METHODS FOR USING MANPOWER TO ASSESS USAF STRATEGIC RISK

DISSERTATION

Calvin J. Bradshaw III, Major, USAF

AFIT-ENS-DS-19-J-021

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT-ENS-DS-19-J-021

METHODS FOR USING MANPOWER TO ASSESS USAF STRATEGIC RISK

DISSERTATION

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

Calvin J. Bradshaw III, MEM, MSOR

Major, USAF

June 2019

AFIT-ENS-DS-19-J-021

METHODS FOR USING MANPOWER TO ASSESS USAF STRATEGIC RISK

Calvin J. Bradshaw III, MEM, MS(OR)

Major, USAF

Committee Membership:

Dr. Alan Johnson
Chair

Dr. Raymond R. Hill
Member

Dr. Christine Schubert-Kabban
Member

Dr. Ross A. Jackson
Member

Adedeji B. Badiru, Ph.D.
Dean, Graduate School of Engineering
and Management

Abstract

With limited personnel resource funding availability, senior US Air Force (USAF) decision makers struggle to base enterprise resource allocation from rigorous analytical traceability. There are over 240 career fields in the USAF spanning 12 enterprises. Each enterprise develops annual risk assessments by distinctive core capabilities.

A core capability (e.g. Research and Development) is an enabling function necessary for the USAF to perform its mission as part of the Department of Defense (DOD). Assessing risk at the core capability is a good start to assessing risk, but is still not comprehensiveness enough. One of the twelve enterprises has linked its task structure to Program Element Codes (PECs).

Planners and programmers use amount of funding per PEC to assess tasks needed to address a desired capability. For the first time, a linkage between core functions, core capabilities, PECs, tasks and manpower has been developed. We now can provide an objective nomenclatured way to compute personnel risk.

All resources *planned* are not *programmed* (i.e. resource allocated and budgeted); the delta between the two translate into capability gaps and a level of strategic *risk*. A USAF career field risk demonstration is performed using normal, sigmoid and Euclidean-norm functions. Understanding potential personnel shortfalls at the career field level should better inform core capability analysis, and thus increase credibility and defensibility of strategic risk assessments.

AFIT-ENS-DS-19-J-021

Thanks to my wife and kids for allowing me to pursue this opportunity.

Acknowledgments

I would like to extend my utmost thanks and appreciation to my research advisor, Dr. Alan Johnson, and my committee members, Drs. Schubert-Kabban, Hill and Jackson, for their guidance, support, and patience through the course of this dissertation endeavor.

Calvin J. Bradshaw III

Table of Contents

List of Tables

Page

List of Figures

Page

Page

List of Acronyms

Acronym	Definition
ACS	Agile Combat Support
ANN	Artifical Neutral Network
AFRAF	Air Force Risk Assessment Framework
AFS	Air Force Specialty
BN	Bayesian Network
BCC	Banker, Charnes and Cooper
CCR	Charnes, Cooper and Rhodes
C3RAF	Comprehensive Core Capability Risk Assessment Framework
CF	Core Function
DEA	Data Envelopment Analysis
DOD	Department of Defense
DPG	Defense Planning Guidance
FE	Functional Equity
I&MS	Installation and Mission Support
L&S	Logistics and Sustainment
LCM	Life Cycle Management
MAJCOM	Major Command
POM	Project Objective Memorandum
PPBE	Progamming, Planning, Budgeting and Execution
R&D	Research and Development
RR	Relative Risk Ratio

Acronym	Definition
SCF	Service Core Function
SP3	Strategic, Planning and Programming Process
T&E	Test and Evaluation
USAF	United States Air Force

METHODS FOR USING MANPOWER TO ASSESS USAF STRATEGIC RISK

I. Introduction

Personnel are a major United States Air Force (USAF) capability and are critical to inventory management, logistics asset readiness and supply chain risk management. Effective personnel management is difficult particularly in the logistics and supply chain domain. However, there are analytical tools that can aid more objective personnel risk assessment. This work places select techniques into a methodology for logistics and supply chain manpower analysts to assist senior decision making. This research starts with a literature review of those select analytical procedures to objectively assess personnel risk and four quantitative methods that yield promising results for the logistics and supply chain domain. These methods and respective applications are then described in a set of technical papers. Each paper will set the context, describe the problem/challenge, present a methodology and provide a demonstration of that methodology. The goal is to provide a methodology the USAF can exploit to better assess strategic risk using manpower analysis. This over-arching goal will better aid senior decision making as it relates to the management and prioritization of USAF personnel capability focused on the logistics and supply chain domain, and assist with respect to the objective assessment of USAF strategic risk.

This research adds another dimension to the assessment of USAF enterprise risk. This work ascertains whether efficiency should be considered as a component of assessing risk. For example, what if senior decision leaders were able to know if current management of manning resources of one organization was subpar compared to similar organizations. Should similar organizations with similar personnel makeups and missions be compared with regards to personnel utilization? If so, could these efficiency comparisons be statistically evaluated with respect to risk and inferences be gained to help senior decision leaders and planners better advocate and prioritize resources? This research purports that before personnel risk can be more accurately assessed, efficiency should be examined.

Background

The current Agile Combat Support risk assessment (ACS RA) process lacks traceability to the justification of risk assessments, which severely weakens defensibility and significantly decreases credibility in strategic risk assessments presented to senior decision makers. The problem requires a systematic resolution in order to revamp the risk assessment process.

The enterprise risk assessment entails various components: people, data, time, stakeholders, and other various resources. The people component consists of various practitioners like operations research analysts, program analysts, planners, functional area experts and senior decision makers. At times, these practitioners do not share the same philosophy or approach to resolve problems. A structured process is needed in order for practitioners to reach commonality while working shared tasks and responsibilities to meet collective goals.

The data component involves the use of personnel data in the form of the number of personnel by career field and respective funded requirements, Program Element Codes, core capabilities and task activities. These data elements are in different databases and require linkage before analysis can occur.

The time component is a finite dimension which consists of plans and schedules designed to meet milestones to achieve a given end state. The ACS RA has various stakeholders in the form of customers, owners, enablers, experts and facilitators. These groups may have different goals and as a result may possess different agendas and make problem resolution challenging. Resources in the form of limited time, available subject matter expertise and constrained budgets make dedicated resource allocation to the ACS RA effort difficult. As a result of the aforementioned components to the ACS RA, a framework is created as a means to guide USAF risk assessment practitioners as it relates to problem resolution.

The framework involves five specific methodologies. First, a methodology is presented comparing USAF core function (enterprise) risk. Second, a repeatable way to compute personnel efficiency is demonstrated. Efficiency is the ratio of *useful work* to the *total energy expended* in order to accomplish a task (Pisupati, 2018). In general, efficiency is the ratio of outputs and inputs (Dario and Simar, 2007) . Third, a procedure is developed examining relationships between efficiency and risk. Fourth, a personnel enterprise risk assessment methodology is developed. Fifth, an application of the personnel enterprise risk assessment is presented. Figure I-1 is a sequence of analytical methods used to revise the ACS RA.

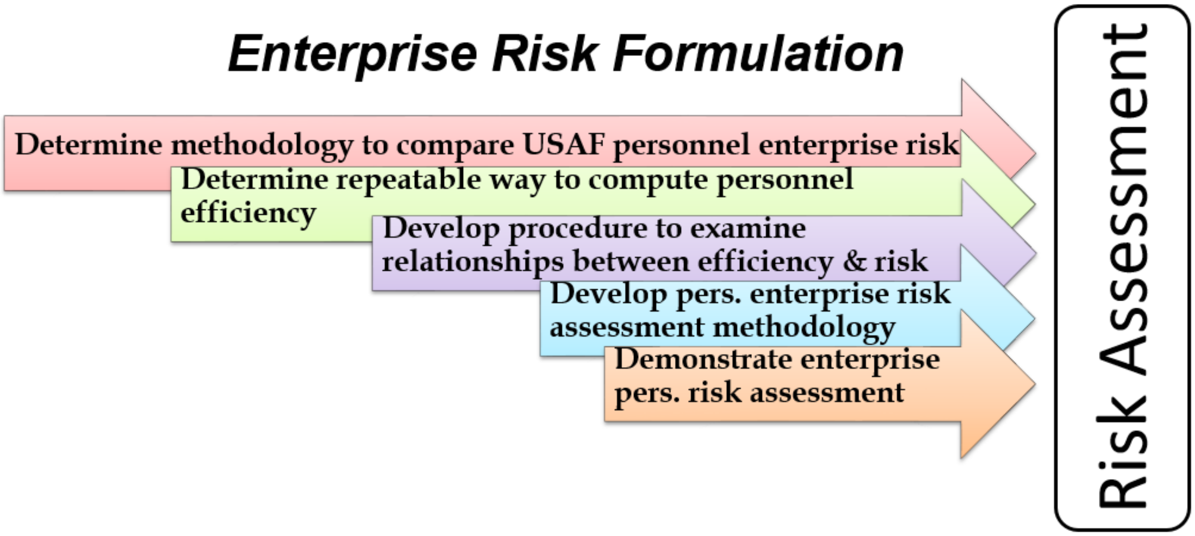


Figure I-1: ACS RA Risk Formulation

This research explores various analytical methods to assess personnel *efficiency* and *risk* and examine if there are noteworthy relationships between these two factors. Specifically, this research demonstrates the assessment of USAF personnel risk through the specific analtycial tools: logistic regression, a normal distribution, Data Envelopment Analysis, non-parametric correlation analysis and L^p spacing.

<u>Risk</u>

Merriam-Webster defines risk as the degree of probability of a loss (Merriam-Webster, 2017). The subject of risk can be traced as far back as 3200 B.C. by a Tigris-Euphrates group called the Asipu (Covello, Mumpower, 1985). The Asipu would try to identify and understand the problem, develop courses of actions (COAs), collect data and establish likely outcomes to include profit/loss or success/failure of each COA (Covello, Mumpower, 1985). Over 2400 years ago, the Athenians offered risk assessments before making decisions during the Peloponnesian War (Aven, 2003).

Military risk is a highly complex phenomenon to accurately assess. The United States Air Force (USAF) defines risk as the probability and consequence of an event causing harm to something of value (AFPD 90-16 draft, 2018). Whether subjectively, objectively or both, USAF primarily assesses strategic risk in two contexts: Risk to Mission (RtM) and Risk to Force (RtF). The official USAF definition of RtM is defined as the ability to execute a mission at acceptable human, materiel, financial, and strategic costs (AFMAN 90-1606, 2017). USAF defines RtF as the ability to recruit, maintain, train, equip, and sustain the force to meet strategic objectives (AFMAN 90-1606, 2017). RtM is typically characterized by the levels of capacity (i.e. sufficient force structure) and capability (i.e. air, space, and cyber effects) needed to provide National Authorities when called upon (AFMAN 90-106, 2017). RtF is characterized by the ability to maximize the effectiveness of the force structure chosen to meet the desired operational requirements. RtF are essentially *capability enablers and practices* in the form of munitions, training, equipment, infrastructure, personnel and institutional[1].

These two strategic contexts are measured by four risk (not including endpoints[2]) levels (ordered by increasing risk) within the framework of achieving an objective or goal: low, moderate, significant and high. An example of how the levels are defined and measured is included in Figure I-2 also formally known as the Air Force Risk Assessment Framework (AFRAF).

[1] More details of this strategic risk context are supplied in several strategic planning documents.
[2] Technically, there are six levels of risk, if we include the Success and Failure levels, which are numerically 0% and 100% respectively.

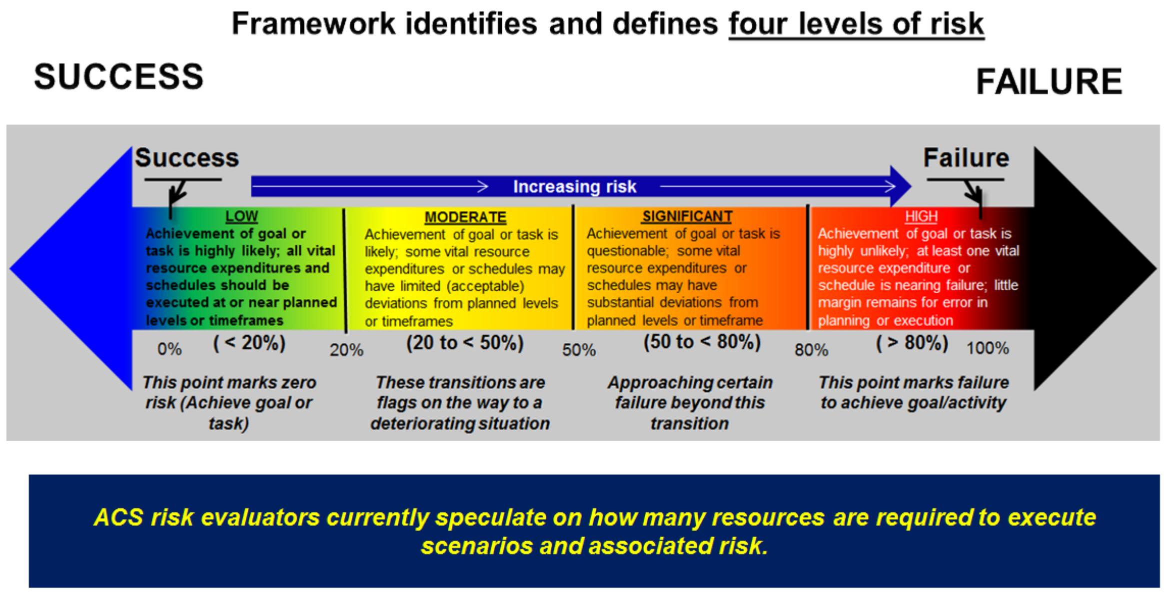


Figure I-2: AFRAF (AFMC/A9A, 2016)

Combining the two strategic contexts (i.e RtM and RtF) with the four risk levels yield a framework in which the USAF assesses strategic risk. Figure I-3 provides an illustration of the two strategic risk areas coupled with the four risk levels, which ultimately help characterize USAF risk.

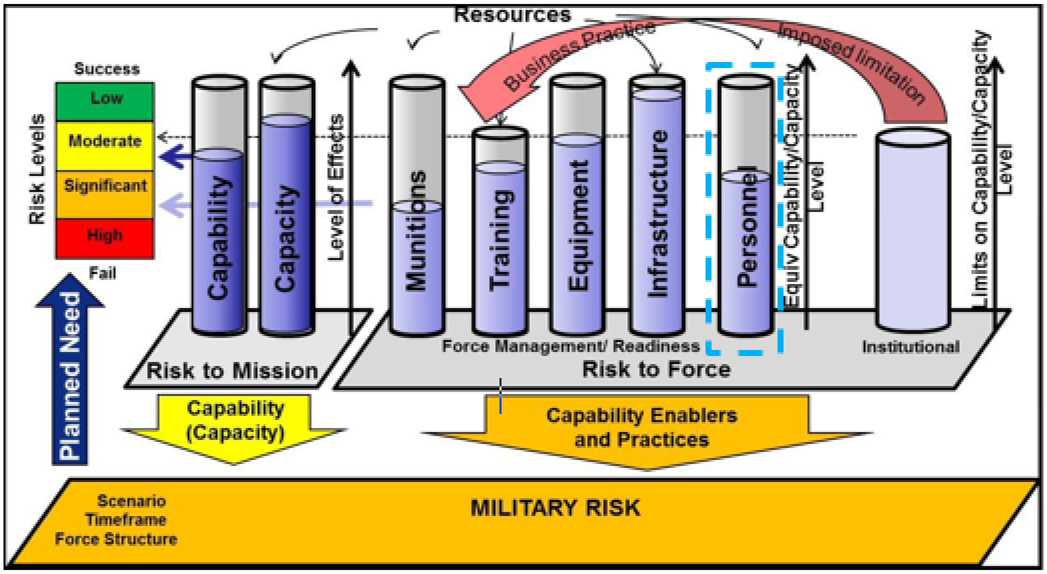


Figure I-3: USAF Military Risk Structure (AFMAN 90-106, 2017)

This research focuses specifically on the personnel piece of the RtF component of USAF strategic risk. RtF must be assessed before RtM in order to more accurately depict USAF risk. This work also assumes there is a relationship between risk and capability. That is to say, the more capability (e.g. fuel, manning, higher mission capable rates (MCRs[3]), positive infrastructure levels (e.g. Common Output Level Standards (COLS)), equipment and supply status, etc.) that exists, the less risk incurred and conversely, the less capability that exists, the more risk incurred. Figure I-4 illustrates this relationship. This concept is further extended to assume there is at least a curvilinear relationship (via Sigmoid function) between risk and capability for Human Resources.

[3] MCR is the degree to which a system, subsystem or equipment is in a specified operable and committable state at the start of a mission, when the mission is called for at an unknown, *i.e.* a random, time.

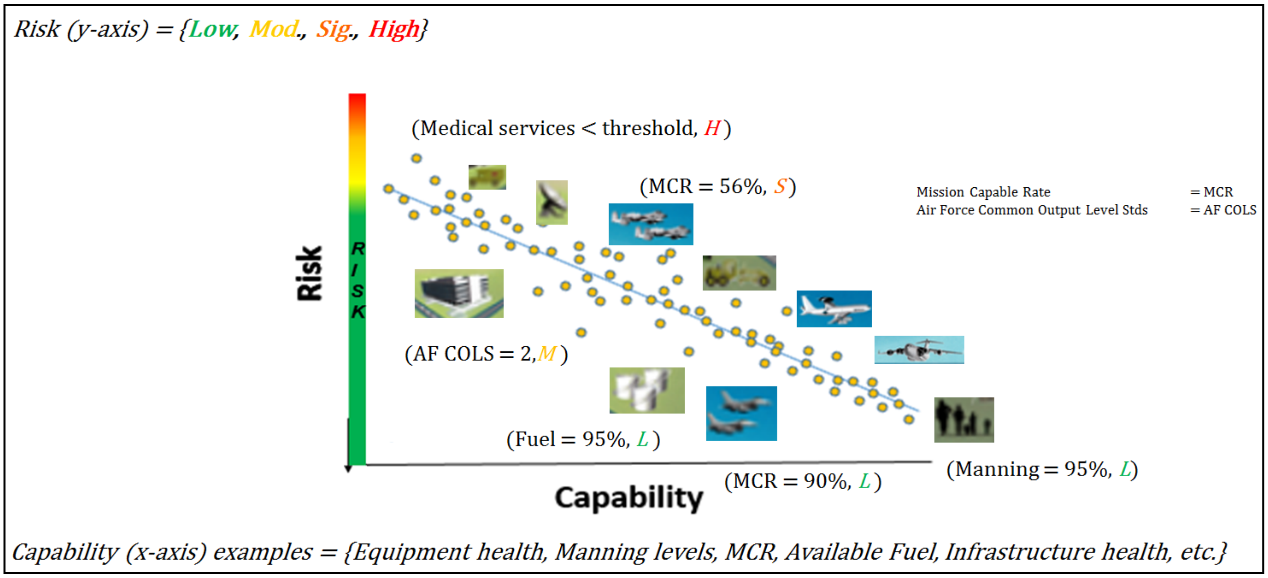


Figure I-4: Capability versus Risk (Bradshaw, 2016)

A key assertion in the current methodology is that before personnel risk can be accurately assessed, managerial efficiency, corporate preference, and objective risk computation, should be examined. This work facilitates that examination. Efficiency is the next topic of discussion.

Efficiency

Efficiency is hard to assess in a dispersed organization. USAF personnel capability is spread across the world. The USAF has hundreds of installations geographically separated across all continents. It is challenging for managers to provide efficiency assessments across these installations if objective data are not used. A 2014 study using data from 35 USAF organizations revealed millions of dollars possibly wasted due to various performance inefficiencies (Boehmke, 2015). The Boehmke study prompts questions, e.g., is there a significant association or relationship between efficiency and risk? If there is a significant association between efficiency and risk, how do we address it?

Data Envelopment Analysis (DEA) is an aggregation technique that allows unit (to include units without price points) (Han and Sohn, 2011) performance to be compared by examining the ratio of weighted outputs and inputs (Colbert et al., 2000). While data in the form of inputs and outputs alone cannot produce a holistic representation of efficiency, a non-parametric objective technique such as DEA yields a potential start to assessing personnel efficiency at USAF bases.

A desirable DEA property is that the weight values for each assessed organization are defined by an optimization algorithm and not decided by the user (Huguenin, 2012). This increases objectivity in determining the significance of the outputs and inputs. DEA combines numerous relevant outputs and inputs into a single number that represents productivity or efficiency (Metters et al., 1999). DEA is an established technique among the management science and operations research communities. Between the inception of DEA (Charnes et al., 1978) and 1992, over 470 articles were published concerning DEA (Seiford, 1994), and the pace appears to have accelerated since that time (Metters et al., 1999).

According to a 2010 DEA literature survey among application-based articles, the top-five industries addressed were: banking, health care, agriculture and farm, transportation, and education. Of approximately 5,000 articles examined, the military industry represented less than 20 of the total sample size or approximately 0.4% (Liu et al., 2013). Of record, it appears only sixteen military articles have been published since 2010 (Zunker and Howard, 2018). This implies there exists a large opportunity for growth and examination of DEA and its application to military organizations.

In summary, this research foci explore various analytical-based methods to compute organizational risk using personnel data. Further, this work examines if there is a statistically significant relationship between personnel risk and efficiency. That is to say, the higher the risk, the lower the efficiency or vice versa. The next section explores this research from an USAF enterprise perspective.

Agile Combat Support

This work uses a repeatable methodology using mathematical rigor to further quantify and qualify strategic personnel risk. The scope of this work is from the Agile Combat Support (ACS) perspective. ACS is a core function that enables air and space power to contribute to the objectives of a Joint Force Commander (JFC). Effective combat support operations allow combatant commanders to improve the responsiveness, deployability and sustainability of forces. ACS allows combat support to be conducted whereby responsiveness can be substituted for massive deployed inventories (Air University.com, 2017).

Further, ACS capability is the process from mission need to mission effect for all Air Force weapon systems, which consists of six enterprises: Research & Development (R&D), Life Cycle Management (LCM), Test & Evaluation (T&E), Logistics & Sustainment (L&S), Installation & Mission Support (I&MS) and Institutional. Figure I-5 illustrates the 'Big picture' view of ACS as it relates to risk delineated by force and mission.

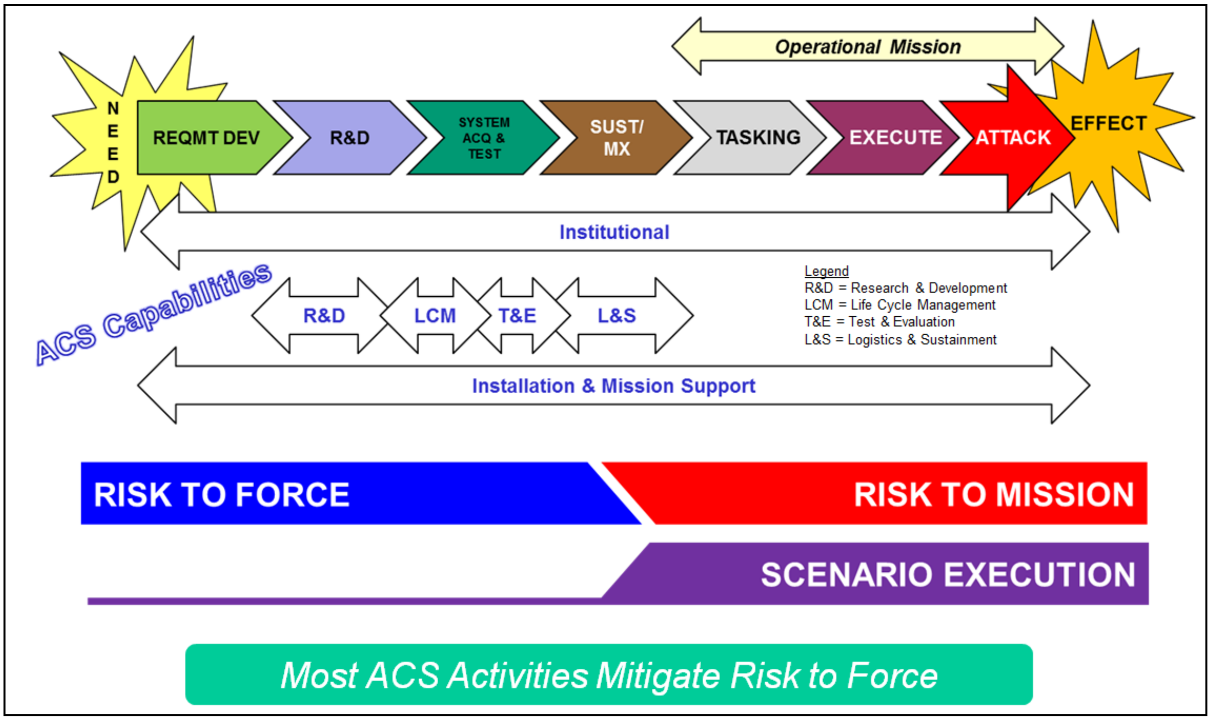


Figure I-5: Agile Combat Support (ACS) Big Picture (AFMC A9A, 2016)

In the USAF, ACS is led by the Commander of Air Force Materiel Command (COMAFMC). AFMC is a major command (MAJCOM) that develops, acquires and sustains the aerospace power needed to defend the United States and its interests for today and tomorrow (AFMC website, 2017). This is achieved through management, research, acquisition, development, testing and maintenance of existing and future weapons systems and their respective components (AFMC website, 2017).

As the core function lead (CFL[4]) for ACS, COMAFMC defines RtM as the ability to provide effects as called for within planning constructs for anticipated threat environments

[4] Since, this writing, CFLs have been removed and replaced with a new leadership construct called the Air Force Warfighting Integration Center (AFWIC).

(e.g. Defense Planning Guide (DPG) scenarios). The DPG provides guidance in the form of goals, priorities, and objectives, including fiscal constraints, for the development of each military department (Acqnotes.com, 2017). RtM is dependent upon creating a *future force* capable of providing the desirable effects. COMAFMC defines RtF as the ability to deliver the *future force* (e.g. Trained Personnel, Weapon Systems, Equipment, Infrastructure) used to evaluate RtM. In other words, RtF should drive RtM. Figure I-6 illustrates this concept.

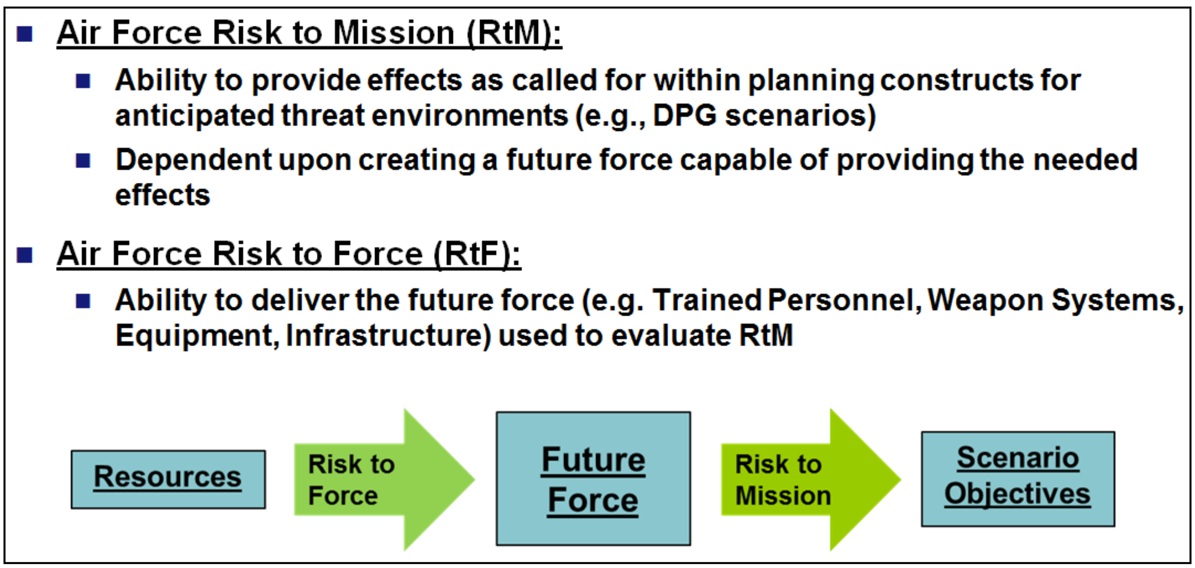


Figure I-6: Agile Combat Support (ACS) Risk Type Definitions (AFMC A9A, 2017)

Problem Statement

There is a widespread perception among Core Functions that (i.e. enterprises of people and systems) the logistics and mission support (*which impacts RtF*) required to execute DPG scenarios (*which impacts RtM*) will be in place for war or (D-Day). The ACS Subject Matter Experts (SMEs) do not agree, but cannot provide sufficient analysis (Pitstick, 2017). A challenge to accurately depict RtF is a conundrum of assessing both programmatic (i.e. weapon system programs) and capability risk. USAF programmatic risk is typically managed in the form of cost, schedule and performance. While this approach is sufficient to track, monitor and assess weapon system delivery and sustainment, it does not adequately address ACS' ability to meet DPG scenario requirements which should be a precursor to determine RtM capability gaps and accurately assess strategic risk. Capability gaps are often categorized into three distinct timeframes: near (0-5 year), mid (>5-10 year) and far (>10-30 year). A more comprehensive risk assessment is needed to characterize potential capability shortfalls for a near, mid or far term crisis. The methodology presented in this work provides a more rigorous alternative to assessing risk in each of the three distinct planning timeframes.

The USAF uses the Strategic, Planning & Programming Process (SP3) as a guide to strategic budgeting and decision making. One of the major outputs of the SP3 is the Program Objective Memorandum (POM). The POM is an annual recommendation from the Military Services and Defense Agencies to the Office of the Secretary of Defense (OSD) concerning the planning and allocation of resources (i.e. ***Personnel***, Infrastructure, Readiness and Modernization & Recapitalization) for programs to meet the Defense and Service (e.g. USAF) planning guidance (Acqnotes.com, 2017). The POM covers the 5-year Future Year Defense Program (FYDP) and presents the Service proposal on the intent of allocation of available resources (Acqnotes.com, 2017).

The POM includes an analysis of capabilities across the aerospace and cyber domains to include objectives, missions, alternative methods to accomplish objectives, and allocation of resources. The resources are planned, managed and executed by 12 Air Force Core

Functions of which ACS is one and has the largest portfolio exceeding 60 billion dollars. All resources *planned* are not *programmed* (resource allocated and budgeted); the delta between the two translate into a level of strategic *risk*. Figure I-7 provides a visual of how the POM is produced.

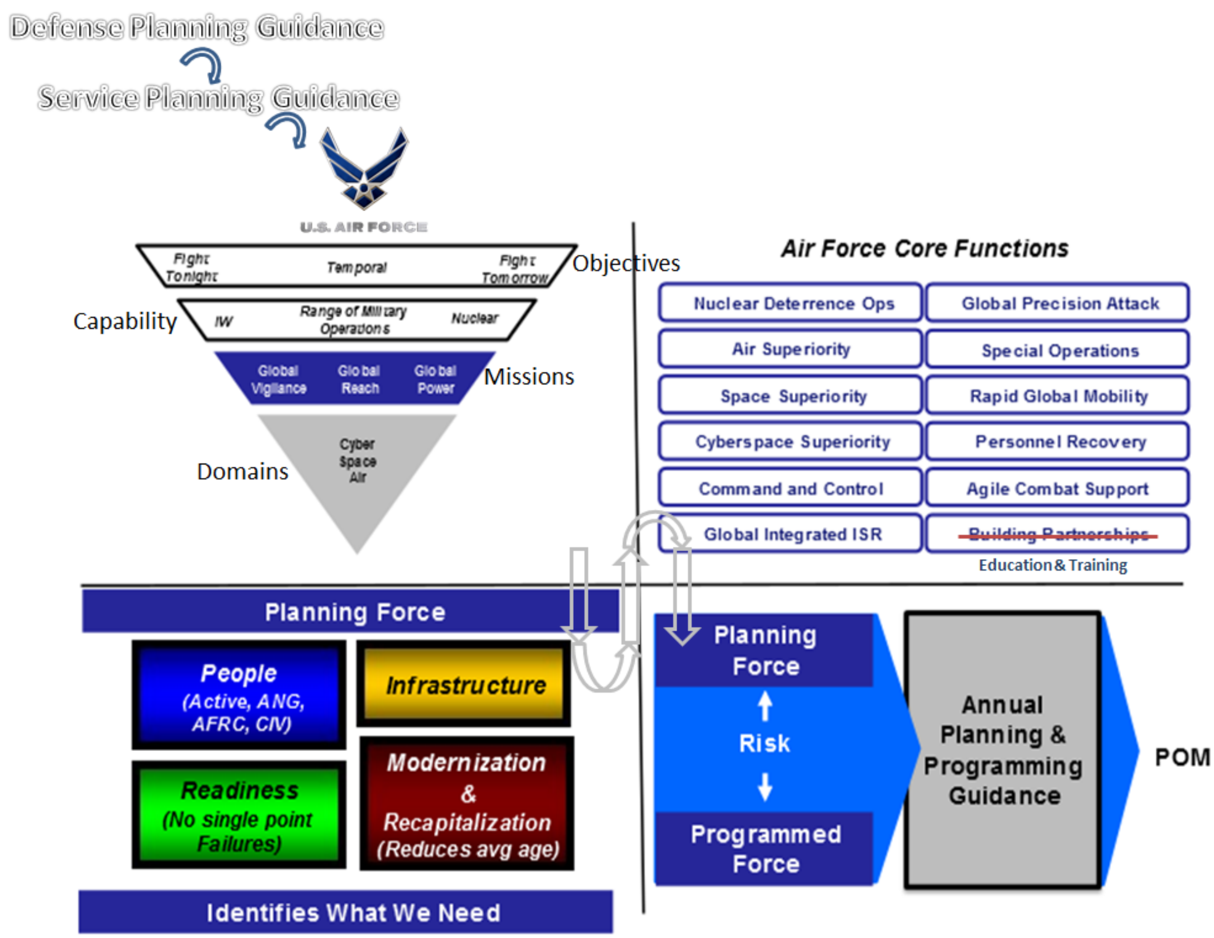


Figure I-7: Notional Strategic, Planning & Programming Process (SP3) (AF 5/8, 2011)

This work will expound upon the aforementioned ideals and provide methods to objectively assess personnel risk and enable senior Air Force leaders to better manage ACS personnel capability and enhance maximization of readiness.

Research Objective and Questions

This research explores and develops a repeatable baseline personnel risk assessment methodology, focused on the following research question: Can a baseline ACS comprehensive risk assessment (ACS RA) methodology be developed that rigorously accounts for personnel capability enablers and practices? This research question requires examination of the following specific questions:

- Is there a meaningful *manning* relationship between USAF Core Functions and full m*anning* levels?
- To what extent can the examination of active duty *manning* increase awareness of USAF efficiency?
- Is there a statistically significant relationship between career field *manning* efficiency and risk, which can enhance resource utilization and prioritization?
- Can an algorithm be used to compute an organizational *personnel* risk assessment?

Insight gained into these questions will enhance traceability of current personnel capability and requirements, will improve defensibility and credibility of the ACS risk assessment, and enhance strategic decision making when faced with tough challenges.

Scope

There are five bedrocks to USAF capability: Personnel, Training, Equipment, Infrastructure and Institutional, which are further characterized as the planning force. It is impossible to provide capability without all of these components. USAF capability begins and ends with the airman. If airmen are not available and trained to perform desired tasks to inject capability, the remaining equipment, infrastructure and institutional components are ineffective. While Figure I-7 summarizes the SP3 process to include the planning force, the data to adequately assess strategic risk regarding infrastructure, readiness and modernization are either classified or not readily accessible to analyze. As a result, this research is scoped to active duty military and civil servant personnel. Assumptions are applied to account for the readiness and training components. Figure I-8 is an illustration of the scoped research effort.

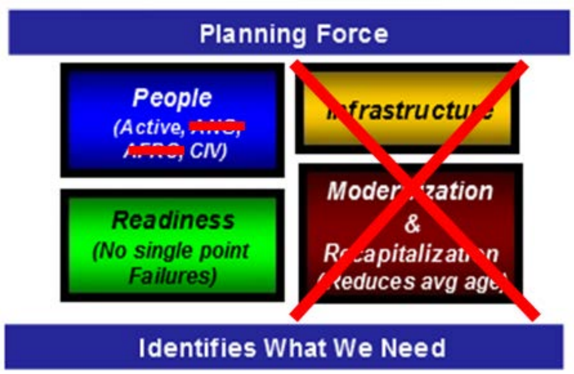


Figure I-8: Scoped Planning Force Analysis

People are needed to plan, manage, distribute and execute USAF capability. A goal of this research is the identification of personnel risk to be used as a precursor to better inform the infrastructure and modernization/recapitalization risk assessments. This approach should produce a more comprehensive strategic risk assessment.

Methodology

The theme of this research is to develop methods to help the Logistics Supply Chain Management community use human resources as it relates to USAF strategic risk assessments. The methodology incorportates advanced operational research techniques into practice using personnel data. This work supports senior decision making as it relates to managing personnel capability.

The first part of the USAF personnel risk assessment series uses statistical comparisons of odds ratios and contingency table analyses revealing manning shortfalls in all 12 Core Functions or large enterprises. From a strategic risk assessment perspective, if capability can be assessed via manning shortfalls, then risk vulnerabilities and drivers become more traceable for decision makers.

The second part uses Data Envelopment Analysis (DEA) to measure and compare efficiency among ten F-16 active duty bases utilizing pilot manning as inputs and sorties as outputs. This work has two-fold purposes: 1.) demonstrate that efficiency can be objectively assessed using personnel manning data and 2.) pave the way for a more comprehensive methodology to assess if a statistically significant relationship exists between USAF personnel efficiency and risk.

The third part uses the classic definition of risk and applies modeling techniques to produce risk values for career fields and determine if statistically significant relationships exist. There are inferences from a statistically significant relationship. For instance, if efficiency is positively correlated with risk, this can infer more efficiency is related to more risk. If more efficiency infers less risk, then, personnel resource planners could recommend career field managers better utilize current manning levels before more resources are considered for allocation. The fourth part surveys risk aggregation techniques to ultimately produce a valid, objective personnel risk assessment. The fifth part provides conclusions and recommendations regarding methodology implementation. These added analytical insights foster better strategic decision making by identifying capability gaps, and provide an increased level of objectivity to support personnel resource allocation. The results of the analysis hope to better inform the USAF Strategic, Planning & Programming Process (SP3).

