties. All levels of combat are unfortunate. However, the reduction of casualties is a noble effort worth pursuing.

Summary and Transition

The topic of EW receiver scan strategy optimization is highly technical and inextricably intertwined with technological improvements. Regardless, the topic can be reduced to a queuing problem that involves four independent variables and their relationship to the dependent variable of response time. The basic concept is simple. Radar waveforms are only detectable for limited periods of time, and EW receivers scan for radars in periodic methods. The desired result is to detect the radar within a certain period in a consistent manner (Pan, Fu, & Yao, 2012).

Of course, the problem becomes much more complex when the scenario becomes dense and dynamic. The probabilistic nature of scan strategy tends to complicate the issue. In essence, users of EW systems place many requirements upon their system and have the potential of operating in a manner that is less than optimal. Furthermore, the degraded performance is not normally realized until it is too late. Thus, it is possible that operators are exposed to more risk than they realize without the possibility of evaluating factors. This study was conducted to demonstrate a method for evaluating the tradeoffs and risks involved with executing a mission that depends on the use of an EW receiver.

The next chapter addresses previous research on radar operations, EW receiver operations, and queuing. In Chapter 2, I explain how radars operate, how EW receiver systems operate, and how they have an adversarial relationship. From the perspective of aircraft survivability, the relationship between the EW receiver and radar systems is a constant game of cat and mouse. Radar engineers are constantly making modifications to detect aircraft at longer ranges while being less susceptible to detection, and EW receiver engineers counter those modifications to detect radars sooner and at longer ranges.

Chapter 2: Literature Review

The focus of this study was EW receiver scan-tune optimization. In order to have a thorough understanding of the EW receiver scan-tune optimization topic, the contributing elements involved must be described. In this case, that requires understanding how radars and the EW receiver operate. These are diverse topics. Technology has led to the development of radars and EW receivers, with similarities and differences. The intent of this literature review is not to present an authoritative review of how all receivers and radars operate. That is beyond the scope of this study. However, the physics that dictate the properties of the electromagnetic spectrum is common across all radars and receivers, thus allowing for a significant common basis for analysis (Asner et al., 2012).

The fundamental understanding of receiver scan-tune optimization relies on the following topics: radar theory, queuing theory, search theory, and EW tactics. The following literature review addresses all of these topics. Additionally, I present the search strategy, theoretical foundation, conceptual framework, and a review of relevant literature. A key point to highlight is the sensitive nature of this topic. EW is not only a highly competitive industry, but a secretive industry given the ability to influence the outcome of warfare. That notwithstanding, the body of information is robust, but it is spread out over several years of publication that includes the mathematical and scientific elements.

Literature Search Strategy

I relied heavily on a combination of books and technical papers that spanned a wide range of publication dates. The technical nature of the field of electronic warfare makes the mathematical elements of the field enduring. In contrast to studies in social science where much of the most relevant studies are recent, much of the literature in this field builds upon decades of valid research. Due to the longevity of this type of research, many authors publish books that are used for the basis of a large amount of technical development.

Technical documentation in the field of radar operations is particularly rich. Several well-known authors are commonly referenced in EW studies including those performed by intelligence centers such as National Air and Space Intelligence Center (NASIC) and Missile and Space Intelligence Center (MSIC). Authors such as Adamy (2015) and Kay (2013) are significant in the field of EW receiver operations. Furthermore, the mathematical studies by Richards (1948) and Little (1961) addressed the quantitative elements of queuing and response time.

Overall, there is a significant amount of literature regarding the functionality of radars, EW receivers, and response time. However, publications are spread out over a period of several years. This notwithstanding, the material used is representative of the mathematical principles, not the technical limitations, of the time-period. A more significant issue regarding this research is the likelihood of relevant research never being published because of classification and proprietary issues. The field of electronic warfare is highly competitive and highly specialized. Most research is performed as a function of product development, thus limiting publication (Sonawane & Mahulikar, 2011). The proliferation of patents demonstrates the massive growth in this field, yet there is much less academic publication. Nevertheless, there is sufficient information available to understand how an EW receiver operates and the issues associated with the operations.

The identification of research materials revolved around three basic approaches. The first involved the use of technical books found at the Edwards Air Force Base Technical Library and the Naval Air Warfare Center Weapons Division Technical Library. Both libraries contained extensive technical books related to the field of electronic warfare, radars, queuing, and aircraft survivability. These books contained excellent references to academic literature for further research. Upon review of the relevant articles discovered through this method, additional articles were discovered.

All technical research papers identified via bibliographic research were recovered via online libraries both through the Walden library and the Air Force and Navy technical libraries. Additional searches using online databases included the International Electrical and Electronics Engineers (IEEE) Library, the Institute of Operations Research and Management Sciences (INFORMS), the American Institute of Aeronautics and Astronautics (AIAA), and the Defense Technical Information Center (DTIC). The Google Scholar search engine was helpful in finding many academic publications in these fields; however, in many cases, the articles required direct access to the above databases.

The following list includes the search terms used to identify relevant articles. It is important to note that these search terms often led to articles published in trade journals, and were peer reviewed. In most cases, these articles were used only to refine search terms.

1. Electronic warfare
2. Radar warning receivers
3. RWR
4. EW
5. Queuing
6. Queuing theory
7. Search strategy
8. Scan strategy
9. Multi-sensor tasking
10. Radar scan types
11. Radar theory
12. Low probability of detection
13. Airborne intercept radars
14. Probability of intercept
15. Kalman filters
16. Emitter geolocation
17. Aircraft survivability

Overall, the body of literature associated with this topic is different from that of most social science studies. However, this is due to the technical nature of the topic and specialized application. Fortunately, much of the material regarding the topics explored here is based in mathematics and not subject to many of the difficulties associated with social science research. The main difference is that research from the 1950s is still valid, and progression has been much slower due to the complexities of technical integration. As computing power increases, technical modeling and simulation are being used to address many of the fundamental questions like the ones addressed in this study.

Theoretical Foundation

Richards introduced the first theory relating to EW receiver scan patterns in 1948. Richards's approach to EW receiver scan theory was purely mathematical and not considered optimal. Richards's research on the probability of coincidence of two periodically recurring events demonstrated the difficulty in identifying the optimal solution. Richards described the events as windows of time in which the radar scan and EW receiver scan overlap, thus rendering sufficient time for the signal to be processed. However, a key aspect of Richards's findings was the noise that the real world injected into this system.

Regarding the noise, Richards (1948) noted that "the probability of this satisfactory coincidence is first evaluated, and it is found that the solution, while mathematically adequate, is of no value for practical application" (p. 16). Richards seemed to downplay the significance of the research and algorithm. However, engineers were actively using the methods proposed as a means to program an optimal scan strategy. Richards proposed the following equations to calculate a revisit interval:

t_1, t_2 = duration of the events

T_1, T_2 = periods of the events

T_m= minimum satisfactory durations of the coincidence

P = probability of at least one satisfactory coincidence

$P0 = (t_1T_m)*(t_2\text{-}T_m)/T_1T_2$ where $T = \text{Time} – T_m$ (1)

$W = (t_1 + t_2+(2*T_{m)})/T_1T_2$ (2)

A key point regarding this approach is the results are approximate and the method assumes that only T2 has any variation, an assumption that Richards noted was not valid. Regarding the difficulty of this approach, Richards acknowledged the following:

> The circumstance arises from the possibility that, with certain rational ratios of the periods, the events may 'lock in step'. Accordingly, an attempt is made to smooth the probability function with respect to small variations in the ratio of the periods. Due to the difficulties in manipulating the number-theoretic expressions involved, this smoothing is carried through only by the use of certain approximations. Moreover, because of these same difficulties, an averaged value of the probability itself is not obtained, but, in its stead, there is derived a formula for that fraction of randomly related repeated trials in which the original probability will be less than one-half. (p. 16)

Richards assumed very little variation in the factors. Richards acknowledged that not only is a large amount of variation likely, but all of the variables are likely to have variation. This admission demonstrates that these assumptions, while useful for mathematical analysis, render less than optimal results regarding a revisit interval.

Wiley (1985) built upon Richards's work to more directly apply it to EW. In this regard, Wiley expanded the use of the window function to include more than two variables and discussed the role of the required dwell time. According to Wiley, the minimum dwell time is going to depend on the specific requirements of the receiver. Common dwell times can be expected to be anywhere between 10 millisecond (ms) to 100 ms (Wiley, 1985). This is a critical aspect of the window function not presented except in probability-of-intercept literature. Wiley not only expanded the use of the window function to include more variables, but demonstrated that longer required overlap periods have a negative effect on the overall probability of intercept. EW receivers typically have a minimum number of pulses required in order to declare a cluster of pulses valid. A large number of pulses greatly increases the probability of correct identification and reduces the probability of a false alarm. However, a high threshold for required pulses also significantly reduces the probability of collecting enough pulses to initiate a file. Furthermore, as radars reduce their signature, longer required overlap times dramatically increase response times.

Richards's (1948) and Wiley's (1985) work was extensively referenced by Clarkson (1999, 2000, 2003, 2007, 2011) as the basis of estimating the optimal revisit interval. All three authors acknowledged the limitations of the approach, but favored it as it appeared effective. Furthermore, Wiley and Clarkson focused extensively on associated issues such as optimization of the other elements of the EW receiver to improve functionality. However, other researchers implemented Little's (1961) queuing theory as the basis of determining an optimal revisit interval. Little's formula provided the framework for optimization. Furthermore, Hatcher (1976) provided half of the solution for implementing Little's formula.

Hatcher (1976) published an article that addressed the probability of intercept and how it relates to the time to detect a signal. Hatcher used the following derivation:

$$P12(T1) = \int_{-\tau 1}^{\tau 2} PDF(z)dz \tag{3}$$

This derivation yields the following equation that describes the probability of an intercept within a specified time:

$$P12(T) = 1 - [1 - P12(T1)]^{T/T1} \tag{4}$$

This derivation also yields the following equation that describes the observation time required to ensure a specific probability of intercept:

$$T0 = T1 \left[\frac{\ln(1-Poj)}{\ln[1-p12(T1)]}\right] \tag{5}$$

Hatcher's (1976) work is significant because it established a means to determine optimal performance for detecting a signal based on a desired response time. Equation 5 yields the probability of detecting an emitter with a particular scan period within a specific period. Furthermore, Equation 5 gives the degree of confidence in this calculation. However, Hatcher did not directly include how to calculate the optimal revisit interval.

The most important element of Hatcher's (1976) paper was establishing the probability distribution function of the time required to ensure a specific probability of intercept. This paper appears to be the first to suggest the presence of an exponential distribution function with respect to the relationship between the scan of a radar and the desired response time. This is a critical assumption as it relates to Little's (1961) formula. In addition, Hatcher's paper answered two fundamental questions, which are described in the equations above. However, Hatcher did not offer a manner in which to calculate the optimal revisit interval. Instead, Hatcher explained how to calculate the specific elements required to implement Little's formula. Nevertheless, the means by which to determine the fundamental requirements to use the queuing equation are substantial. Hatcher made the direct connection by providing the means to calculate both variables required for an effective queuing formulation.

Washburn (1981) followed Richards (1948) and Hatcher (1976) by employing the Monte Carlo simulation in an attempt to overcome some of the mathematical challenges involved with this problem. One of the main findings of Washburn's research was further reinforcement of the presence of an exponential distribution with respect to the overlapping of two independent pulse trains. In this case, Washburn referred to the overlapping of the radar scan pattern and the EW receiver scan. Additionally, Washburn demonstrated that a prolonged orderliness in pulse trains is highly unlikely. Washburn also demonstrated that the resulting randomness in the pulse trains results in improved detection times. However, Washburn did not demonstrate how to optimize how the scan-tune schedule nor was it intended to demonstrate how the variation in the radar signal could influence detection times. However, the results of Washburn's study are significant in that they supported Hatcher's findings that the assumption of an exponential distribution can be applied to Little's formula.

Little's formula is flexible and can be applied to a wide range of queuing problems. The formula is well suited to calculating the optimal revisit interval of an EW receiver. Little's Formula is stated by the following equation.

$$L = \lambda W \tag{6}$$

Where L = Expected number of units in the system

λ = Expected interarrival time

W = Expected time spent in the system

Little's (1960) proof provided the theoretical framework to approach the optimal method to search for signals. Unlike Richards's work on windows function, Little's queuing function is mathematically proven and not as subject to the assumptions of the windows function. Little's formula is flexible in that the variables can be applied in a number of ways. For the purpose of implementing Little's formula in an EW receiver, L represents the time the radar signal is in the system and λ represents the expect interarrival time. W represents the required revisit interval.

Hatcher (1976) and Washburn (1981) made the case that the expected interarrival time for a radar signal is exponential when compared to a desired response time. Given this relationship, λ is described by the following equation.

$$P12(T) = 1 - [1 - P12(T1)]^{T/T1} \tag{7}$$

Where P12(T1) is the desired probability of intercept. In most cases, 90% or 95% is used. T represents the expected scan time of the radar being searched for and T1 represents the desired response time. As an example, consider a radar with a 10 second scan period and the desired response time is 30 seconds. The desired confidence level is 95%.

$$P12(T) = 1 - [1 - .95]^{10/30} \tag{8}$$

$$\lambda = P12(T) = .63 \tag{9}$$

This relationship is important because demonstrates that Little's formula is suitable for determining the optimal revisit interval. In this example, λ represents the probability that radar scan will overlap with EW receiver scan within the first 10 seconds. If the response time remains the same at 30 seconds, but the radar scan time increases, then the required probability of intercept increases.

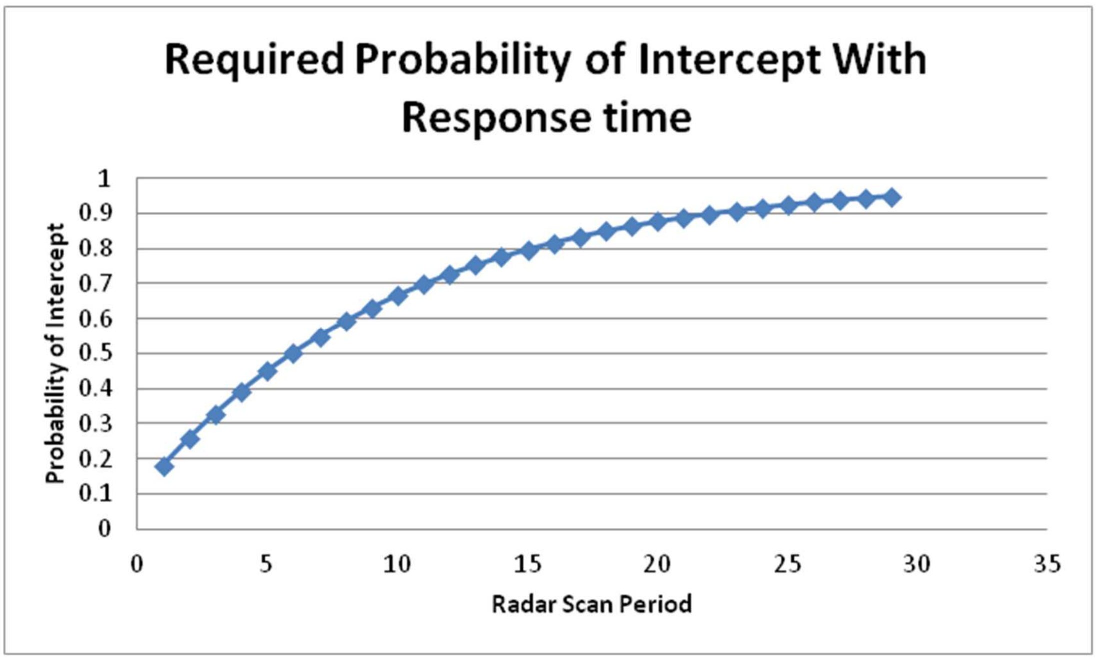

Figure 1. Required probability of intercept with a required response time of 30 seconds.

Note in Figure 1 that a radar with a 1 second scan period has a corresponding response time of approximately .18. This means that requirement to detect the radar within a single scan is low, because there are 30 opportunities given a required response time of 30 seconds. However, if the radar has a 30 second scan period, then there is a required probability of intercept of .95. The required probability of intercept is necessary because the requirement to detect the radar within a single scan must be the highest required.

Now that the denominator is defined, the numerator of Little's formula can be explained. The variable L in this case is described as the amount of time the radar is visible to the EW receiver. Additionally, the amount of time taken to process the signal, the dwell time, must be subtracted from the illumination time. For example, if the radar illuminates the EW receiver for .5 seconds in a single scan and the amount of time required to process the signal is 10 ms, then L = .499 seconds. Generally, the dwell time is not a significant factor in this calculation and can be disregarded. However, as radar technology improves, they become less detectable. Low probability of intercept radars reduce the illumination values and may also require additional processing time (Heinback, Painter, & Pace, 2014).

In solving the revisit interval in the previous two examples, W = .49/.63 = .79 seconds. Some relationships to consider are that if the illumination time increases, the revisit interval increases as well. Likewise, low power signals that have lower illumination times result in shorter revisit intervals. Additionally, complex waveforms require longer dwell times, which can exacerbate the EW receiver workload. The receiver workload is often referred to as the utilization rate, which is described by the following equation.

$$Utilization\ rate = \frac{dwell\ time}{revisit\ interval} \tag{10}$$

High utilization rates indicate that degree to which the receiver has to work to detect a particular signal. Thus, if a radar requires a long dwell time and a short revisit interval, this negatively affects the ability of the EW receiver to search for other signals. For example, if the required dwell time is 100 ms, then the revisit interval is reduced to .63 seconds, which has a utilization rate of 15%. In addition, as the radar scan period approaches the required response time, the revisit interval decreases. Using the original example, if the scan period is increased to 20 seconds, then the revisit interval is decreased to .57 seconds, which further increases the utilization rate.

The capacity of an EW receiver to scan a large volume of the frequency domain in addition to the spatial domain is critical to mission success. A single tasking cannot occupy the entirety of the mission. This implies commutation, which demands balancing the prioritization of the assigned tasks thus forcing less than optimal revisit intervals. Furthermore, all of the values used to determine the optimal revisit interval are subject to variation. Essentially, given the environment in which an EW receiver operates, the dynamic scenario of a moving aircraft and agile waveforms complicate the prediction of response time. This study was designed to shed light on this topic.

Literature Review

Radar Operations

Radar operations are not the primary focus of this study, but understanding radar operations is critical to accomplishing the primary goal of this research which is optimizing electronic warfare receivers to detect radars. As a result, fundamental radar operations are central to the topic and therefore must be discussed and understood. The name RADAR is an acronym for the function of these devices and stands for RAdio Detection and Ranging. This name is derived from the early developments in the 1930s and 1940s when radars were being developed just prior to and during World War II (Guerci, 2015). Radar's have since significantly evolved in their technology and functions. While early radars focused on detecting aircraft to determine range and bearing, later developments included the measurement of velocity. As technology improved, further developments included the ability to create highly detailed maps. Radars serve many functions such as air traffic control, weather observation, distance measuring, and velocity measuring. Radars can be as small as a gun and used by police to measure the velocity of cars driving by or they can be large as buildings to track objects orbiting the earth (Guerci, 2015). In addition to the large number of commercial and civilian applications of radar, the original concepts of military application for threat detection and engagement are of primary concern to the electronic support receiver.

Radars primarily scan the environment by making three to four basic measurements: azimuth, elevation, range, and velocity (Li, Li, & Gao, 2014). Not all radars necessarily take measurements in all of these domains. Basic radars, such as those used for measuring velocity or altitude measure one domain such as range only or velocity. More advanced radars measure in multiple domains. The first domain is range. The primary way that radars determine range is by measuring the time it takes for a single pulse to travel to a target and return. Range is given by the following equation:

$$R = .5 * (t) * (c) \tag{11}$$

R = Range

t = Round trip time of a single pulse in microseconds (μ)

c = Speed of light (300,000,000 m/s)

For example, if a pulse returns within 1,000 μsec, that would equate to a target being 150 KM away. Of course, radars cannot simply transmit one pulse; they must transmit several pulses in order to scan the environment, which imposes an inherent limit regarding range measurement.

Through various types of integration (pre-detection or post-detection), a radar can integrate several pulses and increase the chance of detecting a target (Kulpa, 2013; Yu, Xu, Peng, & Xia, 2012). In essence, a radar is continuously transmitting pulses normally within a period of microseconds. The need to transmit a continuous burst of pulses implies the need to determine how frequently the pulses should be transmitted. Consider the example where the radar transmitted a pulse every 1000 μsec, then it could not detect a target beyond 150 KM. This limit is referred to as the maximum unambiguous range (MUR) (Budge & German, 2015). This also implies an update rate to the radar, which indicates the fidelity of the track. This time in between pulses is called the pulse repetition interval (PRI) and is a critical element that relates to the operation of the radar.

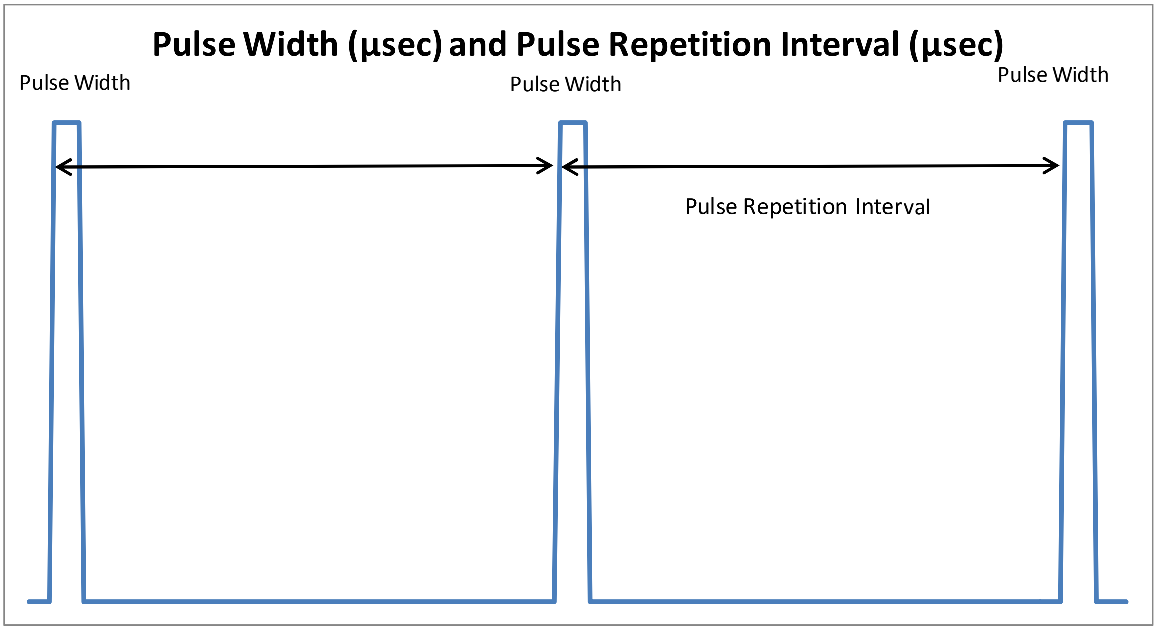

Figure 2. Illustration depicting the pulse width and pulse repetition interval.

As illustrated by Figure 2, a pulsed signal not only requires the choice of a PRI, but of a pulse width (PW). The PRI determines the MUR and the PW determines the fidelity of the range resolution. For a radar to resolve the range of two targets, the difference in range must be such that the trailing edge of the transmitted pulse will have passed the near target before the leading edge of the radar return from the far target reaches the near target (Guerci, 2015). Radars calculate range based on time, but they calculate time based on a crystal frequency that represents the basic unit of time that is considered. This gives a simpler calculation of range by simply allowing the processor to count the number of pulses passed since the last pulse transmitted (Budge & German, 2015). Thus, if the radar has a PW of 1 µsec and PRI 1000 µsec, and the pulse returns after 800 clock counts, then the target is approximate 120 KM away. However, in the example, the clock count is in intervals of 1 µsec, which indicates that the target could be somewhere between 119.85

and 120.15 KM away. A smaller PW decreases this ambiguity while a larger PW increases it. In addition to range resolution, the radar's PW is determined by the amount of power required to detect signals from a selected range. A longer PW represents a larger amount of power being transmitted, which increases the range it can detect a target. Therefore, in pulsed radars, there is a correlation between PW and PRI, which is an indication of the radar's ability to detect targets at a particular range.

The expression of a radar's range capability is expressed by the radar range equation:

$$\text{Rmax} = \sqrt[4]{\frac{PG\sigma Ae\tau}{(4\pi)^2 Smin}} \tag{12}$$

P = Transmitted power

G = Antenna gain

σ = Radar cross section of the target

Ae = Effective antenna area

τ = Pulse width

Smin = Minimum detectable signal

This form of the radar equation is revealing because it illustrates why radar designers make particular choices based on physics and the requirements of the system. As the name RADAR states, ranging is perhaps the most important aspect of most radars, but radars often do much more than ranging and their characteristics must support these functions.

While the PRI indicates the maximum unambiguous range, which essentially states what the absolute longest theoretical detection range could be, the radar range equation uses the physical properties of the radar and target to predict actual detectable ranges. Ideally, the MUR would be near that of the radar range equation for the expected target size. The radar range equation first indicates that an increase in power only increases detection range by the fourth root (Guerci, 2015). Thus, by increasing power by a factor of four only increased range by about 30%. The radar range equation also indicates a similar relationship regarding noise, in that decreasing noise increases range by the fourth root (Guerci, 2015). Similarly, the aircraft's radar cross section affects the detection by the same relationship. Finally, the relationship of antenna size and radar wavelength are of significant interest because they affected by their host and the environment.

The wavelength, which is the inverse of the carrier frequency, is directly related to the size of the antenna. Low frequency radars have longer wavelengths and require larger antennas to support them. Another principle of low frequency radars is that they are less susceptible to atmospheric attenuation (Budge & German, 2015). These relationships force engineers to consider the physical space permitted for a radar and the technical requirements. Radars mounted on aircraft have a significantly smaller space in which to mount the radar and therefore must operate at a higher frequency, which increases the amount of atmospheric attenuation. In order to increase detection ranges, the transmission has to be focused into a smaller area. However, as the transmitted beam is decreased in size, the radar has to implement more complex scanning patterns in order to increase the probability of detecting an adversary (Knott, Locker, & Algermissen, 2011).

The result of this complex set of engineering choices is the implementation of a radiation pattern that is moved about in space in specific manner, that operates on a particular frequency (or set of frequencies), and has a set of PW and PRI optimized to detect targets at required ranges and velocities. These characteristics are critical to the electronic support receiver to determine how to intercept, process, and identify the radar. A better way to view the radar range equation is through the analysis of the transmitted waveform. Figure 3 illustrates a radar beam in a two-dimensional space. The signal can be broken down into three basic elements: main beam, sidelobes, and back lobes. The main beam is the single lobe with the highest amplitude. This is the portion of the signal used by the radar to probe the environment. The main beam is defined by a beam width, which describes the size of the beam in degrees and the effective radiated power (ERP). The sidelobes are the portions of the beam directly adjacent to the main beam. Sidelobes are described by the amount of power they are below the main beam and the number of degrees away from the main beam. Finally, the back lobes are described similarly to the main beam, except that they are defined as being 180º away from the main beam and the amount of power below. In most cases, approximately 90% of a radar's energy is radiated in the main beam (Budge & German, 2015).

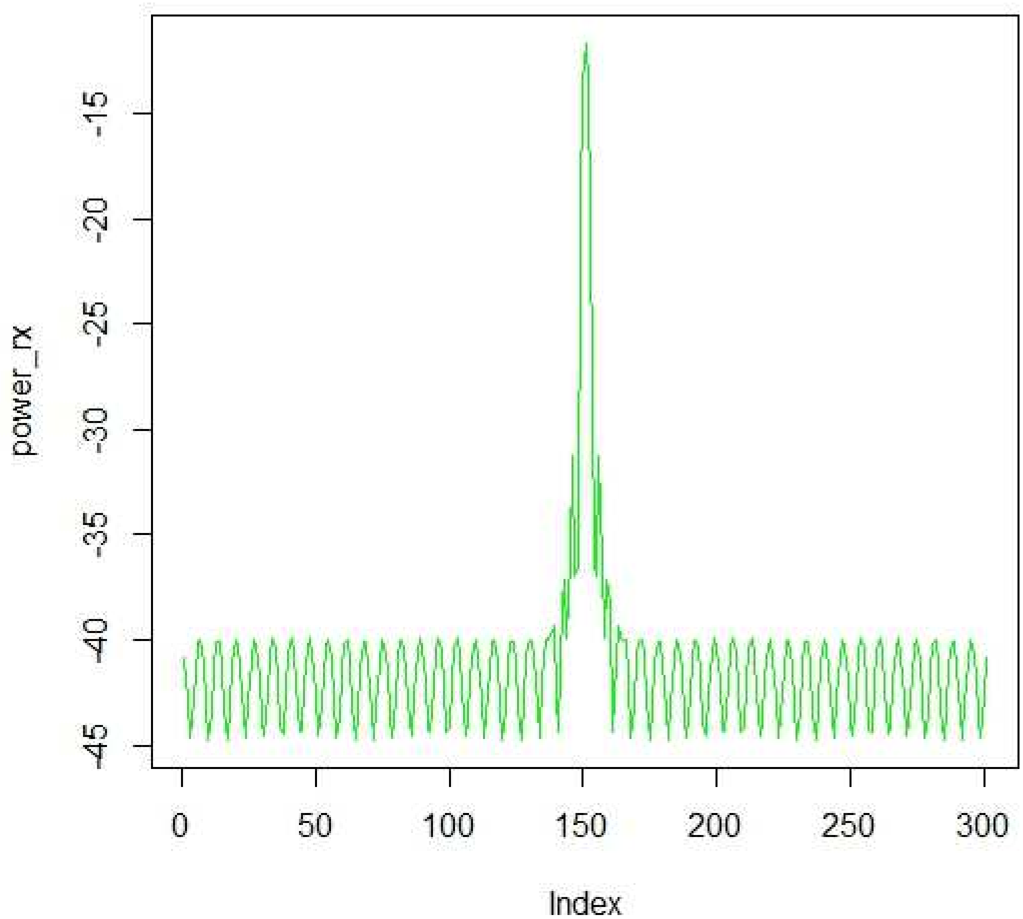

Figure 3. Example of a two dimensional radar beam pattern with a sin (X)/X pattern.

Figure 3 illustrates the two-dimensional view of a radar signal. Figure 4 illustrates a three dimensional of a radar with a pencil beam. The two-dimensional view depicted in Figure 3 neglects that a beam has characteristics in the elevation dimension that are requisite in describing a waveform.

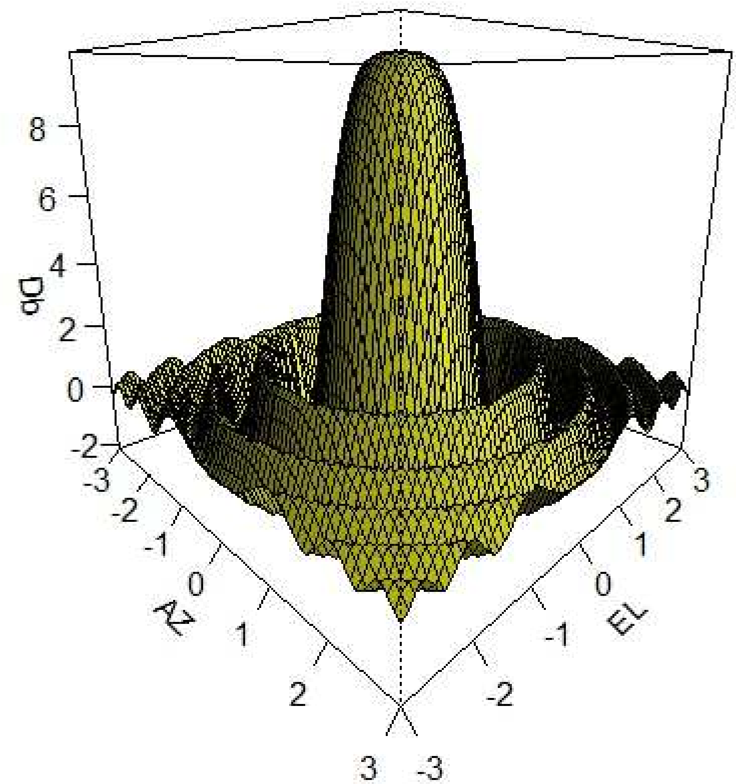

Figure 4. Example of a three dimensional radar beam with a sin (X)/X pattern where the azimuth and elevation beam widths are equal.

Note the symmetrical pattern of the beam and the resulting sidelobes. In the case described by Figure 4, a radar senses the environment by scanning the radar about and is able to calculate targets based on pointing angles in azimuth and elevation. A tight pencil beam permits highly accurate measurements in pointing angles. The power of the radar and the PRI employed determines the maximum ranging capability, while the PW determines the range resolution. This type of beam pattern is common in tracking radars that have a limited field of view (Kulpa, 2013). However, they are not ideal for searching broad swaths of airspace to detect and track a large number of targets.

For this purpose, radars employ an asymmetrical beam pattern where the elevation pattern is much wider than the azimuth. For example, this type of radar would have a 1º beam in horizontal plane and 5º in the elevation plane. At 60 nautical miles, the beam would be approximately 1 mile wide by 5 miles high (60,000 ft). Figure 4 depicts such a beam pattern.

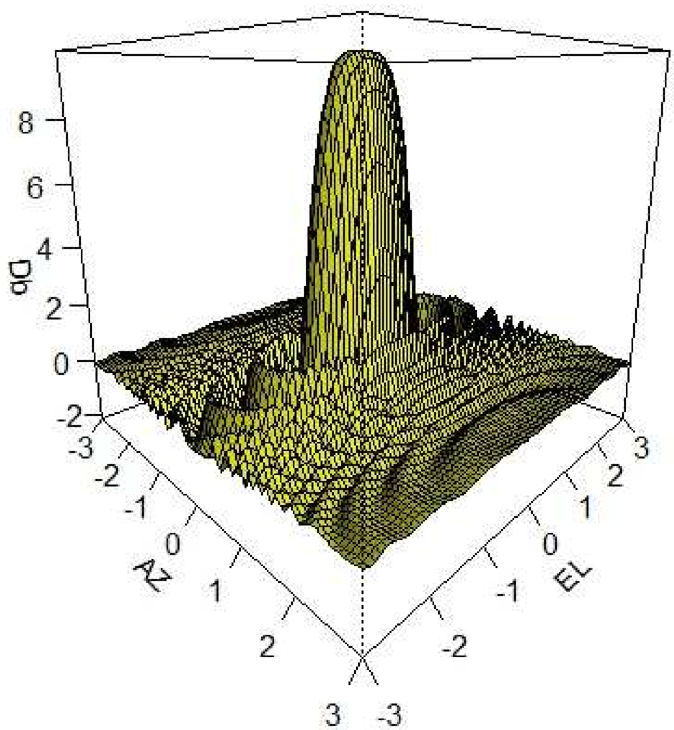

Figure 5. Example of a three dimensional radar beam with a sin (X)/X pattern where the azimuth and elevation beamwidths are not equal.

This type of beam pattern functionally renders a two dimensional view of the environment as the height of the elevation beam is such that there is almost no elevation resolution. Thus, the radar operator can only distinguish azimuth and range. Such radars are commonly used for air traffic control and early warning (Kulpa, 2013). The antenna spins in a circular pattern and functionally provides the operator a *God's Eye* view, which is the appearance of viewing location of aircraft from space. Figure 5 depicts the same pattern as Figure 4, except it displays the intensity of the energy more clearly. Two-dimensional radars (azimuth and range) can modify the elevation beam to provide coverage that is more efficient as even returns from the sidelobes can be processed to provide information on aircraft at higher elevations. A key feature from Figure 6 is the intensity of energy at the main beam and the area around it. Likewise, the first sidelobes emit a significant amount of energy. The electronic surveillance receiver for the purpose of detection, identification, and location can exploit this energy.

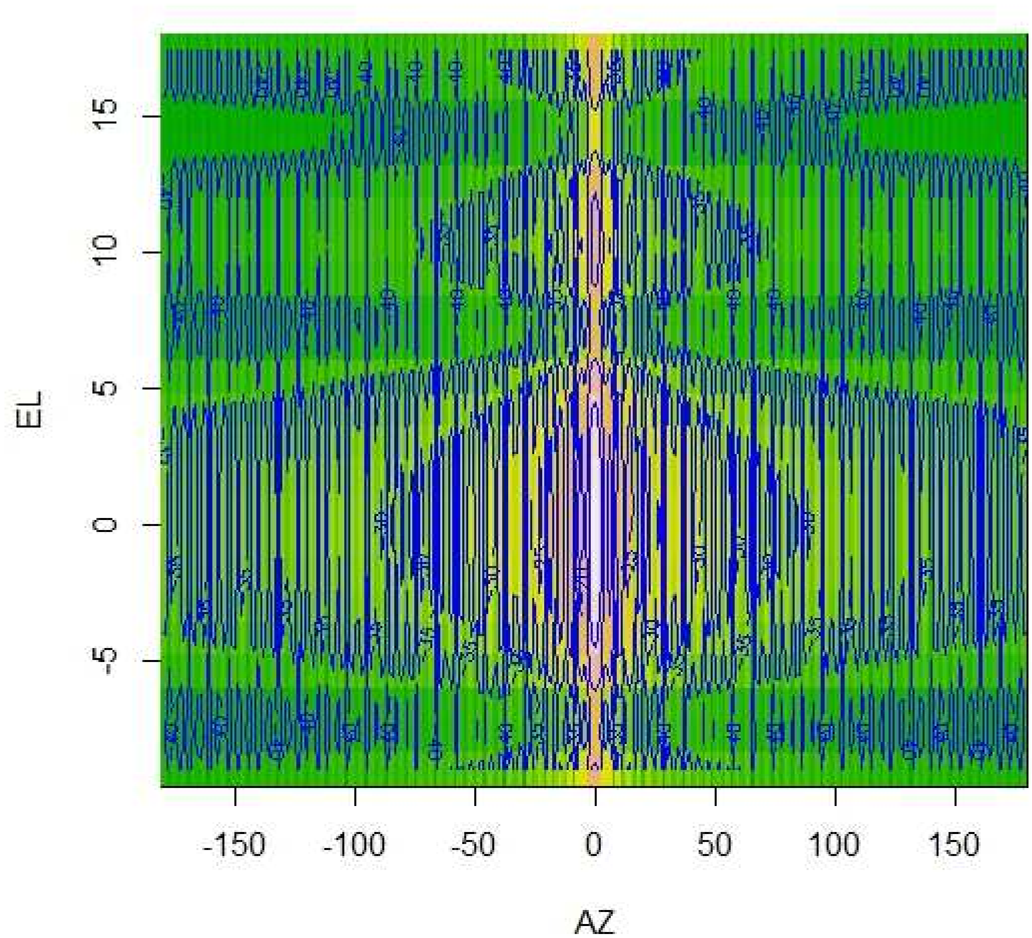

Figure 6. Three dimensional radar beam with a sin (X)/X pattern where the azimuth and elevation beam widths are not equal.

The pattern of a radar beam is a critical factor when determining how to move the beam in order to provide a high probability of detection. The desired purpose of the radar, in addition to the capabilities and constraints of the radar, will influence the manner in which the beam is moved to detect targets. The concept of moving the beam is referred to as scanning. Radars can scan the environment by physically moving the antenna or electronically moving the beam. Electronic movements of the beam are performed by phased array antennas that use signal phase to transmit a shaped beam in a precise direction (Budge & German, 2015). The method in which beams is moved are critical to the radar's probability of detection and to the electronic support receiver's probability of detecting the radar.

There are many types of scanning methods ranging from those that do not scan to those that appear completely random. Radars employ types of scans designed to maximize the other elements of the signal and provide the information necessary to accomplish the desired task. For this reason, some radars are capable of using many different types of scans while others are limited to just a few. However, regardless of the function, radars ultimately employ scans that optimize their probability of detection (Guerci, 2015). Likewise, electronic support receivers need to react to the range of scans and the resulting power distribution in order to optimize their probability of detection. This section covers many of these scans and how they appear to the electronic support receiver.

The most commonly used radar scan is the circular scan. In this case, the radar simply rotates in a circle at a constant speed (Adamy, 2015). A circular scan also assumes that signal is on fixed elevation and does not have an electronically steered elevation scan superimposed (Adamy, 2015). Figure 6 illustrates how a circular scan with a 30 second scan rate appears when amplitude is compared to time. Note how the peak amplitude is reached at the 10 second, 40 second, and 70 second mark. The peak amplitudes are indicative of the main beam sweeping through the same point in time. Essentially, this depiction is accurate from the perspective of a stationary radar and a stationary aircraft. However, if the aircraft were moving, the peak amplitude would vary as displayed in Figure 7.

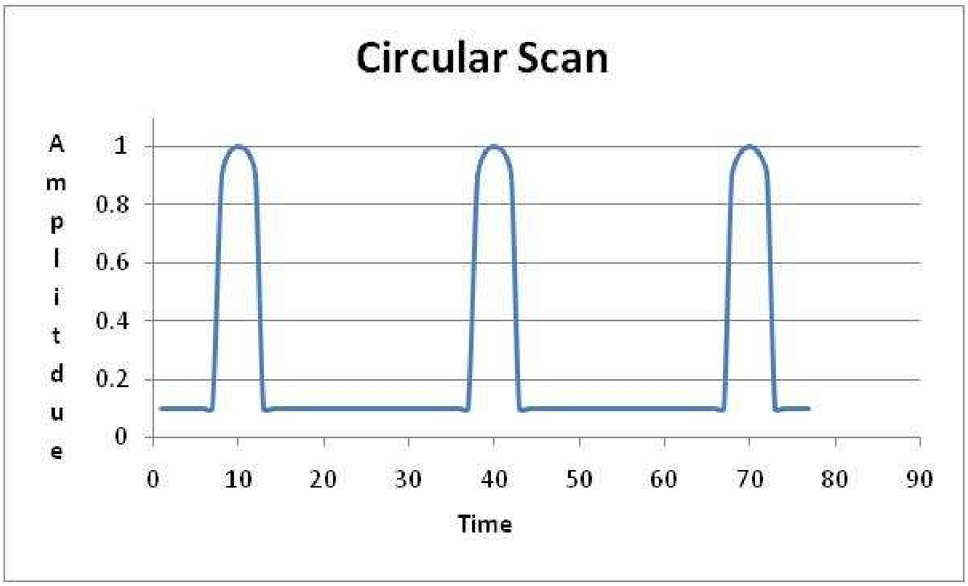

Figure 7. Example of a circular scan with a 30 second scan rate.

The only difference between Figure 7 and Figure 8 is the slight decrease in peak amplitude depicted in Figure 8. The time of the peak in not altered, the amplitude changes as a result of different ranges to the radar. As dictated by the radar range equation, the amount of power reaching the electronic support receiver on the aircraft varies as a result of range from the radar. However, the peak amplitude occurs at the same time.

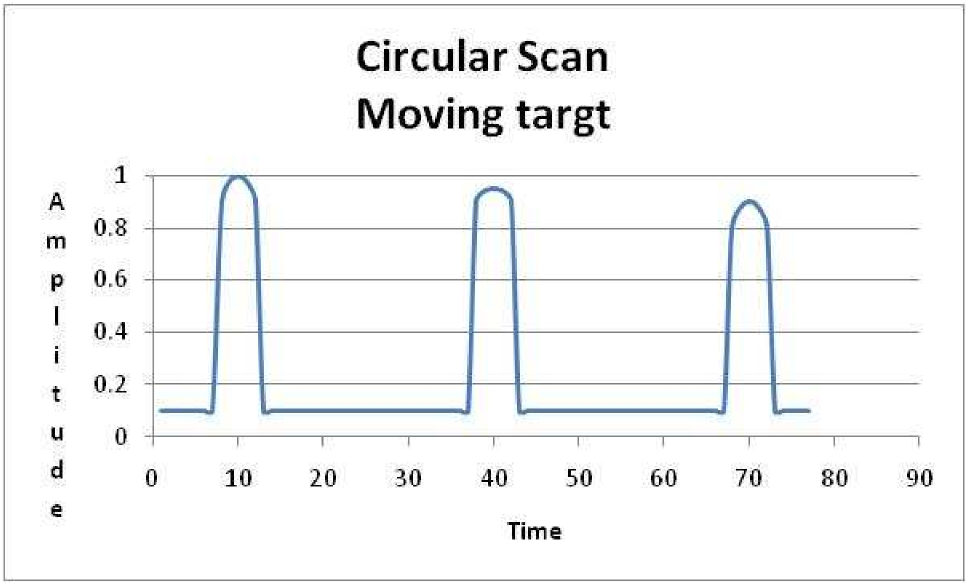

Figure 8. 30 second circular scan with slight degradation over time as the result of a moving target.

While the time in which the signal is above the electronic support receiver's threshold is depicted by the moments of the peak amplitude, the maximum amplitude is relative to the aircraft's position from the radar. Therefore, the amount of each beam that reaches the threshold constantly changes. Richards (1948) estimated that with a circular scanning radar, this variation could be as much as 33%. This change is related to the effective radiated power (ERP) of the radar and the associated sidelobes. Essentially, the element that changes in this scenario is the effective received beam width. If the first and second sidelobes are above the receiver threshold from 90 miles, they may not be detectable from 150 miles.

A bidirectional scan is similar to a circular scan, except that the scan is not 360º such as a circular scan. A bidirectional scan can move in the vertical direction or the horizontal direction. Both have a pattern similar to that in Figure 8. Note the twin peaks in the amplitude as the result of the beam scanning back-and-forth.

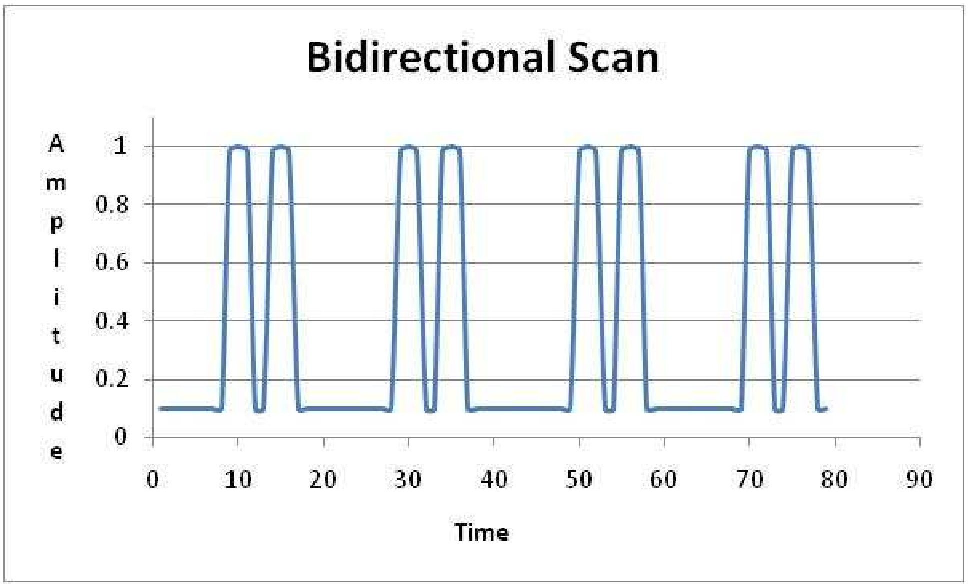

Figure 9. Bidirectional scan with a 20 second rate.

A feature of this type of scan is that it scans only a small portion of the environment at a given time. An example of this of radar is the height finder. As described by Budge and German (2015), height finders are commonly used in conjunction with two-dimensional radar using a circular scan as previously described. Two-dimensional radars do not usually calculate elevation angle and therefore require the use of height finders to determine the elevation angle of targets. As a result of their limited scan space, there is an uneven distribution of time above the detection threshold. If the target is within the scan sector, Figure 9 accurately depicts the scan pattern. However, as Budge and German

(2015) described, radars that use bidirectional scan patterns do not necessarily scan the same points in space on a regular basis. As a result, the only regular element of this scan is the bidirectional scan, not necessarily multiple scans. Furthermore, the radar may not necessarily point in the direction of the electronic surveillance receiver, which limits the potential for detection to sidelobes or back lobes only. Overall, while the scan pattern of the bidirectional radar appears normal, it is only when the target is within the scan space. Typically, either the radar or the target moves, thus the time in which the signal is above threshold has a great deal of variation. The amount of variation is difficult to predict and dependent upon the scenario because it depends on the pointing angle of the radar in comparison to the receiver. However, if the receiver is in the primary scan pattern, the time above threshold is considerably higher than that of a circular scan, which provides more opportunities for detection.

A scan pattern similar to the circular scan is the helical scan. A helical scan is commonly used by whether radars (Budge & German, 2015). A helical scan rotates in a circular pattern but incrementally increases the elevation angle until it reaches a peak, and then incrementally returns the scan pattern to the lowest elevation angle (Adamy, 2015). As illustrated in Figure 9, a peak amplitude occurs at regular intervals, but the peak amplitude occurs on a basis dependent on the number of elevation levels. In effect, this type of scan uses a pencil beam as illustrated in Figure 3 and it moves the beam in a slow and regular pattern over a long period time. In the case of Figure 10, while the antenna angle repeats every 25 seconds, the elevation angle does not return to the original start point for 150 seconds. The effect of this scan pattern is difficult to model from the perspective that the peak amplitude is constantly changing, which can also result in significant variation in the time the signal is above the receiver threshold and the periodicity of the scan.

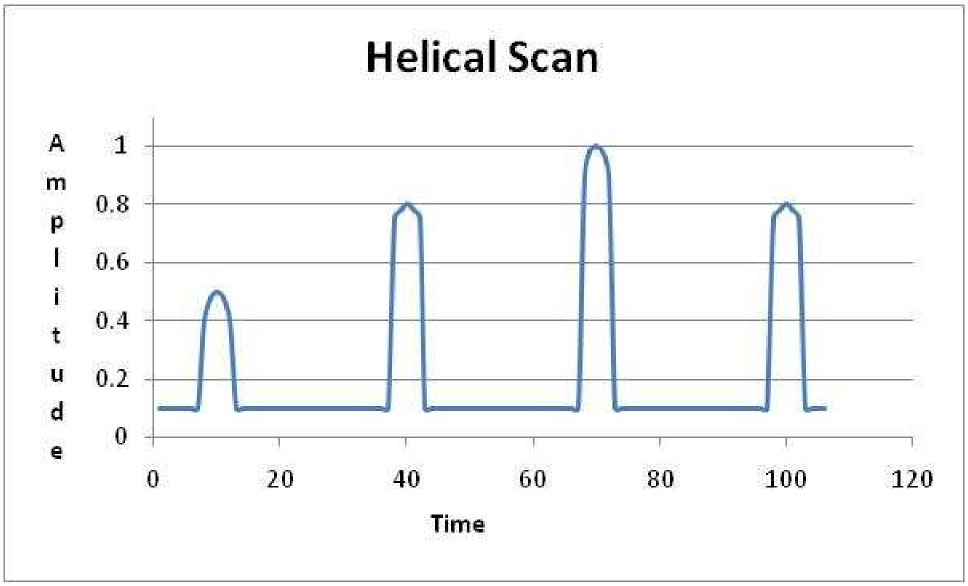

Figure 10. Helical scan with a 25 second rate.

The next scan type to examine is the raster san. Figure 11 illustrates the movements of a raster scan. Raster scans are commonly used by fighter aircraft and ground based target trackers (Budge & German, 2015). Similar to helical scan, a raster scan uses a pencil beam illustrated in Figure 3 and moves the antenna in the pattern below (Adamy, 2015). Figure 12 illustrates a power pattern when the receiver is in the center of the scan pattern. This power pattern also assumes a constant scanning motion. A key element of radars that use raster scans is that they tend to interleave a variety of scans in order to maintain a high level of situational awareness (Adamy, 2015). This interleaving has the effect on the power plot as illustrated in Figure 13.

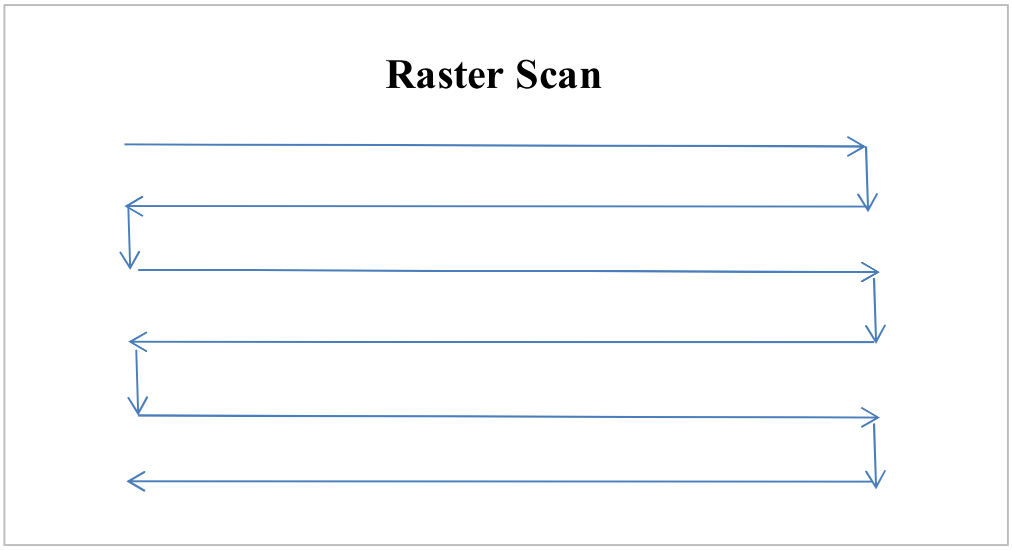

Figure 11. Three bar raster scan with a 2.5 second rate.

Raster scans are highly adaptive in that the center point of the scan is easily moved to a specific area of interest and while keeping the receiver within the field of field. Further adding to the complexity of the scenario is the variation the signal based on the maneuvering of the aircraft using the radar. Essentially, the power plot illustrated in Figure 12 is representative of an ideal scenario where the intercepting aircraft is centered on the receiving aircraft. In all other cases, the frequency and duration of illumination is highly variable. Thus, in order to model the variables required for this experiment, the scenario has to define the engagement. Radars that use raster scans are most commonly target trackers used by ground based missile systems and most airborne interceptor weapon systems (Guerci, 2015). Target tracking radars are high fidelity radars that are able to guide weapons to hit a moving target. Adamy (2015) noted that ground based weapon systems have the benefit of having a more focused tasking with fewer restrictions, such as size and weight, to allow greater flexibility. In effect, ground based systems have more capability to use situational awareness building sensors to include other radars and optics for cueing (Fu, Ling, & Tian, 2012). This permits them to use raster scans less frequently. Airborne systems do not have these benefits and are highly reliant on a single radar scanning a beam over a broad area as commanded by a pilot to find targets. A raster scan is the most efficient way for a small fighter to perform this function and is best used for simulating airborne targets (Guerci, 2015).

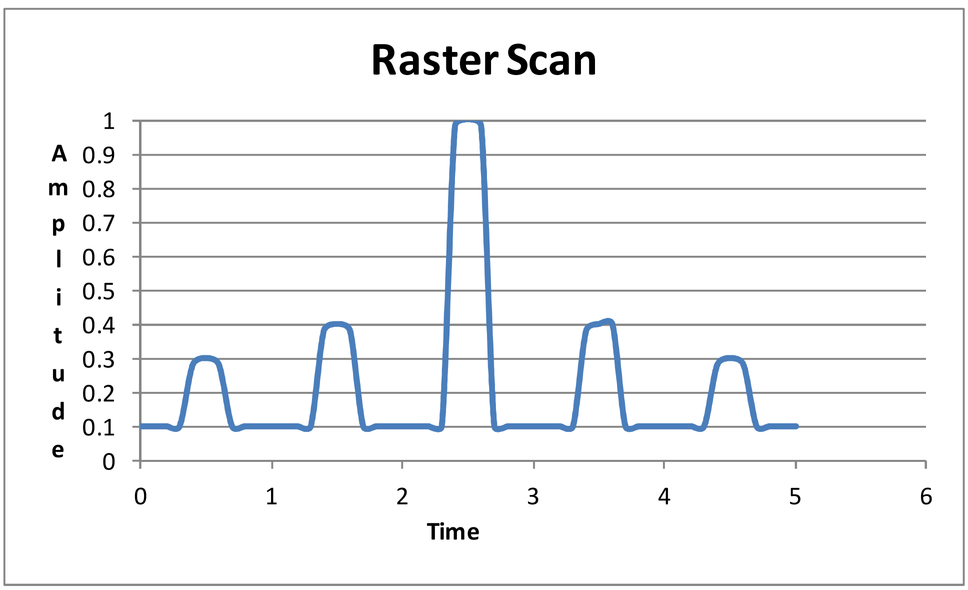

Figure 12. Raster scan with a 2.5 second rate with the target in the middle of the scan.

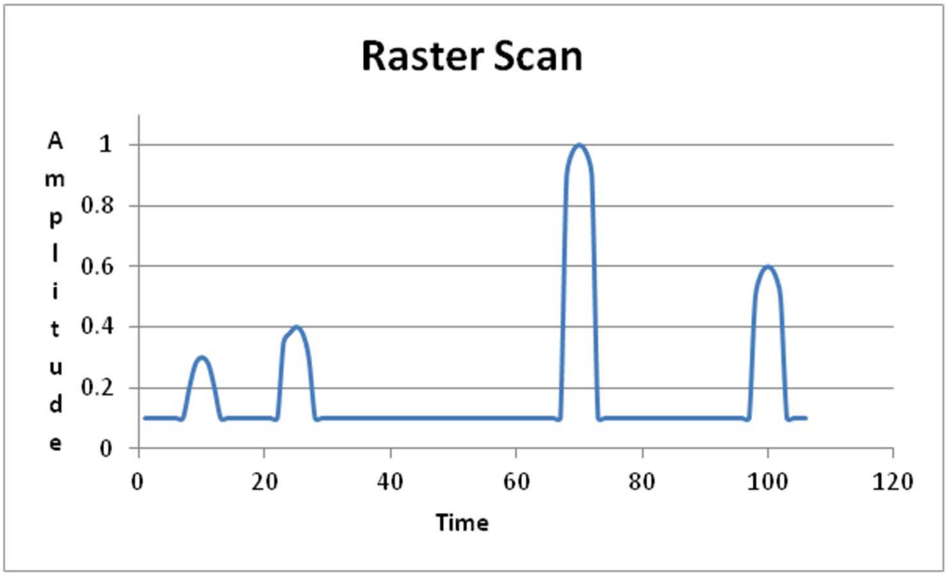

Figure 13. Example of a raster scan with a maneuvering radar.

An important concept to remember is that military-use radars seek to search the environment with a high degree of accuracy, but want to reduce the probability of being detected (Swassing, 2013; Vankayalapati & Kay, 2012). Pace (2004) explained that radar designers intentionally reduce the size of the main beam, reduce the level of the sidelobes, reduce power, and control the direction of the scan in order to increase probability of detecting targets of interest while decreasing the probability of being detected. Stove, Hume, and Baker (2004) further amplified the discussion of low probability of intercept (LPI) radars by demonstrating that the probabilistic nature of detecting radars rules out the simple solution of increasing sensitivity as a means of countering the LPI threat. Other examples of LPI solutions include continuous-wave noise radars and frequency-modulated continuous-wave radars (Malanowski & Kulpa, 2012). All of which represent significant challenges to the development of EW receiver scan schedules.