Assumptions

To date, it appears there are no personnel capability assessments being performed to measure *efficiency* and *risk*, and the implications thereof. USAF strategic risk assessments are currently analyzed at the core capability level. A core capability is an enterprise necessary for the USAF to perform its mission as part of the Department of Defense (DOD). As of calendar year 2017, there were 48 distinct core capabilities. Assessing risk at the core capability is a good start to assessing risk, but is not comprehensiveness enough. There are many missed, unexamined and not well-understood issues that occur below the core capability level, particularly as it relates to RtF which theoretically should influence RtM. Understanding potential personnel shortfalls at the career field level should better inform core capability analysis, and thus increase credibility and defensibility of strategic risk assessments.

Currently, ACS planners and programmers use funding level per PEC, or Program Element Code, to assess tasks needed to address desired capability. All USAF programs have PECs. PECs are generally alphanumeric strings of characters that represent groupings of Air Force Specialties (AFS) or career fields to carry out certain tasks. The PECs are also assigned cost values as the primary means to track and manage funding. While the PECs are linked to ACS tasks, the amount of specific personnel (by career field) needed to accomplish the tasks versus personnel requirements are not connected. Furthermore, there currently is no repeatable way to assess USAF personnel efficiency.

Limitations

The risk of using data from a centrally managed personnel database to develop a personnel risk assessment as a means to baseline personnel capability across all six ACS enterprises has an unquantifiable impact on enterprise risk assessments. If the data are inaccurate, the results are skewed and subsequent risk assessments may be invalid. To compound the issue, some enterprises have independently developed manpower models to assess their ability to meet current and future requirements (i.e. funded and unfunded). Funded requirements are provided in the centrally managed personnel database, while unfunded requirements are not provided to the enduser. Unfortunately, these manpower models have not been validated by the Air Force Personnel Center (AFPC) or the Higher Headquarters Personnel, Manpower and Services Directorate (AF/A1). If the data and manpower assumptions from the A1 database are correct, the traceability, defensibility, objectivity and credibility of the risk assessments increase.

This research used personnel as key force enablers of USAF capability to assess strategic risk. Specifically, is there a rigorous way to assess personnel risk to ultimately inform strategic decision making? Lastly, the analysis is conducted within the HQ AFMC Strategic Plans, Programs, Requirements, and Analyses Directorate (HQ AFMC A5/8/9), whereby the Analyses and Assessments Division (HQ AFMC A9A) serves as the lead integrator. The collection of this information requires support from the HQ AFMC 5/8 (Plans, Programs and Requirements Division).

Implications

ACS Planners and programmers defend the needs of their programs emotionally or base their arguments on precedence instead of articulating what the requirements are and what current capability exists to meet a desired endstate. This results in a lack of credibility regarding the enterprise risk assessments, which are sometimes dismissed as over or understatements of risk by senior officials at higher headquarters.

There is no repeatable, measureable *baseline* personnel capability assessment across the six enterprises in ACS (Pitstick et al., 2016). Currently, each enterprise independently assesses risk (HQ AFMC A9A, 2016). Some enterprises strongly consider manning shortfalls and overages, while others do not (HQ AFMC A9A, 2016). However, ACS enterprises depend upon one another to deliver capability in order to achieve a given mission. Examining the relationship between efficiency and risk among the USAF career fields needs study: for example, what if we discovered, while the Civil Engineering (CE) function may not have adequate manning, it performs more efficiently with its current resources than other career fields. This at a minimum suggests a level of *managerial insight* is available for potential promotion across the rest of the personnel domain. The lack of personnel risk accountability between and among the enterprises results in risk assessments that are sometimes overstated or not comprehensive enough.

A defensible, traceable personnel risk assessment methodology allows all ACS enterprises to defend why they need more resources to perform required tasks.   Further, the successful implementation of a repeatable, proven process lends credence to other core functions using this approach, which should increase USAF strategic risk assessment confidence.

Preview

Chapter II of this research presents a literature review and background of the problem. The literature review examines problem resolution using various statistical and analytical approaches to assess personnel organizational risk to include contingency table analysis, logistic regression, normal, sigmoid and other known mathematical distributions and functions. Chapter III is a paper that reveals mathematical evidence that a corporate preference exists in what enterprises senior leaders choose to fully man or not fully man. Chapter III uses logistic regression, relative risk and odds ratio computations to illustrate significant manning relationships among the USAF's 12 core functions and 32 functional areas. Chapter IV provides a production efficiency demonstration study optimizing USAF F-16 active duty fighter pilot manning and sortie production rates among ten bases. Chapter V utilizes a variant of the logistic function and normal distribution to quantify personnel risk and statistically examines if there is a relationship between risk, capability and efficiency. Chapter VI explores aggregation techniques to depict a core capability as a consolidated risk score to be ultimately subsumed by a more strategic level, comprehensive risk assessment model. Lastly, Chapter VII provides conclusions; dissertation significance; provides recommendations for courses of action (COA); and presents several avenues for further exploration.

II. Literature Review

Introduction

This chapter provides a literature search of various components of risk as it relates to capability. The purpose is to better inform this research by providing past discussions about the relationship between risk and capability. First, we identify the components of a risk assessment. Second, we identify capability. Third, we address the question, what is risk in the context of capability? Fourth, organizational efficiency is explored.

Risk Assessment Framework

A Risk Assessment Framework (RAF), presented by the Defence Research and Development of Canada (DRDC), categorizes risk into three phases: *Problem Formulation and Scoping*; *Planning and Conduct of Risk Assessment*; and *Risk Management* (Bayne and Friesen, 2016). Figure II-1 represents a comprehensive scan of the RAF. What follows is an adaptation of the RAF from a USAF perspective using Phases I and II. Phase III (risk management) is less of a focus area effort for this research.

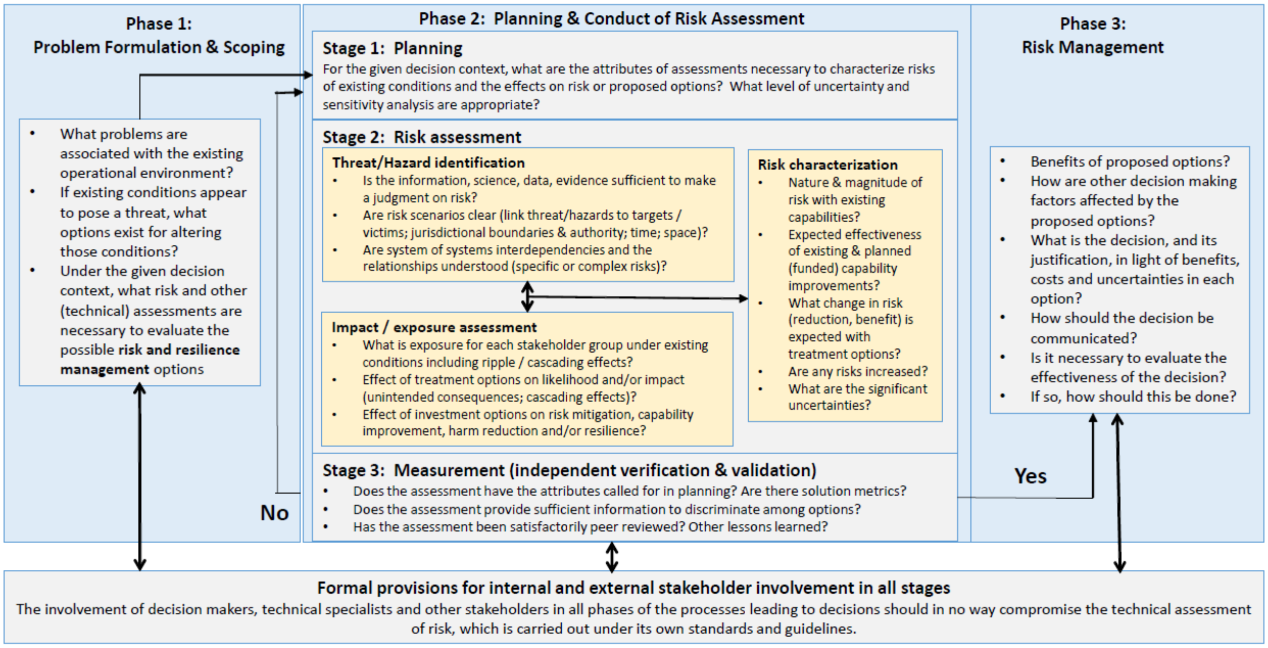


Figure II-1: Canadian Risk Assessment Framework (Bayne & Friesen, 2017)

<u>Framework Adaptation</u>

A U.S. application of the Canadian RAF is used to illustrate Phase I: problem formulation. U.S. military capability is formulated and managed by the Programming, Planning, Budgeting and Execution (PPBE) process. There are volumes of literature on this topic. Figure II-2 provides a visualization of the stages of PPBE. We see the requirements generation stage is conducted in the first phase (Planning). That is to say, a National Security Strategy (NSS) is envisioned by the National Command Authority (NCA).

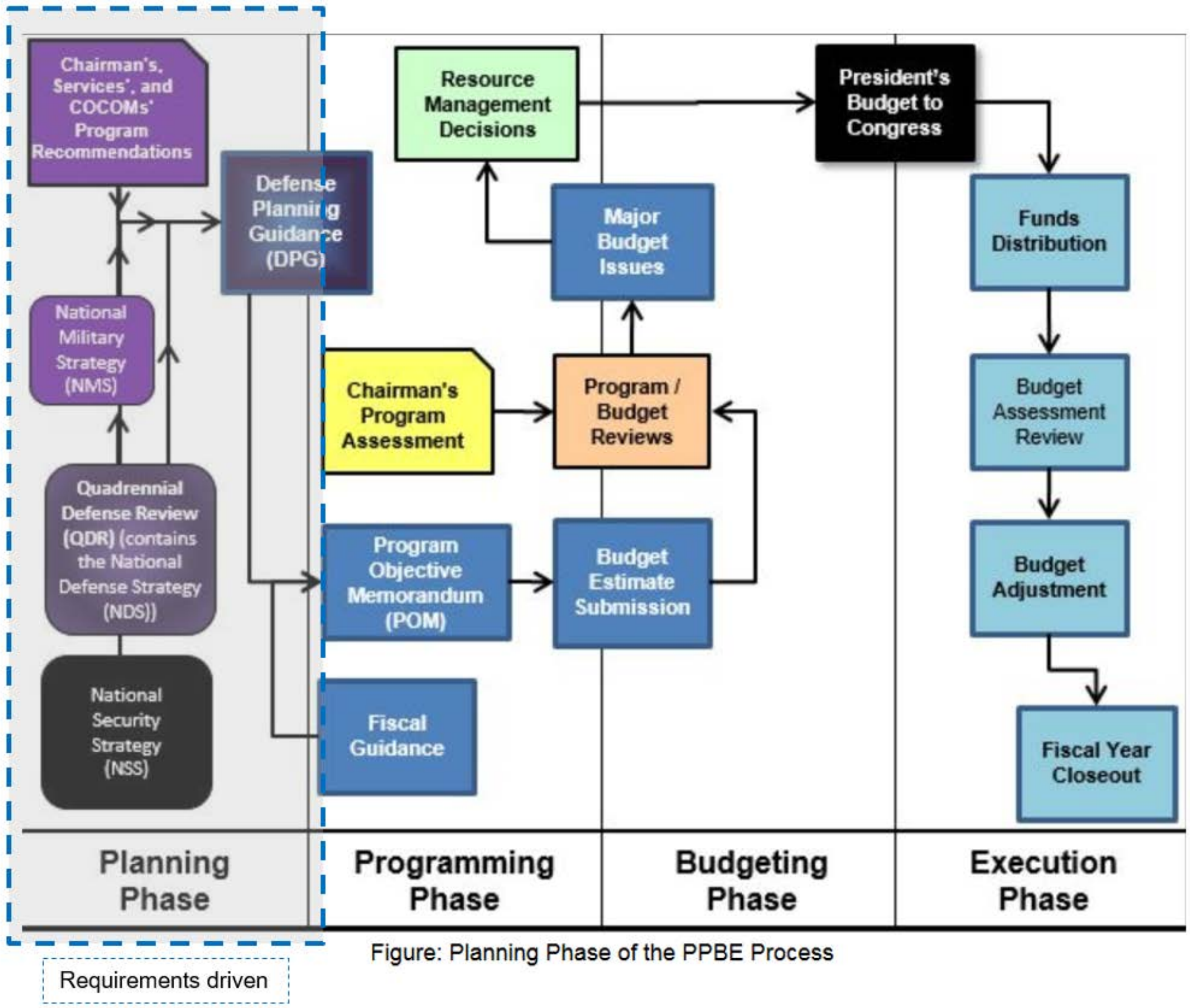


Figure II-2: PPBE Diagram (Manning, 2017)

The NCA consists of the US President, Vice President, Secretary of Defense and Deputy Secretary of Defense. The NCA staff develops the actual NSS. This NSS is created to inform the National Military and Defense Strategies (NMS and NDS, respectively) (Manning, 2017).

From these documents along with the Quadrennial Defense Review (QDR[5]), the chiefs of military services along with combatant commanders and their staffs make recommendations to form the Defense Planning Guidance (DPG). These documents provide the services an idea of the *current and future threats* and *broad resource expectations* to counter the threats. This planning feeds the annual Program Objective Memorandum (POM) and fiscal guidance.

A takeaway from the planning phase of the PPBE process is if planners, programmers and analysts get this wrong, the POM is misinformed; which misinforms the Presidential Budget (PB); which limits the services' ability to deliver, generate and sustain combat capability to meet a desired end-state. This work does not revisit or recreate the military requirements generation procedure. While problem formulation is critical to assessing risk, we assume a well-formulated/scoped problem is defined, and thus, we use an existing baseline of personnel capability and compare it to existing (*and future*) requirements to help assess risk.

Phase II of the RAF is the planning and conduct of the risk assessment. It consists of three stages: planning, risk assessment and measurement. The U.S. would use the Strategic Planning, Programming Process (SP3) to guide the planning piece (stage one) of phase II. This research is scoped to personnel capability and assumes funded personnel requirements take into account the current threat and capability gaps. This assumption addresses the threat/hazard identification component of the risk assessment stage. The impact is further studied and examined in the form of a technical paper, which is discussed later in this research. The focus of this literature review is proper characterization of personnel risk via

[5] QDR is a legislatively-mandated review of Department of Defense strategy and priorities (Manning, 2017).

the classic components: likelihood of failure *to not* meet a desired outcome and impact of this failure. The next section addresses this phenomenon.

Risk Characterization

Risk is the likelihood of failure and severity of the consequences of this failure (Lindbom et al., 2015). Further, risk consists of four factors: events, consequences, uncertainties and tasks (Aven and Renn, 2009). Events are possibilities of unforeseen situations or occurrences that can or will negatively affect an organization (Kenton, 2018). From a personnel risk perspective, the events are probabilities of failures ranging from 0 to 1. Consequences represent the severity of adverse effects (Aven, 2011). The consequences from the distinctive manning rates uses a function that generates a backwards Sigmoid-curve (S-curve). In other words, we seek to develop a mathematical relationship between manning rate (x-axis) and impact (y-axis). The consequences from the distinctive manning rates are developed using a sigmoid function, which is a variant of the logistic function.

Uncertainty is a potential, unpredictable, and uncontrollable outcome (Hansson and Zalta, 2014). This research represents uncertainty as a likelihood of failure to achieve a given manning rate. We explore several well-known mathematical distributions to examine which are the most well-suited for demonstrating personnel uncertainty. A task is an identifiable function of a job or activity (Shockey, 2012). For the ACS risk assessment, the tasks are already defined by SMEs and are categorized by enterprise and PEC.

For further solidification of risk characterization, an example of a strategic risk framework (SRF) is explored. Rowe et al. (2017) promote ways to prioritize investment decisions in military cyber capability using risk analysis assert a SRF should contain independent security layers. Rowe et al. (2017) assert in a cyber context, a security layer could be ‘Shape’. Shape refers to the *change* of motivation behind a threat. For example, overtly promoting peace talks between potential threat nations is a form of shaping. This layer is assigned a probability, which signifies a likelihood of success. By taking the complement, we obtain a likelihood of failure. Figure II-3 illustrates the principle of creating independent security layers across two risk components: *likelihood of failure* and *consequence*. Each blue box represents a security layer. One goal of the SRF is to shape, deter and prevent the threat, thereby reducing the likelihood of a failure. If a likelihood of failure exists, the other goal of the SRF is to contain, adapt, investigate and protect against the consequence of the failure. The overarching goal is to reduce the enduring impacts of the threat.

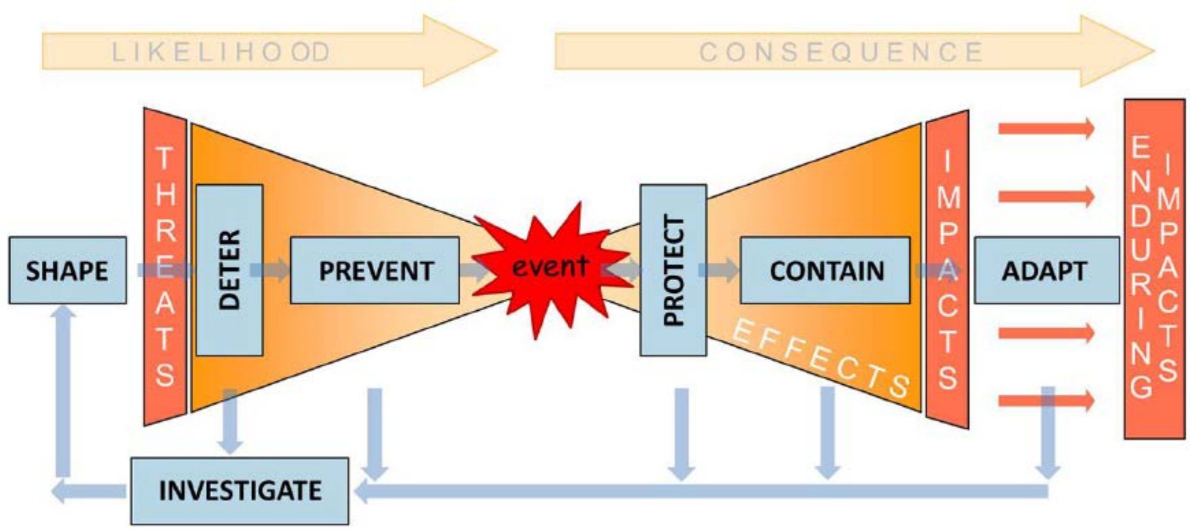


Figure II-3: Cyber SRF (Rowe et al., 2017)

An example of how the cyber SRF could be applied to personnel follows. Perhaps *shaping* is announcing troop increases. Deterrence could be increasing the Nuclear Deterrence Operations (NDO) core functional personnel footprint. Prevention is a plus-up of personnel in certain strategic military installations. After a breach of security, protect could mean a recall of recently retired airmen and national air reserves. Containment is the addition of the National Guard component. Adapt is to support recovery and restoration of potential lost personnel.

The existence of multiple independent security layers infers a joint probability can be computed. The idea of 'independence' formally allows risk practitioners to compute a joint probability (i.e. multiply the probabilities of failures and obtain an overall risk score). A limitation with this approach is the more layers, the more likely risk will increase; the multiplication of probabilities will yield an overall lower reliability or higher risk score.

While a possible credible approach to characterize cyber risk, the methodology cannot be prescriptively applied to the ACS RA for two main reasons. First, manpower is one of the most expensive assets in the USAF inventory. For any of the security layers, *swift* maneuver and deployment of personnel to various locations is not only costly, but in practice difficult to administer. Unlike a cyber maneuver, most actions can be conducted without the movement of forces. Second, the scope of USAF strategic manpower spans across over 250 career fields, encompassing some 600,000 personnel. Each career field is arguably interdependent and *not independent*, which violates the joint probability computation procedure used in the cyber SRF. These levels of complexity make the application of the cyber SRF to the ACS RA ill-advisable. However, the concept of *likelihood of failure* and *severity of the consequence of this failure* to characterize risk is valid. The next section examines risk in the context of capability.

Relationship between Risk and Capability

A study conducted by Lindbom et al. (2015) alluded to a worldwide literature search of ‘capability’ and ‘capability and risk’, which yielded 500,000 and 34,000 hits, respectively. The study mentions that while the querying resulted in large volumes of literature, very few instances defined capability as it relates to risk. The data collected for the study from scientific literature were condensed to 13 guidelines as it relates to the definition of capability. From a military perspective, we present 4 of the 13 below:

I. Capability refers to resources, systems, structures and processes necessary to deliver current and future requirements (Bhatta, 2003).

II. Capability is the framework an organization needs to make use of assets (e.g. resources, competence and knowledge) and skills (e.g. capacity organization has to manage external conditions or events) (Renn, 2008).

III. Capability is the attributes of an organization, such as time, labor and capital primarily used for exploitative purposes to implement a strategy (Kusumasari and Siddiqui, 2010).

IV. Capability is a demonstrable ability to respond to, and recover from, a particular threat or hazard (U.K. Cabinet Office Glossary, 2014).

From these four definitions of capability, the following commonalities are observed: capability is a type of resource; capability is necessary to implement strategy; and capability is necessary in order to respond to a threat. Given these trends, we affirm the Air Force guidance (discussed in Chapter I) and its approach to classify risk and capability. That is to say, the Air Force definition of risk addresses its ability to prepare (capacity) and its ability to respond (capability) to a given threat (Lindbom et al., 2015).

While there is a relationship between capability and risk, the relationship is at this point still mathematically ill-defined. We assume there is a relationship between risk and capability. That is to say, the more capability (e.g. fuel, manning, higher mission capable rates (MCRs), positive infrastructure levels (e.g. Common Output Level Standards (COLS)), equipment and supply status, etc.) that exist, the less risk incurred and conversely, the less capability that exists, the more risk incurred. We explore mathematical functions to examine if personnel risk can be further categorized in the form of a likelihood of failure and impact.

Mathematical exploration of likelihood of failure of an occurrence

Objective ways to compute personnel likelihood of failure are explored. Ultimately, the goal is to obtain an operationally representative probability of having 100% or less available and trained personnel to achieve a task or core capability. The likelihood of failure is just half of risk; we also need the impact of this failure to fully compute personnel risk. This portion of this work focuses on the likelihood of failure component of risk.

The ACS RA data can be either continuous or discrete. Manning rates are treated as continuous whereas manning data decomposed by number of successes (positions filled), number of trials (number of positions) and probability of success (100% manned) are treated as discrete. We consider the following distributions: normal[6] (standard), binomial, lognormal, Poisson, geometric, negative binomial, hyper-geometric and gamma.

The aforementioned distributions are compared using six categories: inputs, probability function ($p(x)$), range of values, expectation ($E(x)$), variance ($V(x)$) and relative

[6] More details on the normal distribution are provided in Chapter V.

application. The probability function *p(x)* estimates the likelihood a career field is not 100% manned, trained and available. Several inputs and parameters are necessary to make this computation. The variable p represents the probability of an event.   The variable q (i.e. absence of a probability of event) represents the complement of p (i.e. $1 - p$).   The probability function is either a probability distribution function (pdf) for continuous distributions or a probability mass function (pmf) for discrete distributions. The range of values is explicitly defined to allow for function feasibility. The expectation is the expected value of a random probability-weighted average of all possible values (Hamming, 1991). The variance is the expectation of the squared deviation of a random variable from its mean (Hays, 1981). Table II-1 presents a summary of these distributions. Of the eight examined, the normal, lognormal, gamma and binomial distributions are the most suited for the baseline portion of the ACS RA.

Table II-1: Distribution Summary (Mendenhall and Sincich, 2007)

Name	Inputs	*p(x)*	Values of *x*	*E(x)*	*V(x)*	Application
Binomial	Probability of success, # of successes in *n* fixed trials	$\binom{n}{x} p^x q^{n-x}$	$x = 0,1, \dots n$	np	$np(1-p)$	The # of successes can be represented by personnel. The # of trials is the number of personnel reqmts. The prob. of success can be either a historical manning rate or 100%.
Negative Binomial	Probability of success, # of trials up through *k*th success	$\binom{x-1}{k-1} (q)^{x-k} p^k$	$x = k, k+1, \dots$	$\frac{k}{p}$	$\frac{kq}{p^2}$	Ideal for determining number of personnel reqmts
Poisson	Number of successes per unit of time, mean	$\frac{e^{-\lambda}\lambda^x}{x!}$	$x = 0,1,2, \dots$	λ	λ	Appropriate for count data where mean and variance are equal.
Geometric	Probability of success, # of trials up through 1st success	$q^{x-1}p$	$x = 0,1,2,3 \dots$	$\frac{1}{p}$	$\frac{q}{p^2}$	Ideal for determining number of personnel reqmts
Hyper Geometric	*N* total # of elements, *M* # of successes, *n* # of elements drawn, *x* # of successes drawn within *n* elements	$\frac{\binom{M}{x}\binom{N-M}{n-x}}{\binom{N}{n}}$	$x = \begin{cases} Max[0, n-(N-M)] \\ Min(r,n) \end{cases}$	$\frac{k}{p}$	$\frac{kq}{p^2}$	Ideal for determining number of personnel reqmts without replacement
*Normal (Gaussian)	Random variable *x*, mean (μ) & standard deviation (σ)	$\frac{e^{-\frac{1}{2}[\left(\frac{(x-\mu)}{\sigma}\right)]^2}}{\sqrt{2\pi\sigma}}$	$\sigma > 0$	μ	$k\sigma^2$	100% manning rate reqmt can be represented as a Random Variable, historical career field rate as μ with respective σ
LogNormal	Random variable *x*, mean (μ) & standard deviation (σ)	$\frac{e^{[\left(-\frac{1}{2}(\frac{\log(x)-\mu}{\sigma}\right)]^2}}{x\sigma\sqrt{2\pi}}$	$x = \begin{cases} > 0 \\ \leq 0, 0 \end{cases}$ $\sigma > 0$	μ	σ^2	Same as normal however data are typically right skewed, and results tend to be parsimonious
Gamma[7]	Shape ($\propto$), scale (β) and random variable (x)	$\frac{1}{\Gamma(\alpha)} x^{(\alpha-1)}\beta^{\alpha}e^{-(\beta x)}$	$x > 0$ $\alpha, \beta > 0$	$\frac{\beta}{\alpha}$	$\frac{\beta}{\alpha^2}$	100% manning rate reqmt can be represented as a Random Variable, and historical std dev. and manning rate as α and β, respectively.
* Indicates the most applicable distribution						

PDFs are stated in Table II-1, but the cumulative distribution function (cdf) is needed in order to compute the probability of being at least 100% manned (p^*). The general cdf is

[7] For parametrization (i.e. assuming normally distributed data), $E[X] = \propto \beta$ and $Var(X) = \alpha\beta^2$, respectively (SOCR, 2017).

presented as $F(x) = P(X \leq x) = 1 - P(X > x)$, where $P(X \leq x)$ represents the probability that a random variable X takes on a value less than or equal to x (Park, 2018). In the probability of failure context, x is 1 or 100% manned. Table II-2 provides a listing of the four relevant cdfs and respective parameters and formulae needed to compute p^*.

Table II-2: CDF Summary

Name	**Parameters**	**CDF (approximation)**
Binomial	$F(x; n, p) = P(X \leq x)$ $0 \leq x \leq n$	$\sum_{t=0}^{x} \binom{n}{t} p^t (1-p)^{n-t}$
Normal	$F(x; \mu, \sigma) = P(X \leq x)$ $-\infty < x < \infty$	$\int_{-\infty}^{x} \frac{e^{-\frac{1}{2}[\left(\frac{(y-\mu)}{\sigma}\right)]^2}}{\sqrt{2\pi\sigma}} dy \approx \Phi(\frac{x-\mu}{\sigma})$
LogNormal	$F(x; \mu, \sigma) = P(X \leq x)$ $0 \leq x < \infty$ $\sigma > 0$	$\int_{0}^{x} \frac{e^{(\frac{-(\ln(x)-\mu)^2}{2\sigma^2})}}{x\sigma\sqrt{2\pi}} dy \approx \Phi(\frac{\ln(x)-\mu}{\sigma})$
Gamma	$F(x; \propto, \beta) = P(X \leq x)$ $0 < x < \infty$ $\propto, \beta > 0$ where $\propto$ is an integer manning std. deviation	$\int_{0}^{x} \frac{y^{\propto-1} e^{\frac{-y}{\beta}}}{\Gamma(\alpha)\beta^{\alpha}} dy = \gamma\left(\frac{\alpha, \frac{x}{\beta}}{\Gamma(\alpha)}\right)$, $\Gamma(\alpha) = \Gamma(\alpha - 1)!$, $\gamma(\alpha, \frac{x}{\beta}) = \int_{0}^{\frac{x}{\beta}} t^{\propto-1} e^{-t}\, dt$

Table II-3 is a summary of notional career field probability of failure rates using lognormal, normal, binomial and gamma functions.

The binomial function behaves the most poorly, arguably followed by the lognormal and gamma. The binomial distribution overstates risk as the illustration of having 77 people, with 77 authorizations and a probability of success of 100% yields a failure probability of 0. The gamma and normal distributions are competitive candidates to determine the probability of not being fully manned given a historical career field mean and variance. The clearest example of comparison is shown in notional sample 5, where the normal output is the most operationally representative of personnel likelihood of failure given the parameters. The interpretation is the Force Support Officer career field based on a historical manning rate of 43% and 1 standard deviation from the said rate with a goal of being 100% manned, has a probability of failure of 0.72. The gamma function returns a probability of 0.87. These values not only account for number of personnel versus funded authorizations, but also available and trained personnel to achieve a task or core capability.   The sole selection of a distribution is based on practititioner experience, which includes a resampling of career field data that reveal the gamma appears more sensitive to outliers than the normal distribution. Further details of the normal distribution are discussed in Chapter V.

Table II-3: Distribution Summary

No.	Career Field	Asgn	Auth	Manning Rate	Hist. Manning Rate	Hist. Std. Dev.	Norm. p^*	Lognorm. p^*	Binom. p^*	Gamma p^*
1	Clinical SW	937	950	0.99	1.04	3	0.50	0.36	1.00	0.09
2	Logistics Plans Officer	65	111	0.59	0.61	3	0.55	0.42	1.00	0.28
3	Aero. Medical Service	77	77	1.00	1.04	1	0.49	0.15	0.00	0.61
4	Security Forces	810	816	0.99	0.99	3	0.50	0.37	1.00	0.11
5	Force Support Officer	25	63	0.40	0.43	1	0.72	0.33	1.00	0.87
6	Civil Eng. Officer	654	662	0.99	1.04	2	0.50	0.30	1.00	0.21
7	Civil Eng. (Electrical)	63	103	0.61	0.66	2	0.57	0.37	1.00	0.40
8	Civil Eng. (Ops Mgmt)	106	174	0.61	0.65	2	0.58	0.37	1.00	0.41

Mathematical exploration of impact of failure

There is a dearth of objective-based literature regarding the *impact* of personnel capability failure. This is mainly attributed to an inherent level of uncertainty. That is to say, even if all personnel requirements are filled, risk is still not completely eliminated. This phenomenon causes risk assessment analysts and managers to make general assumptions about personnel risk assessment practices. For example, in an organizational risk assessment which consists of hundreds of thousands of personnel, we assume personnel capability degradation is not linear. This means for every one funded personnel requirement not filled, there is not a similar reduction in overall personnel capability in a given enterprise. The impact of personnel failure is arguably a hybrid of linear and non-linear effects (Menon et al., 1996).

Sigmoid Function

The relationship between personnel resources and capability satisfaction is arguably not completely linear or entirely non-linear; Figure II-4 visually demonstrates this phenomenon. We seek to better actualize the relationship between the inability to meet manning expectations coupled with the impact of this shortfall. A way to approximate a mix of linear and non-linear effects is to use a sigmoid function (Menon et al., 1996). The sigmoid function is represented as a variant of the logistic function:

$$f(x) = y = \frac{1}{1+e^{-(x)}}, \quad \textbf{Eq. II-1}$$

where e is the natural logarithm base. The inverse is represented as

$$x = \ln\left(\frac{y}{1-y}\right). \quad \textbf{Eq. II-2}$$

Menon et al. (1996) provide theoretical demonstrations of sigmoid function applications as it relates to trigonometry and neural networks. This literature is more theoretical based and does not provide any reference to real-world applications. An application-based utilization of the sigmoid function is published to include the prediction of cost savings (Mahalingam and Vivek, 2016).

Based on historical account balances and respective dates, the algorithm is presented to automate savings management (Mahalingam and Vivek, 2016). The scope is internet banking in India where the currency is the rupee. For example, a bank member savings of 10,000 rupees is equivalent to 141 US dollars (current as of 1/30/2019). The data consist of member bank transactions to include debits, credits and alert messages (e.g. overdraft threshold warnings). A recommended savings percentage (not to exceed 20% of available account balance) is computed using a sigmoid function every 8 days or quarter of a month. For example, with an overall savings goal (e.g. 10,000 rupees), duration goal (e.g. 5 months) and maximum savings rate of 20%, the algorithm computes impact scores. Impact scores are calculated for quarter-monthly current transaction and transaction message values. The maximum difference between the transaction value and transaction message value determines the upper bound input for the sigmoid function. Date intervals are absolute differences of current and future quantized values. Date intervals are computed in 8 day increments within a month (i.e. 1, 9, 17, 25). Figure II-4 illustrates the example.

Date	*Initial balance*	*Savings @ 20%*	*Final balance*
1	10,000	2,000	8,000
9	8,000	1,600	6,400
17	6,400	1,280	5,120
25	5,120	1,024	4,096

Figure II-4: Example Savings Scenario (Mahalingam and Vivek, 2016)

The y-axis represents the output values of the sigmoid function ranging from zero to one. A pictorial representation of the automated savings sigmoid curve is provided in Figure II-5.

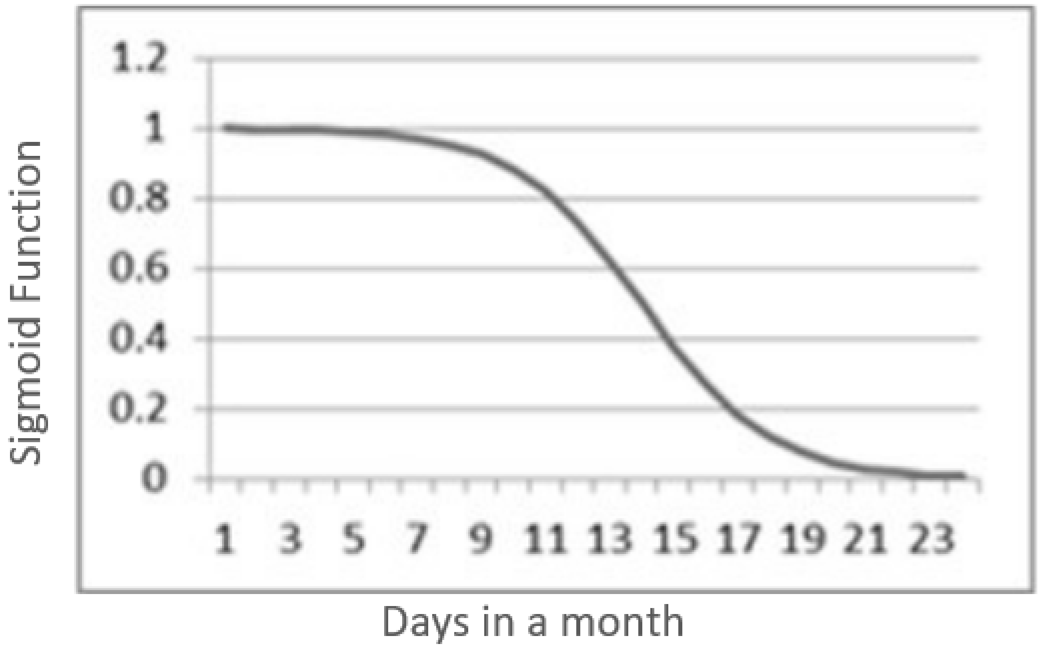


Figure II-5: Automated Savings Curve (Mahalingam and Vivek, 2016)

Other notable applications of the sigmoid function include consumer risk reduction strategies (Mitchell et al., 1999) and enterprise capability assessment prioritization (Bryan et al., 2010). A perceived risk theory study is presented examining consumer behavior during holiday periods (Mitchell et al., 1999) using artificial neural networks (ANNs). ANNs are fairly sophisticated models that require inputs and outputs typically coupled with the use of calculus (e.g. back propagation) to attempt to predict a phenomenon under examination (Hecht-Nielson, 1992). Mitchel et al. (1999) use the classic definition of risk (i.e. probability of failure coupled with impact of failure) as a focal point of risk foundation. The central premise of this research stems from the ideal that if more tourism marketing insight can be gained through perceived consumer risk behavior, then strategies among the holiday travel promotion industry can become better focused to ultimately increase revenue and build branding. Further, this work uses a survey instrument comprised of 60 questions with 152 British undergraduate respondents to collect tourism data to assess the following two objectives: 1.) what are the perceived risk and risk-reduced strategies associated with holiday-package purchases; and 2.) determine if a relationship exists between perceived risk, risk reduction and purchase intent.

The most popular ANNs consist of three categories or layers of units: input, hidden and output. A layer of ‘input’ units is connected to a layer of ‘hidden’ units, which is connected to a layer of ‘output’ units (Rumelhart et al., 1986). The connections are often referred to in neuroscience terms as ‘synapses’ similar to an interworking process of the human brain. The activity of the input units represents the raw data fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the synapses between the input and the hidden units. Similarly, the behavior of the output units depends on the activity of the hidden units and the weights on the synapses between the hidden and output units. ANNs have training components. The training of the network consists of feeding it multiple training samples and calculating the output for each of them. After each sample, the weights are adjusted in such a way so as to minimize the output error, defined as the difference between the desired (target) and the actual outputs (Vasilev, 2019). In the holiday package perceived risk study, the input units are risk variables (likelihood of perceived risk and impact), while the outputs are purchase intent and risk reduction strategy.   Figure II-6 provides a basic visualization of an ANN with one hidden layer.