Functions of a Receiver

The objective of this study was to characterize how the variations in the radar and receiver scan patterns affect response time. The previous section described how radars function and how their scan patterns change. This section discusses the operations of the EW receiver. Generally, an EW receiver has to search the signal environment for signals, sort the signals into bins of unique signals, identify the signals, and locate the signals (Matuszewski, 2012). While the focus of this study was on the search element of the EW receiver, it is necessary to understand all of the functions as they directly influence the search strategy employed. A primary element of any search algorithm is the time required to process the signal. The time required to process a signal is highly dependent on the functions required for process. While EW receivers are different, they must perform many of the same functions. The manner in which they perform the required functions are dependent upon the technology available at the time they were designed, the mission requirements, and budget available. Regardless of these factors, all EW receivers must search the signal environment and process the signals detected in order to render actionable results (Gini, Hoogendoorn, & van Lambalgen, 2011). This implies a queuing process that has a point of optimum performance. Finding the point of optimum performance requires understanding not only the radar environment, but the receiver functions as well.

Search and Search Theory

The scan strategy is the most important aspect of every EW receiver because it is the basis of all of the functions. The effectiveness of the scan strategy is measured by the time it takes to first detect a signal interest. Measurement of response time, however, can only be performed in a cooperative environment where the signals are instrumented such that the time they begin emitting is recorded. Overall, the concept of the scan strategy is technically less challenging than the other major functions. However, the scan strategy must be paired with these functions, and is heavily influenced by general search theory (Jun, Jones, Coleman, Leonard, & Ratnam, 2012). Search theory researcher Alpern (2015) wrote a series of papers and books on the general topic of search strategy. The research focused on various search strategies associated with finding various types of targets. This general search theory sheds light on the possible performance of an EW receiver scan plan in a dynamic scenario.

Alpern's (2015) key point was that when a searcher is searching for a player that is evading, even in a constrained system, this seemed to be a trivial problem, but modeling indicated that it was much more complex. In such a system, optimization appeared to be associated with a mixture of search techniques. This finding suggested that variation is more practical than pre-determined pattern searches. "Consequently the minimax theorem of Alpern and Gal [4] can be used,…to establish the existence of the value $V(Q)$, an optimal mixed searcher strategy, and an ε-optimal hider mixed strategy. Recall that a strategy is ε-optimal if the expected payoff is at least $V-\varepsilon$ against any strategy of the opponent" (Alpern, Fokkink, Lindelauf, & Oldser, 2008, p. 1178). Note that this scenario is closely matched to that of an EW environment in that there the elements that are hiding have a constrained field. However, the targets can move and delay being found. Alpern et al. went on to say, "We have established bounds $15/11 \leq V \leq 13/9$ on the value of the game by developing a variational theory that can be used to evaluate certain mixed strategies which start according to a continuous distribution on the interval" (p. 1189). Similar to an EW search environment, where some targets are able to delay detection, they noted that the target's movements take on characteristics of a continuous distribution. While this may delay detection, randomized search strategy bounded the detection time. This finding directly relates to the EW environment.

Another key point made by Alpern (2015) related to how the search start point affected the detection times for a mobile target. In this case, Alpern (2015) determined that optimal conditions for a start point in this scenario is still a low probability of detection. However, Alpern (2015) noted that the optimal start point is far better than the alternative. This study developed a theory of arbitrary-start search games. The optimal search strategies found in these games represented the best worst-case methods for searching. Additionally, they are applicable to many search problems where there is no active antagonist (Alpern, 2015). Therefore, Alplern concluded that in this case, pure random selection is more effective than trying to employ a more sophisticated logic. This conclusion suggests that increased randomization in an EW search strategy is more effective than deterministic methods.

Overall, Alpern (2015) noted the difficulty in using a single optimal strategy that meets all of the desired performance objectives. After studying and trying several methods against a wide range of search problems, Alpern (2015) consistently noted overall difficulty in crafting a single search strategy that was optimal for all situations. The best solutions involved adaptive techniques that were based on the tactics used by the entity being pursued. In essence, each problem has an optimal solution, but the problem is constantly changing. This constant change is the dilemma presented in the field of EW and specifically applies to EW receiver scan strategy (Hobson & Clarkson, 2011). Some radars employ techniques that seek to delay detection while others do not. Some radars operate in a manner that present detection challenges based on their behavior, but not for the explicit purpose of complicating the detection problem.

The search function of an EW receiver is possibly the most important aspect of an EW receiver because without a sufficiently high success rate, then the operator is likely missing cues to important pieces of information. “An EW receiving system is confronted with the incredible task of intercepting, detecting, and processing this multitude of signals in order to extract and identify only those signals that are of interest” (Parwani & Purohit, 2012; Vaccaro, 1993, p. 43). Essentially, while an EW receiver must perform a number of functions, they all rely on high rates of detection.

Recalling how radars operate, they move their beam throughout the environment searching for targets. This yields periods when the power radiated from the radar break the threshold of the EW receiver. However, the EW receiver has to scan a large frequency range in order to detect a variety of radars (Hero & Cochran, 2011). This implies that the receiver has to scan a specific frequency range in a periodic manner such that it has a high probability of having a search period overlap a radar scan period (Vitus, Zhang, Abate, Hu, & Tomlin, 2012).

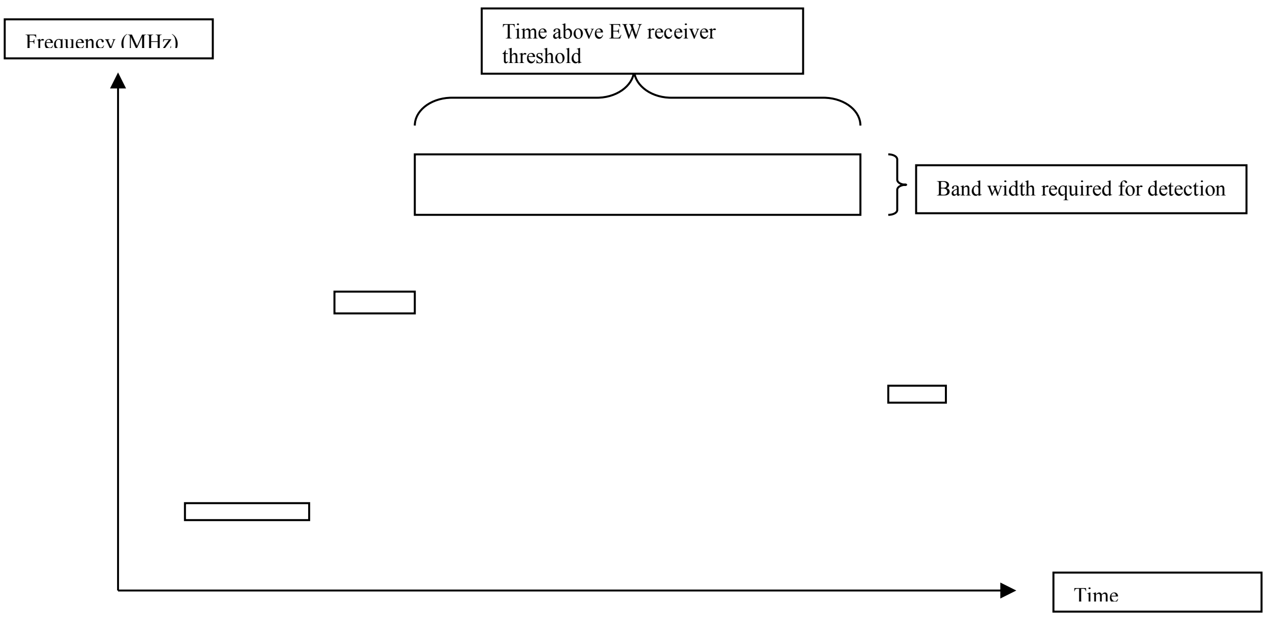

Figure 14. Example of EW receiver scan strategy.

Figure 14 is an example of how an EW receiver has to dwell in narrow portions of the spectrum for a defined timeframe. This dwell is mutually exclusive of dwelling in any other portion of spectrum at that time which necessitates a periodic revisit interval. Ultimately, the EW receiver has to dwell in the required frequency bands frequently enough to detect radar signals that are only detectable for brief timeframes (Hero & Cochran, 2011; Li et al., 2011).

The process of scanning the frequency spectrum in a systematic manner is referred to as a scan strategy. Fundamentally, the development of an effective scan strategy is reliant a number of assumptions and calculations. The first step in developing an optimal scan strategy is calculating the optimal dwell time and revisit interval for emitters of interest for an expected mission. This calculation is based upon several factors such as the radar of interest ERP, beam width, scan type, scan time, sidelobe level and back lobe level. Additionally, factors about the receiver influence this calculation. Variables such as receiver sensitivity and range from the radar affect the optimal revisit interval (Ling, Fu, & Tian, 2011).

Unfortunately, none of these values are static. As discussed in the previous section, while many radars move their beam in a predictable and repeatable manner, there is still a significant amount of variation in the detectable amount of energy. Additionally, as the signal environment becomes congested, EW receivers need to adopt different techniques regarding variation in dwell times and revisit intervals to meet the demands of the mission (Diaba, Affume, & Oyibo, 2015). Furthermore, radars that use methods to reduce the probability of intercept add significant variation into this process, thus further complicating the development of an optimal scan strategy. Essentially, an engineer does not develop a scan strategy around a static scenario, but a dynamic scenario with constantly changing variables (Shi, Johansson, & Qiu, 2013).

Understanding the functions of the EW receiver is a critical first step in grasping the scan strategy. The functions of the EW receiver are important to the topic of response time because they dictate the quantity of data required and the time constraints involved. The next section discusses the methods of geolocation, parameterization, and identification. These are the primary functions of an EW receiver. The information rendered from this process enables the aircrew to safely maneuver through hostile environments.

Geolocation

One of the most important functions of a radar receiver is the ability to determine location. The fidelity of the location estimate is determined by the mission of the platform that employs the receiver. As Adamy (2015) explained, aircraft that use radar warning receivers for the purpose of self defense only require an accuracy within 5 miles to optimize employment of their weapon system. However, weapon systems that intend to employ precision munitions require an accuracy within 50 meters (Adamy, 2015). The requirement for accuracy is closely related to the mission of the aircraft employing the radar receiver. The greater need for accuracy also increases the amount of time required to make precise measurements. Therefore, there are three fundamental methods that geolocation is calculated: power measurement, Least Squares Method, and the Kalman Filter (Brown, 2012). The key element for each of these methods is the time required to perform their function. This study focused on the queuing aspect of optimizing receiver operations. Optimization requires insight into the amount of time required to perform a function. The relative time to perform this particular function is critical to this analysis.

Determining the location of a radar using a power measurement is the least accurate method. However, it has the benefit of being fast and relatively simple. Highly tactical receiver systems that do not require a high degree of accuracy are able to estimate location by comparing received power to a known maximum power to estimate range along a line of bearing (Adamy, 2015). This method is used in radar warning receivers on tactical fighter and bombing aircraft where the detection of the threat is the highest priority. The exact location of the threat is not as important as it is assumed to be close enough to be tactically relevant. Therefore, power measurement was primarily used as a means to indicate the required counter maneuver as a means to increase survivability (Swassing, 2013). This method is fast, as it requires very little information. It only requires enough pulses to establish a direction of arrival and a power measurement to superimpose the range (Adamy, 2015). This has the possibility of effectively rendering a location within milliseconds of initial detection Adamy (2015). The short duration required to render a location significantly improves the probability of intercept by reducing the time to process. However, it comes at the cost of accurate geolocational accuracy, thus demonstrating a compromise that favors speed over accuracy.

This method of geolocation only requires a receiver system that is capable of measuring a line of bearing (LOB), performing an identification, and measuring power. There are many methods of measuring LOBs, but Adamy (2015) stated that tactical aircraft most commonly use a method employing multiple antennas with an amplitude comparison. Interferometry is also very common, but is typically reserved for platforms that have a more dedicated electronic warfare function, as this method is more complex. However, for the purpose of using power measurement to determine location, differential amplitude is suitable as a reasonable estimate of range and bearing. This method relies heavily on the identification of the signal as it references a database that correlates to a known effective radiated power of the transmitter. This is a vital piece of information as it necessary for the calculation of the range. The following equation:

d = distance in kilometers

F = frequency in megahertz

L_s = Effective Radiated Power (ERP) – received power

$$d = antilog\{[L_s - 32.4 - 20\log(F)]/20\} \tag{13}$$

This simple equation only relies on two measurements to determine range: received power and frequency. Of the two measurements, received power is much more significant that the measured radio frequency of the radar. The measured radio frequency can be more than 100 MHz off and only affect the measured distance by about 1.5 KM. However, an error of received power measurement can lead to an error more than ten times greater.

For this method, the calculation of the radar location is not particularly time consuming. Instead, the identification of the radar and the measurement of the power are the two most important elements. Identification heavily relies on the collection of enough pulses to correlate a pattern to a known sequence. Only by establishing the identification of the radar of interest can a reasonable location be established. However, regardless of the number of pulses required to perform an identification, this method is still the fastest of the three methods discussed here because it does not rely on iterative measurements that update over time. Unfortunately, the accuracy of this method suffers as a result of the sensitivity to the power measurement.

In contrast to the power measurement method, the least-squared error (LSE) method relies on triangulation. This requires continual revisits to collect lines of bearing (LOBs) and a calculation of where the LOBs intersect. However, while this method is more complex, it can render better solutions as well (Brown, 2012). This improvement in performance comes at a cost though. Increased requirements for radar pulses also requires longer time to collect more pulses in order to refine the estimate of the location. Therefore, a choice must be made regarding the need for quicker operations versus the need for better geolocation capability. Generally, the LSE method is performed using the following steps.

First, similar to that of the power measurement method, the receiver system has to make a measurement of the signal to create a LOB. In contrast to the power measurement method, a precise measurement is necessary to reduce the size of the elliptical error probability (EEP). Therefore, interferometry or a spinning direction finding antenna is the most commonly applied (Brown, 2012). Interferometry is a system of using multiple antennas spaced in a geometrical pattern that measure a difference in phase, thus rendering a LOB (Vaccaro, 1993). A spinning antenna is a much simpler method, but much more cumbersome to implement on aircraft as they require much more space and often require bulbs on the fuselage (Brown, 2012). The spinning antenna turns the antenna at a rate between 50 rotations per minute (RPM) and to 300 RPM (Brown, 2012). The LOB is determined by measuring amplitude. In either case, the LOB is used in concert with multiple other LOBs to estimate the location of the radar of interest.

Figure 15 illustrates how the simple triangulation works. The arrow pointing upward represents the path of an aircraft. As the aircraft flies along, it takes multiple LOBs that overlap. Ideally, all three LOBs would converge on a single point in space. However, given the amount of measurement error in any complex system, this is virtually impossible. Fortunately though, barring any major measurement errors, the LOBs will converge relatively closely. Normally, the LOBs will converge in a manner that creates three intersections. These intersections serve as the basis for estimating the location of the emitter.

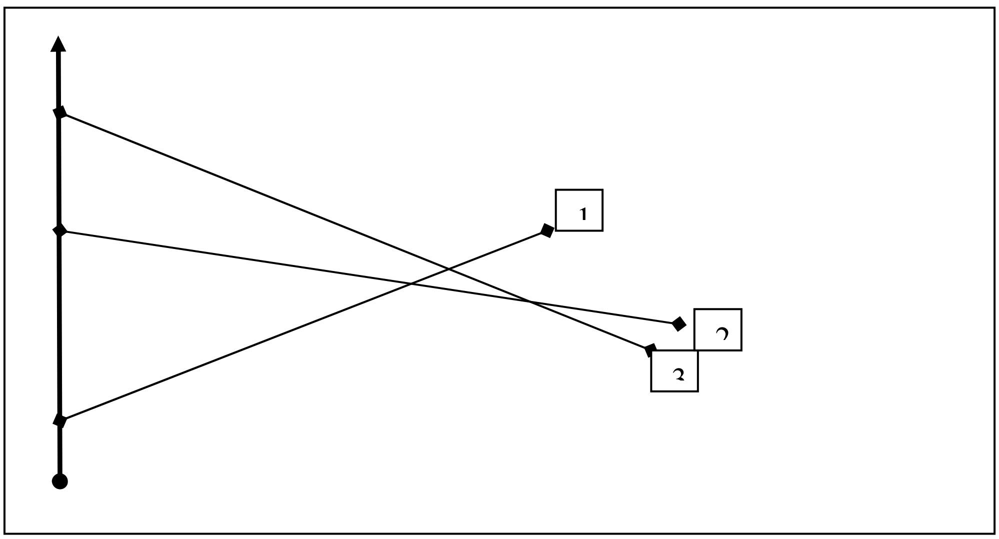

Figure 15. Triangulation with three lines of bearing.

A popular nonstatistical method of determining the computed location is to use the intersection of the angle bisectors. However, as Wiley (1985) pointed out, this method yields an actual radar location outside of the calculated EEP over 60% of the time.

Furthermore, in many cases, numerous LOBs are taken, thus providing multiple location computations that have to be merged. Figure 16 illustrates a case with four LOBs.

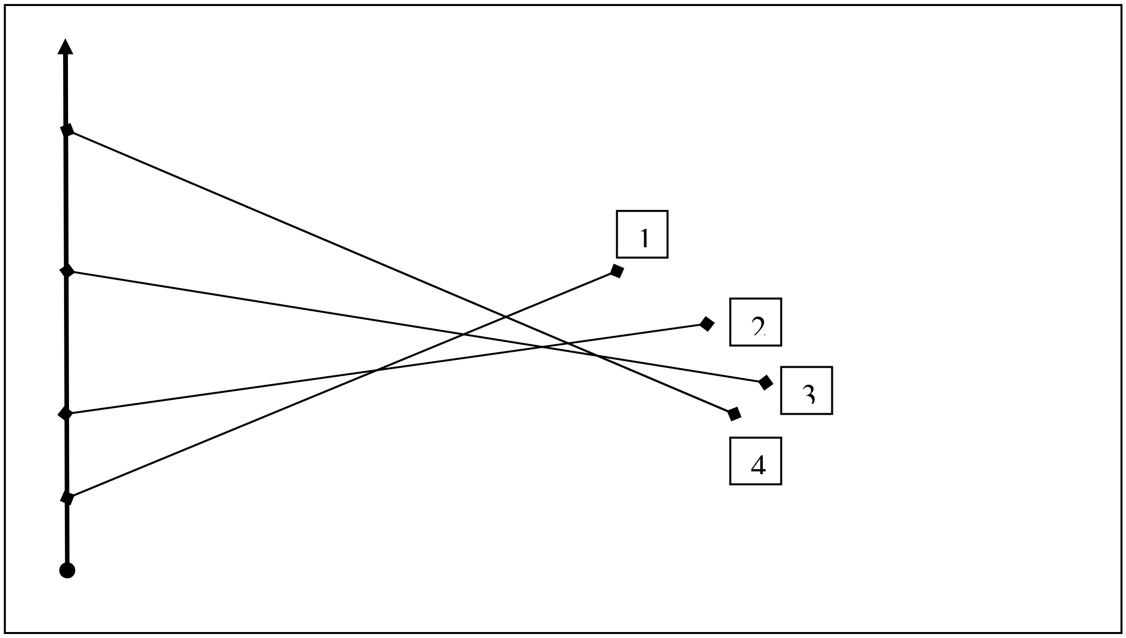

Figure 16. Triangulation with four lines of bearing.

Note how four LOBs yields three different triangles with different potential centroids. These centroids can be averaged to calculate a single location, however, this method often leads to biased results (Brown, 2012).

The LSE seeks to find the optimum centroid based upon the minimum error between the parameter being estimated and the previously calculated locations (Brown, 2012). Brown described over a dozen specific LSE algorithms, but they tended have many of the same characteristics. Their accuracy depended heavily upon the collection of new LOBs, hence their recursive calculation methodology. LSE methods also performed poorly in the face of noise. The general LSE equation is given by the following formula (Brown, 2012).

$$min\|H\theta - x\|_2 \tag{14}$$

In this version of the LSE method, H represents the observation matrix, and x represents the measurements. The objective is to place the centroid in the location that minimizes θ and express the variance in a manner that represents an ellipse error probable (EEP) or a circular error probable (CEP). The expression of error typically contains an orientation of the EEP and the size of the semi-major and semi-minor axes. CEPs do not require an orientation, but they do convey the radius.

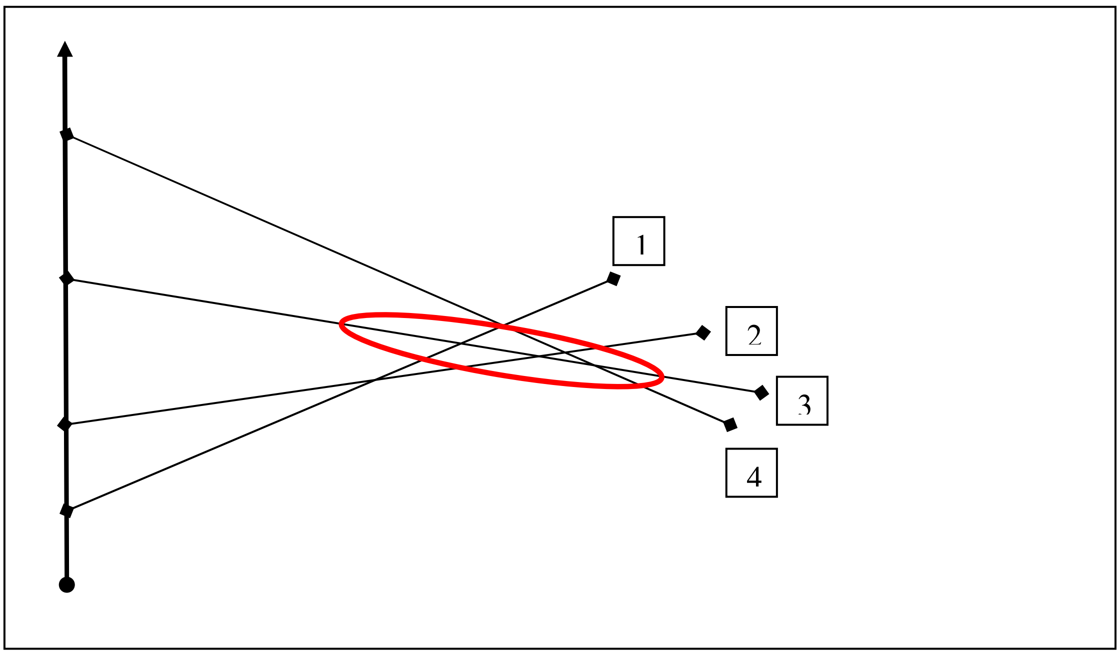

Figure 17. Triangulation with a ellipse error probable.

Figure 17 illustrates how the LSE could take the LOBs and calculate a center location and estimate the error using an ellipse. A CEP would convey similar information; only it would use a circle. This method, however, has less fidelity and is typically used less often.

Overall, while LSE is much more capable of determining location than the power measurement method, it is prone to bias and error in the face of challenging scenarios. Furthermore, the LSE method requires significantly more time to render usable geolocations. While each LOB is not likely to take any more time than the power measurement method, many LOBs must be collected. This overall requirement can potentially weigh heavily in the queuing process of the receiver.

A primary detriment to the LSE is the sole reliance on the observed information and the ability to statistically calculate the data. Essentially, a critical element to understand about the LSE is that predictions regarding the actual location are never used. Instead, all LSE calculations use observed data to determine a centered position that minimizes the error with the expectation that the actual radar position will be near predicted position. The capabilities of the Kalman filter were publicized when Kalman published a seminal paper in 1960. The fundamental concept of a Kalman filter with respect to geolocation is that the previous estimations of location serve as prediction of the next measurement. Similar to the LSE, the location measurement is described by an error ellipse probable (EEP). However, in contrast to LSE, Kalman filters have a method to accommodate the complexity of multiple changing variables as the result of aircraft motion and measurement errors. As new measurements are taken, the EEP can expand or contract based upon the difference between the predicted measurement and the actual measurement. In essence, the Kalman filter provides a dynamic approach to estimating location rather than a purely recursive method.

Processes that use Kalman filtering require frequent updates and recalculations in order to refine location estimates. Additionally, the process continuously updates error covariants to express the estimation of confidence of the location. The result is that the initial location estimates tend to be poor but rapidly improve as more data is collected.

The Kalman filter is best described as a circular method of processing that blends predictions with measurements. The first step is the predicted state. In the early phases, a seed may be required to initialize the matrix, but this seed is quickly updated with further updates. In step one, the state prediction where the location and the error covariance is used as the basis for qualifying the next observation. Step one also initializes the covariance matrices from predicted state and error measurement noise are updated. Step two is important because it illustrates the dynamic nature of this method determining location. Each iteration provides an opportunity to account for the noise in the system and make accommodations for it.

1. State prediction and prediction of covariance matrix of states

$$S_i = \vartheta S_{i-1} + Bu_{k-1} \tag{15}$$

$$\gamma_i = \varphi \gamma_{i-1} \varphi^t + Q \tag{16}$$

In step two, the covariance matrices from predicted state and error measurement noise are updated. Step two is important because it illustrates the dynamic nature of this method determining location. Every iteration provides an opportunity to account for the noise in the system and make accommodations for it.

In step two, the second accommodation for measurement error is taken into consideration. R represents measurement error in the system and is used to calculate the predicted location given the known error.

2. Kalman gain matrix computation

$$K_i = \gamma_i H^t (H \gamma_i H^t + R)^{-1} \tag{17}$$

In step three, the new measurement is received and merged with the existing state matrix. This step is important because it updates the displayed location of the radar. However, the calculation is incomplete because the error covariance has yet to be determined. Step four provides this function.

3. Update state estimation

$$S_i = S_i + K_i(z_i - H_i S_i) \tag{18}$$

4. Update covariance of matrix of states

$$\gamma_i = (I - K_i H)\gamma_{i-1} \tag{19}$$

Following step four, the system uses these calculations to start at step one again and repeat the cycle.

The strength of the Kalman filter is the speed and accuracy of the estimates even in the face of noise. The iterative nature in addition to the application of an accurate prediction model enables speed and accuracy. Additionally, as Brown (2012) and Vaccarro (1993) recognized, the Kalman filter method is flexible enough to blend multiple models such as a combination of triangulated locations in addition to time difference of arrival methods or elevation derived methods.

The ability of an EW receiver to locate radars is a critical function. The fidelity of that function is based upon the mission of the platform that employs the receiver. Fighter aircraft that use a radar warning receiver for the function of threat avoidance and counter tactics can sufficiently operate with low fidelity systems provided by power measurement methods. In this case, the overall demands of geolocation are relatively light compared to the normal functions of the receiver. However, in multirole platforms that perform multiple missions including electronic support, the requirements for geolocation increase substantially.

Ultimately, the required fidelity is dependent upon the priority placed upon the electronic support receiver. For platforms where electronic support is considered a tertiary role, the required fidelity is lower than a platform with a primary role of electronic support. Regardless of the specific role, multirole platforms are more likely to use a LSE or Kalman method of performing geolocation (Adamy, 2015). As Brown (2012) suggested, multiple method calculation is common as a means of optimizing speed and accuracy. Exact implementations are subject to proprietary calculations. Regardless, an important element to stress is the criticality of geolocation to any mission.

In many cases, the approximate location of a radar is the most important piece of information to the user. This conveys information such as the priority the radar represents to the mission at hand. For example, a threat radar that is 150 NM away likely poses very little threat at the moment. However, if a radar 60 NM away with a missile capable of hitting a target within 50 NM is highly relevant. Additionally, the location of a radar is important within the context of the particular mission it performs and how it interacts with other radars. A network of radars renders the location of a single radar much less relevant.

As a result of the importance of the location of the radars being processed, the electronic support receiver has to consider these demands on the queuing process. In this regard, the receiver has to perform a search in a manner that permits frequent updates to the detected signal in order to update the possible location of the signal. This implies not only specific dwell time, but a revisit interval that meets the demands of the operator.

Measurement and Identification

The environment an EW receiver operates in is complex and full of ambiguity. The electromagnetic spectrum is filled with several types of signals that clutter the environment with both real signals that are desirable for processing and those that are undesirable for processing. As a result, EW receivers have complex hardware and software to sort through the signals. This section discusses the fundamental description of an EW receiver. Additionally, this section discusses how an EW receiver collects pulses to serve the primary function of identifying the signals collected.

Electronic support receivers operate by collecting enough pulses in clusters to establish a pattern (Grajal, Yeste-Ojeda, Sanchez, Garrido, & Lopez-Vallejo, 2011). Pulses can be clustered in the domains such as frequency, temporal or spatial. For example, incoming pulses can be grouped based on radio frequency (RF), pulse width (PW), and direction of arrival. This example uses all three domains. However, other combinations are possible and clustering can be done in one or more dimensions within a domain. For example, pulse clustering can be done all within the time domain by using PW and the pulse repetition interval (PRI).

The process of sorting the pulse environment is referred to as deinterleaving and it is required to translate the millions of pulses per second into a manageable system of records. In turn, these records are managed with measurement updates to parameters to include RF, PW, PRI and emitter location. This information is used to identify the radar and provide context of this information to the operator. This information can also provide information regarding how the radar is being used. For example, target-tracking radars have highly distinguishable modes that used to provide higher fidelity track information for the purpose of targeting. A radar that performs the search function using pulsed-Doppler processing usually needs to switch to a medium pulse repetition frequency (PRF) mode to resolve range ambiguity issues (Guerci, 2015). This medium PRF mode is indicative of a mode used to engage an aircraft with either missiles or anti-aircraft artillery (AAA).

Figure 18 describes a generic EW receiver. The signal first enters a system via the antenna and then enters a feature extractor. The term feature extractor describes a generic processor designed to take an analog signal and convert it to a digital signal to be converted to pulse descriptor words (PDW). PDWs are a series of measurements taken from pulse train that describe the characteristics of the signal. Regardless of the process used to create the PDWs, the feature extractor is a time-based digitizer that converts the raw signal into values to describe the signal (Lin, Chen, & Hsueh, 2014). The EW receiver processes each pulse as it received into a PDW to be clustered by the deinterleaver. The deinterleaver uses an algorithm to determine how the PDWs fit together.

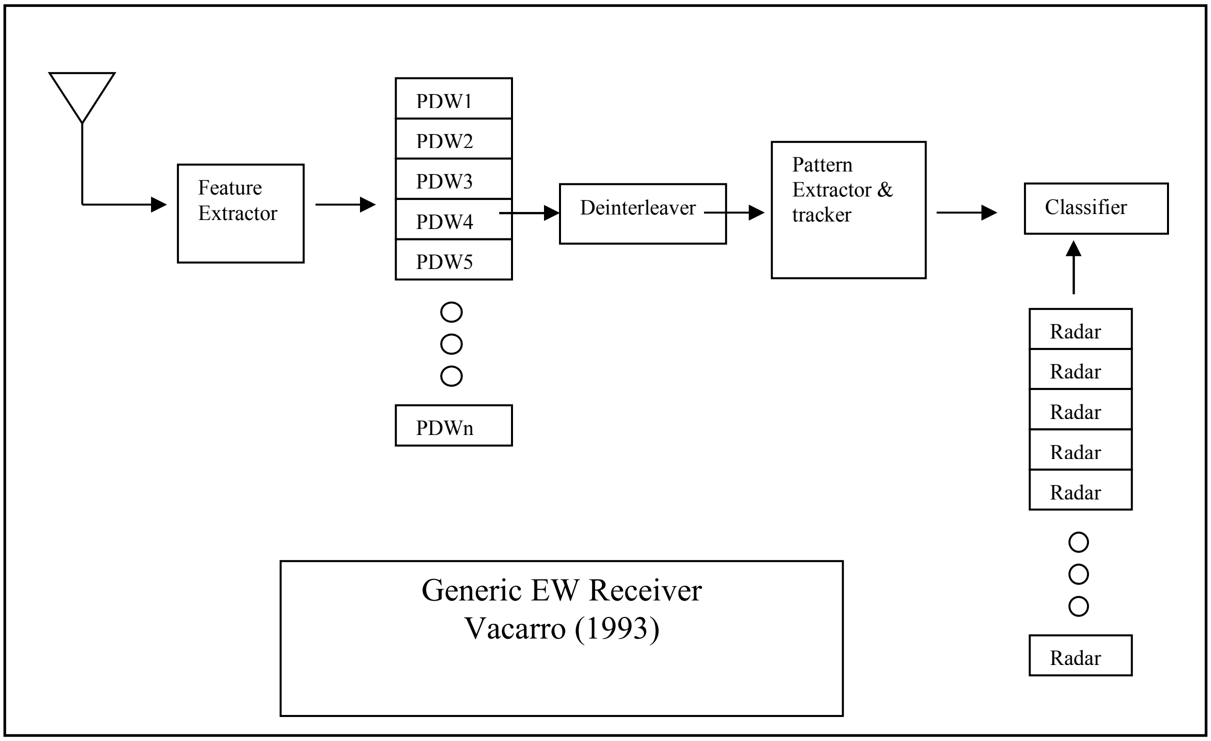

Figure 18. Generic EW receiver as depicted by Vacarro (1993)

The deinterleaver is a critical element in this chain because the algorithm employed determines how the PDWs from the intercepted signals are clustered together to establish a track (Albaker & Rahim, 2011). A track is a mechanism receivers use to manage data. A track is the first level of data the operator can work with. The track requires a predetermined minimum level of pulses that meet a set of requirements (Albaker & Rahim, 2011). As previously mentioned, RF and DOA are commonly used to cluster pulses. However, pulse rejection logic is required to reduce the presence of false targets. For example, there is a phenomenon known as multipathing where pulses that are reflections from another surface are received as though they are part of the original waveform (Sen & Nehorai, 2011). However, the characteristics that distinguish them from the original waveform such as lower amplitude and tend to be in trail on the order of 3 μs to 80 μs from the leading pulse. Without rejection logic, there is a much higher probability of false tracks or tracks with incorrect parameters (Swiercz, 2011). Essentially, the deinterleaver is the heart of the EW receiver. It ensures that pulses are clustered correctly while excluding invalid pulses.

However, the deinterleaver does not operate on its own. As Vacarro's (1993) diagram illustrates, a pattern extractor and tracker are required to manage the tracks. This includes adding new observations to existing tracks, merging tracks, deleting old tracks, and extracting patterns such PRI, RF or PW. This is the final step before identification. At this point, the track should have enough information to establish the identity of the radar. Several identifying features can be exploited. These features include RF, RF agility, multiple RF, PW, multiple PW, PRI, pulse modulation, pulse synchronization, intentional modulation on pulse (MOP) and unintentional MOP (Matuszewski, 2014). In most cases, a single parameter in and of itself is not sufficient to render an accurate identification. In some cases, a radar can only be identified to a type of radar, not a specific model.

Radar identification is heavily dependent on electronic intelligence (ELINT), which is a database that stores the key identifying features of radar. Ideally, this would be a static database that simply accounted for new radars. However, there are several different databases that account for these parameters, but every EW receiver requires a specific format for implementation. For the purpose of this paper, it is referred to as a type file. However, given that many radars are designed to be used in combat, most users are reluctant to publish parameters and reserve some modes in the event of a serious combat challenge. These are referred to war reserve modes (WARM) that often include variations on the typical identifying parameters. WARM not only frustrate efforts to identify signals, but to degrade them in the event that jamming is required. WARM can also include frequency agility modes intended to reduce the probability of detection, identification, and jamming.

In addition to intentional deception techniques, radars implement simple parametric variations as a matter of performance optimization. Radars are complex equipment and as such tend to have unique characteristics, which sometimes render a large set of potential parameters. Radars often work within a network of other radars and are located in positions designed to provide specific coverage. This often necessitates specific frequencies and modes that result in a specific PRI or combination of parameters. The end result is that modern radars have the ability to mix a wide range of parameters in a flexible manner that make identification significantly more reliant on ELINT.

In addition to ELINT, the electronic order of battle (EOB) is used. The EOB is a database of known locations of specific radars. Unfortunately, the EOB is primarily only of use against ground based systems as airborne and shipborne platforms are mobile and their identification primarily relies on ELINT. The combination of an accurate EOB and type file significantly improve the probability of a correct ID. Depending on how the EOB and type file were made and the assumptions involved, mobile platforms can even benefit from Bayesian logic for identification (Adamy, 2015). If the intercepted parameters match five different radars, but one radar is known to be the site detected, then the probability is very high that the detection is emanating from the radar known to be at that location. For mobile systems, a similar logic applies, but has more ambiguity. This model is only accurate if the area of operation is suited for this logic. For example, if a country in the area of operations is the only one to use a certain type of aircraft, then an EOB can be used. However, if several closely adjacent nations use similarly equipped aircraft, then their identification is ambiguous.

Discussion on Revisit Interval

Literature essentially indicates two distinctly different methods of calculating a revisit interval. Richards's theory preceded Little's and was specifically designed to find the overlap of independent events as applicable to electronic warfare. Additionally, Richards approached the topic of determining the optimal revisit interval from a deterministic approach. In doing so, Richards emphasized the complicated nature of the research. In contrast, Little's formula was a broadly generalized queuing formula that is mathematically proven and designed to optimize system performance based upon inputs and desired performance.

A key element of Richards's approach is that it was specifically designed to be used in the arena of sensor scheduling and can be adapted to include more than two events. Wiley (1985) demonstrated that algorithm as designed by Richards could be applied to multiple windows. For example, an EW receiver may have to search in multiple domains such as time, frequency, and direction. The windows function is easily adaptable to accommodate sensor scheduling among multiple domains. However, the ease of use of this function is a less than optimal result. Yet, most scheduling algorithms are suboptimal, and in some cases intractable (Atia, Veeravalli, & Fuemmeler, 2011; Shi, Cheng, & Chen, 2011). This aspect of the sensor-scheduling problem focuses the research on managing the risks and trade-offs associated with EW receivers (Nino-Mora & Villar, 2011).

Nonetheless, it worth noting that while the windows function is less than optimal, many researchers continue to use it as the basis of their sensor-scheduling plan. This research uses Little's formula as the baseline optimal revisit interval value. The expectation is that simulation will demonstrate the predictability of Little's formula as the basis for sensor scheduling. However, the topic of this paper is not whether one method is better than the other. The research question focuses on the effect of variation from the optimal condition. In order to perform this analysis, the optimal value must be attained. Little's formula is mathematically proven and is assumed to be applicable in this case. The basis of this analysis is that in optimal conditions, at least 95% of the intercepts will be detected within the stated required response time. This implies that of the 5% that are longer than the required response time, those times are unpredictable. Therefore, as Wiley (1985) demonstrated, the resulting distribution of response times resembles a gamma distribution pictured in Figure 19.

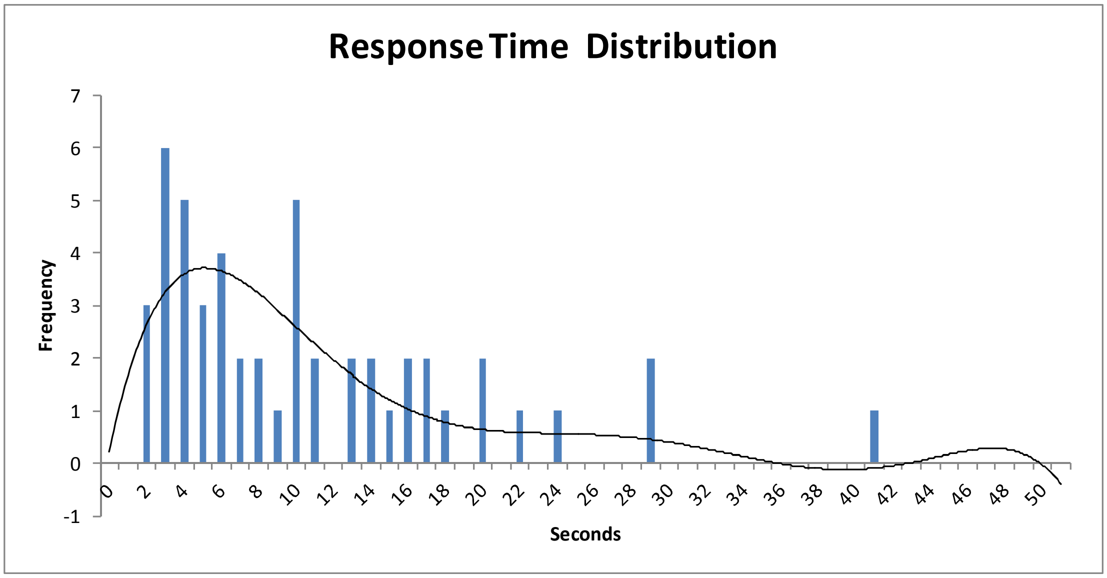

Figure 19. Response time distribution

In this case, 98% of the samples are below the required 30-second detection time. However, a single sample is well beyond that requirement. This distribution is typical of response time analysis as there cannot be a negative value for a response time and unusually long times relative to the average are always a possibility. As a result, the assumption of normality was rejected with respect to the analysis of this data as well.

Discussion on EW Receiver Scan Plan and the Effects of Variation

The complexity of the EW receiver scan plan has resulted in numerous studies on this topic. In contrast to the earlier efforts, EW receiver engineers are challenged with the added complexity of trying to detect radars with significantly more advanced waveforms. "The chief source of periodicity in radars is the scanning pattern of its main beams, either through mechanical movement of the antenna or, in more modern and sophisticated radars, through electronic 'beam steering'" (Clarkson, 2003, p. 2). Ultimately, electronic beam steering means that radar designers are able to change the patterns that made detection possible. Additionally, the frequency spectrum is becoming increasingly crowded to where signals of interest can hide beneath the high-powered commercial signals (Wu, Jia, Johansson, & Shi, 2013). As a result of the constantly evolving nature of electronic warfare, EW receiver engineers are considering how to integrate complete scan plans that give optimal results in the signal environment at the time the mission is being executed.

Clarkson (2003) wrote “A practical problem of interest to the operator of an SHR is how to set the sweep period of the SHR to minimize in some sense the intercept times for not one but possibly many radars on a threat emitter list” (p. 14). Clarkson proposed the use of Farey Series analysis in order to find the ratios of the PRI between multiple signals in order to determine the coincidence of multiple pulse trains. As such, sweep times can either lead to optimally short periods required for detection or functionally infinite detection times. Given the possibility of unsatisfactorily long detection times, Clarkson’s procedure revealed how a constant sweep period performs with radars with constant circular sweeps and constant PRI. This research is significant because it illustrates how critical the problem of synchronization can be (Shen, Chen, Pham, & Blasch, 2011). In this case, Clarkson approximated how radars with constant values and a scanning receiver using constant sweep rates can yield predictable response times. Additionally, Clarkson’s research assumes a minimal dwell period of two pulses. Overall, the practicality of the Farey Series calculations are limited to theory of demonstrating the potential severity that synchronization poses to timely intercepts.

In a 2011 paper, Clarkson conducted an experiment to evaluate the effectiveness of an EW receiver optimization strategy. In this work, Clarkson proposed a minimum-maximum dwell time and revisit interval as an alternative to the sequenced methods that utilized a fixed dwell time across all the bands. Clarkson's objective was to demonstrate that the proposed optimization method was superior to the jitter search methods. Clarkson (2011) said the following:

> Increasingly, modern radars are able to operate in a number of modes and are agile between these modes to achieve better performance. For instance, pulse repetition frequency (PRF) jittering, a switching, and staggering are used to resolve range ambiguities. RF agility is useful in evading detection. Furthermore, the scanning strategy of the radar need not be circular, but may be concentrated in sectors using for example raster, spiral, or lobe-switching scan strategies. How to do these characteristics of a modern radar affect a receiver sensor-scheduling strategy based on the min-max intercept-time principle? Alternatively, how can the sensor-scheduling strategy be adapted to take account of these characteristics. (p. 1780)

Clarkson concluded that factors needed to be accounted for and could extend the detection time if it required additional dwell time to gather a sufficient number of pulses. Altmeyer, Davis, and Maiza (2011; 2012) supported Clarkson's conclusions by showing that minimum/maximum queuing schemes are more effective at overcoming the unknown elements of the environment and issues associated with blocking. Queue weighting and prioritization methods are only effective when the systems involved in the queue are appropriately accounted for.

In a 2007 article, Clarkson and Pollington (2007) wrote the following:

> Hence, we conclude that, according our interception model, there is no substitute for intelligence on the scan periods of threat emitters, whenever that can be obtained. If the scan periods are known to good accuracy, maximum intercept times can then be calculated and minimized within a deterministic, periodic search strategy. Otherwise, the best that can hoped for is good interception on average. (p. 649)

Clarkson and Pollington acknowledged the role that predictable scan periods play in reliable response times. This implies that irregular scan periods have the potential to significantly degrade the reliability of the response time.

Clarkson, Perkins, and Mareels (1996) explored the deterministic aspect of calculating the effectiveness of EW receiver scan strategy. The authors sought to expand the basic body of literature on the problem by considering more complex problems found in the EW community. Their examination discussed two sub-problems, which were the effect of the phase of one pulse train being a random variable and having two pulse trains being random variables. A critical element of their findings was that the revisit intervals they used were constant and constrained to only two pulse trains. In reality, there are multiple pulse trains and a dynamic effect on processing and the motion of the aircraft will alter the parameters vital detection (Pizzocaro, Preece, Chen, Porta, & Bar-Noy, 2011).

Kelly, Noone, and Perkins (1996) wrote regarding the effects of synchronization on the probability of intercept. Their research in the field of random phase theory detailed a number of equations regarding probability of intercept. The first equation predicts the mean number of intercepts during a single sweep as:

T0 = Scan period of the radar

T1 = Scan time of the EW receiver

$$P1 = \frac{T1}{T0} \tag{20}$$

Which can also be written as:

τ0 = duration of the scan

τ1 = duration of the receiver scan

T1 = Scan time of the EW receiver

$$P1 = \frac{\tau 0 + \tau 1}{T1} \tag{21}$$

The probability of at least one intercept in n number of scan is calculated by:

$$Pn = 1 - (1 - P1)^n \tag{22}$$

$$Tp = T1 \frac{loge(1-P1)}{\log(1-P)} \tag{23}$$

The implications of Kelly et al. (1996) confirm that variation in the phase of the scans actually improve the probability of intercept. They offer very little information regarding the optimization of calculating the revisit interval. Their research dealt with probability expressions rather than response time in terms of seconds. Much of their (Kelly et al., 1996) work followed Washburn's (1981) findings when they said, "it has been recognized by Washburn that the validity of this approach improves as the magnitude of jitter in one of the pulse train increases, i.e., as the random phase assumption becomes increasingly valid" (Kelly et al., 1996, p. 214). Additionally, they realized that a random jitter in the revisit interval helped offset the effects of an unfavorable initial scan. Regarding this possibility, they said, "When the parameters of the sought pulse train are unknown, attempts to intercept it with a uniform pulse train run the risk of operating in a probability minimum and possibly with an unfortunate initial phase so that interception may never occur" (Kelly et al., 1996, p. 218). Overall, their research demonstrated that variation of the revisit intervals improve the probability of intercept. However, their findings fell short in two main areas. First, they did not provide much insight into the degree of variation. Next, they did not establish that their initial revisit interval was optimal. Finally, their results dealt with the topic of probability of intercept and never translated their results into response time. Response time is clearly a function of probability of intercept, but the actual time that is required to detect the signal is fundamentally what is of importance to the operator. An 80% probability of intercept (POI) is an abstract value compared with a statement that a signal has a 95% probability of being detected in 10 seconds or less.

Kay (2013) defined the POI as a percentage of pulses the receiver will collect in a certain signal environment. Kay added to this definition by listing caveats such as pulse density and distribution of the pulses in the environment. Therefore, POI is a very loosely defined term

$$POIaoa = \frac{\theta a}{\theta t} \qquad (24)$$

$$POIBW = \frac{Br}{B} \tag{25}$$

$$POI = POIaoa * POIBW \tag{26}$$

"When the antenna coverage is equal to or greater than the area of interest and the instantaneous bandwidth equals the input bandwidth, the overall POI is 100%. However, it must be emphasized that even under this condition, the receiver can still miss some pulses. One situation is that some the signals are outside the instantaneous dynamic range as discussed in the section above. Another situation is that if one signal is following very closely by a second signal, the second may be missed by the receiver" (pp. 76-77).

In a paper published by Winsor and Hughes (2012), they focused on what they called the probability of report (Pr). The concept of a Pr represents the combination of a probability of intercept and probability of detection. This translates into the probability that the receiver will be tuned to the right RF and collect the requisite number of pulses to generate a report. Winsor and Hughes reflected on work by Clarkson and noted its attempts at optimization does not vary the dwell sequence and does not render a truly optimized solution. In contrast to Clarkson, Winsor, and Hughes used a genetic algorithm to determine an optimal dwell sequence. Using Monte Carlo simulation, they conducted six experiments with varying dwell sequences and made the following conclusions:

1. As the revisit interval increases, the number of intercept opportunities increase, but that this only improves the probability of intercept for the first scan and has diminishing returns thereafter.

2. Shorter dwell periods are more beneficial than longer ones. The shortest dwell period possible should be used and the revisit interval should be applied as a compromise the desired probability of intercept and revisit interval.

Overall, this article is relevant because it acknowledged the general lack of research into optimization strategies in the field of EW receivers. Additionally, the methods employed by Winsor and Hughes is similar to those proposed in this paper. A key difference is that Winsor and Hughes focused on the complete sequence. However, they did not address the fundamental requirement to detect a single emitter and how that is translated to the entire scan schedule. They seemed to assume that an emitter-by-emitter scan optimization could be calculated. Regardless though, their findings and methods are very important and helpful in determining how to balance the conflicting scan requirements of multiple emitters. Fundamentally, this paper assumes a dynamic process will be applied and that denser signal environments with varying factors will degrade performance. However, the key question is how much will these variations due to density degrade performance?

Summary and Conclusions

A significant portion of the literature review was directed at the study of radar operations. Specifically, it is critical to understand the concepts associated with the waveform. This refers to the physical aspects regarding radio frequency (RF), pulse width (PW), pulse repetition interval (PRI), antenna patterns, scan pattern, and radar power. Understanding these concepts are vital to understanding the EW receiver operations because it is these radiated characteristics that are observable to the EW receiver. A radar actively radiates energy with a synchronized knowledge of how that energy is radiated.

As a result of the coordinated transmission of energy, the processor is capable to translate the information from the radar returns. This can include information such as range, bearing, elevation angle, and velocity.

An EW receiver does not have the benefit having specific operating knowledge of radar a priori. The stochastic nature of this queuing process adds to the complexity of evaluating and optimizing and EW receiver system (Ferreira, Andrade, Filipe, & Coelho, 2012) The radar uses a matched receiver to capture the information from the received pulses. An EW receiver is an unmatched receiver and must capture the pulses in order to accomplish it mission (Sarkosh, Emami, & Mitchell, 2012). From an electrical engineering perspective, the EW receiver is un-optimized because specific characteristics such as the intermediate frequency, pulse repetition interval and scan type are either too diverse to permit optimization or known only after the fact. However, the EW receiver has at least one advantage in that it only requires only one-way travel, which gives it a significantly earlier detection capability compared to the radar.

Given the unmatched nature of the EW receiver processing, it places additional requirements on the system. An EW receiver must detect a radar, measure key parameters associated with the radar, identified the radar, and locate the radar (Sen, Tang, & Nehorai, 2011). This study focuses on the detection element, however, the requirement to parameterize, ID and locate have significant implications on the ability to detect the radar. Therefore, these concepts are relevant to the topic of scan-tune optimization. Essentially, the processing requirements drive the scanning requirements. The more data required by the receiver demand longer dwell times. Longer dwell times and more frequent revisit intervals increase the utilization rate of the receiver.

These topics directly relate to the concepts of search theory, probability of intercept, queuing, and response time. Ultimately, the problem under study is how to find a signal that may or may not care if it is detected. Search theory as described by Alpern provided insight into the complex concepts of finding targets in a wide range of scenarios. Richards (1948) provided specific applications relating to electronic warfare receiver search theory. Queuing theory from Little (1961) provided the mathematically proven method associated with optimizing a scan-tune schedule. Further development provided details regarding how probability of detection is affected by more complex scan-tune schedules. As the electromagnetic spectrum becomes more diverse, more difficult to detect, and more difficult to track, the problems associated with optimizing a scan-tune schedule becomes more difficult (Nguyen, Nasrabadi, & Tran, 2011).

A key element noted throughout several years of literature is the lack of research regarding the effect of how variation among the key variables associated with probability of intercept have on response time. Overall, the literature tentatively suggests that some variation among these variables will improve the response time. However, no single source of literature detailed how much variation is involved nor did the literature reflect how much improvement can be expected. Additionally, the literature suggests conflict among researchers regarding concepts such as probability of intercept and often do not translate how probability of intercept relate to response time. The diverse research in this area suggests that a significant amount of research is still required. This literature review is specifically targeted at understanding how variations in radar operations and variations in EW receiver operations affect EW receiver response time. Ultimately, EW receiver response time represents the amount of time it takes to detect a signal from the time it becomes detectable. The operational environment is diverse and dynamic leading to a mathematically challenging problem. However, this is the question most relevant to users of EW receiver systems. The variables associated with the EW receiver can be manipulated and the variables associated with the radar environment can be predicted (Liang, Cheng, & Samn, 2010). As a result, response time can be predicted.

Chapter 3: Research Method

The purpose of this study was to examine how variations in the independent variables affect the dependent variable: EW receiver response time. Due to the nature of this study, quantification of the effects was extremely difficult. As a result, Monte Carlo simulation techniques were used to accomplish a large number of samples in order to achieve a high degree of confidence in the results. The upcoming sections present a thorough description of the design and rationale for the method selected. Additionally, this chapter includes the sample size selection, power of the study, data analysis, and threats to validity.

This study was a true experimental design that used design of experiment concepts to determine not only how the individual variables affected the response time, but how they interacted with one another to influence the response time. Furthermore, the design of this experiment was an orthogonal design using a 2^k factorial design in which each factor had a predetermined high setting and low setting. The intent of this type of design was to quantify how each factor individually and in concert with the others influenced the results. However, only the effects of the high and low settings were quantified. Given the assumption of normality, the effects were assumed to be linear between the low and high settings.

The study of EW receiver response time is difficult given a large amount of variation in the results and the difficulty in reliably setting up the test conditions in a nonsimulated environment. However, in a simulated environment, the conditions are easily controlled and the results are much more quantifiable. Therefore, in this study I sought to determine not only how each of the individual variables affected the response time, but how the interaction of the variables affected the response time.

Research Design and Rationale

There are three fundamental research design methods: qualitative, quantitative, and mixed methods. The qualitative approach was immediately ruled out because the various qualitative designs were not well suited to answer the research questions. There is a place for qualitative research regarding EW receiver operations, which requires a specific focus on a single system and operator feedback. I examined a broader range of queuing theory regarding EW receiver scan strategy, thus eliminating the qualitative approach. The mixed-methods approach was immediately ruled out because of the scope involved in implementing the required qualitative approach. Therefore, I chose the quantitative method. Upon selection of a quantitative study, the next question to address is the selection of an experimental or quasi-experimental design. Generally, a true experimental design is preferable to a quasi-experimental design. For this study, I designed software to simulate the EW environment in order to implement a true experimental design. A simulated environment is the only way in which EW receiver response time can be studied using an experimental design. Open-air flight testing is too unstable to implement an experimental study. Therefore, given the resources available and the benefits of using an experimental design with a simulation, I chose this design for the study.

The purpose of this study was quantifying how the independent variables (EW receiver dwell time, EW receiver revisit interval, radar scan time, radar illumination time) affected the dependent variable (EW receiver response time). Furthermore, the moderating variables were defined as the interaction between the independent variables. The interaction of the variables was of significant concern and was a major factor in the decision to use the 2^k factorial design.

The choice of the design of experiment (DOE) 2^k factorial design methodology was based on the strength of the method to evaluate the joint effects of multiple factors. This is especially true in large industrial settings where one-factor-at-a-time studies are not well suited to efficiently optimizing the system. In this type of design, most of the work is performed in setting up the experiment by using a complete array of variables and their interactions. Additionally, a key component of this design method is to efficiently determine the optimal solution assuming that each replicate is costly (Jenkins & Castanon, 2011). However, the 2^k factorial design method is well suited to a simulated environment where replicates are not expensive. The design method is thorough and mathematically grounded.

For this study, the 2^k factorial design was ideal because it acted as a survey to evaluate which factors and interactions were of significance. Other design methods for consideration included 3^k factorial design or response surface methodology. This was ruled out given the lack of information on how the variables interact. The literature regarding the effect that variation on any of the independent variables will have on the response time is mixed. Furthermore, the literature does not address the possible implications of interactive effects. Without further understanding of the impact these variables have on response time, a study using response surface methodology was unadvised.

A 3^k factorial design is a possible alternative to a two-level factorial design. A three-level design is nearly identical to a two-level design with the exception that an intermediate level is used in conjunction with the high and low levels. However, Montgomery (2005) noted that a three-level design is not an efficient method to model a quadratic relationship. Additionally, Montgomery stated that a two-level design augmented with center points could still detect a curvature while maintaining a simpler study. Essentially, there was no analytical advantage to using a three-level design. Additionally, the three-level factorial design with four factors is significantly more complicated because there are 81 possible interactions rather the 16 with a two-level design. This was a prohibitively complicated approach considering that a two-level design method could still accomplish the same results.

Overall, a two-level design was ideally suited for this type of study. It was the most accurate, simple, and appropriate design for the research questions. Given the amount of knowledge on this particular topic, a two-level design provided the most efficient method to determine how the factors interacted. A key assumption of this research was that some variation among the variables is always present. The variation can be manipulated in some cases and predicted in others. However, normal variation is always going to occur to some extent. I ran simulations without variation for the purpose of comparison, but all other runs included some level of variation. The degree of interaction among the variables was the critical question being answered. Depending on the results of this study, future researchers will likely use response surface methodology to provide better fidelity regarding the interaction between the levels.

Methodology

The approach was a quantitative experimental method using Monte Carlo simulation. I coded the simulation using Microsoft Visual Basic for Applications (VBA) with the results displayed in Microsoft Excel. Monte Carlo simulation is the ideal method for studying how variations among the four independent variables interact and possibly affect the dependent variable of response time (Kim, Kim, & Lee, 2011). Monte Carlo simulation is ideal because it permits the collection of large sample sizes in a controlled environment suitable for data analysis. Additionally, the control of the simulation is conducive to the analysis plan using the DOE technique of 2^K factorial. The method used in this simulation specifically focused on the variables at play in order to evaluate their effect on the response time.

A key aspect of this study was the implementation of the 2^K factorial analysis method. This method requires identification of the high and low values of a variable. Given the potential for significant variation in concert with the limited research on the effects of variation, this method appeared appropriate with a slight modification. The simulated environment permits additional data points to be collected that add to the analysis; therefore, simulations with no variation add an element to the analysis.

Figure 20 illustrates a traditional 2^K factorial experiment where the factors are as indicated.