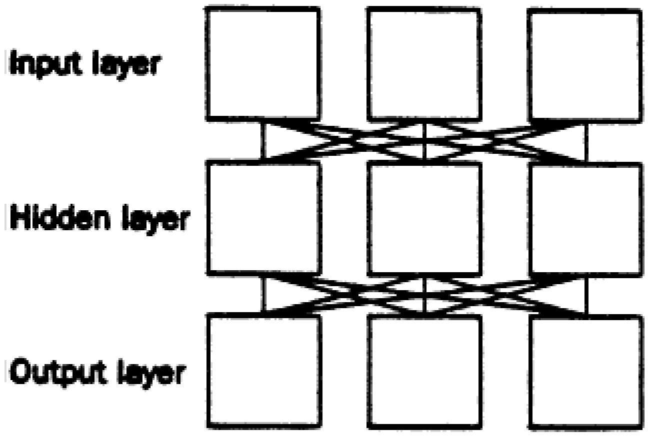


Figure II-6: ANN example (Mitchell et al., 1999)

The sigmoid function is relevant to the ANN because it is used as a nonlinear function that has the ability to propagate error through the network through the use of thresholds. The threshold is modeled via the sigmoid function that maps values from zero to one as stated in the previously discussed automated cost application. Typically referred to as a loss activation function, the derivative of the sigmoid function is expressed as:

$$f'^{(z)} = \frac{e^{-z}}{(1+e^{-z})^2} = \frac{1}{(1+e^{-z})} * \frac{(1+e^{-z}-1)}{(1+e^{-z})} = \boldsymbol{o}(1-\boldsymbol{o}), \qquad \textbf{Eq. II-3}$$

where *z* represents the *net* of the desired input vector, output vector and hidden layer. The error expression is generalized to include all squared errors at the outputs k =1, 2, 3…K. The end result is the output vector ($\boldsymbol{o}$) multiplied by its complement vector. The number of hidden vectors depends on the dimension n of the input vector and on the number of separable regions in n-dimensional input space.   For the personnel risk application, when the manning rates are large, the sigmoid function slopes steeply to signify minimal impact, but the curve steadily grows through a midpoint and continues to incline until a gradual ascend to the maximal impact as manning rates are very low. Mitchell et al. (1996) purport the use of ANNs allowed a relationship between perceived risk and risk reduction strategies such that holiday travelers see increasing knowledge of destination by reading and watching relevant television programs as a useful way to increase confidence in a trip. Further, travelers are less likely to become as adversarial when situations arise that require adaptation.

The last exploration of sigmoid function application relates to an enterprise capability assessment and prioritization methodology from Idaho National Labs (INL) supporting the Department of Energy's (DOE) interest to help develop a rigorous way to assess and prioritize capability gaps of an US Army enterprise (Bryan et al, 2010). An enterprise is an organization or undertaking of scope that involves complication and risk (American Heritage, 1993) that possesses capabilities such as facilities, equipment, hardware/software, *skilled personnel* and knowledge management (Bryan et al., 2010). In order to identify capability gaps, a structured approach is needed to assess risk. A pre-cursor to implementing a structured approach to risk assessment is to assess the current or baseline capability against a set of required capabilities to support an enterprise mission (Bryan et al., 2010). To support this tenet, INL developed a tool called Gap Relationship & Interface Planning (GRIP) to examine enterprise relationships, identify and prioritize capability gaps and assess risk.

The analytical underpinnings associated with the tool are not disclosed in the article. However, Figure II-7 provides a visualization of an US Army Brigade Control Team effectiveness using a nonlinear utility curve which notably resembles a sigmoid function. The x-axis represents a measure of effectiveness score from 0 to 5 (higher is more favorable), while the y-axis represents a required capability performance level between 0 and 1 (higher is more favorable).

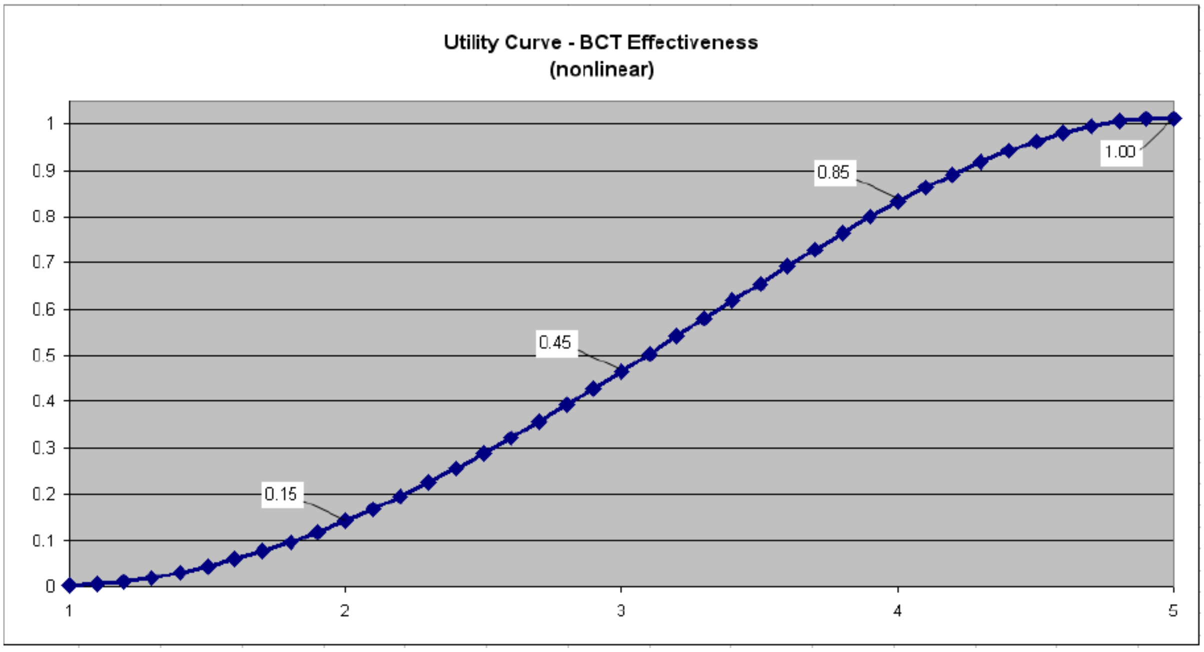


Figure II-7: Notional Utility Curve (Bryan et al., 2010)

INL developed a tool called Gap Relationship & Interface Planning (GRIP) to assess and prioritize capability gaps of an US Army enterprise. The INL developed framework could be a potential topic of interest for further research as the USAF matures its risk assessment process.

Generally, there are five stages of risk assessment: planning, identification, computation, mitigation and monitoring. This research in this dissertation assumes the planning guidance is provided and primarily focuses on the identification and computation stages of a risk assessment.

The sigmoid function explored in the aforementioned use cases are used in various contexts and are intended to inform further research as it relates to assessing impact of personnel manning deficiency. This research uses the sigmoid function as a static function to represent impact values from personnel manning rates. The values are then translated from the Air Force Risk Assessment Framework (AFRAF) to an impact score. The classifier function adaptation is applied in Chapter III. The static function adaptation is applied in Chapter V.

Using an S-curve function computation accounts for the personnel impact portion of risk computation. The S-curve uses a manning rate from (0-100%) coupled with a special case of the logistic function to arrive at a probability. These probabilities are used to translate into personnel risk factor values from the AFRAF risk scale. Using both the normal distribution to compute a probability of failure occurrence and the S-curve function coupled with the AFRAF risk scale to compute impact of failure; yields an overall risk for a given career field. This methodology allows for objective prioritization of resources as it affords senior personnel capability planners to readily identify career fields with greater risk, which arguably should be considered for more resource advocacy than career fields with less risk. This premise is based on equal equity among career fields. Statistical techniques used to examine categorical data response variables are further explored. This work better informs the examination of career field equity in the view of the corporate USAF.

Determining relationships through categorical data

USAF personnel risk assessments are quite challenging because while each career family or functional equity (FE) provides distinctive abilities as a means to achieve desired effects, each career field[8] is evenly valued by a governing body. For example, the USAF is mandated to keep all career fields manned at certain historical averages or even 100% at certain units (Schiefer et al., 2007). This makes prioritization of resources quite challenging because all career fields are theoretically evenly valued or weighted. While governing guidance is to man all career fields at the maximum of the two conditions (i.e. 100% or historical world-wide average), is there an objective approach to validate that this guidance is being applied across the enterprises or functional equities? In other words, is there any statistical evidence of corporate preference towards certain core functions (CFs) or FEs? Whether intentional or un-intentional, the existence of corporate preference could shed insight into how the USAF corporately views certain CFs or FEs. If some CFs or FEs are better manned than others, there inherently exists a weight structure among CFs, FEs or even specific career fields that can be used for prioritization of resources. Statistical techniques such as contingency table analysis, generalized linear modeling and odds-ratio analysis are ways to examine this phenomena.

When we seek to compare estimated probability of events or examine if variables are independent, we can use contingency table analysis. A way to categorize an experiment with categorical data from the same population is to construct a table of frequency counts called a contingency table. Samples from the same population should yield equivalent contingency tables. Contingency table analysis via hypothesis testing can be used to statistically examine associations or dependence between categorical variables from the same population (Haug,

[8] A career field is a subgroup of a career family. For example, an analytical scientist is a subgroup of the acquisitions career family.

2019). The main premise of the analysis is to determine independence between the variables. Each partition within the contingency table represents a cell. Further, hypothesis test computations using contingency tables examine whether or not certain effects (i.e. relationship between row and column variables) are present. That is to say, are the levels of the row variable differentially distributed over levels of the column variables?

There are five steps to conduct contingency table analysis: 1) state the hypothesis; 2) identify the structure of the table; 3) determine the test statistic to create a rejection region; 4) analyze the data; and 5) interpret the results. The identification of a hypothesis test examining independence between categorical variables can be stated as follows:

$$H_0\ (null) = Row\ variables\ and\ Column\ variables\ are\ independent$$

$$H_A\ (alternative) = Row\ variables\ and\ Column\ variables\ are\ not\ independent.$$

Once the hypothesis is identified, we can examine the structure of the contingency table to determine the associated distributions. Theoretically, if one random variable (*Y*) is a response variable and the other an explanatory or fixed variable (*X*), then F(*Y*) has a probability distribution (Agresti, 2013). Further, assuming *Y* is in columns, then the row totals represent the conditional probability: P ($Y \mid X$) or P ($Y \mid X$ = x). If both row and column variables are responses, then the cells represent outcomes for the joint distribution (X, Y). The row and column totals equate to subsets of a collection of random variables or marginal distributions. Table II-4 is a theoretical matrix, which depicts the general structure of a contingency table, where f_{ij} represents the probability (X, Y) occurs in a cell of column and row variables *m* and *p* respectively within row *i* and column *j* with sample size *n*. Therefore, the sample size *n* is equivalently written as $\left(\sum_{i=1}^{p}\sum_{j=1}^{m} f_{ij}\right)$.

Table II-4: Theoretical Contingency Table

		Column Variable (m columns)					
		1	***...***	***j***	***…***	***m***	***proportions***
Row Variable (p rows)	***1***	f_{11}	$\cdots$	f_{1j}	$\cdots$	f_{1m}	$p_{r1} = \frac{\sum_{k=1}^{m} f_{1k}}{n}$
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
	i	f_{i1}	$\cdots$	f_{ij}	$\cdots$	f_{im}	$p_{ri} = \frac{\sum_{k=1}^{m} f_{ik}}{n}$
	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
	p	f_{p1}	$\cdots$	f_{pj}	$\cdots$	f_{pm}	$p_{rp} = \frac{\sum_{k=1}^{m} f_{pk}}{n}$
	proportions	$p_{c1} = \frac{\sum_{k=1}^{p} f_{k1}}{n}$	$\cdots$	$p_{cj} = \frac{\sum_{k=1}^{p} f_{kj}}{n}$	$\cdots$	$p_{cm} = \frac{\sum_{k=1}^{p} f_{km}}{n}$	***1***

Extrapolating these concepts, we derive an expected value e_{ij} under H_0 as follows:

$$e_{ij} = n * p_{ri} * p_{cj} = (sample\ size) * (row\ ith\ proportion) * (column\ jth\ proportion)$$

$$= n * \left(\frac{\sum_{i=1}^{p} f_{ik}}{n}\right) * \left(\frac{\sum_{j=1}^{m} f_{kj}}{n}\right) = (ss) * \left(\frac{row\ ith\ total}{ss}\right) * \left(\frac{row\ jth\ total}{ss}\right)$$

$$= \frac{\left(\sum_{k=1}^{m} f_{ik}\right) * \left(\sum_{k=1}^{p} f_{kj}\right)}{n} = \frac{(row\ ith\ total) * (row\ jth\ total)}{ss} \qquad \textbf{Eq. II-4}$$

where i and j represent the indices of the number of p row and m column totals (sample sizes) respectively, from $i = 1, \ldots . p;\ j = 1, \ldots ., m$.

A popular approach to determine independence among category variables is to conduct a chi-square test for independence. For example, fully manned (i.e. 100% or more manned) versus not fully manned. Significance in this hypothesis test infers dependence. Non-significance infers independence. The chi-square statistic used to reflect the difference between the observed value and the expected value is represented as:

$$\chi = \sum_{i=1}^{p} \sum_{j=1}^{m} \frac{(f_{ij} - e_{ij})^2}{e_{ij}} = \frac{(f_{11} - e_{11})^2}{e_{11}} + \frac{(f_{12} - e_{12})^2}{e_{12}} + \cdots + \frac{(f_{1m} - e_{1m})^2}{e_{1m}}$$

$$+ \frac{(f_{21} - e_{21})^2}{e_{21}} + \frac{(f_{22} - e_{22})^2}{e_{22}} + \cdots + \frac{(f_{2m} - e_{2m})^2}{e_{2m}} + \cdots +$$

$$+ \frac{(f_{p1} - e_{p1})^2}{e_{p1}} + \frac{(f_{p2} - e_{p2})^2}{e_{p2}} + \cdots + \frac{\left(f_{pm} - e_{pm}\right)^2}{e_{pm}}. \qquad \textbf{Eq. II-5}$$

Eq. II-5 is a Pearson chi-square statistic summarized as follows (Agresti, 2013):

$$Pearson\ \chi^2 = \sum_{i=1}^{p} \sum_{j=1}^{m} \frac{(O-E)^2}{E} \qquad \textbf{Eq. II-6}$$

where O and E[9] are observed and expected values of the dataset, respectively.

Recall, the null hypothesis is the row and column variables are independent, which implies the alternative hypothesis is the row and column variables are not independent. As $e_{ij} \geq 5$ for every $\boldsymbol{i}$ and $\boldsymbol{j}$, the chi-square test with level of significance (α) is as follows:

[9] For proper usage of the Pearson chi-square, each expected value needs be greater than or equal to 5.

$$H_o: Row\ variable\ is\ independent\ of\ column\ variable$$

$$H_A: Row\ variable\ is\ not\ independent\ of\ column\ variable$$

The rejection region is defined as:

$$Reject\ H_o: \chi^2 > \chi^2_{(p-1)(m-1),\alpha} = G^2$$

$$Fail\ to\ Reject\ H_o: \chi^2 \leq G^2,$$

where G^2 is computed from $P\left(\chi^2_{(p-1)(m-1),} > \chi^2_{(p-1)(m-1),\alpha}\right) = \alpha.$ Therefore, the *p*-value is $P\left(\chi^2_{(p-1)(m-1)} > \chi^2\right).$

Another approach to determine statistical significance between row and column variables is to compute a Likelihood Ratio Test (LRT). There are many versions of LRTs to use as an estimator depending on the functional form of the data under examination. The LRT is another goodness of fit test. An alternative more complex function to determine a LRT is to use a logarithm function defined as $(Argresti, 2013)$:

$$-2lnL.R. = 2\sum_{i=1}^{I}\sum_{j=1}^{J}\left[e_{ij} * \ln\left(\frac{e_{ij}}{f_{ij}}\right)\right] = G^2. \qquad \textbf{Eq. II-7}$$

If the LRT has a significant p-value (i.e. less than α), this infers a ‘more than chance’ relationship exists between the row and column variables. Dividing this value by 2 yields similar results to the chi-square test statistic.

Another method to examine relationships between row and column variables is via an odds ratio. The odds ratio is one when the *odds* and *probabilities of success* are the same for each group. Consider a 2x2 contingency table with two dichotomous sample sizes or classes: Group 1 is *X* and Group 2 is *Y* which is expressed in Table II-5.

Table II-5: Example of 2x2 Contingency Table

Group\Outcome	**Successes**	**Failure**	**Total**
Group 1	$\sum_{i=1}^{m} x_i$	$m - \sum_{i=1}^{m} x_i$	m
Group 2	$\sum_{i=1}^{n} y_i$	$n - \sum_{i=1}^{n} y_i$	n
Total	$\sum_{i=1}^{m} x_i + \sum_{i=1}^{n} y_i$	$(m+n) - (\sum_{i=1}^{m} x_i + \sum_{i=1}^{n} y_i)$	$m+n$

The odds ratio is the ratio of the odds for two groups: OR = odds$_X$ / odds$_Y$. The odds ratio can be expressed as (Conover, 1980):

$$OR = \frac{odds_X}{odds_Y} = \frac{\frac{\sum_{i=1}^{p} x_i}{m - \sum_{i=1}^{m} x_i}}{\frac{\sum_{i=1}^{n} y_i}{n - \sum_{i=1}^{n} y_i}} = \frac{\sum_{i=1}^{m} x_i \,(n - \sum_{i=1}^{n} y_i)}{\sum_{i=1}^{n} y_i \,(m - \sum_{i=1}^{m} x_i)}. \qquad \textbf{Eq. II} - \textbf{8}$$

An odds ratio of one suggests the condition or event under examination is equally likely to occur in both groups. An odds ratio of greater than one suggests the event is more likely to occur in Group 1. An odds ratio of less than one suggests the event is less likely to occur in Group 1. The odds ratio must be be nonnegative, otherwise it is undefined.

In determining the likelihood of an outcome (e.g. determining the likelihood of a functional equity or service core function being fully manned) the logistic function can be used. Logistic regression analysis describes how a binary (success or fail) response variable is associated with a set of explanatory variables (categorical or continuous). The general form of a logistic function is $f(z) = \frac{1}{1+e^{-z}}$, where the value of $f(z)$ is dependent on the value of z (Chatterjee and Chatterjee, 2010). To obtain the logistic model from the logistic function we write *z* as a function of independent variables *X*s and undetermined coefficients *βs*:

$$z = \alpha + \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n = \beta\boldsymbol{x}\,. \qquad \textbf{Eq. II-9}$$

From this expression we write the logistic model as follows:

$$f(\beta\boldsymbol{x}) = \frac{1}{1+e^{-(\alpha+\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}} = \frac{e^{(\alpha+\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}}{1+e^{(\alpha+\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n)}} \qquad \textbf{Eq. II-10}$$

The general logistic function is

$$P(x) = p(x) = e^{\left(\frac{(\alpha+\beta x)}{(1+e^{(\alpha+\beta x)})}\right)} = \frac{odds}{1+odds} \qquad \textbf{Eq. II-11}$$

where *x* is the independent variable and *e* is the exponential function, and *p*(x) is the probability of a functional equity or core function being fully manned.

A relationship exists between the logistic function and the odds ratio. All formulae and theory are adapted from Agresti's Categorical Data Analysis text (Argresti, 2013). The outcome variable of the logistic function is the log odds ratio via logistic transformations (logits), which are computed and compared among CFs and FEs. The logistic odds is represented as

$$Logit[p(x)] = \ log(odds) = \ log\left(\frac{p(x)}{1-p(x)}\right) = \ \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n \qquad \textbf{Eq. II-12}$$

where β_0 is the intercept, β_n (the parameter) is the log odds ratio of one unit increase in an independent variable *X* whereas e(*β*) is the odds ratio of one unit increase in *X* (Agresti, 2013).

The log-odds interpretation is a function of the logit distribution. We can motivate the logit model in terms of the odds of success vs. failure, which is given by: $(\frac{p}{1-p})$, where *p* is a probability of an event occurrence. The logistic transformation (logit) is the logarithm of the odds. Hence, model estimates from the logit are properly referred to as 'log-odds' estimates. The appeal of applying a logistic function $f(z) = \frac{1}{1+e^{-z}}$ to the data from a personnel manning perspective is due to the following reasons:

1. Estimates always range between 0 and 1 in personnel being either fully manned or not. Such a probability provides an estimate of the risk a CF or FE will not be fully manned as required.

2. It has an S-shaped curve, which indicates for low values of *z* the risk of not being fully manned remains minimal, until some threshold is reached. Then the risk rises rapidly as *z* increases, and then again reaches its asymptotic limit and remains high once *z* gets large enough (Stanford Logistic Regression Tutorial, 2018).

To obtain estimates of odds and odds ratio from logistic regression we need to rewrite the logistic model in the logit form. By definition, if *p* is the probability that an event will occur and is represented as follows:

- Odds are defined as $\frac{p}{1-p}$, i.e. probability that event will occur divided by the probability that the event will not occur or $\frac{p}{q}$.
- The logit of *p* is as follows:

$$\text{Logit }(p) = ln\frac{p}{1-p} = \ln(odds). \qquad \textbf{Eq. II-13}$$

The logistic model in terms of a conditional probability of being fully manned or not (F =1 or 0) is denoted as:

$$P(F|X_1, \beta\boldsymbol{x}) = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e}^{\boldsymbol{\beta x}}} \qquad \textbf{Eq. II-14}$$

$$1 - P(F|X_1, \beta\boldsymbol{x}) = \frac{\boldsymbol{e}^{-(\boldsymbol{\beta x})}}{\mathbf{1}+\boldsymbol{e}^{-(\boldsymbol{\beta x})}}$$

$$\therefore Odds = \frac{P(F|X_1, \beta\boldsymbol{x})}{1 - P(F|X_1, \beta\boldsymbol{x})} = \frac{\mathbf{1}}{\boldsymbol{e}^{-(\boldsymbol{\beta x})}} = \boldsymbol{e}^{\boldsymbol{\beta x}}$$

$$\therefore logit(P) = ln(odds) = ln\frac{p}{1-p} = ln(\boldsymbol{e}^{\boldsymbol{\beta x}}) \qquad \textbf{Eq. II-15}$$

Thus, the logit form of the logistic model yields an expression for the log odds of being fully manned for a CF or FE with a specific set of independent variable Xs. Therefore, $logit(P_{X_1}) - logit(P_{X_0}) = \beta_1$, where, β_1 represents the change in logistic odds that would result from one unit change in independent variable X.

For odds ratio development, we know from algebra that $ln(b) - l\,n(a) = ln(\frac{b}{a})$.

Therefore,

$$logit(P_{X_1}) - logit(P_{X_0}) = ln\frac{\frac{P_{X_1}}{(1-P_{X_1})}}{\frac{P_{X_0}}{(1-P_{X_0})}} \qquad \textbf{Eq. II-16}$$

$$= ln\frac{odds(X_1)}{odds(X_0)} = ln(odds\,ratio) = \beta_{1.} \qquad \textbf{Eq. II-17}$$

Therefore, $e^{\beta_1} = e^{ln(odds\,ratio)} = OR$.

Generalized linear models (GLMs) are a broad class of models that include categorical response variables (Agresti, 1999). There are three components that are common to all GLMs:

- Random component;
- Systematic component; and
- Link function.

The random component refers to the probability distribution of the response *Y*. We observe independent random variables $Y_1, Y_2, \ldots, Y_N$. The random variables Y_i, I = $1, 2, \ldots, N$, have expected values μ_i, I = $1, 2, \ldots, N$. The systematic component involves the explanatory variables $x_1,\ x_2, \cdot\cdot\cdot, x_k$. as linear predictors:

$$\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdot\cdot\cdot + \beta_k x_k. \qquad \textbf{Eq. II-18}$$

The link component of the GLM 'links' the random and systematic components**.** It determines how the mean **μ** = E(*Y*) relates to the explanatory variables in the linear predictor through specifying a function $g(\mu)$ and is denoted as:

$$g(\mu) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdot\cdot\cdot + \beta_k x_k\ . \qquad \textbf{Eq. II-19}$$

For the logistics model, the link function is:

$$ln[\frac{\pi(x_1,x_2,\ldots,x_k)}{1-\pi(x_1,x_2,\ldots,x_k)}] = g(\mu). \qquad \textbf{Eq. II-20}$$

The observations $Y_1, Y_2, \ldots, Y_N$ have a binomial distribution (the random component). Thus, for logistic regression, the link function can be rewritten as $\ln(\frac{\mu}{1-\mu})$ and is called the logit link.

When the model is fit with only an intercept (i.e. no predictors), the value of the likelihood equation (the probability of the data) at its maximum value translates to a -2LogLikelihood (-2LogL). If we subtract the -2LogL of a reduced model (i.e. intercept only) from the -2LogL of a full model (i.e. intercept and *k* predictors), this has a chi-square distribution with *k* degrees of freedom under the null hypothesis (i.e. βs = 0). If the null hypothesis is rejected, at least one of the k predictors is significant (i.e. at least one of the $\beta \neq 0$), which suggests at least one parameter is statistically significant.

Popular variation metrics such as R-square and MSE are not very helpful in examining model performance when using logistic regression. Misclassification rates and Area Under the Curve (AUC) metrics are two of several model performance indicators used to assess logistic regression model performance. The complement of a misclassification rate is a classifier rate. A classifier rate is computed from a confusion matrix. A confusion matrix is expressed in terms of true and false positives and negatives, respectively. Table II-6 provides a general confusion matrix.

Table II-6: A confusion matrix.

	Matrix	
Actual Success	Positive (Success)	Negative (Failure)
Successes	a	b
Failures	c	d

Components of a confusion matrix are as follows:

- a is the number of successes correctly classified.
- b is the number of successes misclassified as failures.
- c is the number of failures misclassified as successes.
- d is the number of failures correctly classified.

Therefore, the classifier rate (A_j) defined over all classification errors is represented as:

$$A_j = \frac{a+d}{a+b+c+d}\,. \qquad \textbf{Eq. II-21}$$

Further, classifier performance can also be distinguished by true and false positives a^+ and a^- respectively denoted as:

$$a^+ = \frac{a}{a+b}; \;\; a^- = \frac{c}{c+d}. \qquad \textbf{Eq. II-22}$$

True positives are often referred to as *sensitivity* and false positives are referred to as (*1-specificity*), where specificity represents the true failure or negative rate (Sensitivity and Specificity, 2018).

A common approach to visually represent tradeoffs between true and false positives is to construct Receiver Operating Characteristic (ROC) curves (Karimollah, 2013). ROC curves are plots of the rate of correctly classified true positives (a^+) with respect to the percentage of incorrectly classified false positives (a^-). JMP 12 (used for part of this research) software computes specificity and sensitivity values to build ROC curves and establishes a tangential line to the most optimal position of the ROC curve to build an AUC or 'goodness of fit' metric. AUCs are expressed as values within the lower and upper bounds of zero and one, respectively. AUC interpretations are subjective, but one common interpretation is any value greater than 0.50 suggest modeling predictions have more than a 'chance' of being accurate (Narkhede, 2018).

Given the restrictions regarding the way USAF personnel are viewed and managed, we can prioritize personnel capability by risk. That is to say, if career field A has greater risk than career field B, career field A should receive more prioritization with regards to resources than career field B. This portion of the chapter focuses on objectively computing personnel risk by core function and functional equity. The next chapter seeks to add another dimension to the assessment of personnel risk.

Organizational Efficiency

Is there a strong correlation (positive or negative) between risk and efficiency? This work seeks to add another dimension to the assessment of personnel risk. We seek to ascertain if efficiency should be considered a component of assessing risk? That is to say, the more organizational efficient, the less organizational risk, and conversely, the less organizational efficient, the more organizational risk. For example, what if senior decision leaders knew if current management of manning resources of one organization was subpar compared to like organizations? Should similar organizations with similar personnel makeups and missions be measured with regards to personnel utilization? If so, could these efficiency comparisons be statistically compared to risk and inferences gained to help senior decision leaders and planners better advocate and prioritize resources? We argue before personnel risk can be more accurately assessed, efficiency should be examined.

Figure II-8 is a notional schematic of how ACS efficiency could be assessed as it relates to personnel impact in order to maintain, sustain and deliver capability. The arcs are directed from the top (Core Capability) to bottom (Career Fields). In other words, to what extent with regards to risk can a core capability (e.g. Research & Development) conduct its steady state operations to support the warfighter? The core capability is measured by tasks which have sub and sub-sub tasks. These tasks are linked to Program Element Codes (PECs) that are linked to Air Force Specialties (AFS) or career fields.

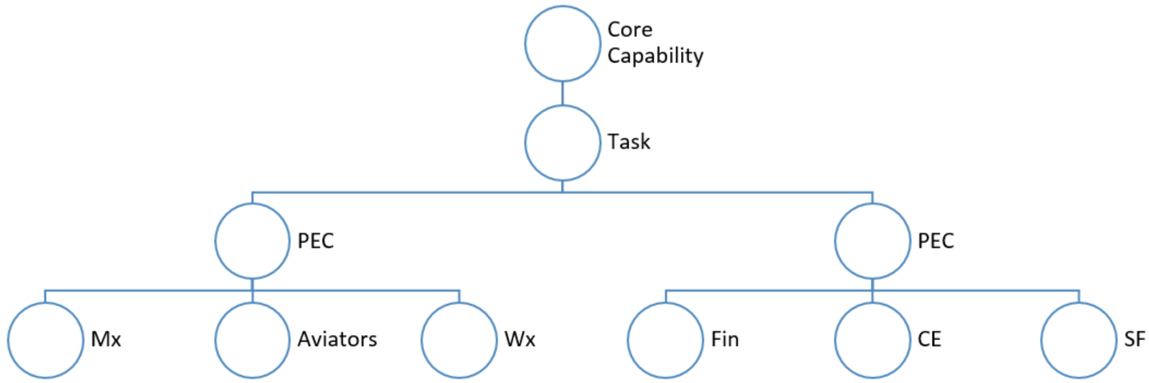


Figure II-8: Notional ACS Risk Assessment (Personnel Centric) node structure

If outputs could be obtained at the various tasks, subtasks, and sub-sub task levels, a technique entitled Data Envelopment Analysis (DEA) may be useful in examining potential personnel efficiency before assessing risk.

DEA is an aggregation technique that compares unit (to include units without price points) (Han and Sohn, 2011) performance by examining the ratio of weighted outputs and inputs (Colbert et al., 2000). Fundamentally, DEA requires *m* inputs, *s* outputs, *k* organizations and a sample size *N* to ultimately measure efficiency (Subhash, 2004).

A series of related DEA techniques were published by multiple authors in the early 1950s [(Debreu, 1951; Shephard, 1953)]. The objective of DEA is to produce the maximum quantity of output from a specific input bundle (Subhash, 2004). The benchmark is determined by the comparison of the actual output produced with the benchmark quantity yielding a measure of *technical efficiency* between Decision Making Units (DMUs) (Subhash, 2004). A Decision Making Unit (DMU) is technically efficient (TE) if it can produce the maximum possible output from its capacity (Atkinson and Cornwell, 1994). A DEA formulation of technical efficiency is (Huguenin, 2012):

$$TE_k = z = \frac{\sum_{r=1}^{s} \boldsymbol{U}_r \boldsymbol{Y}_{rk}}{\sum_{i=1}^{m} \boldsymbol{V}_i \boldsymbol{X}_{ik}}, \qquad \textbf{Eq. II-23}$$

where TE_k is the technical efficiency of an observed DMU *k* using *m* inputs to produce *s* outputs. $\boldsymbol{Y}_{rk}$ represents the quantity of output *r* produced by DMU *k*. $\boldsymbol{X}_{ik}$ represents the quantity of input *i* consumed by DMU *k*. $\boldsymbol{U}_r$ and $\boldsymbol{V}_i$ are weights of the output *r* and input *i* respectively. DEA modeling requires prerequisite knowledge of the following properties: returns to scale, orientation, model type and slack. *Returns to scale* (RTS) refers to the rate by which an output changes if an input is changed by the same factor (OECD, 2001).

DEA variants can accommodate two foundational types of returns to scale: constant and variable [(Charnes et al., 1978; Banker et al., 1984)]. The constant return to scale or (CRS) model created by Charnes, Cooper and Rhodes (CCR) reflects the ability of a DMU to maximize outputs from a given set of inputs (Mogha et al., 2015). CRS can also be interpreted as overall technical efficiency (OTE). CRS models are appropriate when all DMUs under examination have a linear relationship i.e. the outputs increase at the same rate of inputs (Ozcan, 2014). The Banks, Cooper and Charnes (BCC) or Variable returns to scale (VRS) model is more appropriate when all organizations (DMUs) under comparison do not have the same rate of change with regards to proportion of outputs to inputs (Banks et al., 1984). VRS models determine pure technical efficiency (PTE). For DEA CRS and VRS models, *scale efficiency* (SE) is computed as the ratio of respective CRS and VRS efficiency values (Alvarez et al., 2016) regardless of orientation (i.e. input or output). OTE, PTE and SE are often referred to as relative efficiencies due to computation distinctions (Mogha et al., 2015).

Another DEA property is *orientation*. There are generally three types of DEA orientation: input, output (Charnes et al., 1978) and directional distance (Chambers et al., 1996). Input oriented (*io*) models measure how much an organization can decrease its inputs (e.g. manning) to achieve given outputs such as sales or generated combat sorties, compared to its most efficient peers. Output oriented (*oo*) models reverse the idea and identify how much additional output should be possible for given inputs, again relative to the organization's most efficient peers (Jarzebowski and Bezat-Jarzebowski, 2014). For completeness, the directional distance DEA model is briefly discussed. Directional distance-type models are universally oriented, i.e. there is no need to distinguish between input or output orientation (Toloo and Tavana, 2017). Directional distance models are typically used to distinguish between desirable and undesirable variables (Cheng and Zervopoulos, 2012). While the majority of inputs and outputs for this research are not considered interchangeable, an excursion is discussed in Chapter V illustrating an application of the said orientation.

A third DEA property involves *model type* of which this study considers two: radial (Charnes et al., 1978) and additive (Lovell and Pastor, 1995) models. Radial DEA models require that all inputs be contracted and/or outputs expanded from a center (e.g. origin) or radius. These models are the first of several explored to compare and contrast DMU efficiency.

The CRS and VRS DEA model solutions identify efficiency frontiers. All DMUs which fall on the efficient frontier (i.e. CRS or VRS) are said to be technically efficient (i.e. there are no shortages or overages of the inputs/outputs). These shortages or overages are known as negative or positive slack values respectively. DMUs with zero slack set the standard or 'benchmark' for other DMUs that are spatially located some distance from the efficiency frontier. A practical interpretation is that DMUs operating below the efficiency frontier are deemed to have potential for performance improvement (Huguenin, 2012). All of the said models use two-stage[10] optimization to compute slack variables. For output orientation DEA models, the first stage (envelopment or primal form) of optimization maximizes the ratio of weighted outputs to weighted inputs while assuming this ratio is less than or equal to unity for all DMUs (Cook and Zhu, 2005). The second stage (multiplier or dual form) of DEA optimization minimizes inputs radially to maximize outputs levels (Cook and Zhu, 2005).

The other DEA model type examined in this work is an additive model (AM) or slacked based model (SBM). The major difference between the radial and additive model is the way by which technical efficiency is computed. DEA additive models simultaneously consider positive and negative slack variables (Charnes et al., 1985) in order to determine technical efficiency.

The summation of the weights of the ratio of DMU outputs and inputs are used to determine managerial implications (Bowlin, 1985). There are differing managerial implications depending on DEA decreasing or increasing RTS. Decreasing or non-increasing RTS (DRS) suggest DMU reduction in size (e.g. base reduction in manpower). Non-decreasing or increasing RTS or (IRS) infers the DMU is being mismanaged to an extent as resources are being underutilized [(Lu, 2010); (Cook and Zhu, 2005)]. The aforementioned types of managerial implication are further explored in the analysis portion of this study.

[10] Two stage DEA optimization refers to first: optimizing the DMUs for model type (e.g. radial) efficiency and second: computing the possible input excesses and output shortfalls or slacks to determine technical efficiency (Alvarez et al., 2016).

A brief exposition of DEA terminology is provided. Specific DEA modeling formulae now follow in the form of non-linear and linear programs succeeded by applications.

Models

<u>CCR</u>

Farrell (1957) published a nonlinear program formulation of DEA. A fractional program maximizing technical efficiency of the observed DMU *k* is stated below to include two constraints (Huguenin, 2012):

$$max \frac{\sum_{r=1}^{s} \boldsymbol{U}_r \boldsymbol{Y}_{rk}}{\sum_{i=1}^{m} \boldsymbol{V}_i \boldsymbol{X}_{ik}} \qquad \textbf{Eq. II-24}$$

$Subect\ to$:

$$\frac{\sum_{r=1}^{s} \boldsymbol{U}_r \boldsymbol{Y}_{rj}}{\sum_{i=1}^{m} \boldsymbol{V}_i \boldsymbol{X}_{ij}} \leq 1;\ \ j = 1, \dots N \qquad \textbf{Eq. II-25}$$

$$\boldsymbol{U}_r\ , \boldsymbol{V}_i > 0;\quad \forall_r = 1, \dots, s;\quad \forall_i = 1, \dots, m. \qquad \textbf{Eq. II-26}$$

Eq. II-24 is the maximum technical efficiency of an observed DMU *k* using *m* inputs to produce *s* outputs. $\boldsymbol{Y}_{rk}$ represents the quantity of output *r* produced by DMU *k*. $\boldsymbol{X}_{ik}$ represents the quantity of input *i* consumed by DMU *k*. $\boldsymbol{U}_r$ and $\boldsymbol{V}_i$ are optimal weights of the output *r* and input *i* respectively. Eq. II-25 requires that the ratio of weighted outputs and inputs for each of the *N* DMUs cannot exceed one. Eq. II-26 restricts the weighted outputs and inputs to positive values. DMU *k* is CCR-efficient if TE_{k*}= 1, and there exists at least one optimal set of weighted input and output bundles $(\boldsymbol{U}_{r*}\ , \boldsymbol{V}_{i*})$, otherwise, DMU *k* is CCR-inefficient (Cooper, 2007). After algebraic manipulation, we can reformulate the nonlinear fractional program as an LP (*primal form*[11]*-oo*) and obtain the following CRS model (Cooper et al., 2007):

$$\min z = \sum_{i=1}^{m} \boldsymbol{V}_i \boldsymbol{X}_{ik} \qquad \textbf{Eq. II-27}$$

$Subject\ to$:

$$\sum_{r=1}^{s} \boldsymbol{U}_r \boldsymbol{Y}_{rk} = 1 \qquad \textbf{Eq. II-28}$$

$$\sum_{r=1}^{s} \boldsymbol{U}_r \boldsymbol{Y}_{rk} - \sum_{i=1}^{m} \boldsymbol{V}_i \boldsymbol{X}_{ij} \leq 0; \;\; \forall_j = 1, \dots, N \qquad \textbf{Eq. II-29}$$

$$\boldsymbol{U}_r, \boldsymbol{V}_i \geq 0; \quad \forall_r = 1, \dots, s; \quad i = 1, \dots, m. \qquad \textbf{Eq. II-30}$$

Eq. II-27 (objective function) minimizes the quantity of weighted bundle input $\boldsymbol{V}_i$ consumed by DMU *k* for all *m* inputs. Eq. II-28 is a constraint that ensures the quantity of weighted output(s) $\boldsymbol{U}_r$ consumed by *k* DMUs for all *s* outputs sum to one. Eq. II-29 is a constraint that ensures the difference between the *quantity* or bundle of weighted outputs $\boldsymbol{U}_r$ consumed by *k* DMUs for all *s* outputs, and the *quantity* of weighted inputs $\boldsymbol{V}_i$ consumed by *j* DMUs to the total amount of DMUs for all *m* inputs, is less than or equal to zero. Eq. II-30 constrains the weighted bundled outputs and inputs to positive values.