	Factor A	Factor B	Factor C	Factor D
Level	Radar illumination time	Radar scan time	EW receiver dwell time	EW receiver revisit interval
1	0.75	0.6	0.5	0.9
-1	0.25	0.1	0.1	0.1

Figure 20. Factor definitions and settings.

A traditional 2^k factorial design uses the matrix as illustrated in Figure 21. This matrix is a standardized format that ensures every combination of variables. This method exhaustively tests how the interactions of variables affect the dependent variable. By using a code of either -1 or 1 to emphasize the outer edge of a realistic boundary, the possibility of an interactive effect can be detected. Therefore, if an interaction occurs at the outer edge of a boundary, then further research is necessary to map the extent of the interaction at lesser levels of deflection. However, if no effect is detected, then it is unlikely that any interaction occurs with lower levels of deflection.

	Factors			
Run #	A	B	C	D
1	0	0	0	0
2	-1	-1	-1	-1
3	1	-1	-1	-1
4	-1	1	-1	-1
5	1	1	-1	-1
6	-1	-1	1	-1
7	1	-1	1	-1
8	-1	1	1	-1
9	1	1	1	-1
10	-1	-1	-1	1
11	1	-1	-1	1
12	-1	1	-1	1
13	1	1	-1	1
14	-1	-1	1	1
15	1	-1	1	1
16	-1	1	1	1
17	1	1	1	1

Figure 21. Illustrates the 2^4 factorial design model.

If the existence of a cause and effect relationship is established, additional studies using more granular analysis techniques are employed. Response surface methodology is a common follow-up study to a 2^k factorial design. Unfortunately, the existing body of literature is not developed enough to support a response surface methodology. However, given that this study was based on a simulation, a modification to the traditional 2^k factorial design was possible. Figure 22 illustrates the modification.

Factors				
Run #	**A**	**B**	**C**	**D**
1	0	0	0	0
2	-1	-1	-1	-1
3	1	-1	-1	-1
4	-1	1	-1	-1
5	1	1	-1	-1
6	-1	-1	1	-1
7	1	-1	1	-1
8	-1	1	1	-1
9	1	1	1	-1
10	-1	-1	-1	1
11	1	-1	-1	1
12	-1	1	-1	1
13	1	1	-1	1
14	-1	-1	1	1
15	1	-1	1	1
16	-1	1	1	1
17	1	1	1	1

Figure 22. Illustrates the 24 factorial design model with a control run.

In Run 1, the variables have no variation at all. If no variation is realistic, then a different design method can be employed. However, no variation is not realistic. However, the existing body of research normally assumes no variation as a method of simplifying the problem. Therefore, a control run with no variation to demonstrate performance in a static environment was performed.

The 2^k factorial design was ideal for this study because of the need to examine the effects of multiple variables interacting. Regarding this method, Montgomery (2005) noted that “factorial designs are widely used in experiments involving several factors where it is necessary to study the joint effect of the factors on a response” (p. 203). Additionally, the results were analyzed using multiple regression models and analysis of variance (ANOVA) techniques. DOE has been instrumental in industrial experimentation and analysis for many years. The techniques are designed to optimize the experimental scenarios such that accurate results are obtained with fewer resources. The primary intent of DOE is to understand how complex systems with multiple variables behave given different settings of the independent variables. The techniques espoused in DOE are valid for use in simulation as well.

This study fundamentally simulated a complex scenario by simplifying a large number of variables into four independent variables. The question was how the variation of these variables affects the dependent variable: response time. The existing body of research suggests that a mild amount of variation may improve response time by reducing the probability of a scan-on-scan scenario in which the radar scan and EW receiver scan are of equal time and out of sync. However, the existing body of research also indicates that effects of more significant variation are unknown. Furthermore, previous researchers acknowledged that the combinatorial effect of the variations involved has yet to be studied. The use of the 2^k factorial design in a simulated environment offered an excellent opportunity to study how these variables interacted and ultimately influenced the time it takes for an EW receiver to detect an emitter.

Simulation

The software used to host the simulation was not a significant factor to the study and could have easily been hosted in programs such Matlab, Java, or R. VBA has the advantage of being easily accessible as a standard package of Microsoft Office and is easily reproducible. This section presents an in-depth description of how the variables are represented to the user, how they are applied in the code, and how the results are calculated and displayed.

I interacted with the software via a Microsoft Excel worksheet with the variables appropriately labeled. Figure 23 illustrates the graphical user interface (GUI). Note the GUI has three sections. The first section consists of the variables modified during the course of this study. The rows highlighted in yellow are the four independent variables modified in the experiment. These variables received either the low or high amounts of variation as required in the mode plan to determine the effect on the dependent variable: EW receiver response time. The second section consists of variables that were not modified. The third section consists of administrative data management details for the purpose of controlling the simulation and marking the data for analysis.

Simulation Variables	Simulation Setting	Unit
Scan Time	3	Seconds
Scan Time Variation	0.9	Percent
Illumination Time	0.75	Seconds
Illumination Time Variation	0.75	Percent
Dwell Time	8400	Microseconds
Dwell Time Variation	0.1	Percent
Revisit Interval	0.88	Seconds
Revisit Interval Variation	0.9	Percent

Fixed Variables	Simulation Setting	Unit
Desired Response Time	5	Seconds
Desired Probability of Intercept	0.95	Percent
Required Pulses Collected Time	8000	Microseconds

Simulation Characteristics	Setting	Data Type
Number of Samples	1000	Integer
Scan Time Variation Code	1	Binary
Illumination Variation Code	1	Binary
Dwell Time Variation Code	1	Binary
Revisit Interval Variation Code	1	Binary

Figure 23. Simulation graphical user interface.

The first section contains the variables available for modification during this study. The graphical user interface (GUI) requires direct variable input rather than pre-codified entries that correspond to the settings designed for this study. Ultimately, this helps maintain a flexible simulation scenario. The units listed in this section are not adjustable. The units describing the radar scan time and illumination time are expressed in terms of seconds. Programmatically, no minimum value or maximum values exist for the radar scan pattern factors. However, expected values range from .1 seconds to 300 seconds. A radar scan period of .1 seconds is extremely low and not representative of any operationally deployed radars. A maximum radar scan period of 300 seconds was used because that represents the longest reportable response time. Most radars have scan periods between two and 60 seconds. A 300 second response time is considered an unusually long period of time for an EW receiver to detect a radar. Any response times beyond 300 seconds are treated as no-detections, and are recorded as such.

The EW receiver dwell time is expressed in units of microseconds and revisit interval is expressed in seconds. All times are converted to microseconds for the purpose of the simulation. The values in the GUI are used to simplify entry to prevent user error. EW receiver dwell times are most commonly expressed in terms of microseconds (μs) as this is the common unit to express the pulse repetition interval (PRI) of the radar. EW receivers typically have a minimum threshold of pulses required. This minimum threshold is easily translated into units of time, which is used in this study. The EW receiver revisit interval is stated in terms of seconds. In all cases of this study, this value is calculated using Little's formula. All factors of variation are expressed in terms of percent.

The second section of Figure 28 contains values used to calculate Little's formula. These values must remain constant throughout the study. A key point in this simulation is that the planned dwell time are not be less than the minimum required dwell time because that creates a scenario where a detection is never possible. The third section of the GUI is administrative. This section defines the number of samples required and mark the results with the variable codes used for data analysis. These values wee manually labeled and must be double-checked to ensure they reflect the proper settings.

Overall, the GUI was intentionally designed to be simple and easily modified to meet the requirements of the simulation. All values require manual settings except for the revisit interval. The revisit interval was always assumed to be based on the calculated optimal performance value as calculated by Little's formula. Therefore, when independent variables require no variation, then a value of zero in each of the factors was used to express no variation.

The simulation is conceptually basic. It relies on two timing loops that have a least significant bit (LSB) of 1 microsecond. The first clock represents the timing required for the radar and the second clock represents the EW receiver. The radar clock indicates when the illumination time begins and how long the illumination lasts. The scan period and illumination time were set in the GUI. The amount of variation in these factors were also defined by the user in the GUI. The variation was applied as a continuous random variable with normal distribution around the selected value. For example, if the radar scan period is 10 seconds with 25% variation. The random variation was performed using the inverse normal distribution command that uses the RAND() function as the first argument. The next argument in the function represents the mean. In this simulation, this value was set to 1 because the resultant value is the multiplication factor. The final argument of the function is the standard deviation. This value was set by dividing the degree of variation by 3. The final function in this example would be written in MS Excel as follows: =NORMINV(RAND(),10,0.25/3). If this function is applied several times, then a random value centered around 10 with a deviation of approximately 25% is the result. This value was used a multiplier and was multiplied by the average scan time. The results of 1000 trials are demonstrated in Figure 24.

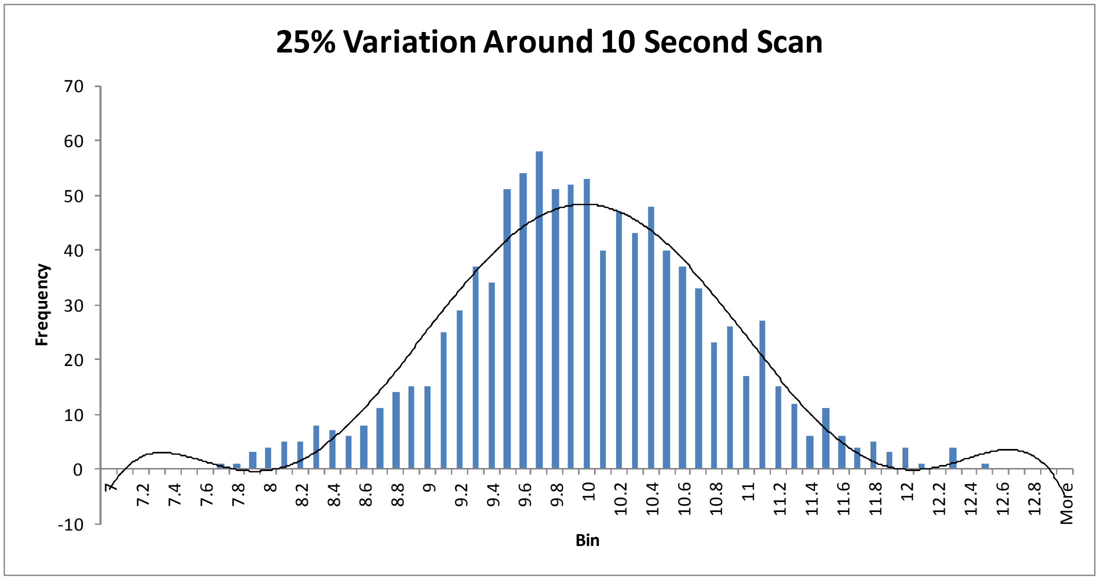

Figure 24. Example of 25% variation around 10 second scan.

Regarding Figure 24, note the symmetric distribution around the 10-second mark with the tales spanning appropriately from 7.5 seconds to 12.5 seconds. This method of creating random continuous variables was used to control when the next event will occur and how long the planned event will occur. The assumption of a Gaussian distribution was based on radar theory that documents the shimmering effect of reflected energy (Anitori, Otten, Van Rossum, Maleki, & Baraniuk, 2012). This assumption was applied to this scenario because of the similar features of dynamic motion, environmental factors, and terrain features.

Each loop in the simulation represents the LSB. Each timer defines the next start time and how long the defined event will occur. The variation function that defines the time of the next event and the duration was implemented and those values are applied. The simulation was started by selecting a random radar start time between zero and the user defined scan time. The EW receiver always started with a scan at time zero. After each radar scan and EW receiver scan, the next scan and dwell period was randomly defined based on the variation function. The simulation event was terminated when the EW receiver timer overlaps with the radar scan period for the minimum time required. In this simulation, the minimum time was 8000 microseconds. Clearly shorter minimum times improve response time, but fewer pulses decrease the fidelity of the measurements. This study held required collection values steady at a conservative value to represent the functions required of an EW receiver.

Once the run was terminated, the simulation was reset and run again. The power of Monte Carlo simulation is realized through the generation of several thousand samples. The number of samples was defined by the user in the GUI. The results of this study indicated that even under ideal conditions, the dependent variable has a significant amount of variation. The degree of variation was expected to increase as the independent variables are varied based on the variation functions. Thus, 1000 samples per scenario were taken to provide sufficient resolution. Each sample was recorded with the response time, the first radar scan time, the number of radar scans, and the scenario settings.

Population

A simulation was used to generate all data for analysis. No human subjects were used in any manner. Thus, there is no population from which a sample would be selected.

Sampling and Sampling Procedures

A simulation was used to generate all data for analysis. No human subjects were used in any manner. Thus, there is no population from which a sample would be selected.

Procedures for Recruitment, Participation, and Data Collection (Primary Data)

A simulation was used to generate all data for analysis. No human subjects were used in any manner. Thus, there is no population from which a sample would be selected.

Data Analysis Plan

The focus of this study was how different levels of variation on the four independent variables affect the response time. This focus is summarized by four research questions:

- How does the application of the 16 test conditions affect response times compared to the control sample?
- How do the mean response times from each treatment compare to each other?
- How do the variations in response times from each treatment compare to each other?
- Is there a relationship between the variables that can reliably predict the response time of an EW receiver given the independent variables?

The intent of this study was to characterize how the variations of the independent variables influence the time it takes an EW receiver to detect a signal.

The underlying principle is that the ideal conditions that lead to the desired response time are rarely in an optimized state. Rather, the conditions are subject to constant change independently. Therefore, the variables are better described by probability distributions because of the dynamic environment due to the following factors: aircraft movement, waveform motion, and adaptive targeting. In essence, the EW receiver is normally in a condition where the independent variables are not in the pre-planned state of optimality. Therefore, this implies that various combinations of states must occur.

The first research question seeks to answer how these variations compare to the control group that has no variation among the independent variables. This is a unique aspect of this study, as open air testing cannot readily construct an experiment to control the variables such that there is no variation among the independent variables. The following is the null and alternate hypothesis:

> H_0: The application of the 16-test conditions does not affect mean (μ) response times compared to the control sample ($\mu 0 = \mu 1 \ldots = \mu 16$).
>
> H_1: The application of the 16-test conditions does affect mean (μ) response times compared to the control sample ($\mu 0 \neq \mu 1 \ldots \neq \mu 16$).

This question was evaluated using a two-tailed paired observation. Each of the 16 test cases was compared to the control group where the independent variables did not have any variation placed upon it. This method was used because it provided for a baseline comparison against the idealized performance in a condition with no variation. The requirements for this statistical procedure assumed an equal number of samples and a normal population distribution. Normality was not expected, and a transformation was required for analysis. Given this expectation, a Box-Cox transformation was used to normalize the data for analysis. Also, the non-parametric technique, Wilcoxon Matched-Pairs T-test were used to evaluate the results. In the event that the assumptions for the parametric test are not met, the Wilcoxon Matched-Pairs T-test will be used to determine if the means between the data sets are significantly different.

While the control group is a condition that is not considered attainable in practice, it is useful for modeling. Thus, the first research question really seeks to understand performance difference between the assumed conditions in a static environment and those of a dynamic environment. By comparing each treatment to the control sample, the range of performance variation can be assessed. Each test condition has a unique combination of variables that comprehensively cover all combinations. A one-by-one comparison to the control sample offers insight into how the progression toward more complex scenarios varies from the baseline of the control sample.

Another basis of analysis for the first research question was the use of the binomial random variable. EW receiver response is inherently binomial as each sample either detects the signal within the required time or it does not. Little's formula specifically permits the selection of a probability of success. In all cases for this study, 95% probability of success was used to calculate the EW receiver revisit interval. This means that at least 95% of the samples must be detected with the required response time. By this logic, if there are 1000 samples, at least 950 of them must pass. This level of analysis is important because if the paired samples prove different, then this implies that the actual probability of achieving the desired response time is lower than 95%. The actual probability of detection can be derived from the binomial random variable equation. For example, a series with a 95% probability of detection within the specified detection time, the probability of detecting 950 out of 1000 samples is .0578 with a .001 probability of detecting 923 samples and .001 probability of detecting 974 samples.

This implies that even when 95% of the samples should be successful, there is a low probability that exactly 95% of the samples will be successful. In this case, a reasonable range is between 923 and 974 successes. Anything outside of that range suggests a fundamentally different probability of success. While this study is principally interested in the mean response time, the probability of detecting the signal within the desired response time is also of interest as the mean response times can be moved by the increased magnitude of variation within the system. However, even with increased variation, the required detection times could still indicate successful accomplishment of the mission.

The second research question considers how the mean response times from each treatment compare to each other? The null and alternative hypotheses are:

H_0: The mean (μ) response times that receive treatment are not different from each other (H_0: $\mu_2 = \mu_{3\ldots} = \mu_{17}$).

H_1: The mean (μ) response times that receive treatment are different from each other (Not all μ_i($i = 2,\ldots.,17$) are equal).

Fundamentally, this is a series of questions trying to determine if the data sets differ from each other. Analysis of Variance (ANOVA) with a Tukey test is the best way to determine if there is a variance of significance. Confidence intervals were also used ascertain the range of response times. A critical element of this research question was that the control group was not among the groups being analyzed. In this case, the primary assumption was that some variation always occurs, thus performance differences between the test conditions with variation are critically important.

Given the sample size, this test will have exceptionally fine resolution. An alpha of .01 with a beta of .01 are possible with a fidelity of approximately .25 seconds. Due to the large sample size with the assumptions of normality being met, ANOVA was the best analysis technique for this research question. An alternative analytical technique was the non-parametric alternative to ANOVA which is the Kruskal-Wallis test. Much like ANOVA, the Kruskal-Wallis is an analytical technique used to compare population means of multiple data sets. However, the Kruskal-Wallis test has less fidelity than the parametric methodology of the ANOVA. Furthermore, Kruskal-Wallis is most effective when the assumptions of the parametric test cannot be met. For this study, the criteria for ANOVA were met and thus the parametric method is ideal.

The third research question addressed if the variation among the treatment types are equal. This is a fundamental question given that must be answered in order to perform other parametric tests, but is also important in characterizing the observed effects on response time. The null and alternative hypotheses are:

H_0: The variation (σ^2) among response times that receive treatment are not different from each other (H_0: $\sigma^2_1 = \sigma^2_{2\ldots} = \sigma^2_{17}$).

H_1: The variation (σ^2) among response times that receive treatment are different from each other (H_1: Not all σ^2_i ($i = 1,\ldots,17$) are equal).

This test was performed using the F-test for equality of variance. The assumption of variance is critical for the use of ANOVA. Thus, in order to improve the quality of this research, this assumption was verified by applying the F-test to each comparison.

If the assumption of equal variance is rejected, then the parametric tests used in the other research questions will be augmented with non-parametric methods. Specifically, the Kruskal-Wallis test and the paired sample Wilcoxon test are well suited for detecting differences in means in populations where the assumptions of equal variance are not met. Beyond the need of verifying assumptions, variance is a critical element to response time.

A possible outcome to the study is that the mean response time has varies little between the conditions, but there is a substantial amount of variance. This possibility has important consequences to the operators in that signals could occasionally have dramatic outliers. Any outliers will be illustrated with box plots. Additionally, a complete matrix of paired F-test comparisons will illustrate where the variance are statistically different. These tables and illustrations will demonstrate how the test conditions effect the variance in the response times.

The final research question addresses if a linear relationship exists between the response variable response time and the regressor variables. The null hypothesis and alternative hypothesis are stated as follows:

H_0: The relationship (β) between the variables can reliably predict the response time of an EW receiver given the independent variables (H_0: $\beta_1 = \beta_2 = \ldots = \beta_j = 0$).

H_1: The relationship (β) between the variables can reliably predict the response time of an EW receiver given the independent variables (H_1: $\beta_1 \neq 0$ for at least one j).

This research question was answered using multiple regression analysis. The intent is to determine if a linear equation can predict the performance of an EW receiver given the amount of variation on the independent variables. The expectation was that the ideal queuing values can be determined assuming a static environment, and that the amount of variation on the independent variables can be predicted. If a strong linear relationship exists, it offers aircrew operators the ability to understand operational limitations to their systems.

The multiple regression analysis was greatly aided by the design of the experiment. The use of coded variables and the orthogonal design significantly improve predictive capability of the model. Essentially, this method of analysis permits the analysis of the effects and interactions independently. Furthermore, the use of coded variables and the orthogonal design simplify the analysis by removing non-significant terms simultaneously. As a result of the design, the reduction of the data should be much simpler. In all cases, the adjusted R-squared value was compared to the R-squared value. Additionally, potential models were checked for adequacy. Residual analysis was required to detect the presence of heteroscedasticity, normality, and curvilinear relationship.

Data analysis software R and Microsoft Excel was the primary analytical software used for this experiment. R is a free software environment developed in a collaborative effort among the academic for statistical computing and modeling. The software is available at the following website: http://cran.r-project.org/. R is capable of performing the required statistical analysis and graphical displays used in this study. Microsoft Excel with VBA was used to host the simulation environment and store data results. VBA is extremely flexible programming language that is designed to work with Microsoft products. With VBA, complex scripting is possible, thus enabling simulation. Furthermore, Microsoft Excel is well suited to displaying graphics such as histograms, bar charts, and basic data displays. Additionally, Excel datasets were easily imported into R for additional analysis.

Overall, this study utilized a blend of well-established techniques to examine a series of complex research questions. The first three research questions are a series of pair-wise comparisons seeking to detect differences among the test conditions. The final research question uses multiple regression techniques in order to assess the effects of the factors at play. The simulated environment offers a unique opportunity to inject specific scenarios and analyze the data in sufficient quantity to provide answers to the research questions. This quantified information permits decision makers the data required to manage resources in an appropriate manner to increase survivability.

Threats to Validity

External Validity

The primary threats to the external validity of this experiment are the assumptions of the simulation. Ultimately, this experiment is best conducted in a simulated environment due to the difficulty of isolating all of the variables. The strength of this experiment is the design, as it permits the isolation and control of the primary variables. However, the assumptions that make up the independent variables are based on adaptively directed waveforms. As described in the literature review, modern radars have the ability to change characteristics of their waveform based on the surrounding environment. Furthermore, the large number of factors that affect the received energy by the EW receiver leads to a significant range of variation.

The main concern is that the four independent variables are not representative of all the variables that actually affect the operation of an EW receiver. The fidelity of a simulated environment always leads to questions regarding external validity. In this case, the simulation was explicitly designed to model EW receiver response time. The specificity of the design increases the fidelity with respect to response time. Furthermore, the design of the simulation is such that it is representative of any type of dwell and switch EW receiver. Essentially, all EW receivers have to dwell in a certain frequency band for a period of time before moving to a different frequency range and then return a frequency range. This simulation was designed to allow the user to set the dwell time and revisit time, thus being able to represent any receiver of this class.

The functions of the EW receiver have a high degree of external reliability. However, the model representing the radar performance has less external validity. The wide range of radar operations make this a difficult problem to model. However, this variation was recognized as a fundamental factor that affects the performance of EW receivers. The exact distribution of the received signal depends on the radar in question and the mode of operation. Literature demonstrated that the assumption of continuous random variables with a normal distribution is valid. However, at any given time, the mode of operation can significantly affect the outcome, thus resulting in a lower level of external validity.

The best way to address the prospect of a wide range of radar performance parameters was to use this assumption in the coded variables. A major assumption of this study was that the EW receiver is not necessarily being tracked by the radar. Given this assumption, the two level factorial analysis where the radar performance characteristics uses a high level of variation improves the external validity. While the high amount of variation has the potential of increasing the standard deviation of the response time, the sheer number of samples still permits a high degree of accuracy in evaluating EW receiver performance under these conditions. Interestingly, the elements that increase the external validity of this study make it more difficult in an open-air environment because the required number of samples is cost prohibitive. As a result, response time can only be assessed in cases with high probability of intercept with low amounts of variation. This means that only a small number of cases in this design can be compared to a real scenario for validation.

Internal Validity

The greatest threat to internal validity is the simulation used to perform the experiment. As with any software, a major challenge was ensuring the code performs correctly to achieve the intended results. This experiment is conceptually simple; however, the implementation involves a high number of steps to accurately simulate the environment. Each step is in an increment of 1 microsecond, thus each run involve literally millions of counts. The simulation ends when the EW receiver scan period overlaps with the radar for the minimum required time.

Review of the simulation was performed in a number of ways. First, a line-by-line code review using user-defined breakpoints to inspect the code is an effective method to observe the implementation of the code. This enabled the review of how the code was using variables, applying formulas, looping, and applying logic. The intent was to ensure that the code is referring to the correct values for calculations and the conditions for applying the simulation are correct. With software, it is common for the debugging process to take as long as writing the original code. The development of the code for this simulation followed that process. Generally, the debugging process detected errors such as infinite loops, variables that were not reset, and logical faults such as an incorrect mathematical sign.

However, while code review is critical, it is not the only method to ensure proper simulation. I programmed code to record certain functions of the simulation to record critical data points within the software. Specifically, the first sample of any series of test points records each EW receiver dwell time, EW receiver revisit interval, radar illumination time, radar scan time. Also, .1% of all events were recorded and plotted for analysis. A single run typically lasts three to five seconds, which equates to 3 to 5 million microseconds. Recording and plotting this large number of samples is impractical. Instead, recording one of every 1000 data point has enough fidelity to illustrate the EW receiver dwells and the radar dwells. The minimum overlap time for a successful dwell is eight thousand microseconds, thus a one thousand microsecond threshold is more than sufficient to visually analyze the overlap of data streams.

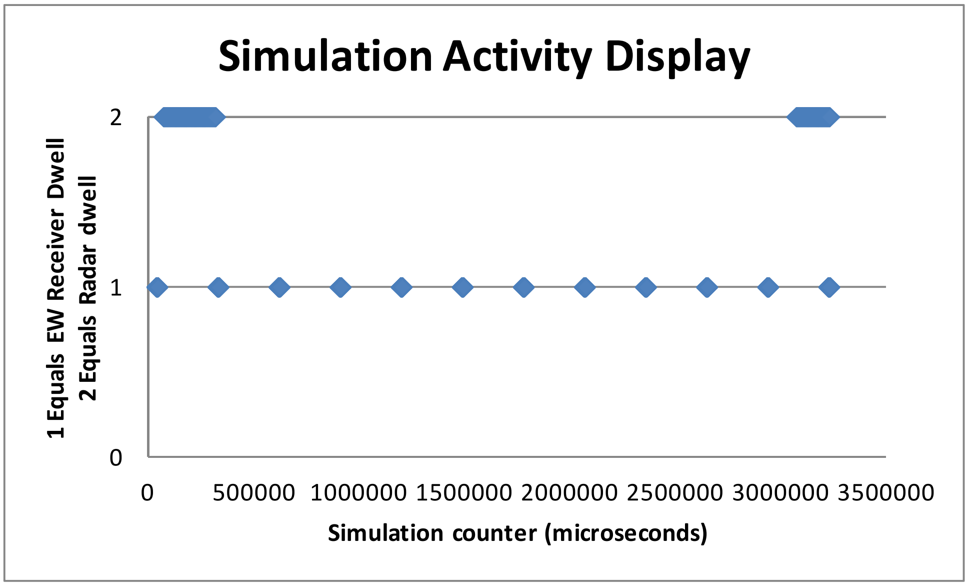

Figure 25. Data recording feature that illustrates the raw data within the simulation.

As illustrated in Figure 25, the Y-axis represents the activity of the simulated EW receiver (coded as 1) and the radar (coded as 2). The X-axis represents the time throughout the simulation. This display was used to ensure the simulation was running the simulation properly.

Overall, the strength of this experiment is the internal validity. The ability to program and control the variables involved give this experiment credibility. However, the strength of this experiment depends on reliable simulation. Development of software is challenging and requires a dedicated effort to fully evaluate the functions it is intended to perform. Given the limited scope of this analysis, an accurate simulation is achievable. Simulations of the flight and radar environment are notoriously difficult when considering all of the variables and functions. Thus limiting the variables to consider focused the research questions render a tractable problem to solve. Even with the limited scope of this experiment, the programming of this simulation still require an extensive amount of analysis and recording to ensure proper representation of the conditions, to give confidence in the results.

Construct Validity

The study's construct validity is dependent on how close the model represents the EW receiver under examination. The intent of the simulation is to allow the researcher to input specifically calculated values for optimized scanning and an amount of variation among those variables. As stated in the assumptions, the modeled EW receiver was multitasked dynamically based upon an algorithm. Furthermore, it assumed that the exact dwell sequence was not predetermined and was subject to change based upon the environment it was operating in.

Given the assumptions of EW receiver performance and radar performance, the expected values can be described as normal variation. However, this study was not predicated on any specific system, but instead was based on a generic EW receiver system. Specific EW receiver performance algorithms are likely to vary from the generic approach implemented in this study. Therefore, future researchers must be aware of specific EW receiver operating parameters if they desire to model a specific system. For example, an EW receiver system may have minimum and maximum limits on the amount of variation permitted in the scan schedule. Other variations may include prioritization rules that alter the scan schedule in a non-uniform manner. These are elements that can be modeled, but are beyond the scope of this study.

However, the knowledge gained from this study can be used to define rules for system designers. Overall, the major threat to the construct validity of this study is the intent of the user. This study was intended to demonstrate the performance of a generic EW receiver in a generic EW environment. Specific scenarios and specific EW systems may have conditions that alter the conditions assumed in this study, thus altering the validity of the results. Compensation for these conditions is possible, but must be known in advance.

Ethical Procedures

This study did not require the use of any human subjects as all data was generated via a simulation. The primary ethical concern regarding this study was the sensitive nature of the topic. Electronic warfare is a competitive field that relies heavily upon revolutionary ideas. Furthermore, the products developed because of these ideas only remain effective if the exact operating parameters remain confidential. As an electronic warfare professional for over 17 years, I have had significant exposure to specific algorithms and methods. As a federal employee of the Department of the Navy (DoN) and a United State Air Force (USAF) reservist, I have signed an oath not to release classified or proprietary information.

Fortunately, this study does not require any type of classified or proprietary information to conduct an accurate assessment of the topic of EW receiver optimization. The concepts relating to EW receiver response time are well documented and founded in mathematical principles. Data required to make this simulation applicable to a specific system are EW receiver sensitivity, EW receiver scan pattern, radar effective radiation power, and radar scan pattern. For this study, these values were taken from unclassified sources representing nominal values that are considered representative of a class of receivers and radars, but they are not specific to any single model.

This method of analysis is common and does violate any protocol. At no time is any system specific information used and it is not necessary. Future use of this study can easily substitute specific system values to derive the desired results. Ultimately this study focuses on the mathematical methods and concepts readily available in open literature and academic studies. Any values that resemble system specific values, but are representative of generic values are acknowledged as open source. Furthermore, all equations, formulas, and algorithms are documented and traced to the specific source.

Summary

The use of simulation and design of experiment techniques are not new. Using them in combination is a powerful approach to research, especially electronic warfare. EW receiver response time analysis is difficult in open air testing. The costs involved are prohibitive to optimization, particularly when characterizing the effect of the factors. A simulated environment was ultimately the best choice for performing this research. For this study, the simulation was designed to emulate the dwell characteristics of the EW receiver and the illumination cycles of a radar. A key factor of this design is the representation of the cumulative effect of the factors that impact the four main independent variables.

The dynamic nature of operations implies a certain amount of variation of the key factors. Variation among these variables is readily acknowledged and believed to affect response time. However, research offers very little insight into the quantification of these effects. The purpose of this study was to quantify the effects and evaluate how EW receiver system operators and engineers can optimize performance. The design of the simulation was intended to support the 2^k Factorial method to characterize the factor effects.

While the specific amount of variation placed upon the primary variables is difficult to accurately predict, the approximate upper and lower boundaries are identifiable. The identification of the variation boundaries in addition to the known distribution of the variation increase the statistical validity of this study. Ultimately, by characterizing the effects of variation, users can accurately predict response time in a dynamic environment. Accurate prediction of response time increases the probability of detecting threat emitters early in the engagement sequence, thus allowing the aircrew to take evasive actions prior to the use of weapons.

Chapter 4: Results

The purpose of the study was to examine how variation on four key variables affected EW receiver response time. As technology progresses, sensor scheduling algorithms become more critical to improving aircraft survivability. Furthermore, technological advances render radar scan patterns that are not only more capable of detecting aircraft, but they are more difficult to detect. EW receivers are working harder to detect more signals that exhibit low probability of intercept characteristics. The result is a scenario that demonstrates variability among the following key factors: EW receiver dwell time, EW receiver revisit interval, radar scan period, and radar illumination time.

Reliable response time prediction is vital to optimizing the employment of the EW receiver. The following research questions examined in this study were intended to characterize a generic EW receiver response under a comprehensive set of conditions.

1. How does the application of the 16-test conditions affect response times compared to the control sample?
2. How do the mean response times from each treatment compare to each other?
3. How do the variations among the response times from each treatment compare to each other?
4. Is there a relationship between the variables that can reliably predict the response time of an EW receiver given the independent variables?

The intent of this study was to provide a quantitative view of the nature of EW receiver response time in a dynamic scenario.

The overall purpose of this study was to provide insight into the optimization of an EW receiver scan-tune strategy in a wide range of scenarios. The existing body of research does not offer quantifiable data regarding how variation on the main factors influences EW receiver response time. Through the use of a 2^K factorial design, this research has the potential to expand the body of knowledge regarding queuing theory and the effects of variation on response time.

Study Results

I conducted the simulation described in Chapter 3 without any deviations. As a result, the simulation produced 17,000 data points that consisted of 17 test conditions where each condition was sampled 1000 times. Examination of the data set indicated that 1000 samples per condition produced sufficient data as defined by a plateau in variation among the data after approximately 300 samples. Also, as predicted, the data was not normal and required a transformation to normalize prior to analysis. This section presents the raw data collected from the simulation, the transformation required to analyze the data, and analysis of the research questions.

The first required element of analysis is an examination of the data set to evaluate for conditions of normality. As identified in the literature review, a Gaussian distribution was not expected. Instead, a Gamma distribution was predicted. As illustrated in Figure 26, the resultant distribution resembles a Gamma distribution.

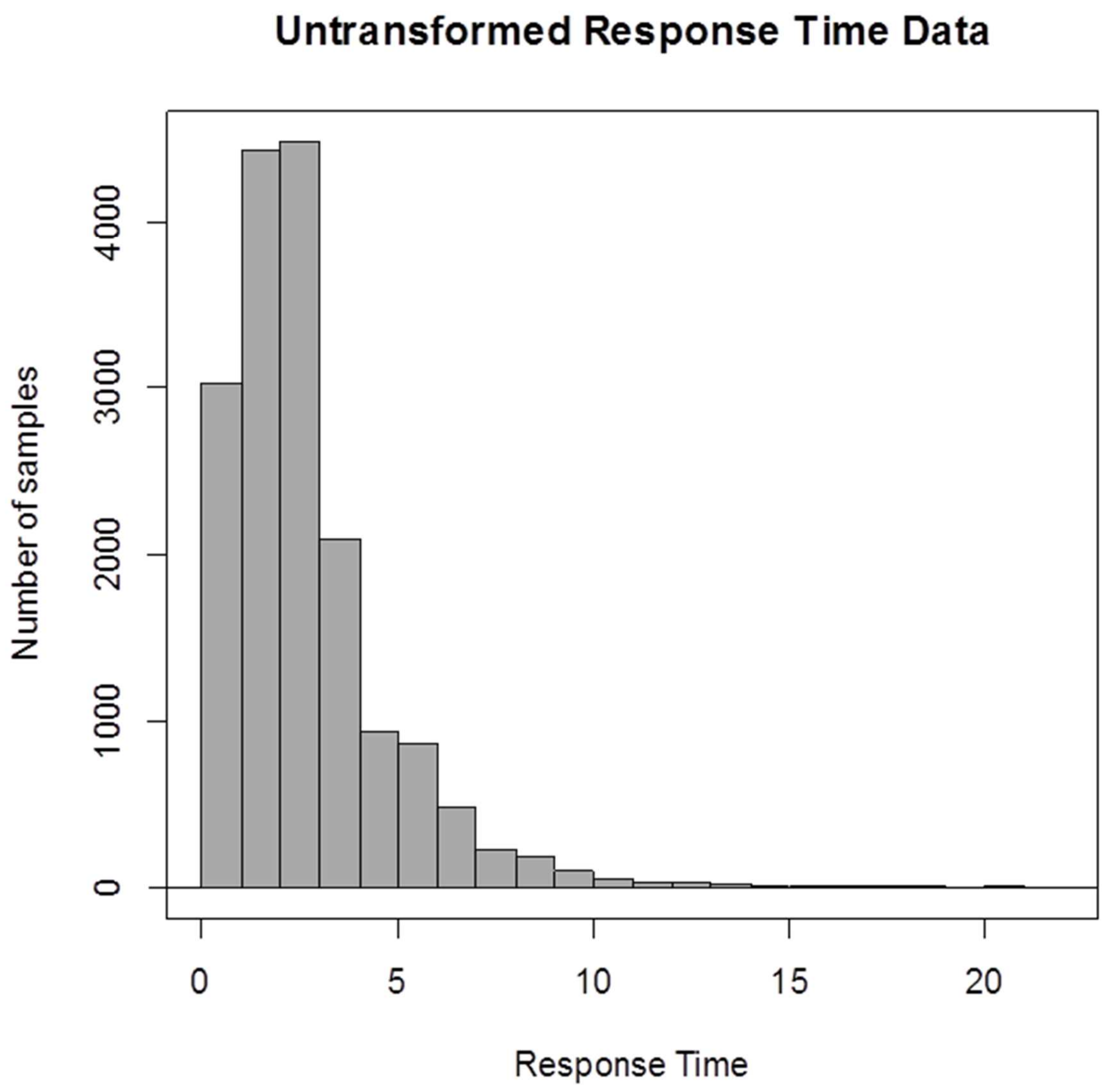

Figure 26. Histogram of untransformed response time data from all conditions.

Figure 27 further amplifies Figure 26 by illustrating data peaks within the .1 to 4 second region of the response times. Additionally, Figure 27 indicates a peak at the 5-second point with a steep decline with a maximum value of approximately 20 seconds. Clearly, this data set is not normally distributed and must be transformed prior to conducting additional analysis.

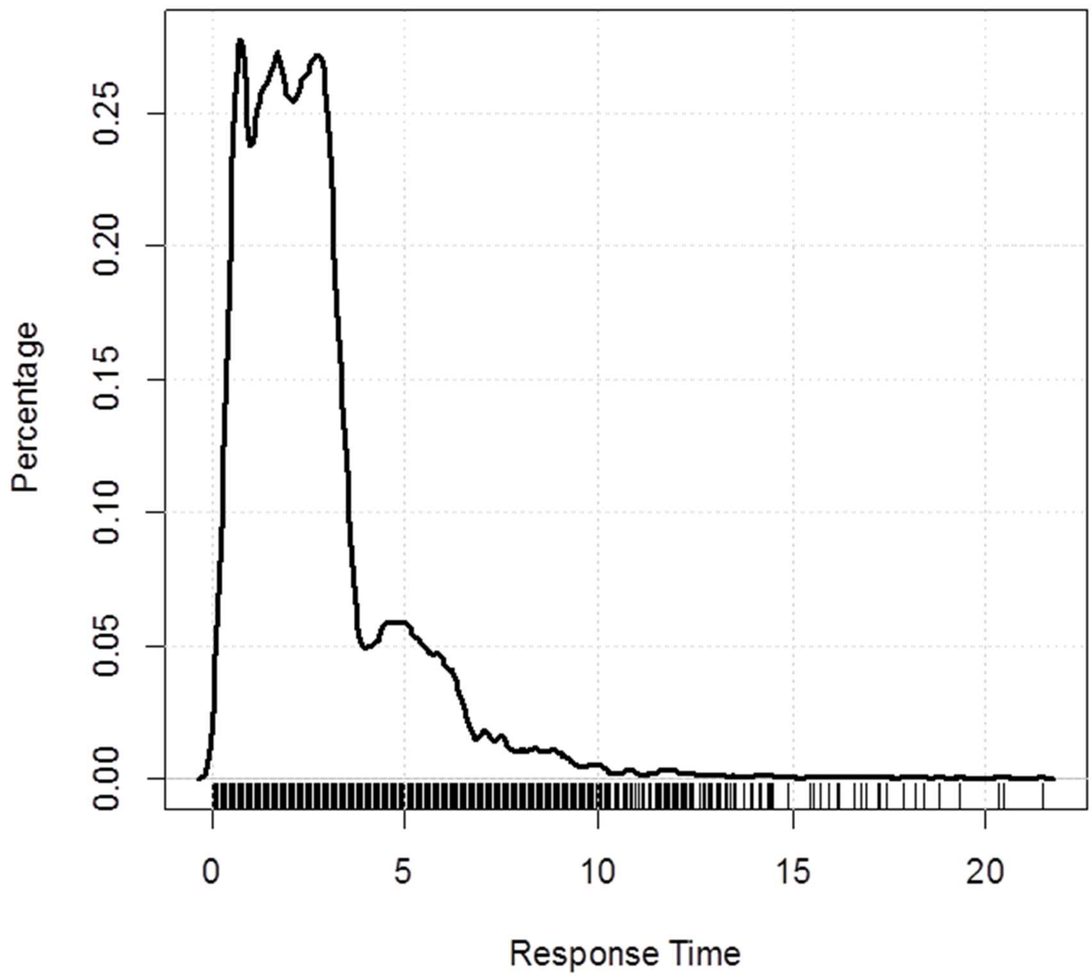

Figure 27. Density plot of untransformed response time data from all conditions.

There are many methods to transform data into a distribution closer resembling that of a normal distribution. In this case, the Box-Cox transformation method demonstrated the best results. The Box-Cox is defined in Equation 27 below. In the data set extracted in this study, an λ of .25 was selected. Figures 28 and 29 illustrate the effects of this transformation.

$$\frac{x^{\lambda}-1}{\lambda} \tag{27}$$

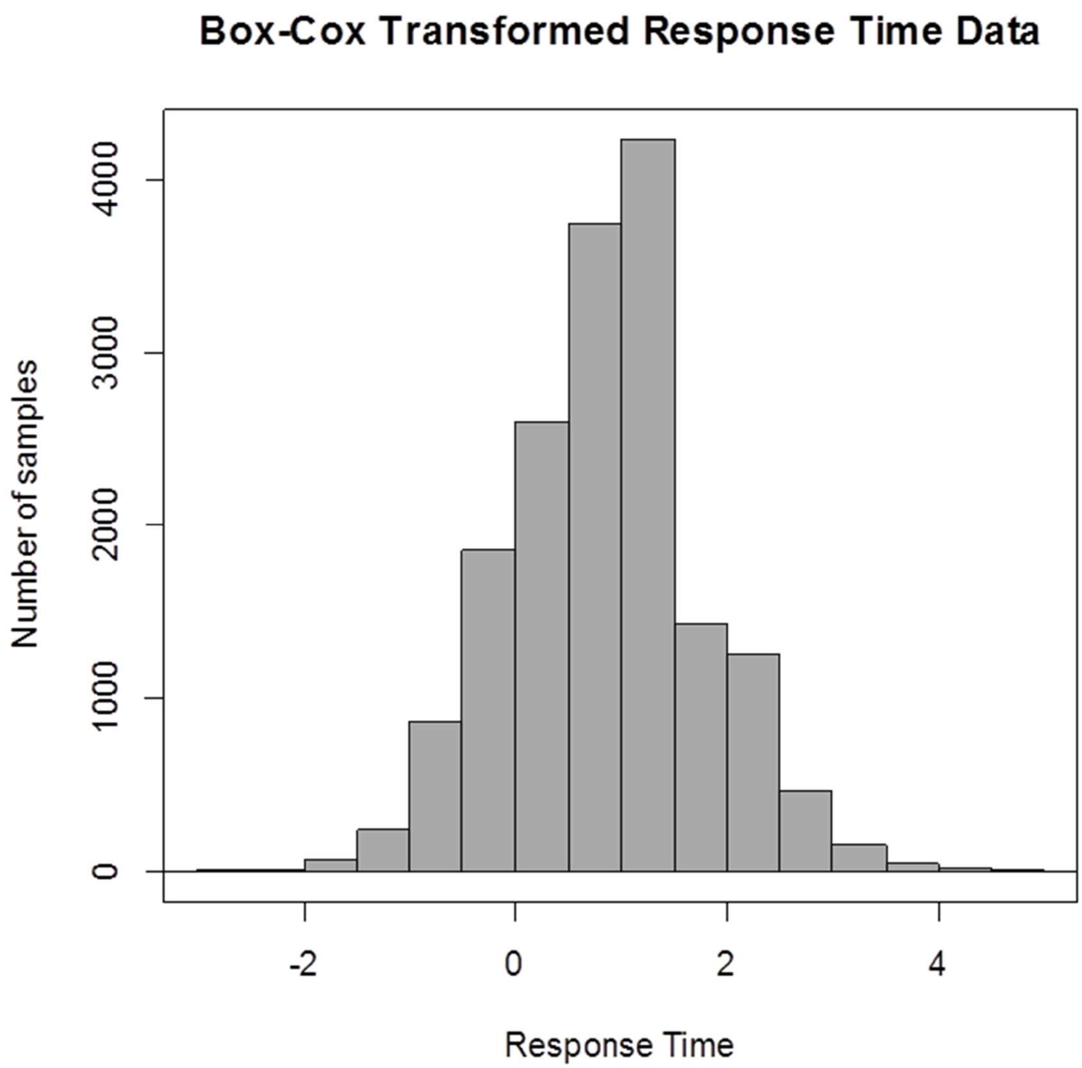

Figure 28. Histogram of untransformed response time data from all conditions.

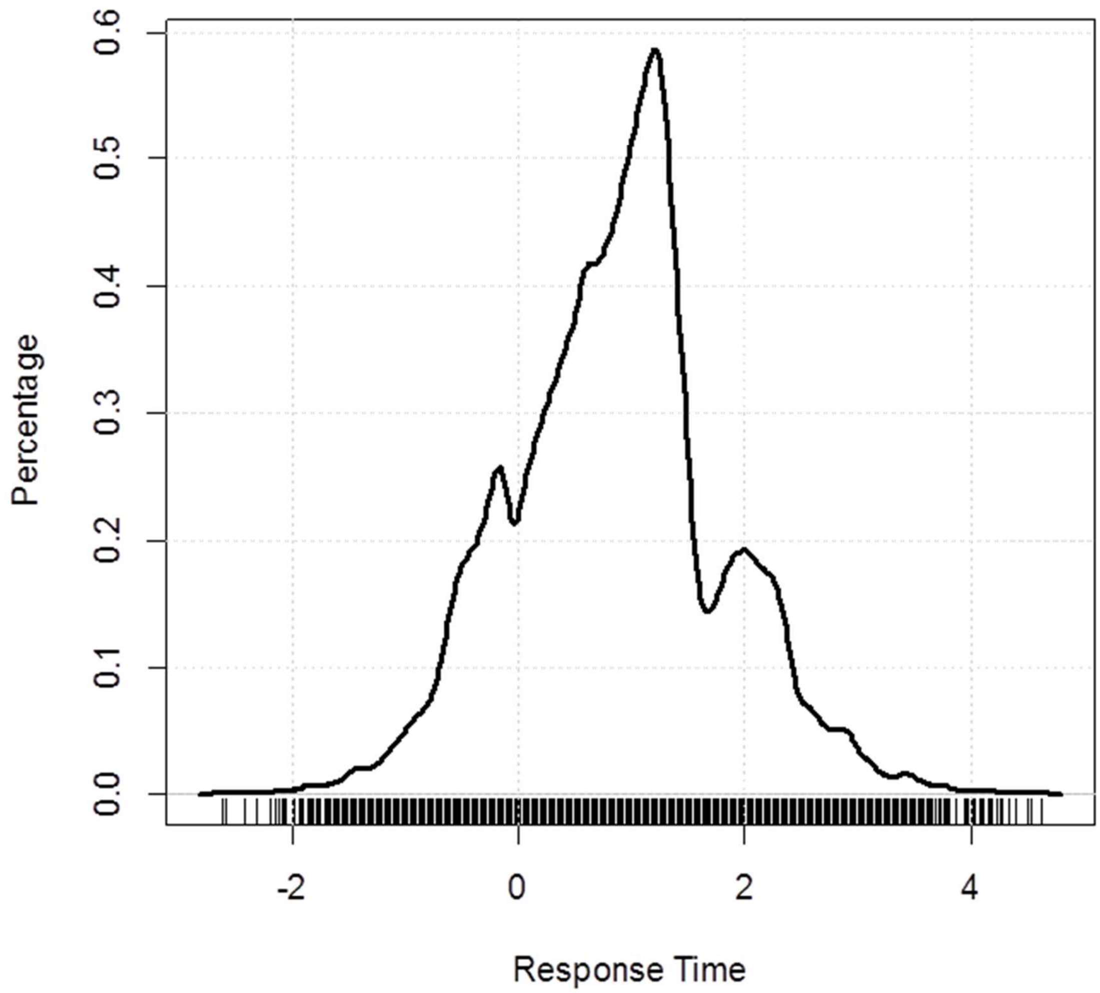

Figure 29. Histogram of untransformed response time data from all conditions.

As illustrated in Figures 28 and 29, the Box-Cox transformation yielded a distribution that approximated a normal distribution. A perfectly ideal normal distribution is desirable, but rarely attainable. The untransformed data is unsuitable for any type of advanced data analysis required in the data analysis plan. Other transformations such as logarithmic and exponential proved less capable of yielding a near-normal distribution. Upon realizing the suitability of the Box-Cox transformation, the primary task was determining the proper setting for λ. An ideal setting is modeled in the statistical analysis software R, and can be confirmed through multiple data plots with varying levels of λ. For this study, λ was set at .25. Transformation of the data permitted a complete analysis of the research questions.

Research Question 1

How does the application of the 16 test conditions affect response times compared to the control sample? The purpose of Research Question 1 was to compare the results of Test Condition 1 in which the variables did not receive variation to Test Conditions 2-17 in which the variables received different levels of variation. Table 1 is a summary of the results.

Table 1

Summary of Normalized Result

Run	Mean	Variance	Standard Deviation	95% Confidence Interval Low	95% Confidence Interval High	Minimum Response Time	Maximum Response Time	Detection within 5 Sec	Probability of Detection within 5 Seconds (95% Confidence)
1	2.08	1.79	1.34	2	2.16	0.04	6.49	927	0.92 - 0.95
2	1.96	1.88	1.37	1.88	2.05	0.02	8.1	932	0.92 - 0.95
3	2.06	1.82	1.35	1.98	2.15	0.14	9.1	910	0.90 - 0.93
4	2.09	2	1.41	1.99	2.18	0.08	13.52	896	0.88 - 0.92
5	1.99	1.99	1.41	1.9	2.08	0.05	18.18	919	0.91 - 0.94
6	2.17	2.01	1.42	2.07	2.27	0.12	14.44	889	0.87 - 0.91
7	2.19	2.07	1.44	2.09	2.29	0.05	17.27	882	0.87 - 0.91
8	2.23	2.15	1.47	2.12	2.33	0.09	13.12	876	0.86 - 0.90
9	2.16	2.45	1.57	2.05	2.28	0.03	15.71	869	0.85 - 0.89
10	2.16	2.16	1.47	2.06	2.26	0.02	20.51	892	0.88 - 0.92
11	2.19	2	1.41	2.1	2.29	0.15	12.8	896	0.88 - 0.92
12	2.18	2.18	1.48	2.08	2.28	0.07	16.23	873	0.86 - 0.90
13	2.23	2.26	1.5	2.13	2.34	0.01	21.45	864	0.85 - 0.89
14	2.35	2.25	1.5	2.24	2.47	0.08	18.39	851	0.83 - 0.88
15	2.38	2.52	1.59	2.26	2.51	0.07	16.6	826	0.81 - 0.85
16	2.29	2.53	1.59	2.17	2.41	0.05	20.34	830	0.81 - 0.86
17	2.35	2.48	1.57	2.24	2.47	0.06	20.48	845	0.83 - 0.87

Note. All applicable data in this table represents the adjusted after being normalized and transformed.

A key observation taken from Table 1 is the overall similarity of the response times between Test Condition 1 and Test Conditions 2-5. Test Condition 1 had a mean response time of 2.08 seconds while Test Conditions 2-5 had mean response times between 1.96 and 2.09 seconds. With Test Condition 6, the response time increased. A key aspect to this observation was the significantly lower response time between Test Condition 2 and Test Condition 1. As demonstrated in Table 2, the *p* value of .076 indicates that there was a statistically significant difference between Test Condition 1 and Test Condition 2. This means that adding a small amount of variation to the each of the independent variables decreased, or improved, the average response time. However, Tables 1 and 2 also indicate that while mean response times were comparable, the variance increased immediately and became statistically significant with Test Conditions 4-5.

Table 2

Summary of Delta Mean, Delta Variance, and P-Value

Test Condition	Delta Mean (μx-$\mu 1$)	P-value	Delta Variance (Var(x)-Var(1))	P-value
2	-0.12	0.076	0.09	0.136776
3	-0.02	0.375	0.03	0.54277
4	0.01	0.827	0.21	0.002083
5	-0.09	0.1	0.2	0.003304
6	0.09	0.228	0.22	0.001381
7	0.11	0.109	0.28	0.000108
8	0.15	0.121	0.36	1.84E-06
9	0.08	0.377	0.66	6.06E-14
10	0.08	0.404	0.37	1.45E-06
11	0.11	0.268	0.21	0.001881
12	0.1	0.226	0.39	3.85E-07
13	0.15	0.475	0.47	5.67E-09
14	0.27	0.001	0.46	9.18E-09
15	0.3	0.0003	0.73	1.11E-15
16	0.21	0.025	0.74	4.44E-16
17	0.27	0.008	0.69	1.38E-14

Note. Negative values indicate a mean or variance value is less than the control sample.

Figure 30 illustrates the confidence intervals comparing the response times across all of the test conditions. Visual examination confirm what the data in Tables 1 and 2 indicate, that mean response times continue to increase as the level of variation placed upon the independent variables increase. Figure 30 also illustrates another pattern of note. Not only are Test Conditions 1-5 similar, Test Conditions 6-13 are similar, and Test Conditions 14-17 appear to be significantly higher. This observation was analyzed in Research Question 2. In Test Conditions 2-5, the independent variables of EW receiver dwell time and EW receiver scan time both have low levels of variation, while Test Conditions 14-17 received high levels of variations.

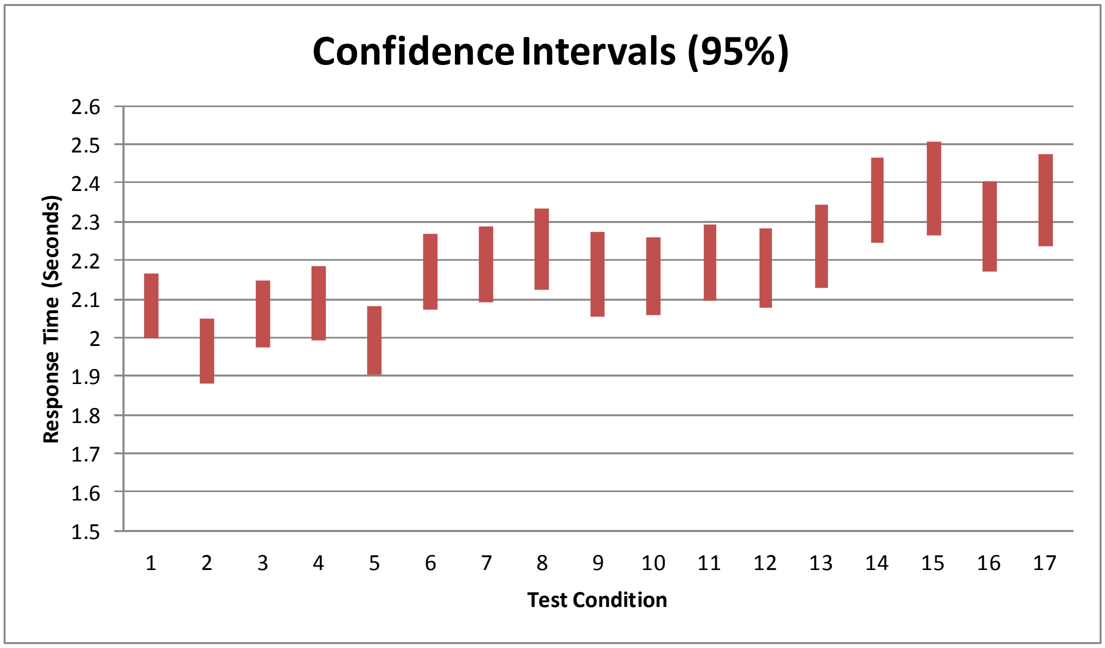

Figure 30. Normalized confidence intervals.

The finding was that small amounts of variation placed upon the independent variables associated with the EW receiver do not negatively affect the performance of the EW receiver. In Test Conditions 2-5, the only independent variables modified were the radar scan time and dwell time. This result indicated that when the independent variables associated with controlling the EW receiver are controlled, the mean response time remains comparable. However, while the mean response time remains comparable, Table 1 also illustrates that the increased variation is associated with decreased success rate. The required response time for a successful detection is defined as 5 seconds for this study. Table 1 illustrates that the success rate increased in Test Condition 2 followed by a slow decrease in success rate from the control run. Overall, this implies that mild variation placed upon all of the variables represents an improved performance from the control test condition. Test Condition 2 has better performance than Test Condition 1 (the control run), and Test Conditions 3, 4, and 5 were comparable even when the radar performance parameters were changing. Additionally, when either of the EW receiver variables had high levels of variation, the mean response time increased and the success rate decreased.