The *dual* of the preceding formulation is as follows:

$$\max \theta \qquad \textbf{Eq. II-31}$$

$Subect\ to$:

$$\sum_{j=1}^{N} \boldsymbol{X}_{ij} \lambda_j = \boldsymbol{X}_{ik} \qquad \textbf{Eq. II-32}$$

$$\sum_{j=1}^{N} \boldsymbol{Y}_{rj} \lambda_j = \theta * \boldsymbol{U}_r \boldsymbol{Y}_{rk} \qquad \textbf{Eq. II-33}$$

$$\boldsymbol{U}_r, \boldsymbol{V}_i \geq 0; \quad \forall_r = 1, \dots, s; \quad i = 1, \dots, m; \quad \lambda_j \geq 0; \quad \forall_j = 1, \dots, N \qquad \textbf{Eq. II-34}$$

[11] For more information on dual/primal LP relationships, reference 'DEA in the Black Box' (Charnes et al., 1994).

Eq. II-31 is the objective function, which is to maximize TE of DMU *k* without the consideration of slack variables. Eq. II-32 constrains the quantity of input *i* consumed by DMU *k* to equate to the sumproduct of the quantity of output *r* produced by DMU *k* and a non-negative vector λ_j. λ_j is introduced as a non-negative transposed vector $(\lambda_j = (\lambda_1, \dots \lambda_N)^T$. The λ_js represent the set of optimal weights for each base. The summation of each base's weighted set determines the RTS (i.e. decreasing, constant or increasing scale). Values greater than one are considered DRS; values less than one are considered IRS and values equal to one are considered CRS (Dario and Simar, 2007).

Eq. II-33 constrains the sumproduct of the quantity of output *r* produced by DMU *j* and a non-negative vector λ_j to equate to a maximized TE of DMU *k* coupled with the quantity of output *r* produced by DMU *k* consumed by *k* DMUs for all *s* outputs. Eq. II-34 constrains the weighted bundled outputs and inputs as well as optimal weights to positive values.

Recall, TE_k is the technical efficiency of an observed DMU *k* using *m* inputs to produce *s* outputs. $\boldsymbol{Y}_{rj}$ represents the quantity of output *r* produced by DMU *j*. $\boldsymbol{X}_{ij}$ represents the quantity of input *i* consumed by DMU *j*. TE_k will result in a value $[0, \infty)$, where 1 represents benchmarked DMU *j*. Values greater than or less than 1 are considered technically (radially) inefficient. The following CCR model is formulated with slack variables.

CCR (with slacks)

A modified version of the CCR (*dual form-oo*) formulation (Eq. II-31) incorporates input and output slack variables into the calculation of DMU efficiency (Cook and Zhu, 2005):

$$max\ TE_k + \varepsilon \sum_{r=1}^{s} s_r^{out} + \varepsilon \sum_{i=1}^{m} s_i^{in} \qquad \textbf{Eq. II-35}$$

$Subject\ to$:

$$\sum_{j=1}^{N} \lambda_j \boldsymbol{Y}_{rj} - s_r^{out} = TE_k \boldsymbol{Y}_{rk};\ \ r = 1, \dots s \qquad \textbf{Eq. II-36}$$

$$\sum_{j=1}^{N} \lambda_j \boldsymbol{X}_{ij} + s_i^{in} = \boldsymbol{X}_{ik};\ \ i = 1, \dots m \qquad \textbf{Eq. II-37}$$

$$\lambda_j, s_r^{out}, s_i^{in} \geq 0;\quad \forall_j = 1, \dots, N; r = 1, \dots, s; i = 1, \dots, m. \qquad \textbf{Eq. II-38}$$

The quantity ε represents a small positive number and s_r^{out} and s_i^{in} represent output and input slack variables, respectively. TE_k will result in a value [1, ∞), where 1 represents benchmarked DMU j. λ_j's are optimal weights for each base. Values greater than 1 are considered technically inefficient.

BCC (with slacks)

Some DEA variations differ by scaling properties (Banker et al., 1984). The Banker, Cooper and Charnes output oriented (BCC-*oo*) LP (*dual form*) formulation is:

$$max\ TE_k + \varepsilon \sum_{r=1}^{s} s_r^{out} + \varepsilon \sum_{i=1}^{m} s_i^{in} \qquad \textbf{Eq. II-39}$$

$Subject\ to$:

$$\sum_{j=1}^{N} \lambda_j \boldsymbol{Y}_{rj} - s_r^{out} = TE_k \boldsymbol{Y}_{rk};\ \ r = 1, \dots s \qquad \textbf{Eq. II-40}$$

$$\sum_{j=1}^{N} \lambda_j \boldsymbol{X}_{ij} + s_i^{in} = \boldsymbol{X}_{ik};\ \ i = 1, \dots m \qquad \textbf{Eq. II-41}$$

$$\sum_{j=1}^{N} \lambda_j = 1 \qquad \textbf{Eq. II-42}$$

$$\lambda_j, s_r^{out}, s_i^{in} \geq 0;\quad \forall_j = 1, \dots, N; r = 1, \dots, s; i = 1, \dots, m. \qquad \textbf{Eq. II-43}$$

The only difference between the CRS and BCC-oo LP formulations is that the BCC model scaling constraint (Eq. II-42) replaces the upper bound inequality with an equality (Huguenin, 2012). TE_k will result in a value [1, ∞), where 1 represents benchmarked DMU j. Values greater than 1 are considered technically (radially) inefficient.

Weighted Additive Model (WAM-VRS)

There are several versions of weighted additive models (WAM-VRS), but we use the Lovell and Pastor weighted technical efficiency algorithm. For additive models, technical efficiency is based solely on input excesses and output shortages (Alvarez et al., 2016). In other words, the model considers total slack of the inputs and outputs when arriving at a point with respect to the efficient frontier (Wen, 2015). Further, the goal of the function is to maintain technical efficiency while simultaneously *maximizing* feasible *decreases* and *increases* in *inputs* and *outputs* respectively.

The WAM-VRS LP formulation is:

$$max\ \sum_{r=1}^{s} \omega_{\boldsymbol{y}} s_r^{out} + \sum_{i=1}^{m} \omega_{\boldsymbol{x}} s_r^{in} \qquad \textbf{Eq. II-44}$$

$Subject\ to$:

$$\sum_{j=1}^{N} \lambda_j \boldsymbol{Y}_{rj} - s_r^{out} = \boldsymbol{Y}_{rk};\ \ r = 1, \dots s \qquad \textbf{Eq. II-45}$$

$$\sum_{j=1}^{N} \lambda_j \boldsymbol{X}_{ij} + s_r^{in} = \boldsymbol{X}_{ik};\ \ i = 1, \dots m \qquad \textbf{Eq. II-46}$$

$$\sum_{j=1}^{N} \lambda_j = 1 \qquad \textbf{Eq. II-47}$$

$$\lambda_j, s_r^{out}, s_i^{in} \geq 0;\ \ \ \forall_j = 1, \dots, N; r = 1, \dots, s; i = 1, \dots, m. \qquad \textbf{Eq. II-48}$$

Two differences between the slack-based output-oriented models and WAM-VRS formulations are: the WAM model objective function (Eq. II-44) does not include technical efficiency, and output/input weight vectors ($\omega_{\boldsymbol{y}}, \omega_{\boldsymbol{x}}$) are introduced as a Measure of Inefficiency Proportions (MIP) (Alvarez et al., 2016). The MIP is defined as:

$$\left(\omega_{\boldsymbol{y}}, \omega_{\boldsymbol{x}}\right) = \frac{1}{\boldsymbol{y}_0}, \frac{1}{\boldsymbol{x}_0} \qquad \textbf{Eq. II-49}$$

where $\boldsymbol{x}$ and $\boldsymbol{y}$ are minimum observed values (Alvarez et al., 2016). TE_k will result in a value [0, ∞), where 0 represents benchmarked DMU j. Values greater than 0 are considered technically (radially) inefficient.

<u>Superefficient Additive Model (SAM-VRS)</u>

There are cases where multiple DMUs within a sample size are considered equally technically efficient. A methodology to provide further distinction between efficient DMUs is to use a superefficiency model. A superefficient DEA model is obtained when a DMU under evaluation is excluded from the reference set (Alvarez et al., 2016). Removal of efficient DMUs from the reference set shrinks the production set, which allows efficient DMUs to become superefficient and yield scores greater 100%. If DEA efficiency results from previous model application (e.g. WAM, which uses all DMUs versus Superefficient Additive Model (SAM) where exclusion of referenced DMU is computed) remain unchanged, then these DMUs are said to be inefficient while scores that change are considered superefficient (Osman et al., 2014).

The basic function of a superefficiency model determines the maximum percentage change which is feasible such that the DMU remains efficient (Vescovi and Favaretto, 2002). Essentially, the observed output exceeds what is necessary for a DMU to be considered efficient relative to other DMUs in the sample (Subhash, 2004). In other words, assuming more than one DMU is efficient; the efficient DMU with greater capacity for reduction of is more super-efficient than the other DMUs. The model is unit and translation invariant (also for slacks) for the VRS specification. That is to say, input or output data may thus assume negative or zero values (Lovell and Pastor, 1995). Thus, superefficiency allows measuring DMU efficiency beyond 100% relative to peers. There are several versions of the supefficiency model, but we use the function in the MATLAB Toolbox (Andersen and Petersen, 1993). The SAM-VRS LP formulation is:

$$max\ \sum_{r=1}^{s} \omega_{\boldsymbol{y}} s_r^{out} + \sum_{i=1}^{m} \omega_x s_r^{in} \qquad \textbf{Eq. II-50}$$

$Subject\ to$:

$$\sum_{j=1,\neq ref.\ DMU}^{N-1} \lambda_j \boldsymbol{Y}_{rj} + s_r^{out} \leq \boldsymbol{Y}_{rk};\ \ r = 1, \dots s \qquad \textbf{Eq. II-51}$$

$$\sum_{j=1,\neq ref.\ DMU}^{N-1} \lambda_j \boldsymbol{X}_{ij} - s_r^{in} \geq \boldsymbol{X}_{ik};\ \ i = 1, \dots m \qquad \textbf{Eq. II-52}$$

$$\sum_{j=1}^{N} \lambda_j = 1 \qquad \textbf{Eq. II-53}$$

$$\lambda_j, s_r^{out}, s_i^{in} \geq 0;\ \ \ \omega_{\boldsymbol{y}}, \omega_x > 0;\ \forall_j = 1, \dots, N; r = 1, \dots, s; i = 1, \dots, m. \qquad \textbf{Eq. II-54}$$

The quantity ω represents in Eq. II-50 a small positive number and s_r^{out} and s_i^{in} represent output and input slack variables. Note Eq. II-50 are Eq. II-44 are equivalent objective functions.

The constraints between the two objective functions are what differ. Eq. II-51 constrains the quantity of output *r* produced by DMU *k* to be greater than or equal to the sumproduct of the quantity of output *r* produced by DMU *j* for all DMUs besides the referenced DMU, and a non-negative vector λ_j. Eq. II-52 constrains the quantity of input *i* produced by DMU *k* to be less than or equal to the sumproduct of the quantity of input *i* produced by DMU *j* for all DMUs besides referenced DMU, and a non-negative vector λ_j. Eq. II-53 constrains the summation of the optimal weights for all bases to sum to one. Eq. II-

54 restricts the weighted bundled outputs and inputs as well as optimal weights to positive values.

A DMU is regarded as super-efficient if score exceeds 100% when measured against a production possibility set constructed from the input-output data of all other firms in the sample (Subhash, 2004). TE_k will result in a value $[0, \infty)$, where a value equal to 0 represents a benchmarked DMU j and is considered technically efficient. The reader should know there are instances where feasibility[12] can not be obtained.

Application

This research uses known mathematical forms to examine and assess complex organizational risk and efficiency using personnel data. A literature survey of DEA published papers in journals indexed by the Web of Science database from 1978 through August 2010 asserted almost two-thirds were application-based, while the remaining one-third was theoretical (Liu et al., 2013). The phenomena under investigation for this research is application-centric versus theoretical. Among application-based articles, the top-five industries addressed were: banking, health care, agriculture and farm, transportation, and education. Of almost 5,000 articles examined, the military industry represented less than 20 of the total sample size or approximately 0.4% (Liu et al., 2013). Highlights from the leading industries of published application-based DEA articles are discussed.

A leading cited article applying the DEA CCR model compares operating efficiencies among 14 branch offices of a savings bank (Sherman and Gold, 1985). Sherman and Gold

[12] Infeasibility of a superefficient model can occur if an efficient DMU under evaluation cannot reach the frontier formed by the rest of DMUs via increasing the inputs or decreasing the outputs, depending on the orientation of the model (Mehdiloozad and Roshdi, 2019).

argue DEA results provide meaningful insights regarding efficiency otherwise not available from other techniques. Further, a study compared 174 Italian banks and concluded efficiency is best explained by productivity specialization, size, and location (Favero and Papi, 1995). DEA was used to examine activity-based accounting with cost as an input and performance as an output of 250 branches in a large Mideast bank (Kantor and Maital, 1999). For health care, efficiency among 3000 urban government and non-government hospitals is compared (Ozcan and Base 5, 1993). The results assert government hospitals are more efficient. As far as agriculture and farming, Australian dairy farms are evaluated to examine efficient irrigation systems (Fraser and Cordina, 1999). Among the transportation industry, operational performance is compared using 15 international airlines to better understand strategic factors of profitability (Schefczyk, 1993). Worldwide public transportation performance in metropolitan areas and small cities is examined and results show Singapore, London, San Francisco, and Chicago are considered scaled efficient (Chu et al., 1992). DEA is used in the education industry to measure the efficiency of Israeli academic departments at Ben-Gurion University (Sinuanystern et al., 1994). Lastly, DEA is applied to economics graduates from United Kingdom universities to evaluate teaching efficiency; results were inconclusive (Johnes, 2006). While relatively a large amount of DEA literature exist for several industries, there appears to be a dearth of military-centric papers. One aspect of this research seeks to add analytical knowledge to the said domain.

Conclusion

Chapter II explored known mathematical functions, distributions and techniques to examine personnel risk and efficiency. While structured to accommodate the ACS core function, this problem resolution framework can be extended to all USAF core functions. Four application-based approaches are examined to assess strategic risk from a personnel perspective. The first approach uses logistic regression, odds-ratios, relative risk and contingency table analyses to assess the 12 core functions in the USAF from a manning perspective. A core function personnel manning comparison has never been conducted, and thus is the first time explored. The second approach uses Data Envelopment Analysis to explore efficiency using personnel data. The third approach uses normal and sigmoid functions to compute probability of failure of not being manned (among USAF career fields) at required levels and the respective impact. These two functions are used to compute risk. The fourth and final paper uses a Euclidean norm to subsume the said computed risk scores that will ultimately produce aggregate risk values for the five core capabilities within Agile Combat Support. These scores are to be subsumed by another risk model controlled by higher headquarters. With the theoretical lens in place, we now use the said application-based approaches to demonstrate a successful USAF enterprise risk assesssment upgrade.

III. Methodology to Determine, Compare and Assess USAF Core Function Personnel Risk

Introduction

As discussed in Chapters I and II, USAF capability is planned, managed, distributed and executed through 12 service core functions (SCFs) or enterprises of personnel. These various enterprises are mandated to provide annual risk assessments to inform resource allocation and prioritization decision making. Capability and capacity are resources consisting of *people*, infrastructure, readiness and training, and modernization and recapitalization. The highest ranking uniformed member of the USAF believes personnel are the service's greatest asset to maintain a global competitive edge (Air Combat Command, 2019). These personnel sum to over 400,000, across 300 career fields ranging from pilots to cooks dispersed all over the world. The career fields are interconnected to ultimately enable and execute air operations whenever, wherever, when needed. USAF career fields are often undermanned and task-saturated which results in a stressed, overworked workforce that equates to increased military risk.

When service planners, programmers and analysts *do not rigorously* define personnel requirements, comprehensively assess capability gaps and risk; a service failure may arise in more accurately informing and enabling senior leaders to advocate for resources given a fiscally constrained environment. In the world of doing either the same amount of workload or less workload with fewer resources, how does one effectively manage resources with respect to assessing personnel capability?

In the past, the USAF has developed numerous MAJCOM manpower assessments and techniques. MAJCOM and Air Force Personnel Center (AFPC) manpower models were the highest tiered enterprise-level personnel assessments. However, since 2010, the USAF has adopted a broader enterprise-level approach via the SCF. A SCF may utilize several MAJCOMs in order to execute its mission. One enduring challenge is accurately assessing personnel deficiencies across the USAF by SCF. If planners could more accurately assess and identify the personnel readiness by SCF, this would help substantiate the risk associated with a lack of required manpower to deliver wartime and peacetime capability. If such statistical evidence exists, this suggests a weighting structure among career fields can be obtained and an interdependency model can be objectively developed. Prior to 2016, no USAF personnel analysis conducted among SCFs existed.

A proposed methodology presents a suite of objective, mathematical approaches to examine and assess personnel risk by SCFs. First, since SCFs differ in sample size, multiple comparison confidence intervals via a Tukey-Kramer test are used to determine if a statistically significant relationship exists between SCF manning rates. Insight from this technique is used to determine if SCF manning rates means are equal. This is considered exploratory analysis. Second, logistic regression is used to determine the probability of being at least 100% or more manned by SCF and functional equity (FE). The results from this analysis can be used to predict future SCF and FE manning levels. This insight reveals if preferential treatment at the corporate USAF level exists as it relates to the way SCF and FE manning is resourced. Third, through the use of logistic regression, logistics odds ratios can be computed to determine the probability of one SCF or FE to be more likely to be fully manned than other SCFs and FEs. This insight is noteworthy because the analysis allows risk assessment practitioners to understand how SCFs and FEs are related as it relates to manning allocation. Fourth, relative risk determine the magnitude (i.e. number of times) one

SCF or FE is more likely of being 100% or more manned than another SCF or FE. These four inferences from the methodology are handy inputs to compute risk as it relates to personnel capability assessments.

A methodological enterprise risk comparison is demonstrated examining 12 USAF core functions and 32 functional equities. This methodology can be used as a way to determine if evidence of corporate preference exists. The methodology decomposes and synthesizes personnel data to compute, compare and contrast enterprise level risk. The methodolgy helps identify capability gaps and serve as a good planning tool for validating risk. This further helps senior leaders to qualify risk with analysis and increase the odds of filling or mitigating personnel capability gaps.

A methodological enterprise risk comparison is demonstrated examining 12 USAF core functions and 32 functional equities. This methodology can be used as a way to determine if evidence of corporate preference exists. The methodology decomposes and synthesizes personnel data to compute, compare and contrast enterprise level risk. The methodolgy helps identify capability gaps and serve as a good planning tool for validating risk. This further helps senior leaders to qualify risk with analysis and increase the odds of filling or mitigating personnel capability gaps.

Background

The primary objective of this methodology is to examine ways to assess and analyze manning data to help senior Air Force leaders manage personnel capability and enhance maximization of readiness. The desired endstate is a more defensible, rigorous methodology to better inform SCF (Figure III-1) strategic risk assessments. This will help SCF personnel planners assess manning shortages to more accurately inform the USAF budget, yielding better management of personnel combat capability.

Manning is defined as the ratio of the number of personnel assigned to the number of funded authorizations:

$$Manning = \frac{Number\ of\ (assigned)\ personnel}{Number\ of\ funded\ authorizations}. \qquad \textbf{Eq. III-1}$$

Each USAF unit has a unit manning document (UMD) which stipulates the number of personnel and funded authorizations. Each authorization represents a funded position. Ideally, funded authorizations should have assigned, trained personnel filling the positions, but this is usually not achieved across the USAF.

Figure III-1: USAF Service Core Functions (SP3 2011)

As of July 2016, there were over 400,000 active duty military and civil servants in the USAF. Of the 400,000+ personnel, 55% are enlisted, 13% are officer and the remaining 32% are civil servants. The USAF has approximately 250 career field specialties or Air Force Specialties (AFS). AFSs are further compartmentalized into Air Force Specialty Codes or AFSCs. The AFSCs are condensed into 32 functional equities (FEs) across the 12 SCFs. A mapping of the career fields to the functional equities is provided in Figure III-2.

Mapping from AFS to Functional area							
Acq	60C, 63A/F/G/S	**Distribution**	25E. 2F0, 2P0, 2TX, 2XX	**Mx**	21A, 2AX, 2M0, 2R0, 2R1	**S&T**	61X, 62X, 8E0
Airfld Ops	1AX, 1PX, 1TX	**Fin**	65X, 6F0, 6F5	**Materiel**	2S0	**Safety**	1S0, 1S1
C2 Sys Ops	1CX	**Force Supt**	30X, 34X, 36-38X, 3DX, 3M, 3R03SX	**Msn Assur**	17X, 81-83, 85, 8X, 90G, 92X, 95-99, 9X 1B0, 1B4, 1F4, 39X, 3AX, 3F4, 3T0, 3V0, 69E, 6A3, 72, 75, 76, 7D	**Sec Forces**	31F, 31P, 31S, 3P0
CE	32E/G/S, 3EX	**Health Srvs**	40-48X, 4X, 9S1	**Muns**	21M, 2WX	**Space/Miss**	13X
Chaplain	52R, 5R0	**Hist**	3H0, 84H	**Ops Mgt**	86M, 86P	**Spec Inv**	71, 71S, 750
Combat Sys	12X	**Inspection**	87G/I/Q, 8IO/T	**Ops Plans**	10C, 16X	**Wx**	1S1, 15W, 1W0
~~**Comm**~~	~~33S, 33V, 3C0, 3C1~~	**Intelligence**	14N, 1NX	**Pilot**	11X		
CC	20C, 80C, 91C, 91W	**Legal**	51J, 5J0	**PA**	35X, 3NX		
Cons	64A, 64P, 6C0	**Log Plans**	21G/L/R/T, 221, 2G0	**RPA**	18X, 1V0		

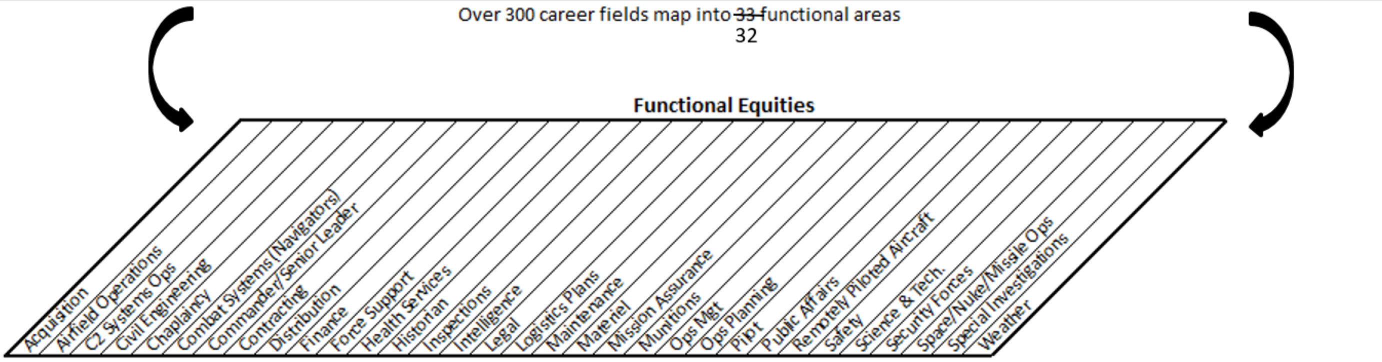
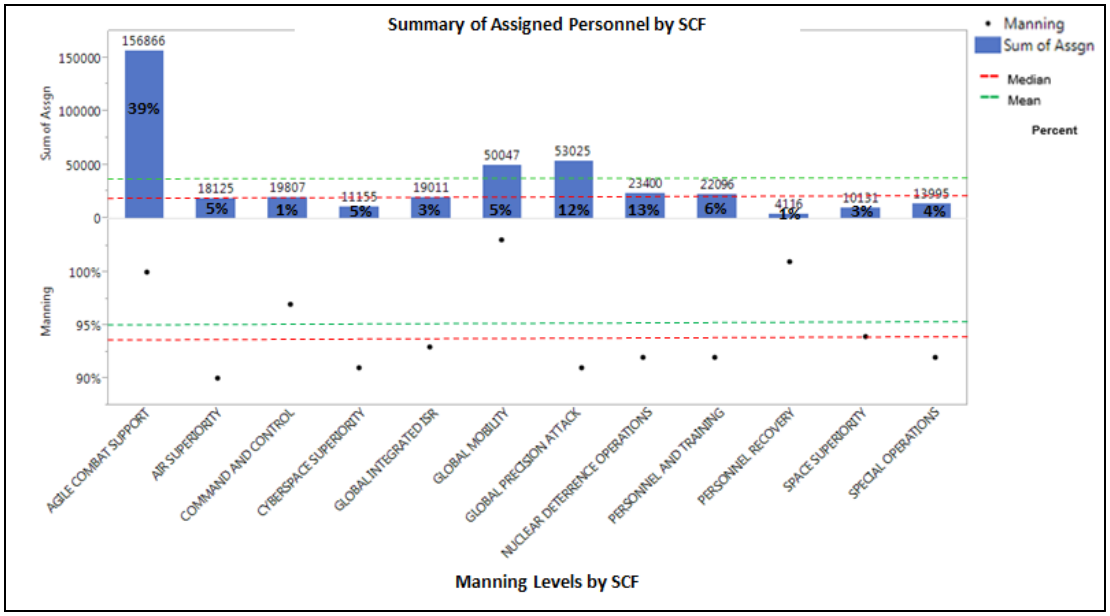


Figure III-2: Functional Equity Mapping

Thirty-two FEs across 12 SCFs equate to a dataset of 375 observations[13]. Figure III-3 shows the assigned USAF personnel by the 12 SCFs in the top chart along with associated manning rates in the bottom chart. Figure III-4 shows manning rates by FE. The amount of personnel differs by SCF. The mean and median are the same for the FEs. Each of the twelve SCFs are supported by Core Function Support Plans (CFSPs), developed and approved by one of the seven Core Function Leads. CFSPs translate the vision for the specific SCFs into risk-informed, resource-constrained, planning force proposals that guide follow-on Program Objective Memorandum (POM) and Science & Technology (S&T) decisions and activities

[13] The reader should be advised not all 32 functional equities are represented in every SCF, so although 32 x 12 is 384, there are actually only 375 observations.



(NAP, 2014).

Figure III-3: USAF SCF Manning Summary

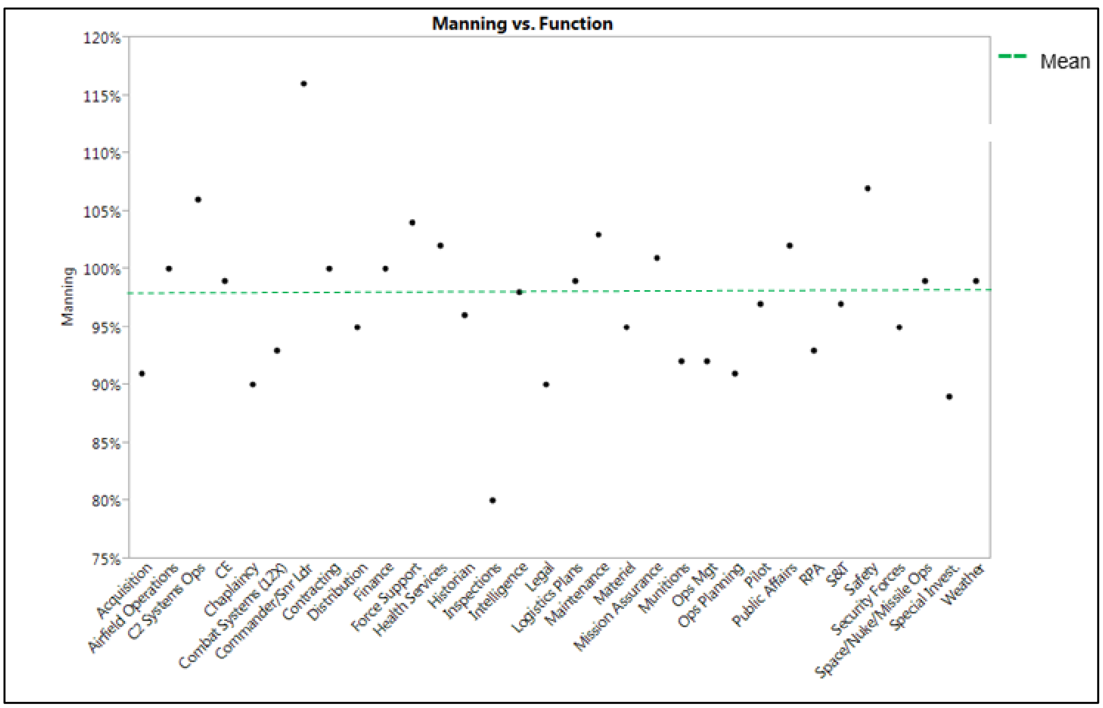


Figure III-4: USAF Functional Equity Manning Summary

Data Overview

This study consists of over 416,485 authorizations collapsed into 375 subsets as of July of 2016 from the Air Force Manpower, Personnel and Services database. Each subset represents a group of FE by SCF. Each observation contains 6 variables listed in Table III-1. The variable type characteristics are categorical (to include nominal and ordinal) and numeric.

Table III-1: Variables for categorical analysis

Name	**Description and effect type**	**Type**	**Levels and notes**
SCF	Service Core Function (Fixed)	Nom.	There are 12 USAF SCFs.
Functional Equity (FE)	Career Field Family (Fixed)	Nom.	There are 32 FEs.
Manning category	Binned manning categories between ≥ 100% and < 80% (Fixed)	Ord.	6 ordered categories
Manning rate	Assigned personnel vs Authorizations (Used to determine 'Fully Manned' & 'Manning category')	Cont.	This is a continuous value.
Fully Manned (Y/N)	Factor which consists of (Fixed) either fully manned or not	Nom.	Binomial variable (outcome)
Overage/Shortage (-)	Number of surplus/shortage of authorizations (Fixed)	Disc.	This is a discrete value.

Methodology

An analytical methodology to conduct SCF personnel risk analysis is provided. The methodology consists of several mathematical techniques to understand, compute and assess enterprise risk. The methodology uses five mathematical procedures to examine USAF personnel data by core function and functional equity. First, a multiple comparison method is used to examine whether the core functions and functional equities are similar. Second, the application of contingency table analyses determines existence of dependency among core functions and functional equities. Third, the use of odds ratios compare the odds of achieving 100% or more manning levels by core function and functional equity. Fourth, logistic regression computes the likelihood of full manning levels by enterprise and functional equity. Fifth, relative risk is used as a quantitative way to compare ratios of the probabilities of success (i.e. probability a SCF or FE is fully manned). These techniques are part of a framework developed to compare and contrast strategic personnel risk.

This SCF manning assessment approach can help identify capability gaps, and serve as a good planning tool and as a means of validating risk. This helps senior leaders to qualify risk with analysis and increase the odds of filling or mitigating personnel capability gaps. A potential tertiary inference is to determine if corporate preference exists. If such statistical evidence exists, this suggests a weighting structure among career fields can be obtained and an interdependency model can be objectively developed.

The interdependency model is the analytical substantiation for a more comprehensive model that takes into account dependent relationships between and among career fields. This improved strategic manning assessment is used to improve the strategic planning and programming process and enable the senior decision makers to better advocate for personnel resources. The subsequent research questions and hypothesis, tested at a 5% significance level ($\alpha = 0.05$) are as follows:

• Is there a meaningful manning relationship between USAF SCFs and full manning levels?

Null Hypothesis (H_0)*:* There is an association between SCF and Full manning levels.

Alternate Hypothesis (H_A)*:* There is no association between SCF and Full manning levels.

• Given, SCFs are unique: is there a rigorous way to compare manning levels among SCFs and FEs?

The goal of this study is to build a SCF and FE comparative manning assessment that decision makers can utilize for personnel capability advocacy. Techniques explored focus on logistic analysis in the form of contingency tables, logistic odd ratios and other methods to compare the SCFs and FEs against the manning levels.

Exploratory Analysis

The next portion uses multiple comparison methods to examine if the 12 SCF populations, that consist of primarily 32 functional equities, are similar. Figure III-5 provides a box and whisker plot by SCF population with a grand mean. Box and whiskey plots are simply visual ways to depict data. Bow and whisker plots do not infer statistical significance.   Visually, there are some mean overlaps, but in order to determine statistical similarity, a multiple comparisons statistical test is required.

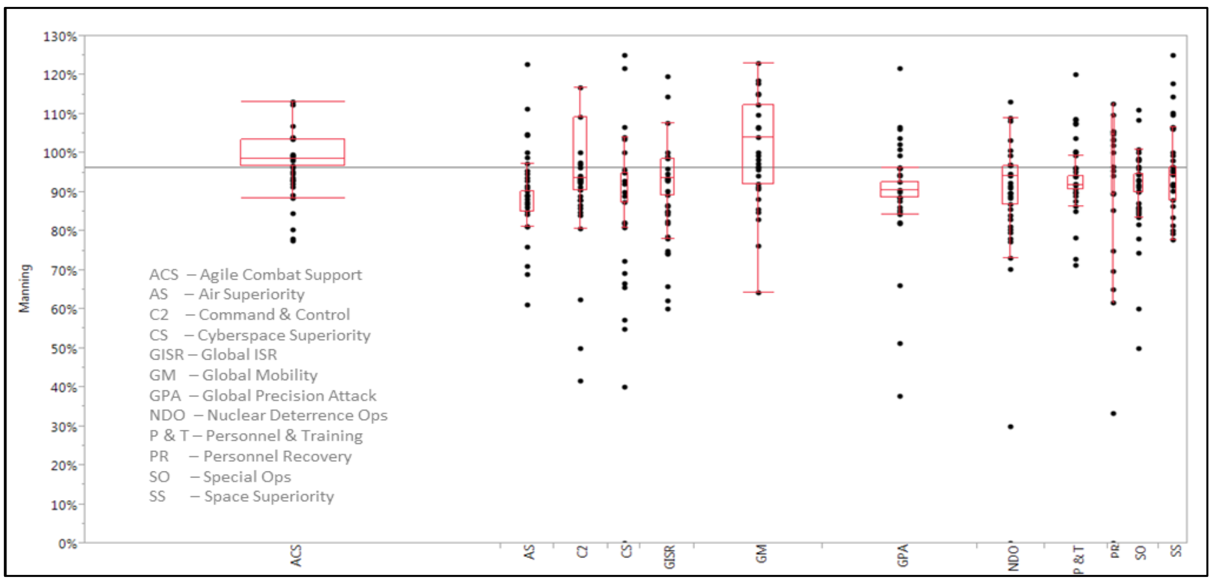


Figure III-5: Box and Whisker plot of SCF Manning Levels

A way to evaluate if there are any statistically significant differences between SCF manning rates is via a confidence interval (CI) simultaneous test. Some key elements of any multiple CI test are the per experiment (*PE*) error rate, per comparison (*PC*) error rate and familywise (*FW*) error rate (Howell, 2007). The *PE* error rate represents the number of Type I errors we expect to make when the Null Hypothesis (Ho) is true.

The *PE* error rate is typically calculated by taking the sum of comparisons and multiply this by the alpha level (e.g. $\propto = 0.05$) (Montgomery, 2013). The *PC* error rate represents the alpha or significance level for each test (Benjamini and Hochberg, 1995). The FW error rate estimates the probability that we have at least one Type I error in the family of comparisons (c) (Denis, 2016). It is typically calculated as follows: $FW = 1 - (1 - PC)c$ (Denis, 2016).

The Tukey-Kramer (for unequal sample sizes) group comparison method is considered one of the most robust comparison techniques (Montgomery, 2013). Unequal sample sizes require the computation of estimated standard deviations for each pairwise comparison (McDonald, 2014). It assumes constant variance, independence and a normal distribution. The Tukey method allows many confidence intervals to be compared while still assuring an overall confidence coefficient is maintained (Tukey, 1949). The Tukey FW error rate (β) is typically expressed as $\propto/k$ where α represents the family error rate and k represents the number of comparisons (NIST, 2015).

The procedure is performed using JMP 11 Pro. An overall significance level of 0.05 or simply there is a 5% likelihood of committing a Type I error (rejecting the null hypothesis, when it is true). Figure III-6 is a Tukey-Kramer multiple comparison among the SCF mean manning rates. Figure III-6 shows evidence of SCF dissimilarity. Specifically, the majority of the Tukey-Kramer test results reveal the SCFs are statistically dissimilar. The only SCFs that appear to be statistically similar are *Special Operations* (SO) and *Personnel and Training* (P&T) as well as *Global Precision Attack* (GPA) and *Cyberspace Superiority* (CS).

Connecting Letters Report

Level											Mean
GM	A										1.0309718
PR		B									1.0051307
ACS			C								0.9997451
C2				D							0.9668473
SS					E						0.9365637
GISR						F					0.9331010
SO							G				0.9235850
P & T							G				0.9232152
NDO								H			0.9181729
GPA									I		0.9088182
CS									I		0.9071678
AS										J	0.8971833

Levels not connected by same letter are significantly different.

Figure III-6: Tukey-Kramer test of SCF Manning Levels

Contingency Analysis

In this analysis, the main response variable is binary (i.e. fully manned or not) and the other factors are fixed nominal and ordinal variables. We use contingency analysis to examine if there are meaningful associations between SCFs and manning levels as well as studying associations between SCFs and FEs. The results visually show there is a clear distinction between Fully Manned and not fully manned core functions and functional equities. A total of 375 samples represent the number of FEs multiplied by the number of CFs (12), which technically is 384, but not every CF has the maximum amount of FEs, so 375 is the final sample size *N*. There exists more failures (i.e. 267 of 375) versus successes

(107) of the total sample size. An illustration is provided in Figure III-7 that demonstrates the use of contingency analysis using the ACS CF.