Research Question 2

How do the mean response times from each treatment compare to each other? Research Question 2 is similar to Research Question 1, but expands the analysis to compare the mean response time from all test conditions to each other. Figure 31 illustrates the results of a Tukey Honest Significant Difference (HSD) test using a *p-value* of .05 as the standard for defining significant difference. All *p-values* are in the lower half of Figure 31 and comparisons with a significant difference are highlighted in red. Additionally, the upper half of Figure 31 illustrates the difference between the two mean values being compared.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1		-0.12	-0.02	0.01	-0.09	0.09	0.11	0.15	0.08	0.08	0.11	0.1	0.15	0.27	0.3	0.21	0.27
2	0.076		0.1	0.13	0.03	0.21	0.23	0.27	0.2	0.2	0.23	0.22	0.27	0.39	0.42	0.33	0.39
3	0.375	0.349		0.03	-0.07	0.11	0.13	0.17	0.1	0.1	0.13	0.12	0.17	0.29	0.32	0.23	0.29
4	0.827	0.166	0.991		-0.07	0.11	0.13	0.17	0.1	0.1	0.13	0.12	0.17	0.29	0.32	0.23	0.29
5	0.1	0.942	0.156	0.084		0.18	0.2	0.24	0.17	0.17	0.2	0.19	0.24	0.36	0.39	0.3	0.36
6	0.228	0.001	0.119	0.159	0.002		0.02	0.06	-0.01	-0.01	0.02	0.01	0.06	0.18	0.21	0.12	0.18
7	0.109	0.002	0.11	0.103	0.005	0.753		0.04	-0.03	-0.03	0	-0.01	0.04	0.16	0.19	0.1	0.16
8	0.121	0.002	0.049	0.08	0.0008	0.638	0.572		-0.07	-0.07	-0.04	-0.05	0	0.12	0.15	0.06	0.12
9	0.377	0.006	0.263	0.344	0.025	0.849	0.766	0.346		0	0.03	0.02	0.07	0.19	0.22	0.13	0.19
10	0.404	0.039	0.19	0.18	0.025	0.697	0.478	0.31	0.834		0.03	0.02	0.07	0.19	0.22	0.13	0.19
11	0.268	0.005	0.067	0.118	0.006	0.837	0.946	0.926	0.624	0.664		-0.01	0.04	0.16	0.19	0.1	0.16
12	0.226	0.002	0.144	0.261	0.008	0.973	0.81	0.502	0.637	0.747	0.97		0.05	0.17	0.2	0.11	0.17
13	0.475	0.001	0.036	0.086	0.001	0.65	0.667	0.789	0.64	0.614	0.619	0.696		0.12	0.15	0.06	0.12
14	0.001	1E-06	0.0001	0.0007	5E-06	0.012	0.11	0.181	0.007	0.017	0.055	0.031	0.255		0.03	-0.06	0
15	0.0003	1E-07	0.0008	0.0008	3E-07	0.026	0.014	0.089	0.012	0.01	0.048	0.032	0.075	0.639		-0.09	-0.03
16	0.025	0.0008	0.004	0.015	0.0004	0.279	0.243	0.653	0.134	0.144	0.34	0.242	0.609	0.442	0.438		0.06
17	0.008	5E-05	0.0005	0.002	3E-06	0.109	0.116	0.208	0.03	0.03	0.038	0.059	0.129	0.547	0.496	0.619	

Figure 31. Tukey HSD and mean response time difference.

The results of the calculations in Figure 31 corroborate the visual analysis of Figure 32 below. In Figure 32, using a plot of means, there is a general increase of mean response time as the amount of variation placed upon the independent variables increases.

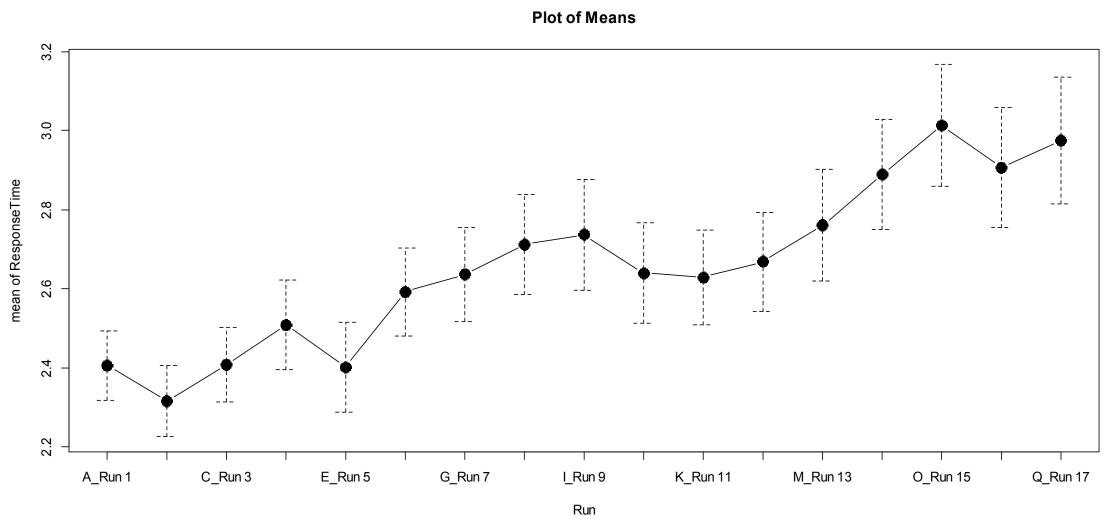

Figure 32. Plot of mean response times.

The data can generally be categorized into three bins: low, medium, and high response times. Test Conditions 1-5 have low mean response times when test conditions that are characterized by low variation placed upon the EW receiver dwell time and EW receiver revisit interval. Test Conditions 6-13 have medium response times and have some test conditions that are significantly different from the low or high bins. Finally, the bin with high response times are comprised of Test Conditions 14-17. These test conditions have statistically higher mean values (*p-value* $>$ .05) than the low bin.

The key point from this research question is the identification of the EW receiver dwell time and revisit interval as the primary factors affecting response time. Significant degradation only occurs when at least three independent variables have high amounts of variation place upon them. In the worst case, the response time for Test Condition 15 was .42 seconds longer than it was for Test Condition 2. However, in Test Condition 15, the success rate was only 82.6% whereas the required response time was 95%. While the there is a statistically significant difference in response time as a result of variation placed upon the independent variables, the amount of degradation is relatively small. The maximum response time and the success rate are much more sensitive indicators of the effects due to variation. As Table 1 illustrates, the maximum response time dramatically increases to more than five times the required time and the overall success rate falls by more than 10%. Yet, despite the dramatic changes in the distribution, the mean value changes very little. Essentially, the mean response times do not appear to reflect the significant effects of variation.

Research Question 3

How do the variations in response times from each treatment compare to each other? The primary purpose of Research Questions 1 and 2 were to examine the role of variation placed upon the independent variables affected the mean response time. Research Question 3 examines how the variation placed upon the independent variables affect the variance of the response times. Essentially, the first two research questions examine the central tendency while Research Question 3 examines the dispersion from the mean. Research Questions 1 and 2 reveal statistically significant differences in the mean response times. The overall magnitude of the differences in the mean is moderate and limited. In contrast, Figure 33 reveals that each test condition has a substantial amount of difference of variance between test conditions.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1		0.09	0.03	0.21	0.2	0.22	0.28	0.36	0.66	0.37	0.21	0.39	0.47	0.46	0.73	0.74	0.69
2	0.136776		-0.06	0.12	0.11	0.13	0.19	0.27	0.57	0.28	0.12	0.3	0.38	0.37	0.64	0.65	0.6
3	0.54277	0.379143		0.18	0.17	0.19	0.25	0.33	0.63	0.34	0.18	0.36	0.44	0.43	0.7	0.71	0.66
4	0.002083	0.111362	0.013484		-0.01	0.01	0.07	0.15	0.45	0.16	0	0.18	0.26	0.25	0.52	0.53	0.48
5	0.003304	0.146601	0.019786	0.888234		0.02	0.08	0.16	0.46	0.17	0.01	0.19	0.27	0.26	0.53	0.54	0.49
6	0.001381	0.086746	0.009561	0.90385	0.793833		0.06	0.14	0.44	0.15	-0.01	0.17	0.25	0.24	0.51	0.52	0.47
7	0.000108	0.017005	0.001097	0.426467	0.349394	0.500013		0.08	0.38	0.09	-0.07	0.11	0.19	0.18	0.45	0.46	0.41
8	1.84E-06	0.001009	3.12E-05	0.089464	0.065965	0.114677	0.366375		0.3	0.01	-0.15	0.03	0.11	0.1	0.37	0.38	0.33
9	6.06E-14	1.58E-09	4.98E-12	8.42E-06	4.35E-06	1.46E-05	0.00025	0.005757		-0.29	-0.45	-0.27	-0.19	-0.2	0.07	0.08	0.03
10	1.45E-06	0.00085	2.53E-05	0.080794	0.059225	0.104081	0.341517	0.961797	0.006658		-0.16	0.02	0.1	0.09	0.36	0.37	0.32
11	0.001881	0.104721	0.012385	0.975825	0.864348	0.927893	0.444299	0.095326	9.68E-06	0.086196		0.18	0.26	0.25	0.52	0.53	0.48
12	3.85E-07	0.000324	7.79E-06	0.044883	0.031862	0.059421	0.225904	0.758251	0.014127	0.794956	0.048214		0.08	0.07	0.34	0.35	0.3
13	5.67E-09	1.38E-05	1.77E-07	0.005773	0.003724	0.008295	0.049271	0.287589	0.089299	0.309848	0.00633	0.449823		-0.01	0.26	0.27	0.22
14	9.18E-09	1.99E-05	2.73E-07	0.007388	0.004815	0.01052	0.059484	0.32623	0.074952	0.350383	0.008083	0.500307	0.934875		0.27	0.28	0.23
15	1.11E-15	6.16E-11	1.28E-13	7.03E-07	3.39E-07	1.3E-06	3.05E-05	0.001079	0.610766	0.001276	8.21E-07	0.003056	0.027271	0.022067		0.01	-0.04
16	4.44E-16	2.48E-11	4.57E-14	3.47E-07	1.64E-07	6.49E-07	1.67E-05	0.000661	0.518627	0.000787	4.06E-07	0.001947	0.019082	0.015286	0.891431		-0.05
17	1.38E-14	4.74E-10	1.27E-12	3.37E-06	1.7E-06	5.99E-06	0.000116	0.003133	0.846595	0.003654	3.9E-06	0.008117	0.058436	0.048376	0.752364	0.65126	

Figure 33. F-test for variance and difference.

In Figure 33, the upper half of the figure is a calculation of the difference of variance between the test conditions and the lower half represents the *p-value* where values of less than or equal to .05 are deemed statistically significant. Note that a majority of the comparisons indicate a statistically significant difference. This is important as it demonstrates how the variation placed upon the independent variables affect the dependent variable. The distribution generally has a mild shift in average response time, but the number of response times outside the 5 second required detection increases.

Not only does the success rate decline, but the maximum detection times increase. Overall, while the response time distribution is characterized as a gamma distribution, the increased variation alters the distribution by extending the tail as the magnitude and quantity of longer detection times increase. Of significant note is the sensitivity of the variance to each test condition. In contrast to the difference in mean response times, the variance is often significant between most of the test conditions. Also of note is that lack of a consistent pattern, which is indicative of a highly volatile system. For example, Test Condition 17 is significantly different from Test Condition 16, but no statistical difference is detected between Test Condition 17 and 16.

Research Question 4

Is there a relationship between the variables that can reliably predict the response time of an EW receiver given the independent variables? The intent of Research Question 4 is to evaluate if the response time is predictable based on the level of variation of the independent variables. This includes the possibility of interactions between the independent variables. Research Question 4 is evaluated using multiple regression where the independent variables (A, B, C, D) are compared to the dependent variable, EW receiver response time. Table 3 illustrates the analysis of variance (ANOVA) table comparing the four independent variables and the interactions.

Table 3

Analysis of Variance (ANOVA) table for all factors

	Estimate	Std. Error	T Value	Pr(>|t|)	
(Intercept)	0.85895	0.007021	122.332	< 2.00E-16	***
A	0.001999	0.007238	0.276	0.782	
AB	-0.007956	0.007238	-1.099	0.272	
ABC	0.004841	0.007238	0.669	0.504	
ABCD	-0.003626	0.007238	-0.501	0.616	
ABD	0.011899	0.007238	1.644	0.1	
AC	-0.006165	0.007238	-0.852	0.394	
ACD	-0.004557	0.007238	-0.63	0.529	
AD	-0.004253	0.007238	-0.588	0.557	
B	0.004602	0.007238	0.636	0.525	
BC	-0.0015	0.007238	-0.207	0.836	
BCD	0.001738	0.007238	0.24	0.81	
BD	0.007695	0.007238	1.063	0.288	
C	0.043723	0.007238	6.041	1.56E-09	***
CD	-0.00229	0.007238	-0.316	0.752	
D	0.044866	0.007238	6.199	5.81E-10	***

Signif. Codes *** = .001 ** = .01 * = .05

Note. Residual standard error: 0.9155 on 16984 degrees of freedom
Multiple R-squared: 0.004852, Adjusted R-squared: 0.003973
F-statistic: 5.521 on 15 and 16984 DF, p-value: 2.289e-11

As illustrated in Table 3, only two variables (C, D) have a significant effect on response time. Variable C represents EW receiver dwell time and variable D represents EW receiver revisit interval. No interactions were statistically significant, but interaction between variables A, B, D have a *p-value* of .1, which indicate a weak association. More importantly, this analysis has an adjusted R-squared of .003973 with a *p-value* less than

.001. Overall, there is a statistical correlation, but the low R-squared indicates that the relationship has very little predictive power.

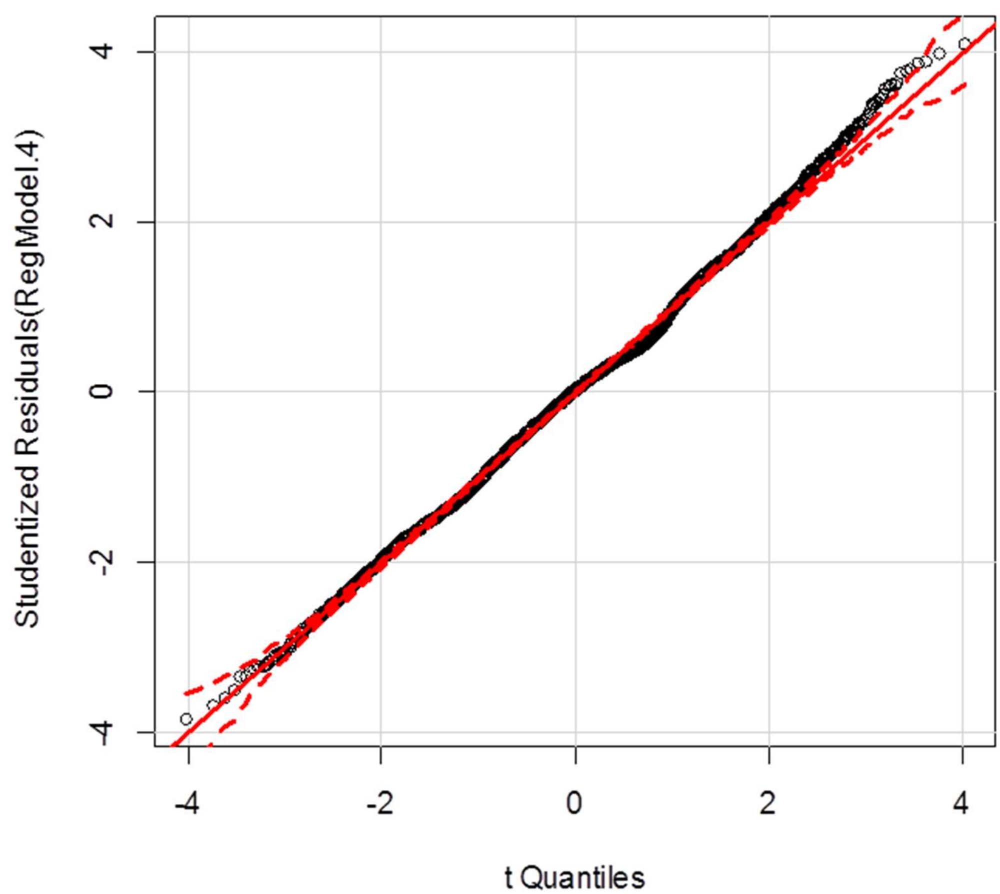

Figure 34. Quantile comparison plot.

Figure 34 is a quantile plot representing the multiple regression plot used to create Table 3 to evaluate validity. Data for this analysis used transformed data using the Box-Cox transformation as previously described. Additionally, the values for the independent variables are coded as -1 for the low setting and 1 for the high setting. These coded values ensure a numerical integrity between the variables to prevent unintentional influence as a result of differences in magnitude. Figure 34 indicates that this is a valid model to represent the relationship between the independent variables and the transformed dependent variable. Given the indication of only two variables that have significant influence, another regression analysis using only independent variables C and D is displayed in Table 4.

Table 4

ANOVA table for primary factors

	Estimate	Std. Error	T Value	Pr(>|t|)	
(Intercept)	0.85895	0.00702	122.35	< 2.00E-16	***
C	0.04372	0.00724	6.042	1.55E-09	***
D	0.04487	0.00724	6.2	5.78E-10	***

Signif. Codes *** = .00 ** = .01 * = .05

Note. Residual standard error: 0.9153 on 16997 degrees of freedom
Multiple R-squared: 0.00439, Adjusted R-squared: 0.004273
F-statistic: 37.47 on 2 and 16997 DF, p-value: < 2.2e-16

Table 4 indicates very similar results as Table 3. Variables C and D are significant factors, but there is very little predictive power in this analysis.

Summary

Overall, the results of each of the research questions were reasonable. Previous research provided nonquantitative insight to which the results of this study added quantitative results. The primary focus of this study was the effects of variation placed upon four independent variables on the dependent variable of EW receiver response time. In order to quantify these effects, this study posed the following research questions:

1. How does the application of the 16 test conditions affect response times compared to the control sample?
2. How do the mean response times from each treatment compare to each other?
3. How do the variation among the response times from each treatment compare to each other?
4. Is there a relationship between the variables that can reliably predict the response time of an EW receiver given the independent variables?

Research Questions 1 and 2 yield similar results, in that the overall mean response time does not indicate dramatic changes. Response times generally remain comparatively similar except when the variation on the EW receiver variables are in high settings. Also of note is the improved performance of the EW receiver when there is low amounts of variation placed upon all of the independent variables. Research question 3 illustrates how the change in the independent variables alter the performance of the EW receiver. While the overall change in average response time is mild, there is a significant amount of variance detected at most levels. As the amount of variation increases, the number of response times that exceed the 5-second requirement increase dramatically as does the amplitude of those failures. Essentially, the EW receiver fails more often and has much longer response times when it does fail. Finally, Research Question 4 failed to produce an accurate prediction of response time given certain amounts of variation. However, the analysis confirmed the observations of Research Questions 1 and 2 that the EW receiver variables of dwell time and revisit interval are the significant factors.

The quantitative findings are critical to understanding how to manage the resources of an EW receiver. This information provides engineers the information necessary to make decisions regarding the development of an EW receiver scan strategy. This not only calls for the establishment of the requirements, but knowing how the unknown factors of the dynamic flight environment can affect the desired processing. This implies the need to recognize the limitations of planning for all the possible variables and instead managing the range of possibilities. In addition to managing the range of possible conditions is prioritization of resources. As demonstrated in this study, EW receiver response time is the product of multiple, complex independent systems that have unique operating characteristics that may prevent consistent response times. Therefore, engineers and users must assess these potential operating characteristics and prioritize their detection requirements based on the possible outcomes. Prioritization and engineering trade-offs are critical to achieving optimal system performance. Those functions can only occur when the effect of the inputs is known. This study provides information regarding the effects, thus permitting prioritization and engineering trade-offs as part of the system resource management.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this quantitative study was to evaluate the effects of variation on the independent variables leading to EW receiver response time. The quantification of these effects is critical to engineers and users who design scan strategies for EW receivers. The quantifiable results provide information that allows prioritization and compromises based on the desired results. Overall, this study demonstrates that mean response time is relatively stable even in a highly variable environment. However, while the mean response times are relatively stable, the variance is highly sensitive to variations of the independent variables. Response time is most sensitive to the changes of the EW receiver dwell time and revisit interval. However, the response time is not predictable given the amount of variation of the independent variables.

The quantitative results are striking because they offer the first glimpse of the effect of variation on the response time. Further interpretation and analysis is required to fully understand the implications of this study. Additionally, this study is the first of its type. Several researchers have recognized the need to quantify the effects of variation on response time. Further studies should not only seek to confirm the findings of this study, but address the key areas beyond the scope of this study.

Interpretation of Findings

The data collected in support of the four research questions rendered valuable information regarding the performance of an EW receiver in a dynamic environment. The following five conclusions were drawn from results presented in Chapter 4:

1. Little's formula accurately approximates a 95% success rate.

2. Adding mild noise improves performance as compared to no noise.
3. High amounts of noise have a mild influence on mean response time.
4. Low amounts of noise have a significant influence on variance and success rate.
5. Response time in a noisy environment is not predictable given the four independent variables used in this study.

These results are consistent with existing theories as they relate to similar fields. A major benefit of this study is the application of queuing theory to examine the effects in the field of electronic warfare.

The explicit use of Little's formula to design an EW sensor schedule is undocumented. Elements of the formula were detailed in a limited set of journals, but the complete implementation in the field of EW sensor queuing is absent. This study confirmed that in an ideal environment, Little's formula renders the desired success rate as programmed. Most literature in this field referred to the non-precise queuing methods prescribed by Richards (1948), while others such as Clarkson (1996, 2003, 2007,2011), Washburn (1983), and Winsor (2012) referenced individualized deterministic methods. The demonstration that Little's formula is applicable and reliable with respect to queuing an EW receiver is significant. It provides the mathematical foundation to reliable prediction of response times in a static scenario.

The next main conclusion is perhaps the most important finding of this study. While confirming that Little's formula is accurate in a static environment is important, demonstrating its accuracy in a scenario with mild noise is critical. In conditions in which each of the independent variables received a mild amount of variation (Test Condition 2), the mean response time decreased and the success rate increased. Therefore, in the context of EW receiver performance, Little's formula is valid in a dynamic environment when variation of the radar illumination time, radar scan time, EW receiver dwell time, and EW receiver revisit interval are constrained to minimal levels. This conclusion significantly aids developers in understanding how to compensate for potential operating conditions. A static scenario in which all values are known and optimized is not possible. However, the knowledge that this scenario is valid for planning in dynamic conditions with low levels of variation enables designing scan strategies for more complex scenarios and evaluating their performance to a baseline that equates to the static ideal scenario.

While the application of mild variation had negligible effects compared to the baseline, the application of large amounts of variation had little effect on the mean response time. This finding is important because it focuses on the evaluation criteria. Even in the worst-case scenario (Condition 2/Condition 15), the mean response time only increased by .25 seconds or 18%. The required response time is defined as 5 seconds. In Test Condition 15, the mean response time was 2.38 seconds. The mild rise in the mean response time was surprising in the face of substantial noise. This resilience must be noted as an indicator of flexibility to the operator, yet there is cost associated with this resilience. The overall success rate of detecting the signal within the required time decreased by 10%. Also of note is the substantial increase of the magnitude of the maximum response times. The maximum response times quickly climbed as the conditions became more complex. Even Test Condition 2 demonstrated a sizable increase in the maximum response time from Test Condition 1 (6.49 to 8.1 seconds). Test Condition 13 had the highest maximum response time of 21.45 seconds.

However, despite the significant increase in the magnitudes of the maximum response times and the increased frequency of fails, the overall mean response was relatively stable.

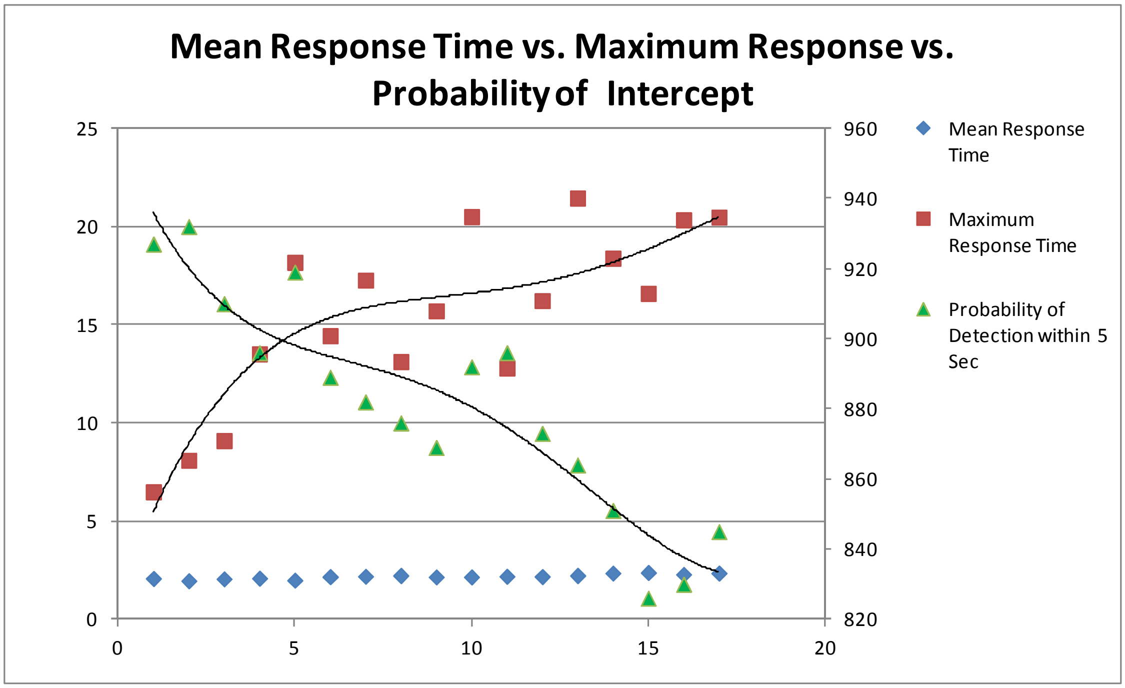

Figure 35. Mean response time vs. maximum response time vs. probability of intercept.

Figure 35 illustrates the relationship as the test conditions become increasingly more complex and the mean response time remains relatively stable, but there are other indicators of instability. The relative stability of the mean response time offers insight that permits engineers and users to make subjective decisions regarding potential trade-offs. For example, in this case while the required response time in this study was 5 seconds, the overall priority of detecting that emitter within the specified time may be very low. Meanwhile, the 5-second threshold for another emitter may be a much higher priority. The emitter with the more stringent requirements cannot withstand the reduced success rate and the increased maximum response time. However, the emitter with the lower priority regarding the response time can withstand the increased variation in performance, but can still benefit from an average level of performance. Therefore, this data suggests that engineers can choose to enforce tighter enforcement of the required EW receiver tuning parameters for the higher priority emitter, while permitting variation of the lower priority emitter tuning requirements. Without understanding the potential trade-off, the primary alternative to meeting required tune times is to change the required response time for lower priority emitters. Overall, the knowledge of having a stable and predictable average response time in the face of a highly unstable environment is critical. This means that engineers can optimize a system via minor adjustments to accommodate priorities to ensure specific requirements are met.

The significance of the average response time is critical, but the variance is also important. As previously indicated, the overall performance of the system is relatively stable. However, the variance of the response time is very sensitive to the amount of noise placed upon the independent variables. While the average response times do not reflect sizeable changes, even when statistically significant, the variance is sizeable and is frequently statistically significant. This data is important because it demonstrates how the less then optimal conditions are reflected in the results.

Figures 36, 37, and 38 depict the individual response time histogram from Test Condition 2 compared to Test Condition 3, 7, and 17. The data is untransformed to demonstrate the effects as observed; however, these test conditions were selected because the results of *f* tests for variance. Test Condition 2 is not statistically different from Test Condition 3 as represented in Figure 36.

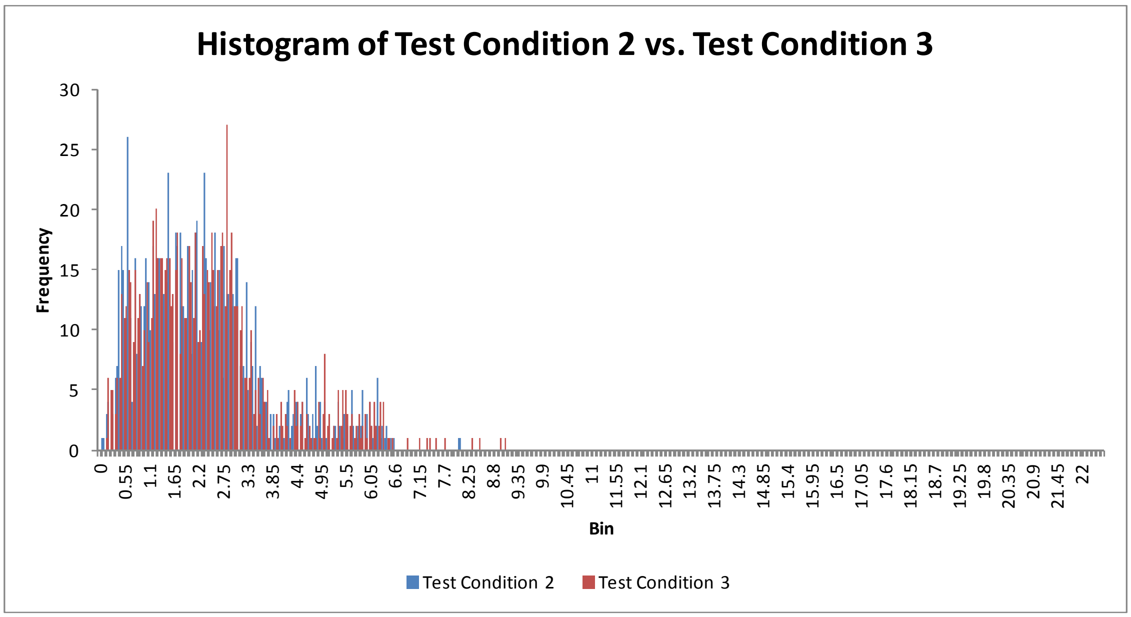

Figure 36. Histogram comparing response time from Test Condition 2 to Test Condition 3.

Note the similarity in the histograms. There appears to be a slight increase in variance as the maximum response time is about 1 second longer than Test Condition 2. Also, note the increase in the number of detections beyond the 6.5-second mark. These artifacts are indicative of an increase of the variance as a result of the variation placed upon the independent variables. Figure 37 illustrates the increased amount of variance between test conditions.