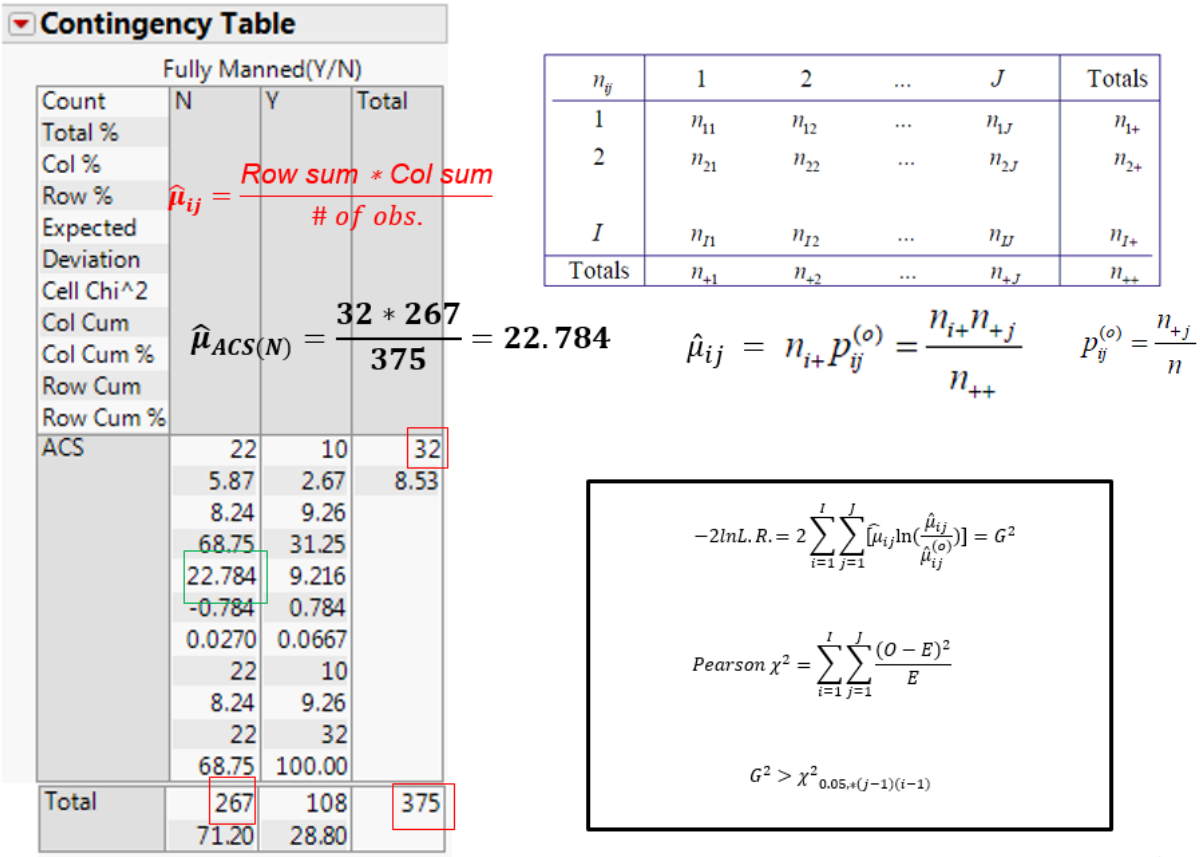
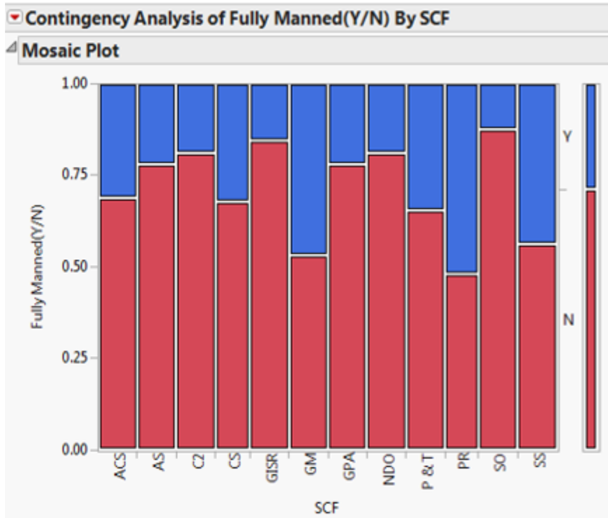


Figure III-7: Portion of SCF Contingency Table Analysis

Figures III-8 and III-9 provide visual results of the overall contingency analysis of the CFs and FEs. The mosaic plots presented reflect the amount of CFs and FEs fully manned and not fully manned. A complete blue vertical bar indicates the CF or FE is meeting personnel requirements. A composition of blue and red indicate the CF or FE is not 100% or more manned. A senior decision maker's preference is that all of the mosaic plots are blue. Figures III-8 and III-9 reveal evidence of only partially filled manning requirements. For example, note how Global Mobility (GM) and Personnel Recovery (PR) core functions get more manning support than Nuclear Deterrence Operations (NDO) and Global ISR (GISR). Simliarly, note how the Commander/Sr Leader functional equity gets more manning support than all of the other functional equities. A procedure is applied to determine if these manning disparities are statistically significant.

In addition to the success and failure inputs, other parameters of contingency analysis include the degrees of freedom, -loglikelihood, Likelihood Ratio Test (LRT) and *p*-value. The degrees of freedom are the number of CFs and FEs minus one, respectively, thus, $12 - 1 = 11$ and $32 - 1 = 31$. The computation for the –loglikelihood is computed using formulae (Eq. II-5 through Eq. II-7), discussed in Chapter II. When the –loglikelihood is multiplied by 2, a Chi-square test statistic is obtained. The LRT statistic shows the chi-square values from the SCF and FE observations are 27.814 and 50.507, respectively. With $\propto = 0.05$, and respective DFs, significant *p*-values of 0.0035 and 0.0153 are obtained from the CF and FE data. These *p*-values suggest there is an association between manning status and CF or FE. This further suggests (whether intentional or unintentional), it appears there is some level of corporate preference among the CFs and FEs.

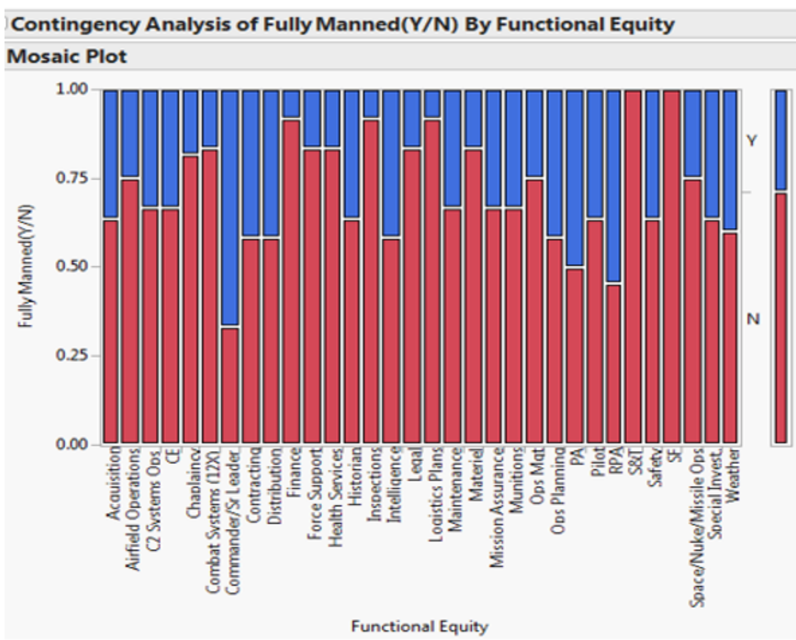


Tests

N	DF	-LogLike	RSquare (U)
375	11	13.907225	0.0618

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	27.814	0.0035*

Figure III-8: SCF manning Contingency Analysis



Tests

N	DF	-LogLike	RSquare (U)
375	31	25.203551	0.1120

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	50.407	0.0153*

Figure III-9: FE manning Contingency Analysis

The analysis implies the SCFs are not similarly manned, which suggests certain SCFs are more favorable towards being at full funding capacity levels than others. Reasons for this phenomenon are not yet understood. Potential reasons could be retention and recruitment shortfalls in certain undermanned career field specialties such as inspections and science & technology (S&T) career fields.

Figures III-10 and III-11 depict results of contingency analysis to examine response homogeneity (i.e. is there a statistically significant difference in the manning levels among CFs and FEs). The manning categorical variable ('Mann_Cat') is an ordinal response with six levels. Each level corresponds to a manning range (e.g. < 80%). The hypotheses for the core functions and functional equity manning level proportions are as follows:

$$H_o: ACS_M = AS_M = C2_M = \cdots SS_M$$

$$H_A: ACS_M \neq AS_M \text{ } or \text{ } C2_M \text{ } or \text{ } \ldots SS_M$$

and

$$H_o: Acq_M = Airfld\ Ops_M = C2\ Sys\ Ops_M = \cdots Wx_M$$

$$H_A: Acq_M \neq Airfld\ Ops_M \text{ } or \text{ } C2\ Sys\ Ops_M \text{ } or \text{ } \ldots Wx_M$$

Only 117 of 375 or (31%) of FEs across 12 CFs are 100% or more manned. Since, the likelihood ratio test *p*-values (computed using Eq. II-7) are smaller than α, the results of both tests suggest at least one SCF and FE manning level is statistically significantly different.

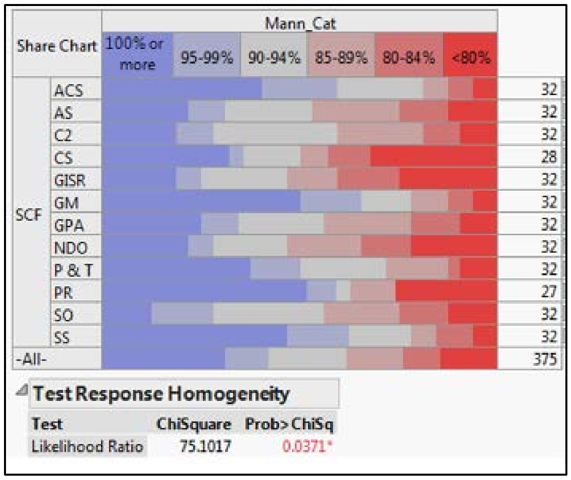


Figure III-10: SCF Ordinal Categorical Analysis

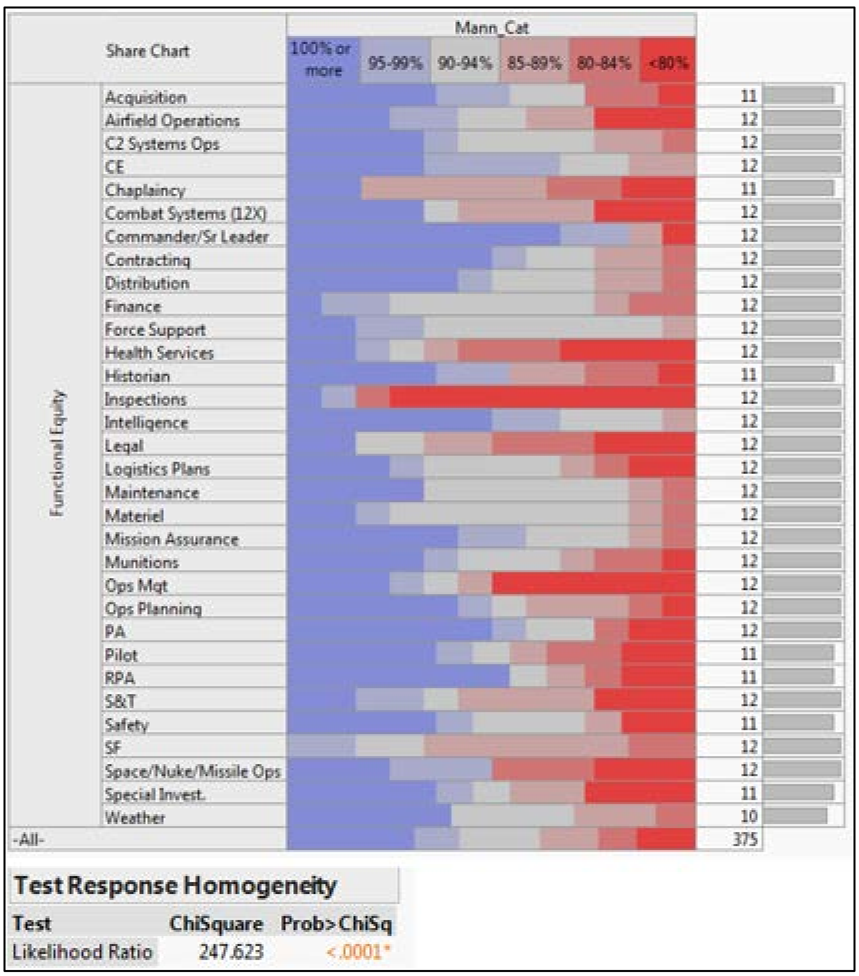


Figure III-11: FE Ordinal Categorical Analysis

The implication of this analysis suggests that while Air Force guidance promotes equal career manning equity across SCF and FE, the statistical results indicate otherwise.

Modeling Approach

A logistic regression model can provide more meaningful insight among the SCFs and FEs as it relates to being fully manned or not. Logistic regression analysis describes how a binary (0 or 1) response variable is associated with a set of explanatory variables (categorical or continuous). The general logistic function is $\pi(x) = \frac{e^{(\propto+\beta x)}}{1+e^{(\propto+\beta x)}} = \frac{odds}{1+odds}$ where *x* is the independent variable or factor and *e* is the exponential function, and $\pi(x)$ is the probability of being at least 100% manned. For this nominal outcome variable, each factor is examined individually and associated model statistics are compared to a joint (combined) model. The joint model has $(k - p)$ degrees of freedoms when both SCF and FE parameters are combined, where *k* and *p* represent the number of groups (44) and parameters (2), respectively.

Negative loglikelihood (*–loglikelihood*) estimates are computed for the full and reduced models. The Full model refers to the model without any predictor variables or simply the intercept. The Reduced model includes the predictor variables. Thus, the Difference *–loglikelihood* model estimate is the difference between the Full and Reduced model *–loglikelihood* estimates. The Chi-square estimate is simply twice the Difference *–loglikelihood* estimate. When the test for model significance is applied, the results of the *p*-value indicate the model results are statistically significant. Figure III-12 provides a summary of the results.

Whole Model Test Results				
Model	-Loglikelihood	DF	ChiSquare	Prob > Chisq
Difference	41.7	42	83.4	**0.0001**
Full	183.43			
Reduced	225.13			
Obs (N)	375			
Missclass Rate	0.24			
AUC	0.78			

Figure III-12: Joint Model Results

The accuracy rates (1- misclassification rate) regarding predictability classifies success 76% of the time. The joint model has an Area under the Curve (AUC) of 0.782. This suggests the modeling predictions have more than a ‘chance’ of being accurate. In fact, a strict interpretation of this model is that when presented randomly with a given number of SCF and FE manning observations that are ≥ 100% and ≤ 100%, there is a 78.2% chance of correct classification. Figure III-12 depicts the model probability estimates of being 100% or more manned by SCF and FE. This means given a similar population, there’s a 78% chance of predicting a SCF by FE is fully manned. This is informative to senior planners, programmers and analysts to better assess personnel capability gaps which are tied to the identification of enterprise risk.

Findings also suggest none of the FEs by SCF are likely to be 100% manned or more. Notably, the Science & Technology and Security Forces FEs are highly likely to not be fully manned in any SCF or FE. Conversely, the commander or senior leader FEs has the potential in the Global Mobility and Personnel Recovery SCFs to have 100% or more manning. This is illustrated via the likelihood color palette scale in Figure III-13. Arguably, rows (FEs) in red are highly less likely to be 100% or more manned. A translation of Figure III-13 in terms of success/fail results is presented next.

	ACS	AS	C2	CS	GISR	GM	GPA	NDO	P & T	PR	SO	SS
Acquisition	0.4198	0.294	0.2514	0.4619	0.2086	0.6146	0.294	0.2514	0.4606	-	0.1659	0.5777
Airfield Operations	0.2576	0.1665	0.1387	0.2916	0.1122	0.4334	0.1665	0.1387	0.2905	0.5211	0.0871	0.3961
C2 Systems Ops	0.3529	0.2389	0.202	0.3929	0.1658	0.5459	0.2389	0.202	0.3916	0.631	0.1304	0.5076
CE	0.3529	0.2389	0.202	0.3929	0.1658	0.5459	0.2389	0.202	0.3916	0.631	0.1304	0.5076
Chaplaincy	0.2064	0.1302	0.1077	0.2358	0.0865	0.3644	0.1302	0.1077	0.2348	-	0.0667	0.3296
Combat Systems (12X)	0.1656	0.1026	0.0844	0.1906	0.0674	0.3044	0.1026	0.0844	0.1898	0.3837	0.0518	0.2729
CC/SL	0.7222	0.5994	0.5468	0.7551	0.4864	0.8514	0.5994	0.5468	0.7541	0.8907	0.4168	0.8309
Contracting	0.4493	0.3195	0.2746	0.4918	0.2291	0.6426	0.3195	0.2746	0.4904	0.7189	0.1832	0.6066
Distribution	0.4493	0.3195	0.2746	0.4918	0.2291	0.6426	0.3195	0.2746	0.4904	0.7189	0.1832	0.6066
Finance	0.0792	0.0472	0.0384	0.0926	0.0304	0.1594	0.0472	0.0384	0.0921	0.2124	0.0231	0.1398
Force Support	0.1656	0.1026	0.0844	0.1906	0.0674	0.3044	0.1026	0.0844	0.1898	0.3837	0.0518	0.2729
Health Services	0.1656	0.1026	0.0844	0.1906	0.0674	0.3044	0.1026	0.0844	0.1898	0.3837	0.0518	0.2729
Historian	0.4198	0.294	0.2514	0.4619	0.2086	0.6146	0.294	0.2514	0.4606	-	0.1659	0.5777
Inspections	0.0792	0.0472	0.0384	0.0926	0.0304	0.1594	0.0472	0.0384	0.0921	0.2124	0.0231	0.1398
Intelligence	0.4493	0.3195	0.2746	0.4918	0.2291	0.6426	0.3195	0.2746	0.4904	0.7189	0.1832	0.6066
Legal	0.1656	0.1026	0.0844	0.1906	0.0674	0.3044	0.1026	0.0844	0.1898	0.3837	0.0518	0.2729
Logistics Plans	0.0792	0.0472	0.0384	0.0926	0.0304	0.1594	0.0472	0.0384	0.0921	0.2124	0.0231	0.1398
Maintenance	0.3529	0.2389	0.202	0.3929	0.1658	0.5459	0.2389	0.202	0.3916	0.631	0.1304	0.5076
Materiel	0.1656	0.1026	0.0844	0.1906	0.0674	0.3044	0.1026	0.0844	0.1898	0.3837	0.0518	0.2729
Mission Assurance	0.3529	0.2389	0.202	0.3929	0.1658	0.5459	0.2389	0.202	0.3916	0.631	0.1304	0.5076
Munitions	0.3529	0.2389	0.202	0.3929	0.1658	0.5459	0.2389	0.202	0.3916	0.631	0.1304	0.5076
Ops Mgt	0.2576	0.1665	0.1387	0.2916	0.1122	0.4334	0.1665	0.1387	0.2905	0.5211	0.0871	0.3961
Ops Planning	0.4493	0.3195	0.2746	0.4918	0.2291	0.6426	0.3195	0.2746	0.4904	0.7189	0.1832	0.6066
Pilot	0.395	0.2731	0.2325	-	0.1921	0.59	0.2731	0.2325	0.4352	0.6718	0.1522	0.5524
PA	0.5442	0.4073	0.3565	0.5862	0.3031	0.7247	0.4073	0.3565	0.5849	0.7892	0.2471	0.693
RPA	0.6036	0.4671	0.4141	-	0.3568	0.7705	0.4671	0.4141	0.6425	0.8269	0.2951	0.7422
S&T	3E-08	2E-08	2E-08	4E-08	1E-08	7E-08	2E-08	2E-08	4E-08	1E-07	9E-09	6E-08
Safety	0.4198	0.294	0.2514	0.4619	0.2086	0.6146	0.294	0.2514	0.4606	-	0.1659	0.5777
SF	3E-08	2E-08	2E-08	4E-08	1E-08	7E-08	2E-08	2E-08	4E-08	1E-07	9E-09	6E-08
Space/Nuke/Missile O	0.2576	0.1665	0.1387	0.2916	0.1122	0.4334	0.1665	0.1387	0.2905	0.5211	0.0871	0.3961
Special Invest/	0.395	0.2731	0.2325	-	0.1921	0.59	0.2731	0.2325	0.4352	0.6718	0.1522	0.5524
Weather	0.4737	0.3412	0.2946	-	0.2469	0.6648	0.3412	0.2946	0.515	-	0.1983	0.6298

Likelihood of ≥ 100% manning

x < 0.15 Low
0.15 < x ≥ 0.25 Mod.
0.25 < x ≥ 0.4 Sig
1.0 ≤ x > 0.4 High

Figure III-13: SCF and FE Likelihood being fully manned[14]

[14] Cells without values indicate the FE was not represented in the SCF.

Modeling Results

Figure III-14 is a matrix of the modeling interpretations of the success/failure probabilities of the 375 observations. Probability of Success $((\frac{1}{1+e^{logit[\pi(x)]}}))$ is considered 100% or more manned or a green 'Y', otherwise blank in the matrix of cells. If the model estimate is greater than 0.50, the results are considered successful, otherwise failure. Cells with '-' notation are not applicable as the FE is unrepresentative for a particular SCF.

	ACS	AS	C2	CS	GISR	GM	GPA	NDO	P & T	PR	SO	SS
Acquisition						Y				-		Y
Airfield Operations										Y		
C2 Systems Ops						Y				Y		Y
CE						Y				Y		Y
Chaplaincy										-		
Combat Systems (12X)												
CC/SL	Y	Y	Y	Y		Y	Y	Y	Y	Y		Y
Contracting						Y				Y		Y
Distribution						Y				Y		Y
Finance												
Force Support												
Health Services												
Historian						Y				-		Y
Inspections												
Intelligence						Y				Y		Y
Legal												
Logistics Plans												
Maintenance						Y				Y		Y
Materiel												
Mission Assurance						Y				Y		Y
Munitions						Y				Y		Y
Ops Mgt										Y		
Ops Planning						Y				Y		Y
Pilot				-		Y				Y		Y
PA	Y			Y		Y			Y	Y		Y
RPA	Y			-		Y			Y	Y		Y
S&T												
Safety						Y				-		Y
SF												
Space/Nuke/Missile Ops										Y		
Special Invest/				-		Y				Y		Y
Weather				-		Y			Y	-		Y

Figure III-14: Likelihood of 100% manning in binary form

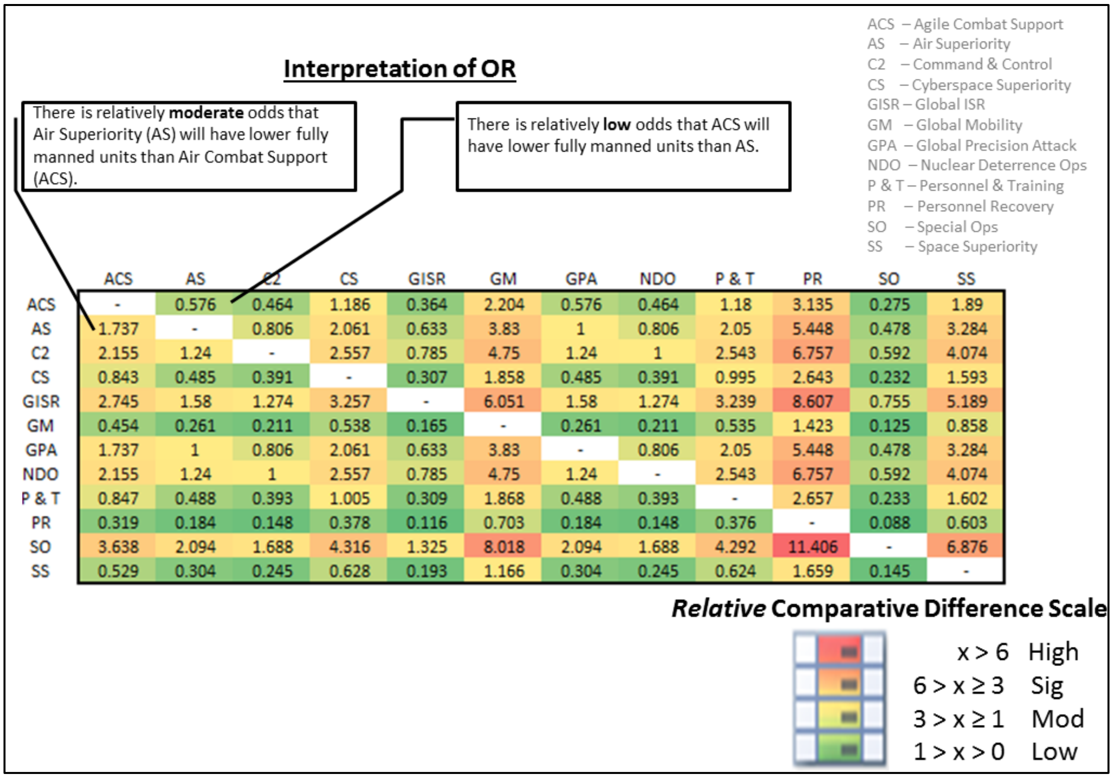
The full joint model equation is listed in Appendix A. The results of Figure III-14 suggest there is statistically significant evidence that the USAF does show preference with regards to which core functions and function equities it chooses to fund and man. Whether the preferential treatment is deliberate or un-intentional, there is evidence of corporate preference, which suggests all career fields are not treated the same. This infers a weighting structure of the career fields exists. This further infers a more comprehensive risk prioritization of career field resource management could be introduced.

Odds Ratio Analyses

The near (within 5 years), mid (5 to 10 years) and far (beyond 10 years) term goal of the USAF is to provide air operations in support of the defense of the nation. To achieve this, planners, programmers, analysts and managers should take advantage of existing data resources and base decisions not only on anectdotes, but also on insights gleaned from reliable data. For example, it may appear intuitive to some risk assessment practitioners that all SCFs and FEs should be equally resourced in terms of manpower and are equally likely to be able to provide or support air operations. This attitude is myopic, and if not tempered with supporting facts can lead to unintended consequences as it relates to proper risk identification. If risk is severely understated, personnel resources can be misallocated and misprioritized. It is possible that other insight might be gained in rigorously identifying which SCFs and FEs are more likely to be fully manned than others. Finding the most valuable indicators is a not only helpful for senior risk assessment practitioners, but is also critical to advanced predictive analytics as it relates to personnel risk assessment to inform senior decision making in the near, mid and far planning timeframes.

Unfortunately, for many companies, these indicators reside across different, siloed databases, which makes analysis difficult. But if the data is successfully and accurately linked together, we can begin to take a more comprehensive look at customer behavior. Looking at odds ratios in relation to a particular target of interest can allow us to gain insights across a wide array of indicators. While interpretation and understanding of statistical or predictive models isn't always simple or straightforward, the ability to interpret odds and odds ratios is a key step in being able to better understand the results of logistic regression output

The outcome variable is a success/fail response variable (i.e. 100% or more manned) so odds ratios via logistic transformations (logits) are computed and compared among SCFs and FEs. The logistic odds is represented as $Logit[\pi(x)] = log(odds) = log\left(\frac{\pi(x)}{1-\pi(x)}\right) = \beta_0 + \beta_1 X_1 + \cdots \beta_p X_p$ where β_0 is the intercept, β_p (the parameter) is the log odds ratio of one unit increase in x whereas $e^{(\beta)}$ is the odds ratio of one unit increase in x (Agresti, 2013). The odds ratios are computed from the joint model previously discussed. A total of 1,124 ($\binom{12}{2}+\binom{32}{2}$) permuted odds ratios are computed and compared of which 45 (34%) and 160 (16%) are considered 'statistically significantly different than one,' respectively. These overview statistics suggest there are significant differences in full manning levels among SCFs and FEs. Figure III-15 is a matrix of the SCF odds ratios accompanied with a scale to aid in interpretation.



	ACS	AS	C2	CS	GISR	GM	GPA	NDO	P & T	PR	SO	SS
ACS	-	0.576	0.464	1.186	0.364	2.204	0.576	0.464	1.18	3.135	0.275	1.89
AS	1.737	-	0.806	2.061	0.633	3.83	1	0.806	2.05	5.448	0.478	3.284
C2	2.155	1.24	-	2.557	0.785	4.75	1.24	1	2.543	6.757	0.592	4.074
CS	0.843	0.485	0.391	-	0.307	1.858	0.485	0.391	0.995	2.643	0.232	1.593
GISR	2.745	1.58	1.274	3.257	-	6.051	1.58	1.274	3.239	8.607	0.755	5.189
GM	0.454	0.261	0.211	0.538	0.165	-	0.261	0.211	0.535	1.423	0.125	0.858
GPA	1.737	1	0.806	2.061	0.633	3.83	-	0.806	2.05	5.448	0.478	3.284
NDO	2.155	1.24	1	2.557	0.785	4.75	1.24	-	2.543	6.757	0.592	4.074
P & T	0.847	0.488	0.393	1.005	0.309	1.868	0.488	0.393	-	2.657	0.233	1.602
PR	0.319	0.184	0.148	0.378	0.116	0.703	0.184	0.148	0.376	-	0.088	0.603
SO	3.638	2.094	1.688	4.316	1.325	8.018	2.094	1.688	4.292	11.406	-	6.876
SS	0.529	0.304	0.245	0.628	0.193	1.166	0.304	0.245	0.624	1.659	0.145	-

Figure III-15: SCF odds ratio Comparison

The matrix in Figure III-15 should be examined from left to right by row. For example, the Air Superiority (AS) SCF compared to the Agile Combat Support (ACS) SCF has 0.576, or low odds, of being fully manned. Conversely, ACS has 1.737 times the odds, or moderate odds, of being fully manned when compared to AS. The top 3 SCFs with better odds of full manning levels are Personnel Recovery, Global Mobility and Space Superiority. This is fairly intuitive as these rows are more green. The bottom 4 SCFs with lesser odds of full manning levels are Command & Control, Nuclear Deterrence Options, Global ISR and Special Operations. Further, the same matrix from Figure III-15 overlaid with turquoise outlines is used in Figure III-16 to illustrate which SCF odds ratios are considered significantly different. Similar analysis is performed by FE. The FE results are listed in Appendices C and D.

	ACS	AS	C2	CS	GISR	GM	GPA	NDO	P & T	PR	SO	SS
ACS	-	0.576	0.464	1.186	0.364	2.204	0.576	0.464	1.18	3.135	0.275	1.89
AS	1.737	-	0.806	2.061	0.633	3.83	1	0.806	2.05	5.448	0.478	3.284
C2	2.155	1.24	-	2.557	0.785	4.75	1.24	1	2.543	6.757	0.592	4.074
CS	0.843	0.485	0.391	-	0.307	1.858	0.485	0.391	0.995	2.643	0.232	1.593
GISR	2.745	1.58	1.274	3.257	-	6.051	1.58	1.274	3.239	8.607	0.755	5.189
GM	0.454	0.261	0.211	0.538	0.165	-	0.261	0.211	0.535	1.423	0.125	0.858
GPA	1.737	1	0.806	2.061	0.633	3.83	-	0.806	2.05	5.448	0.478	3.284
NDO	2.155	1.24	1	2.557	0.785	4.75	1.24	-	2.543	6.757	0.592	4.074
P & T	0.847	0.488	0.393	1.005	0.309	1.868	0.488	0.393	-	2.657	0.233	1.602
PR	0.319	0.184	0.148	0.378	0.116	0.703	0.184	0.148	0.376	-	0.088	0.603
SO	3.638	2.094	1.688	4.316	1.325	8.018	2.094	1.688	4.292	11.406	-	6.876
SS	0.529	0.304	0.245	0.628	0.193	1.166	0.304	0.245	0.624	1.659	0.145	-

Considered Statistically Different

Figure III-16: SCF odds ratio Comparison with Significance Indicators

Figure III-16's results reveal the Global Mobility, Personnel Recovery and Space Superiority SCFs have statistically different manning levels as it relates to being fully manned or not.

Relative Risk

Relative risk (RR) are comparative ratios of the probabilities of success, (i.e. a given SCF and FE being fully manned), and are quantitative ways to compare categories. As the number of categorical levels increases, the number of relative comparisons grows quite large. For example, 12 SCF and FE RR one-way comparisons gives 4,224 ($\binom{12}{2}$ combinations *32 FEs) permutations or possibilities. In this instance, we will only explore relative comparisons to the ACS SCF. The probabilities of success are taken from the joint model results depicted in Figure III-9. If the RR is equal to 1, we conclude independence or FE_1 with respect to a given SCF is neither more likely nor less likely of occurring than FE_2 with respect to the same SCF. If the RR is less than 1, we conclude FE_1 with respect to a given

SCF is less likely of occurring than FE_2 with respect to the same SCF. If the RR is greater than 1, we conclude FE_1 with respect to a given SCF is more likely of occurring than given SCF is less likely of occurring than FE_2 with respect to the same SCF. If the RR is greater than 1, we conclude FE_1 with respect to a given SCF is more likely of occurring than FE_2 with respect to the same SCF. The RRs are computed and shown in Figure III-17.

	ACS	AS	C2	CS	GISR	GM	GPA	NDO	P & T	PR	SO	SS
Acquisition	1	1.43	1.67	0.91	2.01	0.68	1.43	1.67	0.91	-	2.53	0.73
Airfield Operations	1.63	1.55	1.86	0.88	2.3	0.59	1.55	1.86	0.89	0.49	2.96	0.65
C2 Systems Ops	1.19	1.48	1.75	0.9	2.13	0.65	1.48	1.75	0.9	0.56	2.71	0.7
CE	1.19	1.48	1.75	0.9	2.13	0.65	1.48	1.75	0.9	0.56	2.71	0.7
Chaplaincy	2.03	1.59	1.92	0.88	2.38	0.57	1.59	1.92	0.88	-	3.09	0.63
Combat Systems (12X)	2.53	1.62	1.96	0.87	2.46	0.54	1.62	1.96	0.87	0.43	3.2	0.61
CC/SL	0.58	1.2	1.32	0.96	1.48	0.85	1.2	1.32	0.96	0.81	1.73	0.87
Contracting	0.93	1.41	1.64	0.91	1.96	0.7	1.41	1.64	0.92	0.62	2.45	0.74
Distribution	0.93	1.41	1.64	0.91	1.96	0.7	1.41	1.64	0.92	0.62	2.45	0.74
Finance	5.3	1.68	2.06	0.86	2.61	0.5	1.68	2.06	0.86	0.37	3.43	0.57
Force Support	2.53	1.62	1.96	0.87	2.46	0.54	1.62	1.96	0.87	0.43	3.2	0.61
Health Services	2.53	1.62	1.96	0.87	2.46	0.54	1.62	1.96	0.87	0.43	3.2	0.61
Historian	1	1.43	1.67	0.91	2.01	0.68	1.43	1.67	0.91	-	2.53	0.73
Inspections	5.3	1.68	2.06	0.86	2.61	0.5	1.68	2.06	0.86	0.37	3.43	0.57
Intelligence	0.93	1.41	1.64	0.91	1.96	0.7	1.41	1.64	0.92	0.62	2.45	0.74
Legal	2.53	1.62	1.96	0.87	2.46	0.54	1.62	1.96	0.87	0.43	3.2	0.61
Logistics Plans	5.3	1.68	2.06	0.86	2.61	0.5	1.68	2.06	0.86	0.37	3.43	0.57
Maintenance	1.19	1.48	1.75	0.9	2.13	0.65	1.48	1.75	0.9	0.56	2.71	0.7
Materiel	2.53	1.62	1.96	0.87	2.46	0.54	1.62	1.96	0.87	0.43	3.2	0.61
Mission Assurance	1.19	1.48	1.75	0.9	2.13	0.65	1.48	1.75	0.9	0.56	2.71	0.7
Munitions	1.19	1.48	1.75	0.9	2.13	0.65	1.48	1.75	0.9	0.56	2.71	0.7
Ops Mgt	1.63	1.55	1.86	0.88	2.3	0.59	1.55	1.86	0.89	0.49	2.96	0.65
Ops Planning	0.93	1.41	1.64	0.91	1.96	0.7	1.41	1.64	0.92	0.62	2.45	0.74
Pilot	1.06	1.45	1.7	-	2.06	0.67	1.45	1.7	0.91	0.59	2.6	0.72
PA	0.77	1.34	1.53	0.93	1.8	0.75	1.34	1.53	0.93	0.69	2.2	0.79
RPA	0.7	1.29	1.46	-	1.69	0.78	1.29	1.46	0.94	0.73	2.05	0.81
S&T	1E+07	1.74	2.16	0.84	2.75	0.45	1.74	2.16	0.85	0.32	3.64	0.53
Safety	1	1.43	1.67	0.91	2.01	0.68	1.43	1.67	0.91	-	2.53	0.73
SF	1E+07	1.74	2.16	0.84	2.75	0.45	1.74	2.16	0.85	0.32	3.64	0.53
Space/Nuke/Missile Ops	1.63	1.55	1.86	0.88	2.3	0.59	1.55	1.86	0.89	0.49	2.96	0.65
Special Invest/	1.06	1.45	1.7	-	2.06	0.67	1.45	1.7	0.91	0.59	2.6	0.72
Weather	0.89	1.39	1.61	-	1.92	0.71	1.39	1.61	0.92	-	2.39	0.75

Figure III-17: SCF/FE Relative Risk Ratio table

In the ACS column of Figure III-17, the Acquisition FE is held fixed compared to the other FEs within the ACS SCF. If we refer to the Airfield Operations and Acquisition FEs within the ACS SCF, we see a RR of 1.63. The interpretation is that within the ACS SCF, the Acquisition FE is 1.63 times more likely of being 100% or more manned than Airfield

Operations. For the rest of the columns (AS-SS), the RRs are compared within each row or the FE is held fixed relative to the ACS SCF. For example, the 1.43 RR at the intersection of the Acquisition FE and AS SCF, infers that within the Acquisitions FE, the Air Combat Support SCF is 1.43 times likely of being 100% or more manned than the Air Superiority SCF. Similarly, at the intersection of the Acquisition FE and C2 SCF, infers within the Acquisitions FE, the Air Combat Support SCF is 1.67 times likely of being 100% or more manned than the Command and Control SCF. A takeaway from Figure III-16 is ACS has a relative moderate risk to the other SCFs with regards to being 100% or more manned.

Remarks

This research presents a rigorous methodology for assessing USAF manning by SCF and FE by using logistic regression functions and contingency analyses. Statistically, there is an association between SCFs or FEs and full manning levels. Manning relationships among SCFs or FEs can be rigorously prioritized by odds ratio comparisons. There exists statistical evidence of corporate preference towards certain core functions (CFs) or FEs. Whether intentional or un-intentional, the existence of a corporate prefence sheds insight into how the USAF corporately views certain CFs or FEs. Since CFs or FEs are statistically significantly manned more than others, there inherently exists a weight structure among CFs, FEs or even specific career fields that can be used for prioritization of resources.   Statistical techniques such as contingency table analysis, logistic regression and odds ratio analysis demonstrated this phenomena.

Further, this research can inform decision makers of manning capability gaps and substantiate advocacy for more resources to meet combat and peacetime requirements. There are no SCFs fully manned in the USAF. Overall, across the USAF, 'commanders or senior leaders' is the only FE of 32 likely to be fully manned. This methodology helps senior decision makers better qualify risk and enhance the strategic planning & programming process risk assessment, which in turn, enables better substantiation and advocacy.

Limitations

While this research illustrates how manning relationships can be rigorously examined at the SCF level, the methodology has caveats. First, criteria for success using the logistic function is one of two options: 100% fully manned. This intuitively means CF and FE manning levels below 100% are failing. This could be easily mischaracterized as a gross mis-assessment of personnel risk. However, if manning levels are to be resourced at *at least 100%*, the logistic regression analysis sheds credible light on the lack of personnel USAF requirements filled throughout its enterprises. This finding has strategic implications for senior decision makers when advocating for resources among other service components. If a USAF senior decision maker can articulate personnel capability gaps via analytic traceability and defensibility, the advocacy message is more credible at the joint services leadership level and beyond. When we can intelligently (through rigor) argue why we need what we need, this increases the chances of getting the necessary resources to maximize combat capability in a fiscally constrained environment. This methodology demonstrates personnel risk can be objectively assessed at the enterprise level. In the next section, we examine if personnel efficiency can be computed at the squadron level via fighter pilot manning and sortie production. Recall, a primary objective is to examine if a significant statistical relationship exsits between efficiency and risk.

IV. Methodology to Determine USAF Personnel Efficiency via DEA Bootstrapping

Introduction

USAF senior leaders are faced with resource challenges in the form of overseeing personnel and budget. As stewards of these resources, senior decision leaders have to make tough decisions in a fiscally constrained environment. Often times, tradeoffs are made between cost and manpower to provide an airpower capability. That is to say, the amount of required personnel to perform a function is weighed against the cost of these personnel. Managerial insight is required at lower echelons (e.g. installation level) to ascertain if efficiency can be obtained to better utilize manpower to maximize combat capability.

There are five bedrock components to United States Air Force (USAF) capability: Personnel, Training, Equipment, Infrastructure, and Institutional factors. These components are collectively characterized as the planning force (AFMAN 90-106, 2017). It is very difficult to provide mission capability without all five components of the planning force. If adequate levels of personnel are not available and trained to perform desired tasks to provide mission capability, then the remaining equipment, infrastructure and institutional components become ineffective. This research focuses on the personnel component by providing a proof of concept methodology based on DEA for measuring efficiency to better inform USAF enterprise risk assessment procedures. The goal is to increase traceability and strengthen defensibility in strategic risk assessments, which promotes analysis credibility with senior decision makers. In particular, this case study demonstrates the use of Data Envelopment Analysis (DEA) to assess active duty F-16 air base operations efficiency using fighter pilot personnel requirements (spaces) and actual personnel (faces). This work examines *efficiency* i.e. benefits realized and resources used as opposed to *effectiveness* i.e. ability to state and achieve desired goals (Cooper et al., 2000).

A methodology helps objectively determine if USAF efficiency outputs and inputs are linearly or nonlinearly scaled. Specifically, sortie generation efficiency of 10 F-16 active duty flying bases are compared using Data Envelopment Analysis. From a strategic risk assessment perspective, if capability can be assessed via efficiency then risk vulnerabilities become more traceable for decision makers. This added analytical insight can foster better strategic decisions by identifying capability gaps and providing an objective basis to support resource allocation. In addition, objective return to scale (RTS) determination of a USAF dataset is explored. RTS examines whether there is a linear and nonlinear relationship between DEA outputs and inputs. Past DEA application of USAF military data assumes linear RTS and makes no statistical inferences (including confidence intervals) regarding repeatability. Repeatability is the closeness of the agreement between the results of successive measurements of the same measurand carried out under the same conditions of measurement (Trochim, 2006). This is a critical gap in increasing managerial awareness, which is a way to inform senior decision making as it relates to resource management.

Background

When career fields are undermanned, the remaining workforce can become stressed and overworked which equates to increased military risk. Personnel manning is defined as the ratio of the number of personnel to the number of funded authorizations:

$$Manning = \frac{Number\ of\ (assigned)\ personnel}{Number\ of\ funded\ authorizations}\ \text{(Neuhaus, 1990).} \qquad \textbf{Eq. IV-1}$$

Each USAF unit has a unit manning document which stipulates the number of personnel and funded authorizations. Each authorization represents a funded position. Ideally, funded authorizations should have assigned, trained personnel filling the positions, but this is usually not achieved across the USAF.

As early as 1984, DEA has been used for several military applications as a benchmarking mechanism (Charnes et al., 1984). A USAF developmental study of DEA in measuring the efficiency of maintenance units at 14 distinct Air Wings (AWs) was conducted by Charnes et al. (1984). This model's inputs included maintenance manning data while the outputs consisted of a select group of performance metrics (e.g. cannibalization rate). This work is apparently the first published application of DEA using USAF manning data. The study found few statistically significant differences existed in mean Air Wing efficiency scores, which suggests little efficiency separation exists between Air Wings. Cost was not considered in the study.

USAF real property maintenance activities were compared using DEA window analysis (Bowlin, 1987). Window analysis uses DEA to assess efficiency over time (Charnes et al, 1994). In 1989, DEA was used to examine Israeli Air Force maintenance units using time-sequenced data (Roll et al, 1989). More work from Bowlin continued into the 1990s and early 2000s examining aerospace defense finances to include Civil Reserve Air Fleet (CRAF) participation [(Bowlin 1995; 1999; 2004)]. A Tawainese Army study from 2000 used DEA to assess managerial inefficiency, which became a benchmark methodology to assess and compare unit performance (Sun, 2004). Similarly, the National Defense University of Taiwan examined military organizations using DEA and advocated this work as a means to possibly merge like organizations (Lu, 2010).

Boehmke (2015), utilizing 2014 data from 35 USAF organizations, revealed millions of dollars possibly wasted due to various performance inefficiencies. The Boehmke study prompts questions: Is there a significant association or relationship between efficiency and manning? If there is a significant association between efficiency and manning, how do we address it in order to mitigate risk?

A desirable DEA property is that the weight values for each assessed organization are defined by an optimization algorithm and not decided by the user (Huguenin, 2012). Research using DEA within the AF installation sustainment community shows that opportunities exist to gain cost savings by comparing performance in the form of efficiency (Boehmke, 2015). DEA attempts to measure efficiency by accounting for resource inputs, performance outputs and exogenous factors simultaneously (Boehmke, 2015). This case study uses DEA optimization models consisting of ten F-16 active duty (AD) Air Force bases, the fighter pilot career field and an aircraft generation performance metric (i.e. (sortie production)).

Bootstrapping is generally used to increase sample size to increase precision in estimates of a population (Efron and Tibsirani, 1993). For predictive managerial efficiency purposes, bootstrapping RTS can provide insight to anticipate future or expected personnel efficiency levels by installation or career field. A personnel efficiency demonstration using fighter pilot manning and sorties among 10 USAF installations is presented using DEA coupled with bootstrapping techniques to illustrate objective ways to evaluate and predict personnel efficiency. If efficiency is correlated with risk (e.g. the more efficient an installation is, the likelier the installation is to have more risk), senior planners, programmers, analysts and managers can better anticipate and assess risk in the three distinctive planning timeframes (near, mid and far). RTS bootstrapping provides a means to provide predictive analytical insight into personnel efficiency and the assessment of future personnel risk.

Objective

The specific objectives of this case study are:

I. Assess air base efficiency utilizing AD fighter pilot manning using a DEA model.
II. To examine technical efficiency using personnel and sortie production metrics and thereby a way to quantitatively benchmark bases to promote 'best practices' throughout the USAF.

Methodology

Terminology

DEA is an aggregation technique that compares unit performance by examining the ratio of weighted outputs and inputs (Colbert et al., 2000). Fundamentally, DEA requires *m* inputs, *s* outputs, *k* organizations and a sample size *N* to ultimately measure efficiency (Subhash, 2004). A series of related DEA techniques were published by multiple authors in the early 1950s [(Debreu, 1951; Shephard, 1953)]. The objective of DEA is to produce the maximum quantity of output from a specific input bundle (Subhash, 2004). The benchmark is determined by the technology itself and comparison of the actual output produced with the benchmark quantity yielding a measure of *technical efficiency* between Decision Making Units (DMUs) (Subhash, 2004). A Decision Making Unit (DMU) is technically efficient if it can produce the maximum possible number of outputs from its capacity (Atkinson and Cornwell, 1994).

A DEA formulation of technical efficiency is (Huguenin, 2012):

$$TE_k = \frac{\sum_{r=1}^{s} \boldsymbol{U}_r \boldsymbol{Y}_{rk}}{\sum_{i=1}^{m} \boldsymbol{V}_i \boldsymbol{X}_{ik}}, \qquad \textbf{Eq. IV-2}$$

where TE_k is the technical efficiency of an observed DMU k using m inputs to produce s outputs. $\boldsymbol{Y}_{rk}$ represents the quantity of output r produced by DMU k. $\boldsymbol{X}_{ik}$ represents the quantity of input i consumed by DMU k. $\boldsymbol{U}_r$ and $\boldsymbol{V}_i$ are weights of the output r and input i respectively. DEA modeling requires prerequisite knowledge of the following properties: returns to scale, orientation, model type and slack. *Returns to scale* (RTS) refers to the rate by which an output changes if an input is changed by the same factor (OECD, 2001). DEA variants can accommodate either of two types of returns to scale: constant and variable [(Charnes et al., 1978; Banker et al., 1984)]. Constant returns to scale (CRS) models are appropriate when all organizations operate at an optimal scale (Huguenin, 2012). Optimal scale occurs when unit operations are sized such that any modifications to inputs or outputs render the unit less efficient (Masiye, 2007). CRS is an unrealistic expectation in many government service establishments. Variable returns to scale (VRS) is more appropriate when all organizations under comparison do not operate at an optimal scale, which seems typically true for USAF organizations.

Another DEA property is *orientation*. There are generally three types of DEA orientation: input, output (Charnes et al., 1978) and directional distance (Chambers et al., 1996). Input oriented (io) models measure how much an organization can decrease its inputs (e.g. manning) to achieve given outputs such as sales or generated combat sorties, compared to its most efficient peers. Output oriented (oo) models reverse the idea and identify how much additional output should be possible for given inputs, again relative to the organization's most efficient peers. Directional distance-type models are universally oriented, i.e. there is no need to distinguish between input or output orientation (Toloo and Tavana, 2017). Directional distance models are typically used to distinguish between desirable and undesirable variables (Cheng and Zervopoulos, 2012). The inputs and outputs for this research are not considered interchangeable, and therefore, directional distance models are excluded from the methodology.

A third DEA property involves *model type* of which this study considers two: radial (Charnes et al., 1978) and additive (Lovell and Pastor, 1995) models. Radial DEA models require that all inputs be contracted and/or outputs expanded from a center (e.g. origin) or radius. These models are typically the first of several explored to compare and contrast DMU efficiency. For DEA CRS and VRS models, *scale efficiency* is computed as the ratio of respective CRS and VRS efficiency values (Alvarez et al., 2016) regardless of orientation (i.e. input or output).

The CRS and VRS DEA model solutions identify efficiency frontiers. All DMUs which fall on the efficient frontier (i.e. CRS or VRS) are said to be technically efficient (i.e. there are no shortages or overages of the inputs/outputs). These shortages or overages are known as negative or positive slack values respectively. DMUs with zero slack set the standard or 'benchmark' for other DMUs that are spatially located some distance from the efficiency frontier. A practical interpretation is that DMUs operating below the efficiency frontier are deemed to have potential for performance improvement (Huguenin, 2012). All of the said models use two-stage[15] optimization to compute slack variables.

The other DEA model type examined in this work is an additive model (AM). The major difference between the radial and additive model is the way by which technical efficiency is computed. DEA additive models simultaneously consider positive and negative slack variables (Charnes et al., 1985) in order to determine technical efficiency.

Objective RTS determination of a USAF dataset is a topic worth exploration. Past DEA application of USAF military data assumes RTS and makes no statistical inferences (including confidence intervals) regarding repeatability. This is a critical gap in increasing managerial awareness, which is a way to inform senior decision making as it relates to resource management. RTS assumptions can be either linear (CRS) or nonlinear (VRS). Recall, CRS assumes the constant rate of change in outputs and inputs is linear. The VRS DEA model can be used to account for a lack of constant rate of change between inputs and outputs. Some practitioners argue the RTS assumption is not of significance as when both CRS and VRS models are computed, the ratio between the two establishes SE, which determines optimality of inputs and outputs. The desired outcome of RTS assumption is to provide more managerial insight as it relates to technical efficiency repeatability. In other words, through simulation of a given amount of DEA data, can we develop predicted point

[15] Two stage DEA optimization refers to first: optimizing the DMUs for model type (e.g. radial) efficiency and second: computing the possible input excesses and output shortfalls or slacks to determine technical efficiency (Alvarez et al., 2016).

estimates and confidence intervals (CIs) of these data to determine ranges of anticipated performance based on RTS assumption?

This work pursues both (i.e. computation of SE and implications and TE CI interval approximation) approaches and provides objective commentary on each. Further, rather than subjectively debate the RTS assumption, a more objective process can be used to statistically determine RTS of DEA data, TE estimates and TE CIs. We explore a bootstrap methodology proposed by Dario and Simar (2007).

Introduction to Bootstrap Methods to Determine Statistical Inferences

DEA is a nonparametric technique that measures efficiency as a relative estimate of a frontier and as a result is subject to uncertainty with regards to statistical inferences, which makes repeatability challenging (Daraio and Simar, 2007). For a general nonparametric estimator, the following properties are necessary: randomness, positiveness, smoothness, consistency and convergence. Randomness refers to the sample of firms to be identically and independently distributed random variables. Positivity infers the probability of observing a firm on the frontier is positive. Smoothness insures differentiability, which is one component needed to determine optimality. Consistency suggests as the sample size of firms increase, the estimator will converge to the true, but unknown value under estimation. Mathematically, this means as the sample size approaches infinity, the probability of absolute error being greater than zero converges to zero. Convergence is required to determine convexity or concavity, which is essential for global optimality. The aforementioned properties are needed in order to construct a meaningful DEA bootstrap.

If properly constructed, a bootstrap or *simulation* can provide an approximation of the firm distribution. Thus, bootstrap methods increase the number of theoretical versions of the known firm sample to ultimately assess repeatability via the estimation of bias, hypothesis testing and confidence intervals.

The MATLAB DEA Toolbox software uses techniques based on bootstrapping theory advanced and proposed by (Silverman, 1986); (Efron and Tibshirani, 1993); [(Simar and Wilson, 1998; 1999c; 2001; 2002; 2000b; 2006a)]; (Bogetoft and Otto, 2001); (Wilson, 2005a-c); and (Daraio and Simar, 2007). Their summary is stated below with modifications for output orientation models.

1. Obtain a random sample from *N* sample firms *with replacement* from a set of 2*N* reflected original DEA scores: $\{2-\hat{\delta}_1, \dots, 2-\hat{\delta}_N, \hat{\delta}_1, \dots, \hat{\delta}_N\}$, which yields $\{\tilde{\delta}_i^{\,*}; i = 1, \dots, N\}$.

2. Smooth the bootstrap resampled DEA scores by perturbation (random noise simulation) via a Gaussian kernel density function with scale given by an optimal bandwidth *h* defined by the following Mean Integrated Squared Error (MISE) function:

$$h_{MISE} = 1.06 * \min\left[s_N, \frac{r_N}{1.34}\right] * N^{-\frac{1}{5}}, \qquad \textbf{Eq. IV-3}$$

   where s_N is the empirical standard deviation of *N* DEA efficiency scores and r_N is the interquartile range within the sample size *N*. Therefore, obtaining $\bar{\bar{\delta}}_i^{\,*}; i = \tilde{\delta}_i^{\,*} + h\varepsilon_i,\ i = 1, \dots, N$, where ε_i represents random error from a standard normal distribution.

3. Refine the smoothed resampled DEA scores by correcting for the mean and variance:

$$\delta_i^{**} = \ddot{\delta}_i^{\,*} + \frac{\bar{\bar{\delta}}_i^{\,*} - \ddot{\delta}_i^{\,*}}{\sqrt{1+h^2/s^{*2}}}, i = 1, \dots, N, \qquad \textbf{Eq. IV-4}$$

where $\ddot{\delta}_i^{\,*}$ and s^{*2} are the empirical mean and variance, respectively of *N* (DMU values) of DEA scores ($\tilde{\delta}_i^{\,*}$).

4. Reflect the inefficient DMUs (i.e. DEA scores > 1). For $i = 1, \dots, N$, inefficient DEA scores are represented as:

$$\delta_i^{*} = \begin{cases} 2 - \delta_i^{**} & if\ \delta_i^{**} > 1, \\ \delta_i^{**} & \text{otherwise.} \end{cases} \qquad \textbf{Eq. IV-5}$$

5. Generate inefficient outputs or inputs (*depends on orientation*) within the attainable DEA set (Y_i^*) and condition on the original input mix η_i and the original input level X_i. This occurs by defining a bootstrap sample Y^*as follows:

$$Y^* = \{(X_i^*, Y_i^*) \mid X_i^* = X_i \text{ and } Y_i^* = \frac{\delta_i^*}{\hat{\delta}_i} Y_i,\ \ i = 1, \dots., N\}. \qquad \textbf{Eq. IV-6}$$

Courtesy of the Dario and Simar 2007 text, we restate the interpretation of (Eq. IV-6). The denominator of the ratio multiplying the output vector Y_i projects the original observed data point Y_i on the DEA efficient facet (portion) on the ray defined by Y_i. Then, the numerator projects the frontier point inside the DEA attainable set, on the same ray, by the random bootstrap factor δ_i^*. This is completed for each data point $i = 1, \dots, N$.

By iterating the aforementioned steps *B* number of times, we produce a *B* bootstrapped sample Y_b^*. For any fixed point of interest (x, y), a Monte-Carlo sequence of pseudo estimates $\{\hat{\delta}_i^*(x, y)\}_{b=1}^{B}$ is computed by solving preferred CCR or BCC orientation models with reference set Y_b^*. The empirical distribution $\{\hat{\delta}_i^*(x, y)\}_{b=1}^{B}$ is the bootstrap approximation of the sampling distribution of $\widehat{\delta}(x, y)$.

Using Bootstrap methods to determine Return to Scale

Utilizing the aforementioned bootstrapping procedure, Simar and Wilson (2002) propose a test to determine CRS or VRS. Given, a significance level (α) and set of DEA scores (ψ^{∂}), the hypotheses are as follows:

$$H_o: \psi^{\partial} \text{ is globally CRS}$$

$$H_A: \psi^{\partial} \text{ is globally VRS} \qquad \textbf{Eq. IV-7a}$$

$$or$$

$$H_o: \psi^{\partial} \text{ is globally VRS} \qquad \textbf{Eq. IV-7b}$$

$$H_A: \psi^{\partial} \text{ is globally CRS}$$

The test statistic to determine the rejection region is a mean of the ratios of DEA efficiency scores and is defined as follows (Daraio and Simar, 2007):

$$T(X_N) = \frac{1}{N}\sum_{i=1}^{N} \frac{\hat{\theta}_{CRS,N(X_i,Y_i)}}{\hat{\theta}_{VRS,N(X_i,Y_i)}}. \qquad \textbf{Eq. IV-8}$$

The *p*-value of $T(X_N)$ is theoretically defined as:

$$p - value = P(T(X_N) \leq T_{obs} \mid H_0 \text{ is true}), \qquad \textbf{Eq. IV-9}$$

where T_{obs} is the value of *T* computed on the original observed sample X_N. This theoretical *p*-value is practically demonstrated as the following approximation:

$$p - value \approx \sum_{b=1}^{B} \frac{\boldsymbol{I}(T^{*,b} \leq T_{obs})}{\boldsymbol{B}}, \qquad \textbf{Eq. IV-10}$$

where $T^{*,b}$ is equal to the simulated *B* pseudo-samples $T(X_N^{*,b})$ of DMU size *N* under the null hypothesis and ***I*** is an indicator variable, where if $\boldsymbol{I}(T^{*,b} \leq T_{obs})$ =1, $T^{*,b} \leq T_{obs}$ is true, otherwise false and equal to zero (Daraio and Simar, 2007). This assumes CRS is the RTS estimate of the frontier for generating the pseudo-samples. If the *p*-value of $T(X_N)$ is less than α, we reject the null hypothesis (H_o) and conclude the DEA scores are VRS, otherwise CRS (Daraio and Simar, 2007).

Confidence intervals and estimated biases are computed using Monte Carlo simulations and quantiles. Specifically, a confidence interval is constructed using quantile methods from naïve bootstrap principles (Lu and Fang, 2003) and is noted below:

$$Bootstrap\ CI\ for\ \delta(x,y) = [\hat{\delta}(x,y) - \hat{a}_{1-\propto/2}, \hat{\delta}(x,y) - \hat{a}_{\propto/2}], \qquad \textbf{Eq. IV-11}$$

where quantiles $\hat{a}_{\beta}$ are taken from Monte-Carlo distribution quantiles of values $\{\hat{\delta}_b^*(x,y)\}_{b=1}^{B}$ for all $\beta \in [0,1]$. The bias corrected estimator is denoted below (Daraio and Simar, 2007):

$$\tilde{\delta}(x,y) = \hat{\delta}(x,y) - \widehat{bias}\left(\hat{\delta}(x,y)\right) = 2\hat{\delta}(x,y) - \frac{1}{B}\sum_{b=1}^{B}\hat{\delta}_b^*(x,y). \qquad \textbf{Eq. IV-12}$$

For more details, please reference *Dario and Simar 2007* and *Bogetoft and Otto 2001* literature.

Data Overview

Generally, aircraft flying hour training requirements drive sortie production at a given base (AFI 11-102 (Flying Hour Mgmt), 2011). For pilot production, flying requirements is a function of the student load. Therefore, pilot manning is assumed a sufficient input to use to measure sortie production from an efficiency perspective. Analysis to confirm this assertion is provided in the analysis portion of this section. The Air Force Single Flying Hour Model (AFSFHM) provides the methodology and processes that bases need to execute flying hour programs (AFI 11-401 (Aviation Management), 2013). This model determines the number of flying hours needed to attain and maintain combat readiness for all aircrew. This case study examines the active duty fighter pilot portion of aircrew at F-16 bases.

Data for the DEA optimization model consists of ten F-16 active duty bases. The inputs and outputs are fighter pilot career field personnel and respective funded authorizations and aircraft sorties by count and hours. The manning data (inputs) are collected from Air Force authoritative personnel data sources and are current as of September 2018. The outputs are collected through the Logistics, Installations and Mission Support-Enterprise View (LIMS-EV) database and are current as of September 2018. LIMS-EV provides a single-source business intelligence environment that delivers information and capabilities to agencies' fleet managers (DOD Strategic Sustainability Performance Plan, 2012).

Only fighter units that reported data into LIMS-EV were captured in this analysis. Maintenance manning were inputs, but oftentimes maintenance squadrons are tasked to support more than one fighter squadron (i.e. F-16, F-22, F-15, A-10, etc.), which makes alignment of these personnel with specific F-16 units unmanageable and as a result are excluded. More details of the inputs and outputs are provided next.

Resource Inputs/Outputs

Inputs

The input variables included in the optimization procedure are manning rates from the fighter pilot career field (11F). Manning rates are determined as the ratio of the number of personnel by career field and base and the number of personnel requirements by career field and base. Table IV-1 is a career field manning rate and input summary.

Table IV-1: Input Variables for DEA

AD Career Field/ Manning rate (by Base)	**11F Assigned/Authorized**		Manning Rate
Base 1	79	75	1.05
Base 2	33	44	0.83
Base 3	84	100	0.84
Base 4	61	63	0.97
Base 5	34	52	0.65
Base 6	65	64	1.02
Base 7	58	64	0.90
Base 8	36	37	0.97
Base 9	105	108	0.97
Base 10	43	43	1.00

Outputs

An aircraft sortie is defined as an instance that begins when the aircraft moves forward on takeoff or takes off vertically from rest at any point of support and ends after airborne flight when the aircraft returns to the surface and either engines are stopped or the aircraft is on the surface for five minutes, whichever occurs first (AFI 11-401 (Aviation Management), 2013). Sorties are typically measured by hours. We use active duty F-16 sorties and respective hours as indicators of fighter pilot performance by base as outputs. Table IV-2 is a summary of outputs.

Table IV-2: Output Variables by Base for DEA

Aircraft Sorties (by Base)	**Sorties/Hours**		Ratio
Base 1	612	905	0.68
Base 2	147	174	0.85
Base 3	789	984	0.80
Base 4	471	587	0.80
Base 5	522	659	0.79
Base 6	551	705	0.78
Base 7	725	1071	0.68
Base 8	367	462	0.79
Base 9	771	1066	0.72
Base 10	360	498	0.72

Correlation Analysis

A way to determine if appropriateness of outputs and inputs is to perform correlation analysis by statistically examining relationships among the data set. Pearson correlation coefficients are computed among and within input and output combinations. Figure IV-1 provides a correlation matrix of the active duty F-16 bases. The inputs are highly correlated ($r = 0.95$). The outputs[16] are highly correlated ($r = 0.98$). Further, manning inputs are highly correlated with sortie outputs.

[16] In this work, we cannot distinguish between combat and training sorties.

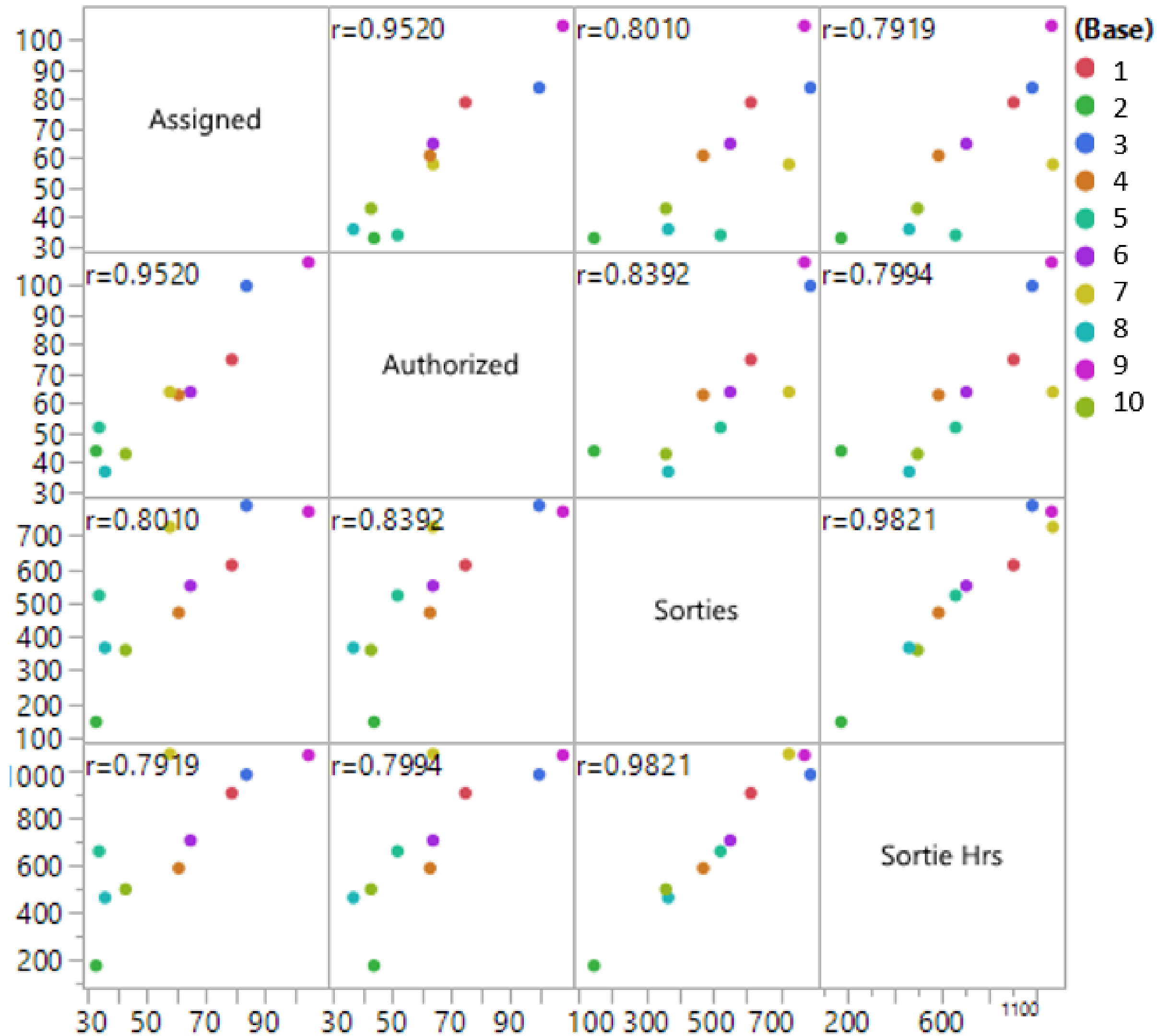


Figure IV-1: Active Duty F-16 Correlation Results

Pairwise correlation analysis among the dataset with α = 0.05 is conducted where all variable estimates are considered statistically significantly correlated. Results, infer there exists statistical evidence a strong relationship exists between sortie production and fighter pilot manning. Therefore, the aforementioned factors are suitable for DEA application.

DEA Analysis

First, we examine RTS via bootstrap analysis. Upon objective determination of RTS, we compute DEA models. Results of the DEA models used to compute efficiencies for the ten F-16 bases are discussed. The DEA modeling is computed using the DEA Toolbox for MATLAB (Alvarez et al., 2016) and results are presented in two groups of findings. Group one shows the results of the radial models. Group two depicts the results of the additive models. The radial group is presented with CRS, VRS and scale efficiency scores.

Return to Scale Estimation

The hypothesis test for the F-16 DEA dataset is as follows:

$$H_o: \psi^{\partial} \; is \; globally \; CRS$$

$$H_A: \psi^{\partial} \; is \; globally \; VRS$$

Based on a 5% significance level (i.e. $\alpha = 0.05$) and 500 bootstrapped DEA CCR-*oo* samples (*B*), the statistical results of the hypothesis test infer the RTS DEA technical efficiency scores are CRS versus VRS. The statistical implications are we can be at least 95% confident in these set of TEs and respective CIs for this dataset. The results do not suggest future DEA results will yield similar results. While the latter is correct, the results can still provide managerial insight into a possibility of future efficiency outcomes by base provided manning and sortie production levels are within some small significance error of the initial results. Table IV-3 depicts the TEs and respective bootstrapped TEs and CIs (Upper and Lower Confidence Levels) by base. The results better inform further DEA model application.

Table IV-3: DEA Return to Scale (RTS) Results

Base	TE	Bootstrapped TE	Boostrapped TE LCL	Boostrapped TE UCL
Base 1	1.3683	1.5370	1.3795	1.7391
Base 2	2.9695	3.3089	3.0051	3.7260
Base 3	1.3929	1.5522	1.4084	1.7437
Base 4	1.5152	1.6313	1.5208	1.8273
Base 5	1.0000	1.2008	1.0169	1.3446
Base 6	1.3158	1.4126	1.3196	1.5905
Base 7	1.0000	1.1666	1.0150	1.2983
Base 8	1.4121	1.2291	1.1452	1.3763
Base 9	1.5868	1.7483	1.5957	1.9585
Base 10	1.3531	1.4827	1.3595	1.6620
Test-statistic = 0.8187; Critical value = 0.7514; *P*-value = 0.1860				

Radial, addictive and superefficiency DEA model results follow.

Radial Results

Recall, for *oo* models, we hold inputs fixed to maximize outputs; and efficiency scores greater than one are considered radially inefficient. Table IV-4 provides CRS-*oo (radial)* inputs, outputs, efficiency score, associated slacks and rank (via efficiency) for each base. Assuming all base outputs increase by the same proportional change as all inputs change, we observe in the context of how well F-16 bases utilize fighter pilot manning for sortie production and conclude Bases 5 and 7 are considered the most efficient as their efficiency scores are one. They are also considered technically efficient because there are no surplus slacks. The existence of slack variables infers an overage or shortage of resources. For example, Base 1's efficiency score of 1.37 with personnel and sortie slacks of 12 and 0.86, respectively, suggest that its current level of output activity could be improved with 12 more personnel and 0.86 more sorties. Further, the efficiency score (compared to other bases) suggests if Base 1 was able to get 12 more additional skilled, trained pilots per approximately 1 sortie hour, sortie production efficiency would increase by 37%.

Further, *without consideration of increasing or decreasing RTS*, compared to Bases 5 and 7, Base 2's slack only exists in sortie hours, which suggests Base 2 has capacity to generate another 100 hours of sortie production without additional manpower. However, if Base 2 has DRS, this suggests the base reduce sortie production by 100 hours in order to be considered technically efficient. The Overall TE average is 1.46, which infers on average a base can increase sortie production by 46% to become technically efficient.

The aforementioned are rigid, mathematical interpretations and should not be taken as exact means to reduce or increase base resources. It is important for the reader to understand the data were taken from a steady-state operations timeframe. Flying squadrons are typically manned and staffed for wartime, contingency operations. Consequently, during wartime operations sortie production will ramp up while manpower is fixed, thus naturally increasing efficiency levels across the base populations.

Table IV-4: DEA Radial (CRS-oo) Model Results

	Inputs		Outputs			Inputs*		Outputs		
DMU (Base)	Assigned (X1)	Authorized (X2)	Sortie (Y1)	Sortie hrs (Y2)	Efficiency Score (φ_i)	Slack X1	Slack X2	Slack Y1	Slack Y2	Base Rank
Base 1	79	75	612	905	1.37	12	0	0.86	0	6
Base 2	33	44	147	174	2.97	0	0	0	100.39	10
Base 3	84	100	789	984	1.39	0	0	0	194.88	7
Base 4	61	63	471	587	1.51	4	0	0	164.83	8
Base 5	**34**	**52**	**522**	**659**	**1.00**	**0**	**0**	**0**	**0**	**1**
Base 6	65	64	551	705	1.32	7	0	0	142.05	4
Base 7	**58**	**64**	**725**	**1071**	**1.00**	**0**	**0**	**0**	**0**	**1**
Base 8	36	37	367	462	1.14	2	0	0	91.53	3
Base 9	105	108	771	1066	1.59	7	0	0	115.76	9
Base 10	43	43	360	498	1.35	4	0	0	45.74	5
$\frac{1}{N}\sum \varphi_i$					1.46					

* Manning slack variables are rounded for practical interpretation purposes.

Table IV-5 provides efficiency estimates (target values) and respective weights by base. For *oo* models, the efficiency value for inputs (X_i) is to hold the given input fixed and subtract the associated slack. Note Base 1's efficient assigned fighter pilots is $(79 - 12 = 67)$. The efficiency value for outputs (Y_i) is computed by multiplying the DEA efficiency score by the given output and add the associated slack value. Note Base 1's relative efficient number of sortie production is $(612 * 1.37 + 0.86 \approx 839)$. The efficiency estimates reveal how the bases should be manned along with associated sortie output levels if they are to be considered radially efficient compared to benchmarked bases. For the *CRS-oo* model, Table IV-5 reveals Base 1 is DRS, which suggests a reduction in size (e.g. sortie reduction). Base 2 is IRS, which suggests a mismanagement of current manpower to produce sortie generation efficiency relative to Bases 5 and 7. Readers should realize although Base 6 is considered

CRS by the summed weights, it has slacks, therefore, it is inefficient compared to Base 5 and Base 7 bases.

Table IV-5: DEA Radial (*CRS-oo*) Targeted Value Results

DMU (Base)	Eff. Asgn (X1)	Eff. Auth (X2)	Eff. Sorties (Y1)	Eff. Sortie hrs (Y2)	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	λ_{10}	$\sum\lambda_j$ (RTS)
Base 1	67	74	839	1238	0.00	0.00	0.00	0.00	0.00	0.00	1.16	0.00	0.00	0.00	DRS
Base 2	33	40	437	617	0.00	0.00	0.00	0.00	0.25	0.00	0.42	0.00	0.00	0.00	IRS
Base 3	84	100	1099	1567	0.00	0.00	0.00	0.00	0.51	0.00	1.15	0.00	0.00	0.00	DRS
Base 4	57	63	714	1054	0.00	0.00	0.00	0.00	0.00	0.00	0.98	0.00	0.00	0.00	IRS
Base 5	34	52	522	659	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	CRS
Base 6	58	64	725	1071	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	CRS
Base 7	58	64	725	1071	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	CRS
Base 8	34	37	419	619	0.00	0.00	0.00	0.00	0.00	0.00	0.58	0.00	0.00	0.00	IRS
Base 9	98	108	1223	1807	0.00	0.00	0.00	0.00	0.00	0.00	1.69	0.00	0.00	0.00	DRS
Base 10	39	43	487	720	0.00	0.00	0.00	0.00	0.00	0.00	0.67	0.00	0.00	0.00	IRS

To obtain scale efficiency, BCC-*oo* model computations are necessary. Recall, SE occurs when the size of DMU (base) operations is optimal such that any modifications will render the base less efficient. Table IV-6 provides BCC-*oo (radial)* inputs, outputs, efficiency score, associated slacks and rank (via efficiency) for each base. Assuming all bases are performing at variable RTS, we conclude Base 2, Base 3, Base 5, Base 7, Base 8 and Base 9 are considered efficient relative to the other bases. Realize how Base 5 has the lowest 11F manning rate (56%), but is considered technically efficient among the other non-efficient bases. The results suggests these bases may possess best practices that the other F-16 bases could adopt. The PTE average is 1.12, which infers on average a base can increase sortie production by 12% to become purely technically efficient. This illustrates one of the beauties of DEA; the procedure is not biased towards higher proportions of inputs and outputs. The measure is focused on comparing DMU efficiency or relative rate of change among weighted *outputs and inputs*. An added benefit to the use of DEA modeling is that it measures efficiency by relative rates of change among DMUs and not by non-normalized proportions. Therefore, higher manning rates or sortie rates do not necessarily translate into higher efficiency. While the RTS of the data is statistically CRS, the VRS results are more operationally representative of the bases.