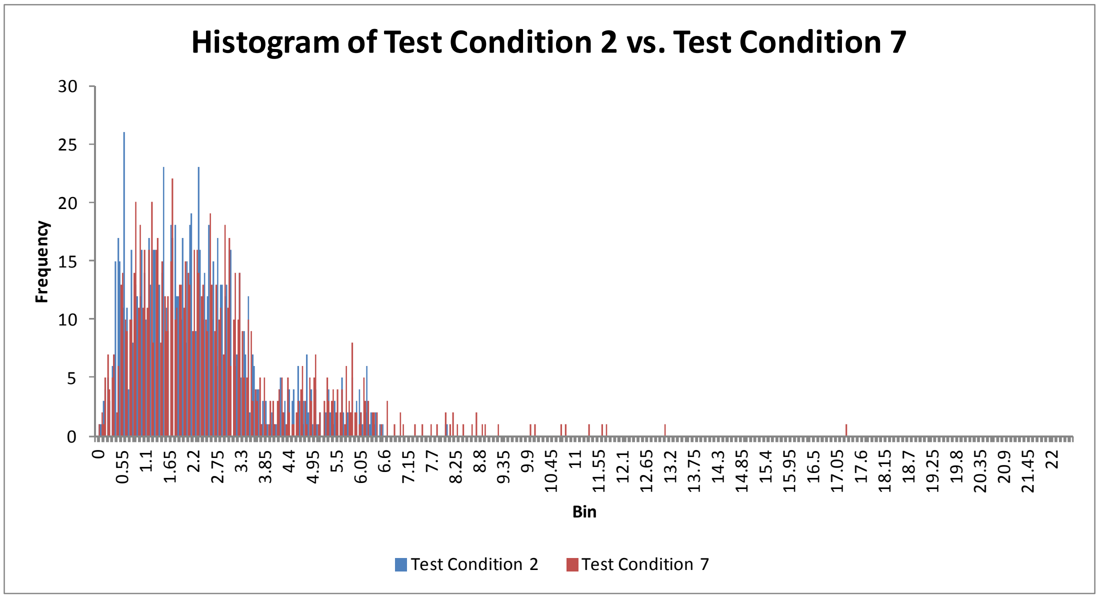

Figure 37. Histogram comparing response time from Test Condition 2 to Test Condition 7.

Figure 37 illustrates the first case in which the difference in variance is statistically significant. The overall appearance of the distributions is very similar with the exception of the numerous instances of detections well beyond the required 5-second range. Figure 38 illustrates the increased variance more clearly as this case demonstrated the largest difference in variance.

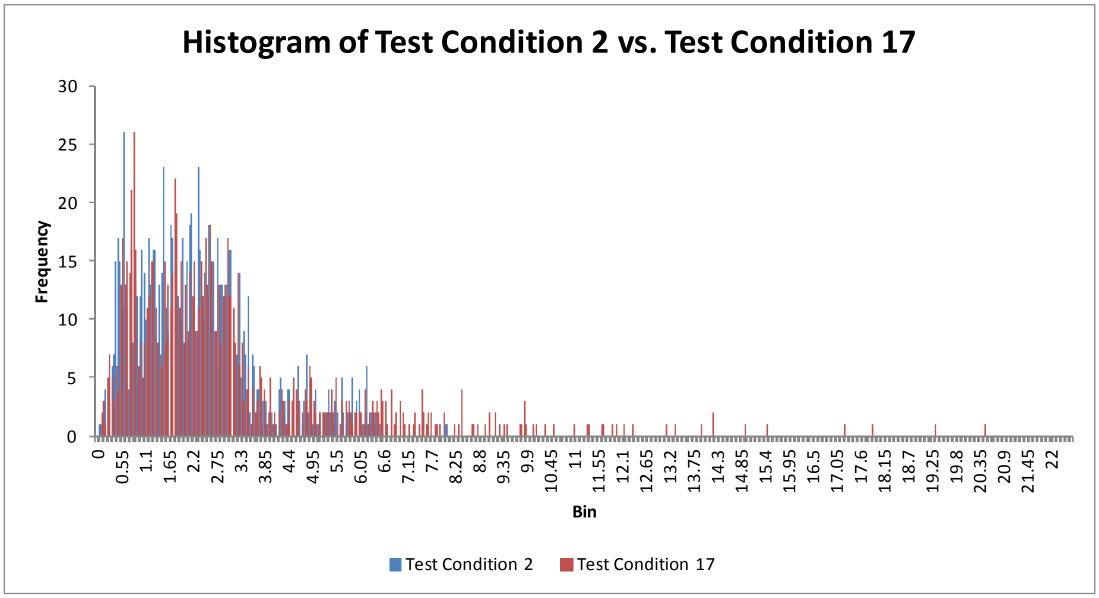

Figure 38. Histogram comparing response time from Test Condition 2 to Test Condition 17.

The most important element to consider from Figures 36-38 is the overall impact that the applied test conditions have on the response time. This data emphasizes the importance of understanding the practical implications of the test conditions such that appropriate trade-offs can be made with confidence. The queuing strategy as prescribed by Little is clearly robust and relatively adaptive to a wide variety of scenarios. The question that must be answered is how much variance is too much? As Figures 37 and 38 illustrate, as the conditions for detection become increasingly less ideal, there are more detections beyond the required response time, and the magnitude of the failed response times increases significantly. However, there are also several responses that are just beyond the 5-second requirement. This justifies a subjective assessment of the desired results as compared to the mission priorities.

The conclusion relates to the prediction of response time using multiple regression analysis. Unfortunately, although there is a relationship, the predictive value of the model is not sufficient to warrant its use. The practical results confirm the findings of the previous research questions that the settings of EW receiver scan strategy are the most important element in maintaining reliable response times. This is a critical finding because it highlights the importance of establishing and maintaining a scan strategy that is designed to accommodate mission requirements. It also highlights that the elements for effective and reliable detection are mostly within the span of control of the operators of the EW receiver. Thus, engineering compromises are possible via the understanding of the results. There is a finite amount of time in which an EW receiver can scan the environment, and the demands of the signal environment can overwhelm the capability of the EW receiver. These effects can be reasonably managed through the adjustment of the EW receiver dwell time and revisit interval to produce acceptable results. Responses to Research Questions 2, 3, and 4 indicate that these parameters can be modified to garner acceptable and predictable results even in the face of high variation of the radar parameters.

Limitations of the Study

The primary limitation to the generalizability of this study is the existence of a wide variety of scan tune algorithms specific to individual EW receivers. The proprietary nature of the electronic warfare industry yields a wide variety of individualized algorithms designed around the unique technologies at the time of the design. As technology evolves, each new system represents evolutionary progress and improvements. However, all systems have inherent strengths and weaknesses, which include software algorithms designed to accentuate strengths while minimizing weaknesses.

These natural compensatory algorithmic implementations represent possible deviations from the scan tune algorithm implemented in this study. This study intentionally assumed non-patterned, neutral deviations from the optimal scan tune condition rather than seeking to implement a version of an idealized strategy. Idealized scan tune strategies are formulated based up upon the specific mission requirements as permitted by the technology of the time. The wide range of scan tune strategies represent a limitless number of possible implementations each with its own unique caveats.

The results of this study cannot possibly represent various implementations with the same degree of accuracy. The existence of single universal scan tune strategy does not appear likely. However, software based optimization designed around the mission requirements and hardware capabilities dictate certain performance parameters. This study assumed the modification of EW receiver parameters did not follow an algorithmic pattern, but rather a random, Gaussian pattern. Deterministic systems such as EW receiver systems do not intentionally implement such random patterns. However, for the purpose of this study, the apparent performance of these systems are best modeled via stochastic methods rather than specific deterministic algorithms. As a result, the scan tune implementation in this study does not specifically represent any particular system which limits the generalizability. The modeled EW receiver behavior is sufficiently representative to permit analysis of potential system performance under the defined conditions. Yet, the results are not specific to any particular system or algorithm. Therefore, the results of this study are likely to be indicative many modes of operations of many systems. It cannot precisely represent any single system under all scenarios. Furthermore, the conditions of divergence from any particular system can only be determined via further evaluation with a specific system of study.

Recommendations

A primary gap in literature this study aimed to fill was the lack of research regarding variation on the independent variables that affect EW receiver response time. Most previous research used scenarios that did not include variation on these parameters. Essentially, previous research tended to use static scenarios in order to propose optimization solutions. Normally, researchers acknowledged the transitory nature of optimal conditions in the face of variable conditions. Furthermore, researchers acknowledged the need to quantify the effects of these variations. However, most research was devoted to designing new scan tune algorithms or sensor queuing concepts. Given the relative gap in the research regarding the effects of variation on EW receiver response time, there are three recommendations for future research: the effects of patterned variation, non-Gaussian random variation, and system specific testing.

This study implemented nonpatterned, Gaussian variation to evaluate the effect on response time. While research supports this approach, research also supports using patterned variations and non-Gaussian variation. The use of patterned variations primarily applies to the EW receiver scan variables of dwell time and revisit interval. As discussed in Chapter 2, EW receivers rely on a significant amount of information regarding the signal environment to establish a baseline scan tune strategy. However, the dynamic environment and limitations to knowing the signal environment preclude a perfect scan strategy. These factors are the basis for variance among the independent variables. The variance on the radar signals cannot be controlled, but the changes to the EW receiver dwell time and revisit interval can be modified in a patterned manner. Therefore, future research should research how controlled variation in these factors effect response time. When the prescribed conditions to achieve optimality cannot be achieved, a controlled variation that implements progressively longer or shorter dwell times and revisit intervals are a viable option to interleave a variety of scan tune parameters in controlled manner to accommodate the requirements of the dynamic scenario. This study should include independent, patterned variation of EW receiver dwell time and revisit interval. It should also include a coupled variation where a change in the dwell time directly affects the revisit interval and vice-versa. The use of predetermined variations from an optimal scenario offer engineers the option to make effective modifications of system resources with a higher degree of control of the system.

Just as the conditions in which the EW receiver scan strategy can have variations different than implemented in this study, the factors relating to the radar specific variables do not have to follow a Gaussian pattern. As detailed in Chapter 2, the assumption of a Gaussian distribution is valid and accepted, but research also points to conditions where non-Gaussian, random distributions exist, especially in a maritime environment. There are a variety of other distributions that can be used to model different scenarios. The effect these distributions have on the response time is important. A primary finding of this research is that EW aircraft operate in a highly dynamic and often unpredictable environment. In many cases, the assumptions of a scenario change throughout a mission based on location, terrain, weather, and tasking. This study started with the most common or likely conditions. The next series of research questions should explore the different conditions that will affect how the radar signal is represented in a free space environment.

The final recommendation for future research is performing this type of study with the attributes of a specific EW receiver system. The primary limitation of this study is the absence of processing logic from a specific system. This study specifically employed generic logic in order to draw conclusions that are representative of a broad class of EW receiver systems. However, each system has unique algorithms that may perform differently. In this regard, the concepts of this study can be easily applied to a specific system and used as a baseline for comparison. As previously discussed, scan strategy optimization is a function of resource management. Each EW receiver system is designed to meet predetermined specifications. These specifications are intended to represent use-case scenarios based on an expected operating environment. The guidance of these specifications do not preclude the necessity of making compromises to arrive at an optimal state. In order to reach an optimal state, dynamic testing that models the variations of the environment is necessary in order to evaluate the impact on response time.

The task of managing EW receiver response time is challenging. There is a vast range of potential scenarios with each one presenting a unique blend of challenges.

Managing the settings of the receiver require that users and engineers understand the quantitative effects that the independent variables have on the response time. The conditions used in this study represented some of the expected operating conditions, but certainly not all. The results of this study demonstrate that variations among the independent variables can have a significant influence on the performance of the receiver. Additional studies are required to determine the extent that different types of variation and receiver logic interact.

Implications

There are a variety of potential benefits this study contributes to positive social change. These benefits include the specific results regarding aircraft survivability, queuing theory, the application of EW principles, and research methodology. The specific intent of this study was very focused and limited to military utility. However, the social benefits of this study have the potential to improve how these systems operate which can lead to improved survivability. This study also included principles regarding queuing theory, and demonstrated how queuing theory applies to EW. Finally, this study merged the concepts of design of experiment research methodology with a simulated test environment. The overall positive social change of this study span organizational benefits, theoretical benefits, and methodological benefits.

The potential for positive social change at the organizational level is most applicable to EW engineers who design EW receiver scan strategies. EW engineers are responsible for programming large amounts of data for a variety of missions. Scan strategy optimization in a wide range of environments is difficult, and robust testing of every scenario is not feasible. In this regard, this study provides quantitative data that offers insight into the possible effects that different signal environments have on response time. This study enables EW engineers the option of evaluating how their system will respond under the variety of conditions within the scope of this experiment. Essentially, this study provides the baseline for regression testing against a set of generic data. This greatly expedites the process of test and evaluation by providing a basis of comparison. Finally, the greatest potential for positive social change is the ability to use this data to improve aircraft survivability. Scan strategy optimization fundamentally improves the likelihood of surviving an engagement by reliably detecting radars within the required time. This study furthers the knowledge of optimizing this process by demonstrating how the principle factors affect response time. Armed with this knowledge, EW engineers can provide guidance regarding implementation and prioritization.

The next potential area for positive social change is the contribution to queuing theory. This study revolved the implementation of queuing theory in the field of EW. However, queuing theory is critical to many fields of study, many of which encounter similar problems regarding dynamic environments. This is most notable in fields regarding computing and technology integration. As technology continues to evolve, multi-tasking and product integration become more common place. For example, cellular phones now routinely perform many functions than simple phone calls. Most smartphones include cameras, Internet browsers, and an endless variety of applications. This concept of product integration has permeated products such as televisions, cars, aircraft, and even houses. Resources are being tasked to perform more functions in less time under more demanding circumstances. Queuing theory is complex and often not the sole the point of investigation during system development. The results of this study offer insight into the effects that a dynamic system has on a queuing system. System developers can use the findings of this study toward the development new integrated products with knowledge regarding how to share resources in an optimal manner.

The final area for potential positive social change is the methodological impact. This study merged two common research methods into a single study. Monte Carlo simulation and design of experiment are well established methodologies that have long histories of scientific inquiry. However, the methodologies are rarely used in combination. Yet, the two methods are well suited for mutual use. The concepts of design of experiment yield efficient methods to evaluate complex systems. Meanwhile, the concepts of Monte Carlo simulation emphasize the use of random sampling to produce large volumes of data. The combination of these methods; however, are well suited to exploring the potential outcomes of complex systems with comprehensible results. This study demonstrates how researchers can perform research in a software-based environment. Generally, design of experiment methods are used in studies involving complex, hardware based systems while Monte Carlo methods are software based and used to provide insight systems involved with chance. Their general use-case scenarios do not preclude their mutual employment for future research. The evolution of hardware and software has enabled the mutual employment of these methods. There are many complex research questions in the field operations research management that can benefit the use of both methods. This methodological advancement expands the envelope of academic research by providing access to previously unattainable concepts.

Overall, this study has a wide range of potential positive social benefits. The primary social benefit provided by this study is the quantitative data demonstrating the effects of variation on the independent variables on response time. EW engineers can use this data to optimize scan strategies and improve aircraft survivability. Beyond the immediate benefits of scan strategy optimization is the contribution to queuing theory. As systems continue to integrate more services, engineers will need to understand and characterize the waning periods of optimization. Finally, the greater academic community stands to benefit from the demonstration of using concepts of design of experiment in conjunction with Monte Carlo simulation. While the two methods are not traditionally employed, they are not mutually exclusive and offer researchers a great deal of flexibility when studying complex research questions that may otherwise be too difficult to study.

Conclusions

The primary conclusions of this study are the following:

1. Little's Formula is valid for use in EW receiver scan strategy development
2. Mean response time is mildly effected by a highly dynamic environment
3. A highly dynamic environment yields a decreased success rate
4. A highly dynamic environment yields much longer response times

These conclusions are all significant to an EW engineer. The validity of using Little's Formula in the development of an scan strategy is important because while there are many methods for determining how to detect a signal, using a mathematically proven theorem is important. The literature review demonstrated many methods and alluded to the use of Little's Formula, none of them explicitly advocated its use. I used Little's formula as the basis of calculating optimal settings. The results from Test Condition 1 demonstrated a success rate approximating 95%, which is the theoretical limit. Results significantly better or worse would have indicated results other than optimal.

The application of variation on the independent variables did not yield an appreciable difference in response time. While certain test conditions demonstrated statistical significance, the mean response times were still well within the 5-second requirement. The variation of the independent variables manifested in the variance and maximum response times. Essentially, the detection of signals had higher incidents of detection beyond the 5-second requirement with a maximum response time being potentially much higher than the 5-second requirement. Overall, the system performed well under highly dynamic conditions, but had a higher likelihood to have very lengthy response times that are well beyond normal response times.

The final message for readers is the importance of using this information for the purpose of allocating system resources. EW receiver scan strategies are difficult to plan. Inevitably, the designer wants to scan as much of the spectrum as possible with the fastest response time. However, actual conditions preclude optimal settings. The best possible outcome is characterizing the potential amount of variation and prioritizing scan requirements to ensure response time requirement compliance in conditions that are critical while relaxing requirements on lower priorities.

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Appendix A: List of Equations

Appendix B: Visual Basic Code

Extract of Visual Basic for Applications (VBA) code:

```
Sub timer()
Randomize
Dim i As Double
Dim LSB As Double
Dim pw As Double
Dim pri As Double
Dim revisit_interval As Double
Dim scan_time As Double
Dim dwell_time As Double
Dim clock_counter As Double
Dim radar_above_threshold_start As Double
Dim radar_above_threshold_flag As Boolean
Dim radar_above_threshold_flag_counter As Long
Dim revisit_interval_start_point As Double
Dim revisit_interval_flag As Boolean
Dim revisit_interval_flag_counter As Long
Dim randomization_value As Double
Dim instrumentation As String

instrumentation = Worksheets("New Config").Range("b23")

script_setting = Worksheets("timer").Range("b23")


Dim record_counter_range As Range
Set record_counter_range = Worksheets("Record").Range("a1:a1000000")
Dim record_counter As Double

Dim record_counter2_range As Range
Set record_counter2_range = Worksheets("Record").Range("d1:d1000000")
Dim record_counter2 As Double

Dim record_counter3_range As Range
Set record_counter3_range = Worksheets("Record").Range("e1:e1000000")
Dim record_counter3 As Double

Dim record_counter4_range As Range
Set record_counter4_range = Worksheets("Record").Range("g1:g1000000")
Dim record_counter4 As Double
```

```
Dim record_counter5_range As Range
Set record_counter5_range = Worksheets("Record").Range("h1:h1000000")
Dim record_counter5 As Double

master_scan_time = Worksheets("New Config").Range("b2") * 1000000
scan_time = master_scan_time
response_time = Worksheets("New Config").Range("b12") * 1000000
master_dwell_time = Worksheets("New Config").Range("b6")
dwell_time = master_dwell_time
required_collect_time = Worksheets("New Config").Range("b14")
start_point = 0
master_radar_above_threshold = Worksheets("New Config").Range("b4") * 1000000
radar_above_threshold = master_radar_above_threshold
radar_above_threshold_flag = False
scan_start_point = Application.WorksheetFunction.RandBetween(0, scan_time)
radar_above_threshold_flag_counter = 0
i = 0
samples = Worksheets("New Config").Range("b17")
revisit_interval_flag = False
revisit_interval_flag_counter = 0

scan_variation = Worksheets("New Config").Range("b3")
illum_variation = Worksheets("New Config").Range("b5")
dwell_variation = Worksheets("New Config").Range("b7")
revisit_variation = Worksheets("New Config").Range("b9")

Little_RI = ((radar_above_threshold - dwell_time) / (1 - (0.05) ^ ((scan_time) /
        (response_time))))
Worksheets("New Config").Range("d8") = Little_RI / 1000000

If Worksheets("New Config").Range("b8") = "" Then
   master_revisit_interval = Little_RI
   revisit_interval = master_revisit_interval
Else
   master_revisit_interval = Worksheets("New Config").Range("b8") * 1000000
   revisit_interval = master_revisit_interval
End If

record_counter1 = 0
record_counter2 = 0

'Dim j As Long
```

```
'Dim record_counter5_range As Range
'Set record_counter5_range = Worksheets("Record").Range("h1:h1000000")
'Dim record_counter5 As Double

result_counter = 1 'sets up the right spacing

scan_time_code = Worksheets("New Config").Range("b18")
illum_code = Worksheets("New Config").Range("b19")
dwell_time_code = Worksheets("New Config").Range("b20")
revisit_time_code = Worksheets("New Config").Range("b21")

Application.Calculation = xlCalculationManual

For j = 1 To samples

script_setting = "N"
If script_setting = "N" And j = 1 Then
   Worksheets("timer").Range("a1:z100000").Clear
   Worksheets("record").Range("a1:z1000000").Clear
   Worksheets("timer").Range("z1") = Now()
End If

Worksheets("timer").Range("a1") = "Response Time"
Worksheets("timer").Range("b1") = "First Scan"
Worksheets("timer").Range("c1") = "Number of Scans"
Worksheets("timer").Range("d1") = "A"
Worksheets("timer").Range("e1") = "B"
Worksheets("timer").Range("f1") = "C"
Worksheets("timer").Range("g1") = "D"
Worksheets("timer").Range("h1") = "AB"
Worksheets("timer").Range("i1") = "AC"
Worksheets("timer").Range("j1") = "AD"
Worksheets("timer").Range("k1") = "BC"
Worksheets("timer").Range("l1") = "BD"
Worksheets("timer").Range("m1") = "CD"
Worksheets("timer").Range("n1") = "ABC"
Worksheets("timer").Range("o1") = "ABD"
Worksheets("timer").Range("p1") = "ACD"
Worksheets("timer").Range("q1") = "BCD"
Worksheets("timer").Range("r1") = "ABCD"

first_scan_start_point = scan_start_point
```

```
revisit_interval_start_point = Application.WorksheetFunction.RandBetween(0,
        revisit_interval)


  Do Until i = 5 * 60 * 1000000

    If i >= scan_start_point Then
      radar_above_threshold_flag = True
      radar_above_threshold_flag_counter = radar_above_threshold_flag_counter + 1


        If j = 1 And i Mod 1000 = 0 And radar_above_threshold_flag = True And
      instrumentation = "Y" Then 'this part is for instrumentation

          record_counter =
      Application.WorksheetFunction.CountA(record_counter_range) + 1
          Worksheets("Record").Cells(record_counter, 1) = i
          Worksheets("Record").Cells(record_counter, 2) = 2

        End If

      If radar_above_threshold_flag_counter = radar_above_threshold Then

        radar_above_threshold_flag_counter = 0
        radar_above_threshold_flag = False

        If scan_variation <> 0 Then
          scan_variation_factor =
      Abs(Application.WorksheetFunction.NormInv(Rnd(), 1, scan_variation / 3))

          If scan_variation_factor <= 0 Then
            scan_variation_factor = 0.01
          End If

        Else
          scan_variation_factor = 1
        End If

        If illum_variation <> 0 Then
          illum_variation_factor =
      Abs(Application.WorksheetFunction.NormInv(Rnd(), 1, illum_variation / 3))

          If illum_variation_factor <= 0 Then
```

```
        illum_variation_factor = 0.01
      End If

    Else
      illum_variation_factor = 1
    End If

    radar_above_threshold = Round(master_radar_above_threshold *
  illum_variation_factor, 0)

    scan_time = master_scan_time * scan_variation_factor

    scan_start_point = scan_start_point + scan_time

    If j = 1 Then
      record_counter4 =
  Application.WorksheetFunction.CountA(record_counter4_range) + 1
      Worksheets("Record").Cells(record_counter4, 7) = scan_time / 1000000
      Worksheets("Record").Cells(record_counter4, 8) = radar_above_threshold /
  1000000
    End If

  End If

End If

If i >= revisit_interval_start_point Then

  revisit_interval_flag = True
  revisit_interval_flag_counter = revisit_interval_flag_counter + 1

  If j = 1 And i Mod 200 = 0 And revisit_interval_flag = True And instrumentation
  = "Y" Then 'for instrumentation

      record_counter =
  Application.WorksheetFunction.CountA(record_counter_range) + 1
      Worksheets("Record").Cells(record_counter, 1) = i
      Worksheets("Record").Cells(record_counter, 2) = 1

  End If

  If revisit_interval_flag_counter = dwell_time Then 'this section determines if the
  radar illum and Rx dwell overlap
```

```
   If radar_above_threshold_flag_counter >= required_collect_time _
   And revisit_interval_flag_counter >= required_collect_time Then 'if they
overlap...then the following

      Worksheets("timer").Cells(result_counter + 1, 1) = i / 1000000
      First_detect = Worksheets("timer").Cells(result_counter + 1, 1)

      Worksheets("timer").Cells(result_counter + 1, 2) = first_scan_start_point /
1000000

      First_detect_plus_first_scan = First_detect -
Worksheets("timer").Cells(result_counter + 1, 2)
      Worksheets("timer").Cells(result_counter + 1, 3) =
Application.WorksheetFunction.RoundUp(First_detect_plus_first_scan /
(scan_time / 1000000), 0)

      Worksheets("timer").Cells(result_counter + 1, 4) = scan_time_code 'A
      Worksheets("timer").Cells(result_counter + 1, 5) = illum_code 'B
      Worksheets("timer").Cells(result_counter + 1, 6) = dwell_time_code 'C
      Worksheets("timer").Cells(result_counter + 1, 7) = revisit_time_code 'D

      Worksheets("timer").Cells(result_counter + 1, 8) = scan_time_code *
illum_code 'AB
      Worksheets("timer").Cells(result_counter + 1, 9) = scan_time_code *
dwell_time_code 'AC
      Worksheets("timer").Cells(result_counter + 1, 10) = scan_time_code *
revisit_time_code 'AD
      Worksheets("timer").Cells(result_counter + 1, 11) = illum_code *
dwell_time_code 'BC
      Worksheets("timer").Cells(result_counter + 1, 12) = illum_code *
revisit_time_code 'BD
      Worksheets("timer").Cells(result_counter + 1, 13) = dwell_time_code *
revisit_time_code 'CD
      Worksheets("timer").Cells(result_counter + 1, 14) = scan_time_code *
illum_code * dwell_time_code 'ABC
      Worksheets("timer").Cells(result_counter + 1, 15) = scan_time_code *
illum_code * revisit_time_code 'ABD
      Worksheets("timer").Cells(result_counter + 1, 16) = scan_time_code *
dwell_time_code * revisit_time_code 'ACD
      Worksheets("timer").Cells(result_counter + 1, 17) = illum_code *
dwell_time_code * revisit_time_code 'BCD
```

```
        Worksheets("timer").Cells(result_counter + 1, 18) = scan_time_code *
illum_code * dwell_time_code * revisit_time_code 'ABCD
        Worksheets("timer").Cells(result_counter + 1, 19) = "Run " &
Worksheets("New Config").Range("b22")

        Worksheets("timer").Cells(result_counter + 1, 20) = Worksheets("New
Config").Range("b3")
        Worksheets("timer").Cells(result_counter + 1, 21) = Worksheets("New
Config").Range("b5")
        Worksheets("timer").Cells(result_counter + 1, 22) = Worksheets("New
Config").Range("b7")
        Worksheets("timer").Cells(result_counter + 1, 23) = Worksheets("New
Config").Range("b9")


        Worksheets("timer").Select
        Worksheets("timer").Cells(j, 1).Activate

        'if there is a detection...this resets the set for the next run
        i = 0
        start_point = 0
        revisit_interval_flag = False
        revisit_interval_flag_counter = 0
        radar_above_threshold_flag = False
        radar_above_threshold_flag_counter = 0
        scan_start_point = Application.WorksheetFunction.RandBetween(0,
scan_time)
        revisit_interval_start_point =
Application.WorksheetFunction.RandBetween(0, revisit_interval)

        GoTo nextj 'this takes the code to the next point

    End If


    If revisit_variation <> 0 Then
        revisit_variation_factor =
Abs(Application.WorksheetFunction.NormInv(Rnd(), 1, revisit_variation / 3))

        If revisit_variation_factor <= 0 Then
            revisit_variation_factor = 0.01
        End If
    Else
```

```
        revisit_variation_factor = 1
    End If

    If j = 1 Then
        record_counter2 =
Application.WorksheetFunction.CountA(record_counter2_range) + 1
        Worksheets("Record").Cells(record_counter2, 4) = (master_revisit_interval *
revisit_variation_factor) / 1000000
    End If

    revisit_interval_flag_counter = 0
    revisit_interval_flag = False
    revisit_interval_start_point = Round(revisit_interval_start_point +
(master_revisit_interval * revisit_variation_factor))


    If dwell_variation <> 0 Then
        dwell_variation_factor =
Abs(Application.WorksheetFunction.NormInv(Rnd(), 1, dwell_variation / 3))

        If dwell_variation_factor <= 0 Then
            dwell_variation_factor = 0.01
        End If
    Else
        dwell_variation_factor = 1
    End If

    If j = 1 Then
        record_counter3 =
Application.WorksheetFunction.CountA(record_counter3_range) + 1
        Worksheets("Record").Cells(record_counter3, 5) = dwell_time
    End If

    dwell_time = Round(master_dwell_time * dwell_variation_factor)

    End If

End If

i = i + 1

Loop
```

```
Worksheets("timer").Cells(result_counter + 1, 1) = "No Contact"
Worksheets("timer").Cells(j, 1).Activate
i = 0
start_point = 0
revisit_interval_flag = False
revisit_interval_flag_counter = 0
radar_above_threshold_flag = False
radar_above_threshold_flag_counter = 0
scan_start_point = Application.WorksheetFunction.RandBetween(0, scan_time)

dwell_time = master_dwell_time
revisit_interval = master_revisit_interval
scan_time = master_scan_time
radar_above_threshold = master_radar_above_threshold

nextj:

Dim result_counter_range As Range
Set result_counter_range = Worksheets("timer").Range("a1:a100000")
result_counter = Application.WorksheetFunction.CountA(result_counter_range)

dwell_time = master_dwell_time
revisit_interval = master_revisit_interval
scan_time = master_scan_time
radar_above_threshold = master_radar_above_threshold

Next j

Call copy_and_paste
Worksheets("timer").Range("z2") = Now()
Application.Calculation = xlCalculationAutomatic

End Sub
```