Table IV-6: DEA Radial (BCC-*oo*) Model Results

	Inputs		Outputs			Inputs*		Outputs		
DMU (Base)	Assigned (X1)	Authorized (X2)	Sortie (Y1)	Sortie Hrs (Y2)	Efficiency Score (γ_i)	Slack X1	Slack X2	Slack Y1	Slack Y2	Base Rank
Base 1	79	75	612	905	1.18	21	10	0.74	0	7
Base 2	**33**	**44**	**147**	**174**	**1.00**	**0**	**0**	**0**	**0**	**1**
Base 3	**84**	**100**	**789**	**984**	**1.00**	**0**	**0**	**0**	**0**	**1**
Base 4	61	63	471	587	1.51	4	0	0	161.41	10
Base 5	**34**	**52**	**522**	**659**	**1.00**	**0**	**0**	**0**	**0**	**1**
Base 6	65	64	551	705	1.32	7	0	0	142.05	9
Base 7	**58**	**64**	**725**	**1071**	**1.00**	**0**	**0**	**0**	**0**	**1**
Base 8	**36**	**37**	**367**	**462**	**1.00**	**0**	**0**	**0**	**0**	**1**
Base 9	**105**	**108**	**771**	**1066**	**1.00**	**0**	**0**	**0**	**0**	**1**
Base 10	43	43	360	498	1.20	2	0	14.74	0	8
$\frac{1}{N}\sum \gamma_i$					1.12					
*Manning slack variables are rounded for practical interpretation purposes.										

We now compute the scale efficiency scores (i.e. overall total efficiency (OTE) versus pure technical efficiency (PTE)). Table IV-7 reveals that Bases 5 and 7 best utilize staffing to generate sorties. Further, average SE is 1.34, which indicates on average a base may be able to increase sortie production by 34%.

Table IV-7: DEA Radial (SE-oo) Model Results

DMU (Base)	CRS (OTE)	VRS (PTE)	SE (Ω_i)
Base 1	1.37	1.18	1.16
Base 2	2.97	1.00	2.97
Base 3	1.39	1.00	1.39
Base 4	1.52	1.51	1.003
Base 5	**1.00**	**1.00**	**1.00**
Base 6	1.32	1.32	1.00
Base 7	**1.00**	**1.00**	**1.00**
Base 8	1.14	1.00	1.14
Base 9	1.59	1.00	1.59
Base 10	1.35	1.20	1.13
$\frac{1}{N}\sum \Omega_i$			1.34

Thus far, the USAF personnel efficiency methodology uses DEA models with an output oriented direction with associated slacks. The next portion of this research analysis investigates the weighted additive model (WAM) which is independent of orientation or direction.

WAM-CRS Results

Table IV-8 provides WAM-CRS (*MIP*) inputs, outputs, efficiency score, associated slacks and rank (via efficiency) for each base. While the slack estimates vary, the target estimates (same as in Table IV-6) and base rankings remain unchanged. Assuming, DRS (*lambdas not shown*), the implications are similar with varying numbers of sortie production. For example, Base 1 results suggest a reduction in manpower by 12 personnel and approximately 227 sorties and 333 sortie hours, respectively. Bases 5 and 7 are still considered efficient. Further, average WAM is 1.15, which indicates on average a base may be able to increase sortie production by 15%.

Table IV-8: WAM-CRS (MIP) Results

	Inputs		Outputs			Inputs*		Outputs		
DMU (Base)	Assigned (X1)	Authorized (X2)	Sortie (Y1)	Sortie hrs (Y2)	Efficiency Score (ψ_i)	Slack X1	Slack X2	Slack Y1	Slack Y2	Base Rank
Base 1	79	75	612	905	0.89	12	0	226.28	333.34	4
Base 2	33	44	147	174	4.52	0	0	289.52	443.08	10
Base 3	84	100	789	984	0.98	0	0	309.96	581.84	7
Base 4	61	63	471	587	1.37	4	0	242.67	467.27	9
Base 5	**109**	**194**	**522**	**659**	**0.00**	**0**	**0**	**0**	**0**	**1**
Base 6	65	64	551	705	0.94	7	0	174	365	6
Base 7	**58**	**64**	**725**	**1071**	**0.00**	**0**	**0**	**0**	**0**	**1**
Base 8	36	37	367	462	0.55	2	0	52.14	157.17	3
Base 9	105	108	771	1066	1.35	7	0	452.44	741.31	8
Base 10	43	43	360	498	0.89	4	0	127.11	221.58	4
$\frac{1}{N}\sum \psi_i$					1.15					
*Manning slack variables are rounded for practical interpretation purposes.										

Superefficient Results

Superefficiency is determined by change in additive model DEA efficiency score with $N-1$ bases. A base is not superefficient if the new DEA score with computed $(N-1)$ sample size is the same as the additive model result. Superefficient bases (*oo*) will have scores less than one. Table IV-6 provides SAM-CRS inputs, outputs, efficiency score, associated slacks and rank (via efficiency) for each base. While the slack estimates vary, the rankings remain unchanged. Bases 5 and 7 are considered superefficient, which implies these bases exceed 100% efficiency.

Table IV-9: SAM-CRS Results

	Inputs		Outputs			Inputs*		Outputs		
DMU (Base)	Assigned (X1)	Authorized (X2)	Sortie (Y1)	Sortie Hrs (Y2)	Efficiency Score (η_i)	Slack X1	Slack X2	Slack Y1	Slack Y2	Base Rank
Base 1	79	75	612	905	1.37	12	0	0.86	0	6
Base 2	33	44	147	174	2.97	0	0	0	100.39	10
Base 3	84	100	789	984	1.39	0	0	0	194.88	7
Base 4	61	63	471	587	1.51	4	0	0	164.83	9
Base 5	**109**	**194**	**522**	**659**	**0.81**	**0**	**15**	**0**	**91.29**	**1**
Base 6	65	64	551	705	1.32	7	0	0	142.05	4
Base 7	**58**	**64**	**725**	**1071**	**0.76**	**16**	**0**	**93.41**	**0**	**1**
Base 8	36	37	367	462	1.14	2	0	0	91.53	3
Base 9	105	108	771	1066	1.59	7	0	0	115.76	8
Base 10	43	43	360	498	1.35	4	0	0	45.74	5
$\frac{1}{N}\sum \eta_i$					1.42					
*Manning slack variables are rounded for practical interpretation purposes.										

Similar targeted outputs and inputs computations illustrated in Table IV-3 are performed with the SAM-*oo* DEA models. Table IV-10 provides target values for inputs and outputs, and weights by base. Note Base 1's efficient assigned fighter pilots is $(79 - 12 = 67)$. The efficiency value for outputs (Y_i) is computed by multiplying the DEA efficiency score by the given output and add the associated slack value. Note Base 1's relative efficient number of sortie production is $(612 * 1.37 + 0.86 \approx 839)$. The efficiency estimates reveal how the bases should be manned along with associated sortie output levels if they are to be considered radially efficient compared to benchmarked bases. Similar to the WAM results, Base 1 is DRS, which suggests a reduction in size (e.g. sortie reduction). Base 2 is IRS, which suggests a mismanagement of current manpower to produce sortie generation efficiency relative to Base 5 and Base 7. Although Base 6 is considered CRS by the summed weights, it has slacks, therefore, it is inefficient compared to Bases 5 and 7.

Table IV-10: SAM-oo Targeted Value Results

DMU (Base)	Eff. Asgn (X1)	Eff. Auth (X2)	Eff. Sorties (Y1)	Eff. Sortie hrs (Y2)	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	λ_7	λ_8	λ_9	$\sum\lambda_i$ (RTS)
Base 1	67	74	839	1238	0.00	0.00	0.00	0.00	0.00	1.16	0.00	0.00	0.00	DRS
Base 2	33	40	437	617	0.00	0.00	0.00	0.25	0.00	0.42	0.00	0.00	0.00	IRS
Base 3	84	100	1099	1567	0.00	0.00	0.00	0.51	0.00	1.15	0.00	0.00	0.00	DRS
Base 4	57	63	714	1054	0.00	0.00	0.00	0.00	0.00	0.98	0.00	0.00	0.00	IRS
Base 5	34	37	425	627	0.00	0.00	0.00	0.00	0.00	0.59	0.00	0.00	0.00	IRS
Base 6	58	64	725	1071	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	CRS
Base 7	42	64	643	811	0.00	0.00	0.00	0.00	1.23	0.00	0.00	0.00	0.00	DRS
Base 8	34	37	419	619	0.00	0.00	0.00	0.00	0.00	0.00	0.58	0.00	0.00	IRS
Base 9	98	108	1223	1807	0.00	0.00	0.00	0.00	0.00	0.00	1.69	0.00	0.00	DRS
Base 10	39	43	487	720	0.00	0.00	0.00	0.00	0.00	0.00	0.67	0.00	0.00	IRS

Analysis Summary

This research shows pilot manning data in the form of personnel and funded personnel requirements can be objectively assessed by efficiency by base. This work only examines 10 AD F-16 bases. There are several Guard/Reserve F-16 bases. These are not considered because the data are not available for this study.

If only pilot staffing is considered, then Bases 5 and 7 become the most technically, radially and scaled efficient of the ten bases. When linear rate of change assumption between outputs and inputs is relaxed (i.e. VRS), Base 2, Base 3, Base 5, Base 7, Base 8 and Base 9 AFBs are considered radially and technically efficient. Since Bases 5 and 7 are ranked first among all DEA computations, this research implies Bases 5 and 7 might be considered as a benchmark for other F-16 active duty bases to gain efficiency in maximizing sortie generation with current fighter pilot manning levels. Additional inputs such as logistics and other support manning should be included in the model before any final conclusions are reached.

Limitations and Final Remarks

There are limitations with the methodology. When outputs or inputs cardinality is larger than the number of DMUs modeled, then discriminatory power is limited (Despotis, 2002). This can limit the number of reasonable outputs and inputs to include in the analysis. Ideally, more career fields should be used as inputs as it takes more than pilots to generate sorties. For example, maintenance, security forces, civil engineering and logistics personnel should also be considered. Further, a more complete assessment involves discussions with the actual squadron personnel (e.g. fighter pilots and maintenance personnel) and base leadership who could provide more insight into their unique staffing and mission constraints. For example, the local weather, infrastructure, and serviceable support equipment at one location might cause greater inefficiencies than at other bases. The challenge with adding more career fields, while preserving the number of DMUs (AD F-16 bases) creates very little distinguishable separation between efficiency values.

This work introduces an objective way to compute RTS. Hypothesis test inferences via bootstrapping computations reveal the F-16 bases globally exhibit CRS RTS. This revelation is to be tempered with the timeframe of data capture (steady state operations). That is to say, sortie production will increase during wartime operations, while AD manning will remain constant. This infers efficiency estimates will improve for each base, which means RTS will need to be re-examined and implications could change regarding base efficiency rankings.

In conclusion, personnel efficiency methodology utilized four output-oriented DEA models, in which all except the VRS model provided consistent results. The analysis suggests Base 5 and Base 7 AFBs could be potential benchmarks for other F-16 bases, but further modeling is needed to verify these conclusions. The goal of this case study is to show how the methodology can be used to assess efficiency at operational bases. This work is a step forward in shedding some light on manning efficiency, which is a component of the strategic risk associated with military combat capability.

Mathematically, a personnel productivity demonstration at the base level is computed using DEA. The next Chapter examines an actual computation of risk by career field at the enterprise level. DEA is utilized to determine efficiency of the same career fields, and statistical methods are used to determine if a significant relationship exists between efficiency and risk.

If efficiency is correlated with risk (e.g. the more efficient a career field is, the likelier the career field is to have more risk), senior planners, programmers, analysts and managers can better anticipate and assess risk in the three distinctive planning timeframes (near, mid and far) regarding personnel allocation and prioritization. RTS bootstrapping provides a means to provide predictive analytical insight into personnel efficiency and the assessment of future personnel risk.

Chapter V uses DEA as part of an over-arching methodology to compute and assess efficiency and risk by career field. Other mathematical functions and distributions are introduced to further compute risk. Due to computational expensiveness, scaled efficiency is the metric of efficiency used to statistically compare to risk in Chapter VI.

V. Methodology to Determine Relationships Between Risk, Capability and Efficiency

Introduction

A series of procedures are developed to objectively compute and assess personnel risk by career field and examine relationships between efficiency, risk and capability. The Chapter presents a repeatable way to demonstrate whether a significant relationship exists between personnel efficiency and risk using correlation analysis and normal and sigmoid functions. It also illustrates how to objectively accomplish manpower resource prioritization. If efficiency is correlated with risk, then we can better anticipate personnel capability gaps in the three distinct planning timeframes (i.e. near, mid and far).

This methodology has three-fold purposes: 1.) demonstrates that efficiency can be objectively assessed using personnel manning data; 2. provides meaningful insight into the relationships of efficiency, risk and capability; and 3.) paves the way for a more traceable methodology to assess USAF personnel efficiency and risk. These added analytical insights foster better strategic decision making by identifying capability gaps and provide an increased level of objectivity to support personnel resource allocation. The results of the analysis may better inform the USAF Strategic, Planning & Programming Process (SP3). The method determines if a statistically significant relationship exists between efficiency and risk.

The chapter provides a brief background of basic risk and applies context to strategic military applications. Objectives are stated, followed by the introduction of normal and sigmoid functions to compute and assess personnel strategic risk. Subsequently, a brief exposition of DEA is provided to compute scaled efficiency. A methodology applying the analytical methods is proposed, followed by an outline of data used to compute the analysis. Analytical results are presented. Lastly, a section entails limitations and summary of findings.

Background

Risk

Maximum resource capacity does not eliminate risk. Risk is the degree of probability of a loss (Merriam-Webster, 2017).   An extension of this definition includes impact and defines risk as the intersection of the following properties of failure: probability of occurrence and impact of occurrence (Dumbrava and Iacob, 2013). Further, these failure properties are mapped on a Cartesian plane delineated into risk categories ranging from Low to High (Figure V-1).   Notionally, 'Low risk' infers low probability of occurrence and low impact. 'Moderate risk' implies high probability of occurrence, but little impact. 'Significant risk' suggests low probability of occurrence, but high impact. 'High risk' usually means both probability and impact of occurrence of failure are high.

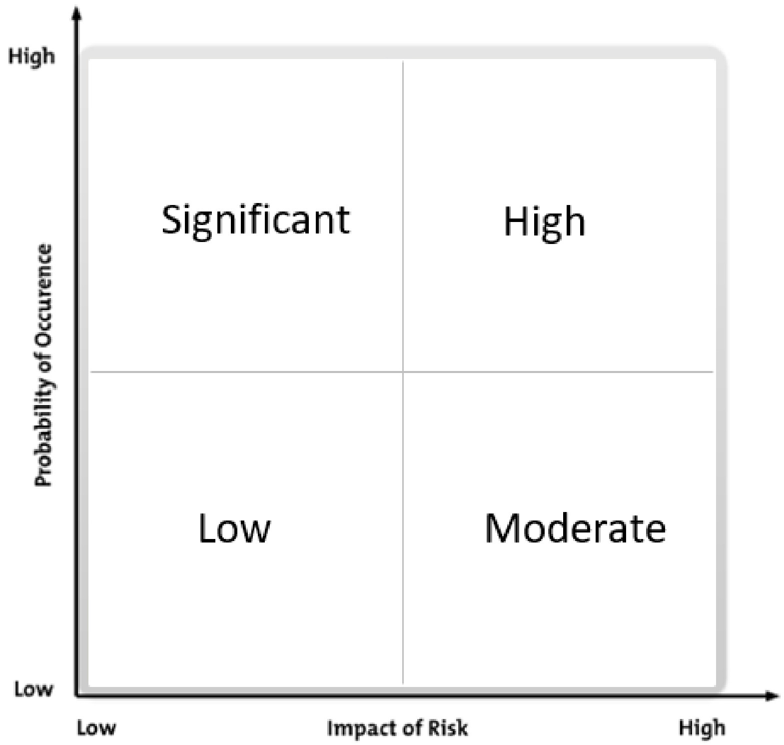


Figure V-1: Classic Risk Grid (www.mindtools.com, 2018)

This aforementioned categorization of risk aids decision making communities in prioritizing resources towards mitigating risk. Practically, we can focus less on low risk items due to the low likelihood of occurrence and low impact. Ideally, risk mitigation strategies should be used on significant and high risk items. We apply this taxonomy towards military risk. Military risk is a measure of the degree friendly forces and operations are vulnerable to adverse strategic consequences (Air Force Policy Directive 90-16, 2018). This work provides a framework to examine career field efficiency, compute career field risk and determine statistically significant relationships between efficiency, risk and capability.

Objective

The objectives of this case study are to: measure and compare USAF active duty and civil servant manning by career field using a DEA model and statistical correlation techniques via the following activities:

I. examine if a normal distribution can be used to calculate the probability of a failure;

II. utilize a variant of the logistic function to compute personnel degradation and couple this algorithm with an approved risk assessment framework scale, thus calculating risk impact;

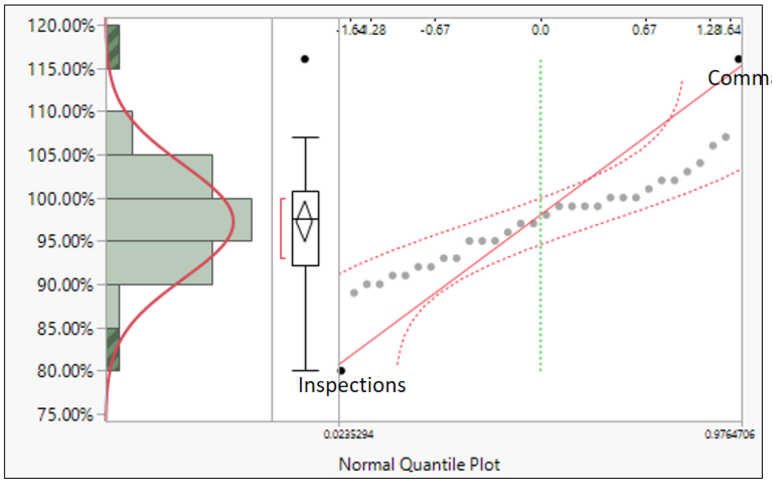
III. use DEA to objectively measure and compare career field manning efficiency;

IV. explore if there is a mathematical way to demonstrate if a significant relationship exists between efficiency and risk.

Normal Distribution and Sigmoid curve (S-curve)

Principally, there is always a degree of uncertainty (or risk) remaining even if 100% of requirements are obtained. A way to illustrate is by example. A restaurant owner has requirements for 62 personnel and has 62 personnel; in this example people represent capability. Does the fact that the owner has 100% of personnel requirements filled, eliminate risk (e.g. risk = not being able to generate one million dollars ($1M) a month)? We argue that even if the restaurant owner has the required amount of personnel, this still does not rule out catastrophic events (e.g. hurricane, earthquake, tsunami, economic dearth, etc.) that could prevent the restaurant from earning $1M for a particular month. Principally, there is always a degree of uncertainty (or risk) remaining even if 100% of requirements are obtained. In order to begin exploration of the said phenomena, we study the application of the normal distribution to modeling risk demonstrating its use on USAF personnel data.

Figure V-2 represents a descriptive statistics summary of the 32 USAF career families (functional equities). The top left chart is histogram with a normal fit curve accompanied with a box and whisker plot and normal quantile plot. The normal quantile plot graphically compares empirical distribution quantiles with quantiles of the theoretical distribution (i.e. normal) (De Laurentis et al., 2010). The y-axis shows the manning rates. The x-axis depicts the empirical cumulative probability for each value. If the observations deviate from a 'straight line' pattern, the data are said to visually fail a normality assumption. Further, all career families besides *Inspections* and *Commanders/Sr Leaders* are within $+/-$ two standard deviations of the mean. The visual results suggest the career field family manning rates are normally distributed. The table on the right in Figure V-2 provides a list of summary statistics associated with the normally fitted distribution of the career field family dataset. The mean manning rate of the data is 97% with a standard deviation of 0.07. The bottom left table in Figure V-2 is a summary of the 'goodness of fit' test using a Shapiro-Wilks metric.



$N(\mu, \sigma)$

Normal(0.97219,0.06608)

Quantiles

100.0%	maximum	116.00%
99.5%		116.00%
97.5%		116.00%
90.0%		105.40%
75.0%	quartile	100.75%
50.0%	median	97.50%
25.0%	quartile	92.25%
10.0%		90.00%
2.5%		80.00%
0.5%		80.00%
0.0%	minimum	80.00%

Summary Statistics

Mean	0.9721875
Std Dev	0.0660759
Std Err Mean	0.0116807
Upper 95% Mean	0.9960104
Lower 95% Mean	0.9483646
N	32

Fitted Normal

Parameter Estimates

Type	Parameter	Estimate	Lower 95%	Upper 95%
Location	μ	0.9721875	0.9483646	0.9960104
Dispersion	σ	0.0660759	0.0529733	0.0878466

-2log(Likelihood) = -84.0727836657212

Goodness-of-Fit Test

Shapiro-Wilk W Test

W	Prob<W
0.967551	0.4347

Note: Ho = The data is from the Normal distribution. Small p-values reject Ho.

Figure V-2: Descriptive Statistics of Career Field Family Manning Rates (JMP 12, 2019)

The Shapiro-Wilks' test statistically determines whether a probability distribution differs from a hypothesized distribution (i.e. normal Gaussian distribution) (Shapiro and Wilks, 1965). For example, if all 32 career field families are plotted with manning rates on the *x*-axis and the number (frequency) of the number of actual observations that fall within each manning rate category (e.g. increments of 5%) on the y-axis, we obtain something similar to the histogram in Figure V-2. Using the mean (location parameter), standard deviation (dispersion parameter), respective standard errors and hypothesis test statistics ($\propto =$ 0.05) of the data, confidence intervals are computed. In this case, the data are normally distributed, so the Shapiro-Wilk test yields a *p*-value *greater* than 0.05, and this is stated in Figure V-2.

We can use a normal distribution to compute probability of occurrence of a given failure because the normal distribution not only calculates probabilities based on probabilities of success (i.e. 100% manning or more), career field manning rate (mean), the spread of the manning mean (standard deviation), but it also accounts for uncertainty (even if personnel requirements are 100% filled). Further, the personnel data of the Agile Combat Support[17] Risk Assessment (ACS RA) follow a normal distribution, therefore, we use this distribution to calculate probabilities of success (manned) and failure (not manned) and incorporate them as factors to calculate risk[18]. This sufficiently satisfies the probability of occurrence portion of the classic risk calculation[19].

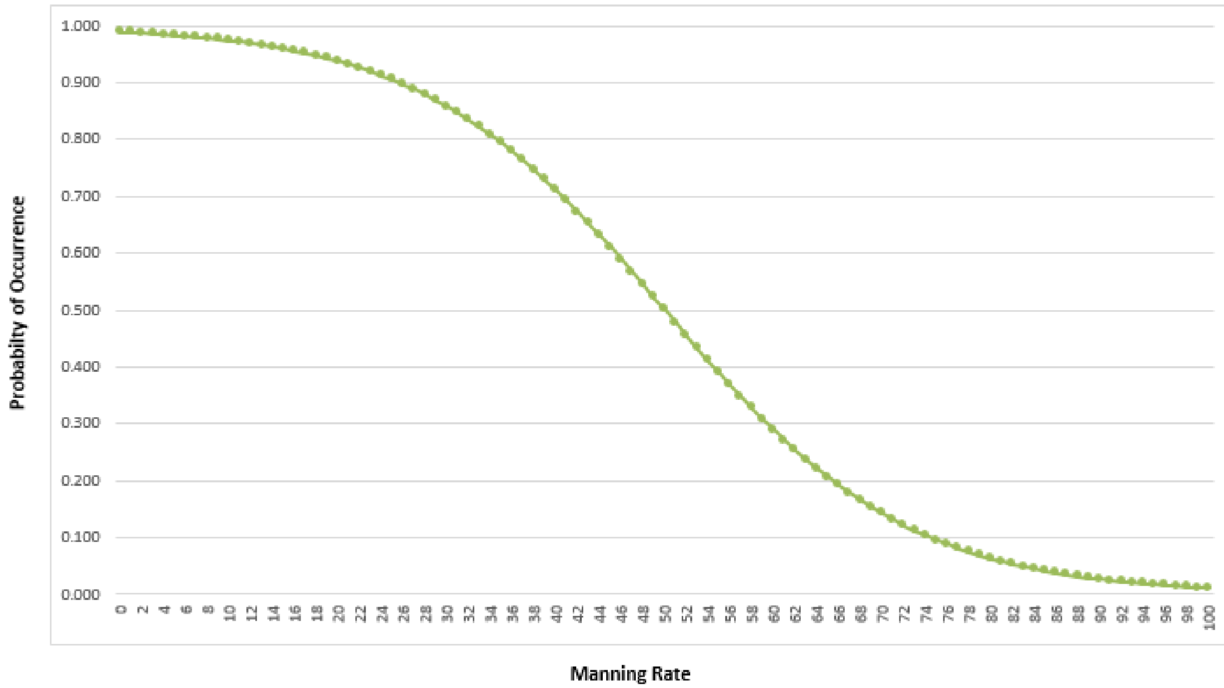
Recall, the other portion of risk is impact. While, the parameters of USAF manning career fields fit the properties of a normal distribution, in reality the normal distribution is ill-suited to compute operationally representative risk *alone*. Arguably, the relationship between personnel and risk follows a curvilinear pattern (e.g. Sigmoid curve or S-curve), where risk impact is inherently high when manning rates are below or at a certain threshold (e.g. 35%) and gradually improve as rates improve (Figure V-3). The Sigmoid function is a variant of the logistic function: $\boldsymbol{f(x) = \frac{L}{1+e^{-k(x-x_0)}}}$, where *e* is the natural logarithm base,

[17] ACS has the largest amount of funded personnel authorizations and personnel.
[18] While the personnel data can also be represented with a binomial distribution, the function fails at providing realistic probability of failure outcomes when manning rates are 0 and 100%.
[19] Classic risk is defined as the probability of occurrence of failure and its associated impact (Mitchell et al., 1999).

$\boldsymbol{x_0}$ represents the midpoint of the curve, L is the curve's maximum value and k represents curve steepness (Verhulst, 1838). The complement of the S-curve yields:

$$\boldsymbol{f(x)^* = 1 - \frac{L}{1+e^{-k(x-x_0)}}}. \qquad \textbf{Eq. V-1}$$

Figure V-3: Notional S-curve depiction



Even if manning is fully achieved, we still reach a manning performance ceiling, as risk (i.e. level of uncertainty) cannot be completely eliminated. Using an S-curve function computation accounts for impact. The S-curve uses a manning rate from (0-100%) coupled with a special case of the logistic function to arrive at a probability. We use these probabilities and translate them into personnel risk factor values from the AFRAF mentioned in Chapter I to a risk scale. Using both the normal distribution to compute probability of failure occurrence and the S-curve function coupled with the AFRAF risk scale to compute impact of failure, we arrive at an overall risk for a given career field. The other consideration of the determination of personnel risk is the measure of efficiency.

DEA

For this work, DEA is the choice of technique to measure personnel efficiency. A detailed exposition of DEA terminology is provided Chapters II and IV. For this particularly application, we are not concerned with slack-based methods as we seek to simply measure efficiency using CRS, VRS and scaled efficiency approaches. The rank (1st rank is considered the most efficient) from the scaled efficiency score is the value used as the efficiency variable to statistically compare against the risk score for each personnel category. What follows are the analytical methods used to demonstrate the assessment of strategic personnel risk. The next section discusses procedures to compute probability of failure and risk impact.

Methodology

Normal distribution

The normal distribution is a ubiquitous function observed in most natural and social phenomena (Kalla, 2019). If we let x represent a point estimate (100% manning requirement), μ equates to the mean manning rate by a given career field and σ represent the standard deviation of the career field manning rate, we can use the following normal cumulative probability density function to estimate probability of failure:

$F_x(\mu, \sigma) = P(X \leq x) = P(X > x) = 1 - P(X \leq x) = 1 - \int_{-\infty}^{x} \frac{e^{-\frac{1}{2}[\left(\frac{(y-\mu)}{\sigma}\right)]^2}}{\sqrt{2\pi\sigma}} dy$ (Conover, 1980). **Eq. V-2**

Since, the function does not have a closed form i.e. not able to be fully integrated using calculus, standard normal numerical approximations are used and thus, yield the following approximation (Conover, 1980):

$$N(\mu, \sigma) = 1 - P(X \leq x) = \ \Phi(x) = \Phi(\frac{x-\mu}{\sigma}). \qquad \textbf{Eq. V-3}$$

$$\Phi(x) = 1 - P(Z \leq \frac{x-\mu}{\sigma}). \qquad \textbf{Eq. V-4}$$

A correction is added to the normal cumulative function, by establishing the risk to be 1, if manning rates are at or below 33%. This ensures career fields with severe manning challenges are identified as higher risk entities. Assumptions of the normal distribution are:

1. The data are from a random sample or population.
2. The probability that a normal random variable X equals any particular value is 0.
3. The standard deviation of the mean is greater than zero.

Table V-1 is an example, where the Civil Engineering (CE) career field has a historical manning rate (mean) of 92%, standard deviation of one and a 100% manning rate requirement or 1, represents the random variable. We seek the probability of the CE career field being 100% or less available and trained. The results yield a cumulative probability of 0.532%. That is to say, given we do not know the amount of available and trained CE professionals, but the historical manning rate and standard deviation are known, we can say there is approximately a 53% chance the CE function will not meet a 100% manning requirement.

Table V-1: Normal probability calculator (Stattrek.com, 2018)

Example Normal Probability Calculation	
Normal random variable (x)	1.00
Cumulative probability: P(X ≤ 1)	0.532
Mean	0.92
Standard deviation	1.00

We theorize these distinctive probabilities can be used to an extent to assess CE personnel probability of failure occurrence. Essentially, satisfying the assumptions of a normal distribution, we can say, the probability of CE not manned at current requirements or more is at least $P(1 < x)$ or 0.532 ~ 53%.

The normal distribution application to the probability of failure occurrence is ideal for several reasons. First, the personnel data fulfill the normal distribution properties. Second, the normal distribution function inherently, appropriately accounts for uncertainty. In other words, if we were to simply use the CE current manning rate 92% to assess risk, we would faultily conclude a 8% (1 - 92%) personnel risk. Third, we no longer need to strongly consider other factors of the actual assigned CE personnel such as training shortfalls, personnel outages due to medical issues, Temporary duties (TDYs), deployments, etc. because the normal function has properties that account for these aforementioned uncertainties. Fourth, the data are continuous which fit nicely with a normal distribution. Fifth, we can use these normal probabilities to build an algorithm that assesses personnel capability by career field, which is one of the primary goals of this research. This sufficiently satisfies the probability of occurrence portion of the classic risk calculation. We further discuss the risk assessment methodology using the S-curve function to compute risk impact.

Sigmoid function

Using an S-curve function computation accounts for impact. The S-curve uses a historical career field manning rate from (0-100%) coupled with the S-curve function to arrive at a probability. We use these probabilities and translate them into personnel risk factor values from the AFRAF risk scale shown in Figure I-1. Using both the normal distribution to compute probability of failure occurrence and the S-curve function coupled with the AFRAF risk scale to compute impact of failure, we arrive at an overall risk for a given USAF career field.

For example, recall, we use the normal function to compute the probability of personnel manning rates at most 100%. However, having 100% of personnel resources does not eliminate risk. Therefore, we assign a raw personnel risk value of 0.01, if the normal function returns a value of 0. This algorithm correction allows risk to always be greater than or equal to 1%. The probability of failure (p^*) and severity of the failure (i^*) computations are combined using the mapping grid illustrated in Figure V-1 and further defnined by Eq.V-5.

The intersection of the probability of failure occurrence and impact equate to personnel risk for career field i.

$$P_i = (x_i . y_i) = (i^*, p^*) \qquad \textbf{Eq. V-5}$$

Ultimately a personnel raw risk value between 0.01 and 1.00 is computed. Eq. V-5 is represented by two variables: p^* represents the probability of being at most manned at the number of current personnel for a given career field; and i^* represents the impact of the said probability using the sigmoid function. In this particular instance, i^* is obtained through the following sigmoid function parameters from Equation V-1: L = 1 (maximum height); k = 0.09 (steepness); x = manning value between 0-100 and x_0 = 50 (midpoint). Figure V-4 provides an illustration of how personnel risk is obtained, assessed and prioritized. For example, if the Air Traffic Control (ATC) career family has a notional impact value of 0.95 and a 0.88 probability of failure occurrence, then the intersection of these two values provides an ordinal risk level of 'High'.

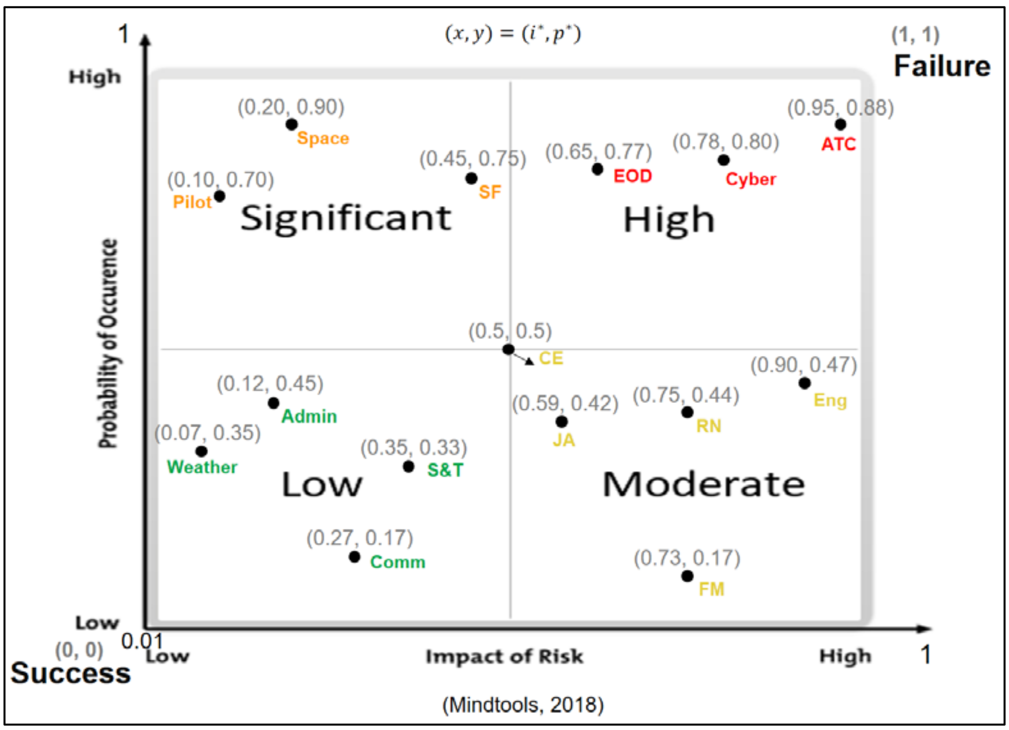


Figure V-4: Personnel Risk Prioritization Example

Figure V-4 is an illustration of how senior planners can visually prioritize risk by career field. If all career families are considered equally important, the inference gained from Figure V-4 suggests Explosive Ordinance Disposal (EOD), Cyber operations and ATC should be higher priority for resource consideration as risk scores are considered more significant than others. Table VI-1 provides a codification of risk illustrated by the Cartesian mapping in Figure V-4.

Table V-2: Composite Personnel Risk Ordinal Ratings

Raw Risk boundary	Risk Rating
$i^* = 0, p^* = 0$	$S_k = 1 \rightarrow Success$
$i^* < 0.5, p^* < 0.5$	$S_k = 2 \rightarrow Low$
$i^* \geq 0.5, p^* \leq 0.5$	$S_k = 3 \rightarrow Moderate$
$i^* < 0.5, p^* \geq 0.5$	$S_k = 4 \rightarrow Significant$
$i^* > 0.5, p^* > 0.5$	$S_k = 5 \rightarrow High$
$i^* = 1, p^* = 1$	$S_k = 6 \rightarrow Failure$

Both risk inputs (i.e. probability of failure occurrence and impact) are equally important (weighted) and scaled from 0 to 1. In order to obtain a composite personnel risk score, the risk inputs are averaged. Ultimately a composite personnel raw risk value between 0.01 and 1.00 is computed. In practice, the computation is as follows:

$$P_i^{**} = f(x) = composite\ personnel\ risk\ = \begin{cases} x = 0,\ x = 0.01, else \\ (\frac{i^* + p^*}{2}),\ . \end{cases} \qquad \textbf{Eq. V-6}$$

Upon computation of the composite personnel risk value, we use the AFRAF scale to determine the qualitative impact or final personnel risk. For example, if the composite personnel risk value of the ATC career field is $(\frac{0.95+0.88}{2})$ or 0.915, this equates to approximately 92% risk. The 92% risk is translated according to the AFRAF scale of impact as high. Therefore, the personnel risk assessment for this particular task, career field, sub-task, etc. would be interpreted as "achievement of goal or task is highly unlikely."

Using a random variable of 100% manned, historical manning rates and standard deviations, ACS career field risk scores are computed. Next, efficiency values and respective rankings using DEA are computed. The career field risk scores and efficiency rankings are compared using statistical correlation procedures to examine if a significant relationship exists between efficiency and risk. If a significant relationship exists, this has inferences. For example, if efficiency is positively correlated with risk, this can infer more efficiency is related to more risk. Conversely, if efficiency is negatively correlated with risk, this suggests the more efficiency, the lesser risk. These inferences have implications to how the USAF strategic decision making community assesses the planning force. For instance, if more efficiency infers less risk, then, personnel resource planners could recommend career field managers better utilize current manning levels before more resources are considered for allocation.

Data Overview

DEA Inputs/Outputs

Conducting DEA, this work uses career fields as DMUs. Since, each USAF career field (AD and civilian) is measured differently, we use career field manning variables as the inputs and outputs of the analysis. These variables are the only entities we can explore that span across all DMUs. For DEA scaled efficiency computations, the number of assigned personnel by career field is the input within ACS. The output is the number of funded authorized positions career field within ACS. We ask whether there are career fields that perform more efficiently than others given the various career field manning requirements within ACS.

Input and Output

Arguably, each career field has a unique skill needed to manage, deliver, execute, maintain and sustain USAF capability. These career fields are further aggregated into seven distinctive career field disciplines by the ACS core function. The 247 air force specialties can be seen in the Air Force Specialty Codes guide (Air Force Officer Classification Directory, 2007). Table V-2 provides a career field summary. The output represents funded requirements by career field (AFS). The input represents the amount of personnel by career field (AFS).

The radial orientation assumption of the dataset requires relaxation as two of the seven examined career family disciplines have assigned personnel (input) *and* an absence of funded authorizations (i.e. output). Recall, from Chapter II, the radial orientation requires outputs and inputs to be positive as normalization is mathematically impossible when values are zero. To account for zero-valued observations within the output, we use the directional distance function (DDF) for the Acquisition and Special Experience career field disciplines. This function allows outputs or inputs to be negative, positive or zero [(Alvarez et al., 2016); (Toloo and Tavana, 2017)]. For more details reference Lovell and Pastor (1999).

Table V-3: AFS Career Field Summary (AFSC Wikipedia, 2019)

Air Force Specialty Designator	**Career Field Discipline Title**
1X (Enlisted Operations (Ops)) 10X (Ops Commander) 11X (Pilot) 12X (Combat Systems) 13X (Space, Missile and Command & Control) 14X (Intelligence) 15X (Weather) 16R (Ops Support)	Operations
2X (Enlisted Logistics) 20X (Logistics Commander) 21X (Logistics)	Logistics
3X (Enlisted Support) 30X (Support Commander) 31P (Security Forces) 32E (Civil Engineering) 33X (Communications) 35X (Public Affairs) 38F (Force Support)	Support
4X (Enlisted Medical) 40C (Medical Commander) 41X (Health Services) 42X-43X (Biomedical Services) 44X (Medicine) 45X (Surgery) 46X (Nurses) 47X (Dental) 48X (Aerospace Medicine)	Medical
5X (Enlisted Professional) 51J (Judge Advocate) 52R (Chaplain)	Professional
6X (Enlisted Acquisition) 61X (Scientist) 62E (Engineer) 63X (Program Manager) 64X (Contracting) 65X (Finance)	Acquisition
7X-8X (Special Experience (e.g. Agent, Instructor, etc.))	Special Experience

Details of the input and output variables are listed in a separate annex. The next section provides an analysis of the outcome from the data.

Analysis

Correlation Results

Correlation analysis is performed using JMP 12 software. A total of eight career field disciplines (to include a combined dataset) are examined. Risk and efficiency ranks for each dataset exhibit strong evidence of left skewedness and fail normality goodness of fit tests. Figure V-5 reveal normality quantile and scatter plots for each variable. The results suggest parametric correlation techniques (i.e. Pearson) are ill-suited. Therefore, non-parametric correlation procedures are used to determine if a positive or negative association exists between risk and efficiency. Specifically, a technique called Hoeffding's Dependence coefficience (*D*) is used to determine if risk and efficiency variables are independent, i.e. no statistical evidence of association (Agresti, 2010).

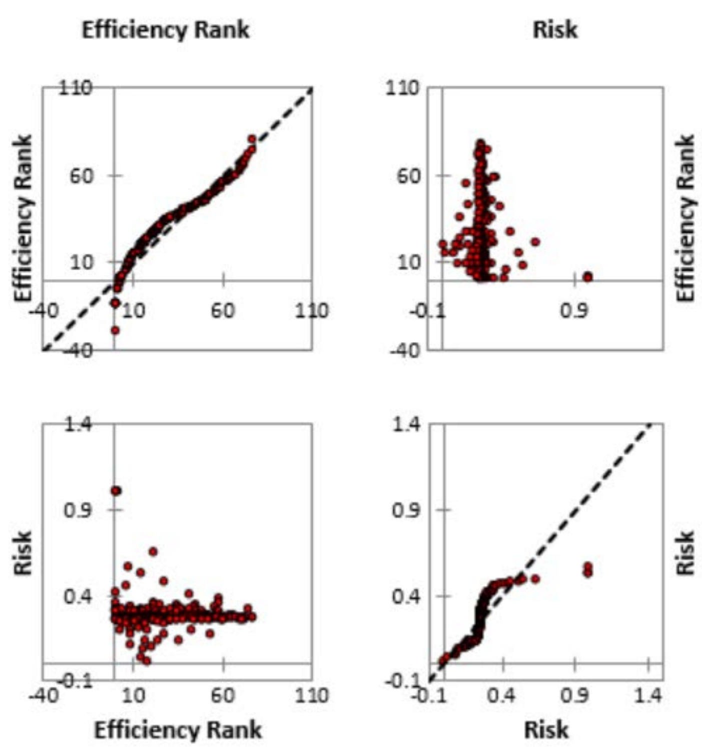


Figure V-5: ACS Career Field Quantile and Scatter Plots for Risk and SE

Hoeffding's D is a rank-based, distribution free measure that only require bivariate data to be ordinal, continuous and random (Hoeffding, 1948). The test determines whether or not the bivariate data are independent and takes on values within 1 to -0.5. Hoeffding's D is considered a superior nonparametric (e.g. compared to Kendall's Tau) when evidence of nonlinearity is present in bivariate data (Clark, 2011). The statistic approximates a weighted sum over observations of chi-square statistics for two-by-two classification tables (JMP, 2018). Hoeffding's D measures the distance between the ranks of joint and marginal CDFs of bivariate data (Hollander and Wolfe, 1999). The two-by-two tables are made by setting each data value as the threshold. If a perfect association exists among the bivariate data, where D = 1, then, the bivariate data are the same or completely dependent. If a perfect association exists among the bivariate data,where D = -0.5, the bivariate data are opposite or independent. If the bivariate data are independent, D = 0. The three steps to conduct the test are listed below (JMP, 2018).

1. Construct a hypothesis (e.g. one or two tailed test). A two tailed test is used and represented as

$$H_0: D = 0$$

$$H_A: D \neq 0. \qquad \textbf{Eq. V-7}$$

2. Compute D:

$$D = 30\frac{(n-2)(n-3)D_1 + D_2 - 2(n-2)D_3}{n(n-1)(n-2)(n-3)(n-4)}, \qquad \textbf{Eq. V-8}$$

where n is the total of observations among the bivariate data (risk, efficiency), $D_1, D_2, and D_3$ are further defined as follows:

$$D_1 = \sum_{i=1}^{n}(Q_i - 1)(Q_i - 2) \qquad \textbf{Eq. V-9}$$

$$D_2 = \sum_{i=1}^{n}(R_i - 1)(R_i - 2)(S_i - 1)(S_i - 2) \qquad \textbf{Eq. V-10}$$

$$D_3 = \sum_{i=1}^{n}(R_i - 2)(S_i - 2)(Q_i - 1) \qquad \textbf{Eq. V-11}$$

D_1 refers to the sumproduct of one plus the number of bivariate ranks (Q_i) with values less than the *i*th point, D_2 refers to the sumproduct of the number of risk and efficiency ranks ($R_i\ and\ S_i, respectively$) with values less than the *i*th point and D_3 refers to the sumproduct of the number of risk, efficiency and bivariate ranks with values less than the *i*th point.

3. Compute the test statistic and determine the rejection region. The hypothesis test characteristics will dictate the rejection region. We use a two-tailed test, therefore, the rejection region is as follows:

   Rejection Region: $|D| > d_{\alpha/2}$, where $d_\alpha$is the α (0.05) tail percentile of the asymptotic distribution associated with *D*, for $n \geq 5$, the approximation is

$$\frac{(n-1)\pi^4}{60} D + \frac{\pi^4}{72}. \qquad \textbf{Eq. V-12}$$

A separate annex lists career field discipline results. Results include career field, manning assigned and authorization numbers, scaled efficiency score, scaled efficiency rank, composite risk score and AFRAF translated composite risk score into an ordinal rating (e.g. 0.92 = 92% risk or ‘High’).

Nonparametric correlations are computed for each bundle of career fields to include an overall bundle. For the combined dataset (Separate Annex Table 1), a Hoeffding’s *D* score of 0.0084 is computed with a corresponding *p*-value of 0.0059. $P(|D| > d_{0.05/2})$ = 0.0059, therefore, we reject the null hypothesis and conclude there is a statistically significant association between personnel risk and efficiency. The Hoeffding’s *D* coefficient is very close to zero, which implies, while the *p*-value is significant, practical, statistical significance between risk and efficiency is suspect.

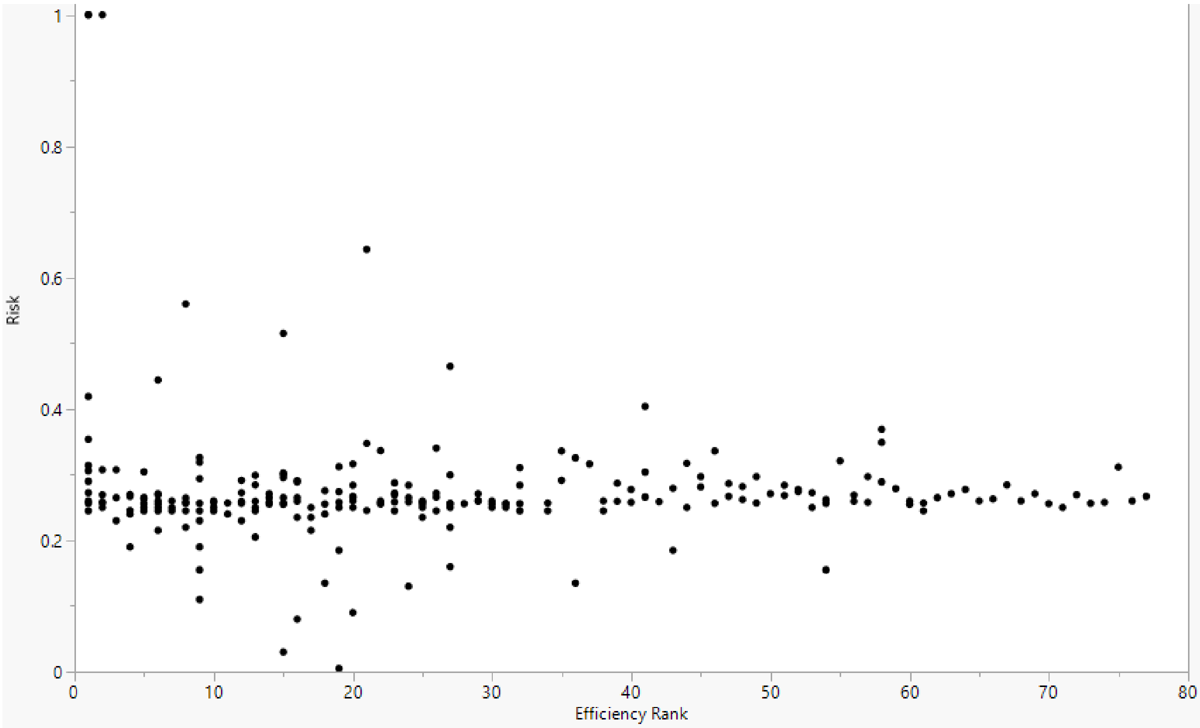


Figure V-6: Scatter plot of Risk vs DEA Efficiency Rank

Removal of one of three potential outliers from the top portion of Figure V-6 increased the *p*-value beyond the 5% significance level using the Hoeffding's *D* coefficient. However, the data are examined as is and are not changed. The complete dataset statistical implications suggest personnel risk increases with efficiency. This intuitively makes sense as when manpower is fixed, with simultaneous maximal output (as shown with DEA), optimal personnel scaled efficiency implies resources are extended to capacity while maximizing output. Further stress and strain on optimized manpower increases risk.

The 247 ACS career field manning data taken from March of 2018 reveals statistical evidence that risk and efficiency are not independent. The combined career field bundle correlation results suggests overall career field risk has a positive association with efficiency ranks. Higher DEA efficiency ranks translate into poorer efficiency. This infers higher risk more likely than not, implies lower efficiency. Medical and Acquisition communities reveal significant negative association, i.e. lower risk tends to yield higher efficiency ranks. This means lower risk more likely than not, infers lower efficiency. Table V-3 provides a summary of correlation results by career field bundle. Table V-4 summarizes the top 10 higher risk career fields with respective efficiency findings.

Table V-4: ACS Career Field Bundle Correlation Summary

Discipline	Hoeffding's *D*	Count	*p*-value
Operations	0.0145	61	0.0552
Logistics	-0.0257	26	1.0000
Support	-0.0158	29	0.9285
Medical	**0.0347**	**77**	**0.0021**
Professional*	0.0000	4	1.000
Acquisition	**0.2201**	**16**	**0.0007**
Special Experience	-0.0005	34	0.3795
Combined	**0.0084**	**247**	**0.0059**

*For sample sizes ≤ 5, Kendall's Tau[20] measure is used in lieu of Hoeffding's *D*.

[20] For specifics regarding the computation of Kendall's Tau, please refer to Agresti's Categorical Data text, 2013.

Table V-5: Top 10 ACS Higher Risk Career Fields

Career Field	Asgn	Auth	Manning Rate	Risk	Risk Rating	*Efficiency Score	*Efficiency Rank
Career Field 1	1	6	0.17	1.00	Failure	1	1
Career Field 2	3	12	0.25	1.00	Failure	1.5	2
Career Field 3	61	207	0.29	1.00	Failure	0.00	1
Career Field 4	3	8	0.38	0.64	Significant	0.12	21
Career Field 5	6	13	0.46	0.56	Significant	1.19	8
Career Field 6	15	30	0.50	0.52	Significant	0.02	15
Career Field 7	26	43	0.60	0.47	Moderate	2.52	27
Career Field 8	8	14	0.57	0.44	Moderate	2.51	6
Career Field 9	10	17	0.59	0.42	Moderate	1.00	1
Career Field 10	134	199	0.67	0.40	Moderate	4.04	10
*Efficiency Scores and Rank are relatively assessed *within* career field bundle							

Evidence suggests higher risk probabilities may lead to lower DEA efficiency ranks. Lower DEA efficiency ranks equate to superior efficiency. Thus, higher personnel risk infers higher manning efficiency. A takeaway is more people (i.e. greater assigned and authorized) equate to less risk however, more people equate to lower efficiency. A second takeaway is if capability and risk are curvilinearly negatively related, then, more people (i.e. more capability) lends to less risk and less capability infers higher risk or lower efficiency. A third takeaway is considering more personnel capability implies greater funding and spending, while resource budgeting is limited, what are the most effective manning levels to mitigate risk? These takeaways suggest tradeoff analysis should be a highly regarded consideration to determine manning levels in light of capability, risk, efficiency and cost.

Figure V-7 illustrates relationships between capability, risk, cost, efficiency and effectiveness. Arguably the four of the five (effectiveness not examined) said areas are at least curvilinearly related. The scope of this work addresses personnel capability, risk and efficiency, but further research may extrapolate the cost and effectiveness aspects. While cost is not explicitly considered in this research, it intuitively makes sense that increased resources will incur some form of fiscal increase. Effectiveness may pose challenges as personnel performance output metrics among homogeneous career fields are scarce.

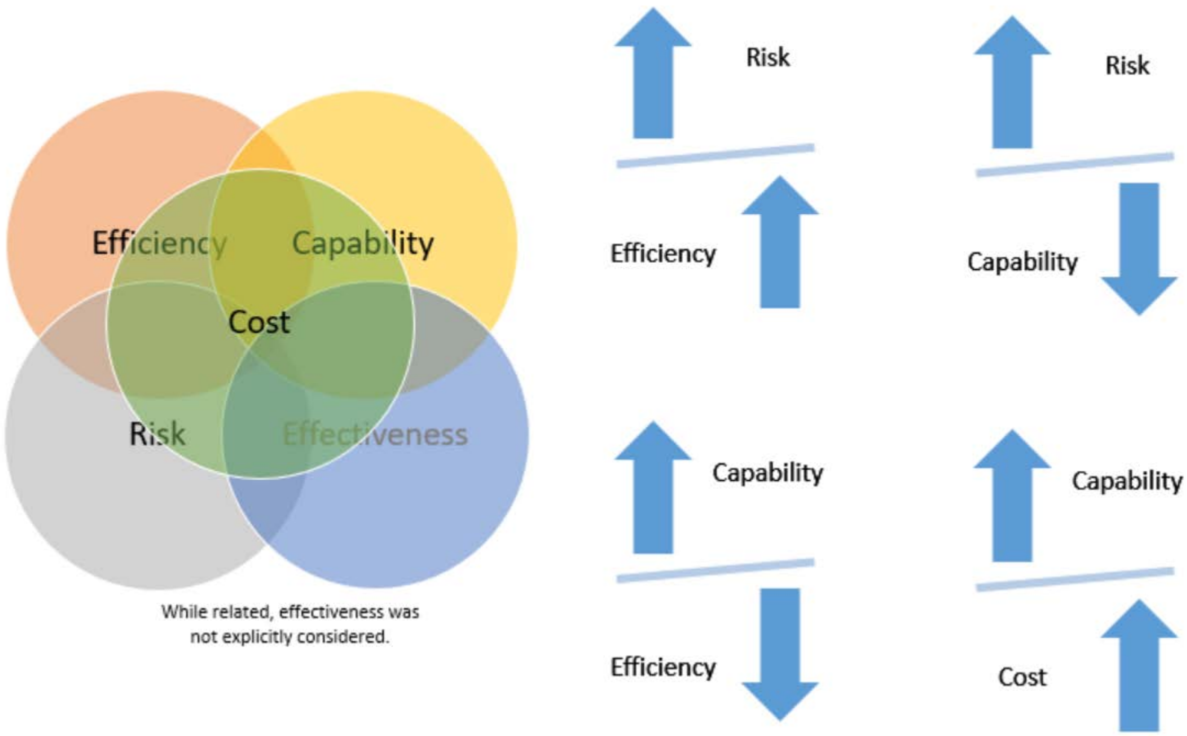


Figure V-7: Summary of Results Relationship Diagram

Limitations/Summary

Evidence suggests higher risk probabilities may lend to lower DEA scaled efficiency scores. Lower DEA scaled efficiency scores equate to superior efficiency. Thus, higher personnel risk infers higher manning efficiency. A takeaway is more people (i.e. greater assigned and authorized) equate to less risk however, more people equate to lower efficiency. A second takeaway is if capability and risk are curvilinearly negatively related, then, more people (i.e. more capability) lends to less risk and less capability infers higher risk or lower efficiency. A third takeaway is considering more personnel capability implies greater funding and spending, while resource budgeting is limited, what are the most effective manning levels to mitigate risk? These takeaways suggest tradeoff analysis should be a highly regarded consideration to determine manning levels in light of capability, risk, efficiency and cost.

A 2018 US Air Force dataset containing 247 career fields is analyzed for significant manning relationships between efficiency and risk. For the first time, career field risk is objectively computed using normal and sigmoid functions. Six out of 247 or 2.5% of career fields have significant to failure risk; 229 are moderate risk and the remaing 12 are either low or success with regards to risk. This research assumes all career field capabilities are equal, which is debatable. Unequally weighing career fields will likely change risk valuations, which may drive varying strategic personnel resource prioritization and allocation decisions.

A series of procedures is presented, objectively computing personnel risk by career field and examining relationships between efficiency, risk and capability. An explanation with demonstrations provides a use case of how career field manning can be used with normal and sigmoid functions to ultimately compute risk, thus enabling objective personnel resource prioritization in fiscally constrained environments.

The next section provides an overview of data elements considered to assess personnel risk within an organizational context. The organizational assessment includes core capabilities, which consist of tasks, sub-tasks, and career fields. A demonstration is provided revealing the use of personnel data to objectively assess enterprise risk.

VI. Methodology Using a Euclidean Norm to Aggregate risk

Introduction

This work provides an aggregation methodology to compute a core USAF personnel capability risk score. Recently, the USAF has adapted its risk-based assessment to become more capability-based. The rationale is when requested by a combatant commander during contingency operations, the service will provide air power, regardless of risk. As a result, the USAF's focus has shifted fundamentally from a risk-based assessment to a more capability-based assessment.

We tailor an algorithm used in Pacific Air Forces Command (PACAF) that used root mean squaring via a weighted p-norm (l^p) methodology to assess personnel capability. For the first time, a personnel risk aggregation methodology is developed potentially enabling enterprise planners and programmers to provide an objective, defensible situational awareness procedure for senior decision makers to get a core capability-level personnel capability assessment. To help assess the connectedness of core capabilities, the USAF Studies, Analysis and Assessments directorate (AF/A9) has developed an interdependency framework called the Comprehensive Core Capability Risk Assessment Framework (C3RAF). C3RAF is a network model that combines risk and multi-domain interdependency data to inform senior leader decisions. The non-linear model uses Core Function inputs (e.g. ACS enterprise inputs) and aims to identify the most influential core capabilities regarding AF-wide risk (AFGM2016-90-1101, 2016). C3RAF also aims to identify how changes in risk affect elements throughout the USAF and identify where planning decisions might influence systemic risk (AFGM2016-90-1101, 2016). C3RAF is being used to influence senior level decision making regarding budgeting of resources (e.g. ACS equities). To lessen the negative impact of 'Garbage In, Garbage Out' to the C3RAF model, it behooves ACS sub-enterprises to carefully examine current capability enablement and the impact on future capability enablement if not resourced.

Data for the ACS RA consists of manning data in the form of personnel and personnel funded authorizations from the ACS Core Function. The personnel data spans across many bases and almost 250 career fields. The ACS core function is linked to six core capabilities with numerous Program Element Codes (PECs).

All USAF programs have PECs. PECs are generally alphanumeric strings of characters that represent groupings of career fields to carry out certain tasks. The PECs are also assigned cost values as the primary means to track and manage funding. Other than recent development by the author, the PECs were not linked to personnel. This linkage now accounts for the amount of specific personnel (by career field) needed to accomplish the core capability *tasks* versus respective personnel requirements in terms of resource dollars.

Figure VI-1 provides the six ACS enterprises and their associated top-level tasks. Each task has subtasks, sub-subtasks, sub-sub-tasks, et cetera. When these sub metrics are aggregated or 'rolled up' for senior decision level making, critical metrics are often smothered and as a result do not accurately depict strategic risk implications for enterprises. For example, we consider the Installation & Mission Support (I&MS) core capability subtask 4.8., which is to 'Provide Installation Support'. The subtask description is very detailed and involves producing and delivering operationally-capable facilities, real property-installed A5/8P, 2016). Producing and delivering operationally-capable facilities, real property-installed equipment, These entities require personnel capability to execute, maintain and sustain.

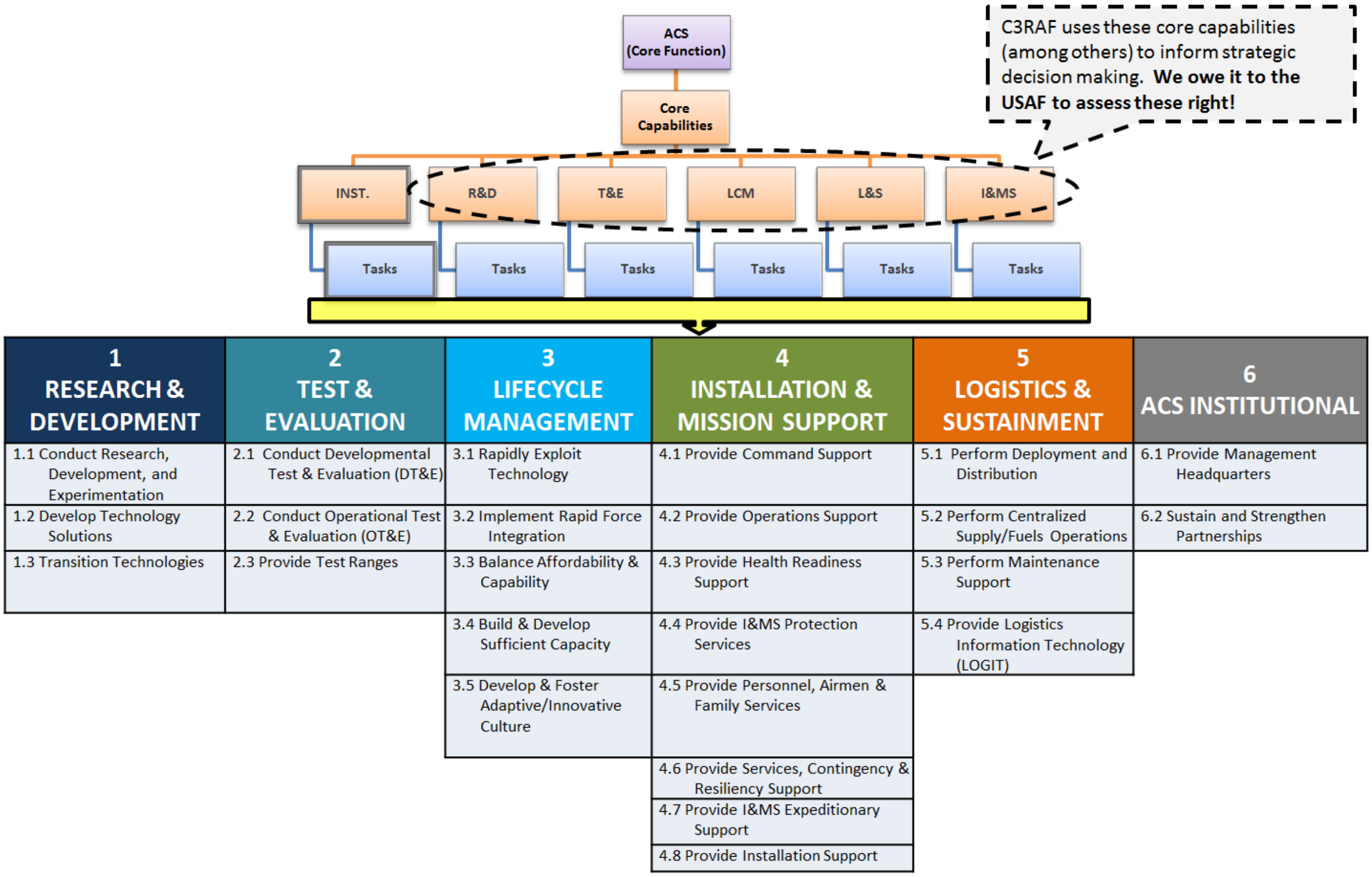


Figure VI-1: ACS Enterprise Task structure…v11.1 (AFMC 5/8/9, 2016)

If this subtask cannot be achieved through lack of personnel, training, funding, etc., can the I&MS enterprise deliver optimal operational I&MS support? Given, the aggregate nature of the USAF strategic assessment, and given, we cannot measure all components of capability, what is a better rigorous procedure to pursue? Assuming, some level of suboptimization[21], is there a rigorous way to assess personnel risk to ultimately inform strategic decision making? C3RAF attempts to address this issue, but there is not a high degree of confidence in the enterprise assessments that the said model uses to increase defensibility and repeatability in assessing strategic risk.

Background

Issue

Some ACS assessments over or understate risk. Specifically, some assessments assume a 'single outcome' (i.e. can either complete task or not) approach. Sometimes organizational assessments can be very one-dimensional. For example, they define success as binary (i.e. success or fail), which does not consider variation and forces senior decision makers and managers to explain more (as in why they lost). This traditional form of measurement can lead to false conclusions and have negative implications. The intent of the AFRAF construct is to measure risk by capability output. Some ACS enterprise risk assessments do not accurately portray capability output. Figure VI-2 is an adaptation of the AFRAF construct. The boundaries of risk are defined by *likelihood* and *impact* of achieving functional objective tasks. An additional consideration for impact is risk mitigation ability during planned timeframes. Timeframes are near, mid and far as discussed Chapter I.

[21] Suboptimization refers to the practice of focusing on one component of a total system and making changes intended to improve that one component and ignoring the effects on the other components (Watkins, 2018).

		Likelihood of achieving functional objective(s) or tasks	**Impact** on vital resource expenditures & schedules	**Impact** on planned levels or timeframes (Near, Mid, Far)
Risk Boundary	**Success**	Assured	All	At or above
Risk Levels	**Low**	Highly Likely	All	At or near
	Moderate	Likely	Some	Limited (acceptable) deviations
	Significant	Questionable	Some	Substantial deviations
	High	Highly Unlikely	At least one	Failed or nearing failure; little margin for error in planning or execution
Risk Boundary	**Failure**	Impossible	At least one	Failed & mitigations unavailable

Source: ACS Risk Assessment Methodology WikiPagev5, Feb 2017

Figure VI-2: ACS adaptation of AFRAF

There are several ways to compute aggregative computations for organizational risk assessments. What follows summarizes are summaries of techniques useful for computing organizational risk.

Organizational Risk Assessment Approaches

Bayesian Networks

Bayesian networks (BNs) are growing in popularity particularly as it relates to organizational assessments. BN implementation is used in risk analysis and predictive analytics for decision making (Parra and Garrido, 2012). BNs are based on a mathematical theory known as Bayes' theorem, which is used to calculate the probability of an event occurring given a known related piece of information (Cummings et al., 2008). Bayes' theorem states,

$$P(A|B) = \frac{P(B|A)*P(A)}{P(B)}. \qquad \textbf{Eq. VI-1}$$

P(*A*) is the prior probability or the initial estimate of the probability. *P*(*B*|*A*) is the conditional probability or the probability of *B* given *A*. *P*(*A*|*B*) is the posterior probability or the probability of *A* given *B*.

BNs are a set of random variables (nodes) and directed edges (arcs), with each node having a finite set of states or a set of values. For each random variable A, with parent nodes $B_1 \dots B_n$, there exists a table of probabilities P(A|$B_1 \dots B_n$) (Jensen, 2001).

BNs represent a potential approach for improving the understanding of how personnel resources are strategically assessed, and a literature gap seems to exist on application in the USAF human resource allocation domain. BNs use neobayesian attributes (Pearl, 1990) to attempt to provide reasoning to a phenomena with uncertainty (Wang, 1993). The three main attributes are:

- Willingness to accept subjective belief as an substitute for raw data or a priori.
- Adherence to Bayes' conditional independence as the primary mechanism to provide new information about a phenomena under examination [(Heckerman, 1999); (Pearl, 2000)].
- All Markovian states and uncertainties of phenomena under examination are known to have probability distributions (Postlewaite and Schmeidler, 1984).

BNs are defined by a directed acyclic graph (DAG) structure of random variables (nodes) with joint probability distributions that can be factored into smaller local probability distributions (Scutari, 2017). In other words, each variable is conditionally independent of all its nondescendants in the graph given the value of all its parents (Davies and Moore, 2016). For example, consider random variables *X* and *Y* to be conditionally independent, and

$P(X,Y|Z)$ is to be determined. The aforementioned can be decomposed into $P(X,Y|Z)*P(Z)$. Further, using the idea of conditional independence we obtain $P(X|Z)*P(Y|Z)*P(Z)$.

While the current structure of the personnel career fields is not in nodal form, we know the (quasi) network consists of undirected and directed arcs. Essentially, conditional independence is in constant violation due to the various interdependencies among the career fields. This assumption violation suggests BNs may not be ideal (Sanford and Moosa, 2012) for using personnel interdependencies to assess risk. For example, most of the maintainer community (officer and enlisted) depend on each other to meet the demands of a flying schedule. Bi-directional relationships among these career fields exist in order to effectively communicate disconnects, issues, concerns, goals, instructions, et cetera. Arguably, there is very little conditional independence in this community. We assert similar arguments apply to the aviation medical and legal career fields. Figure VI-3 illustrates this concept.

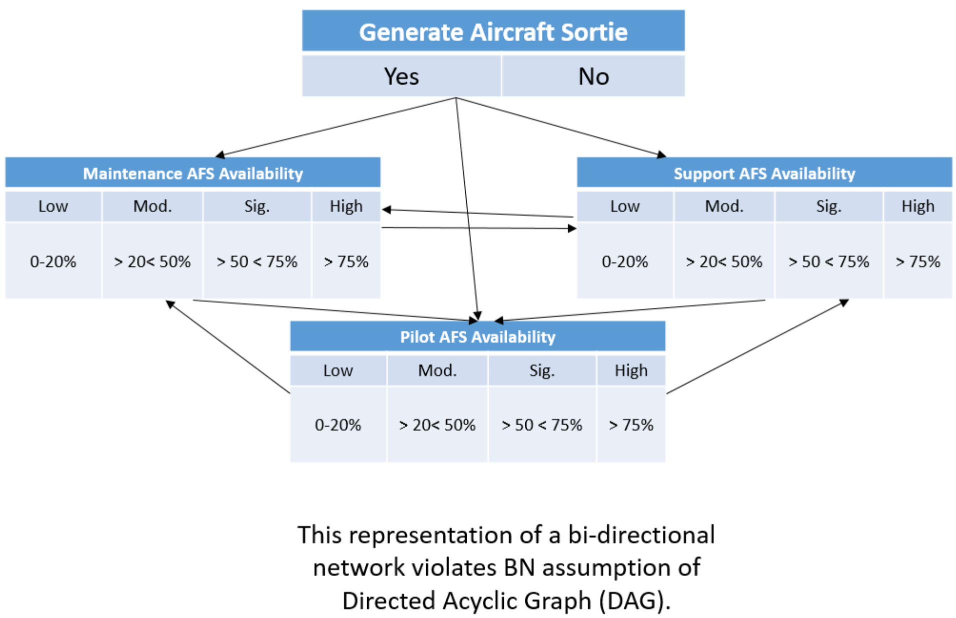


Figure VI-3: Notional USAF AFS Network

Further, if we consider career fields ability to generate aircraft sorties to be binary (i.e. generate sortie or not) and there are 247 variables (career fields) to examine, we must computationally consider at least $2^{(247-1)}$ or 1.13078E+74 configurations (Scutari, 2017). Not only is this approach (if violations were not applicable) computationally expensive, it can also be misleading if there are decent amounts of dependent correlations among the variables.

The literature express five commonalities relating to BNs [(Boehmke, 2016); (Lockamy and McCormacket, 2011); (Koller and Pfeffer, 1997)]. One, the assumption of a DAG exists, which implies directed arcs within a network. Two, the states and associated probability distributions have to be enumerated. Three, a priori of the portfolio are required. Four, a periodic update of risk profiles is necessary. Five, software and simulation are needed in order to better account for certain dynamics and simultaneity. Four of the five assumptions are fairly attainable, however, the DAG relationships are a major concern.

While possible opportunities to extend this research may include further BN exploration, this work focuses on value-frame theory (VFT) or weighted average and systems engineering aggregation techniques. Average, weighted average and systems reliability approaches are compared using a generic enterprise. Case studies are explored in the next section.

Averaging and Weighted Averaging

For multiple outcome organizational risk assessments where units or elements are large ($n > 30$), averaging techniques can be explored. A Pest Risk Assessment (PRA) performed in New Zealand conducted by the National Resources Institute of the United Kingdom examined the incorporation of various averaging (to include weighted) methodologies as a means to aggregate risk [(Zhu et al., 2000); (Holt, 2005); (Black, 20xx)]. After exploring advantages and disadvantages of using averaging risk factors, Zhu, Holt and Black conclude weighted averaging coupled with normalization are sufficient techniques to use when 1.) there exists a large number of risk elements (e.g. tasks); 2.) there is no historical record of valid computations; and 3.) immediate action is required.

With the aforementioned, we consider a generic enterprise comprised of many organizations. An organizational risk assessment can be computed as the average of a set of point estimates and is represented as follows:

$$Avg_i = \frac{1}{n}\sum_{i=1}^{n} p_i, \qquad \textbf{Eq. VI-2}$$

where *n* represents the number of units (organizations) under examination and p_i is the point estimate value. This is one of the simplest techniques to use when assessing aggregate data. The approach is appropriate when the spread of unit effects are equally likely. For units with more effects than others, a weighted average approach can be used. This is represented as

$$Weighted\ Avg_i = \frac{1}{n}\sum_{i=1}^{n}(w_i p_i), \qquad \textbf{Eq. VI-3}$$

where a weight (w_i) is added to every i^{th} unit in Eq. VI-3 representing the amount of relative impact of a particular unit (e.g. career field, task, sub-task, etc.). There are various ways to set weights (i.e. by SME or objectivity). When organizations are unique and expertise is voluminous, SME weight setting is a valid approach. Conversely, when there exists very little insight on the organization, using an objective approach such as a normalization technique is a common approach (Zhu et al., 2000). These approaches will be applied to an USAF enterprise, but we first explore a systems reliability approach. The next aggregation technique adapts principles from systems reliability principles.

System Reliability

One way to measure system component relationships is to construct reliability block diagrams (RBDs) in serial, parallel or a combination thereof and assign reliabilities or probabilities of success to each component (Blanchard and Fabrycky, 2006). Serial relationships are mathematically defined as

$$R = (R_A)(R_B)(R_C)(R_D), \qquad \textbf{Eq. VI-4}$$

where R_i are reliability rates of individual components. Of course, when any value of the serial chain is less than one, the sumtotal of the chain or overall reliability will always yield a value less than one. Further, if any value of the serial chain is zero, the overall system reliability is zero. Parallel relationships are defined as

$$R = 1 - (1 - R_A)(1 - R_B)(1 - R_C)(1 - R_D). \qquad \textbf{Eq. VI-5}$$

Systematically, if one component fails, while the remaining are operational, the overall system reliability impact is relatively negligible compared to a serial configuration. Combinations of parallel and serial components are defined in numerous configurations. An example is listed as

$$R = (R_A)(1 - (1 - R_B)(1 - R_C)(1 - R_D). \qquad \textbf{Eq. VI-6}$$

The substitution of notional reliabilities for components *A* through *D* yield the following probabilities:

$$R_A = 0.95, \qquad R_B = 0.98, \qquad R_C = 0.99, \qquad R_D = 0.$$

Based on Equations VI-4 through VI-6, we obtain the following overall system reliabilities: 0, 0.999999 and 0.949810 or risk values 0.000001 and 0.050190, respectively.

If we consider a personnel system by USAF core function, we can construct a notional RBD. Figure VI-4 illustrates multiple functional equities (FEs) of career families distributed across a network defined as a system. Each FE can be assigned a probability of success (i.e. manning rate). Based on the relationship of Figure VI-5, the dependency begins with the communications FE, where commander's guidance is provided to planners, thereby base support (e.g. Safety, Force Support, Legal services, Contracting, Security Forces, Civil Engineering, etc.) is executed. These collective services are needed in order for flightline operations (e.g. Distribution, Maintenance, Airfield Ops, Weather, etc.), which then allow for sortie generation by pilots, combat systems navigators and remotely piloted aircraft operators. The notional structure of the RBD infers if any one of these serial components is unavailable (i.e. 0% manned), the entire system fails to provide capability.

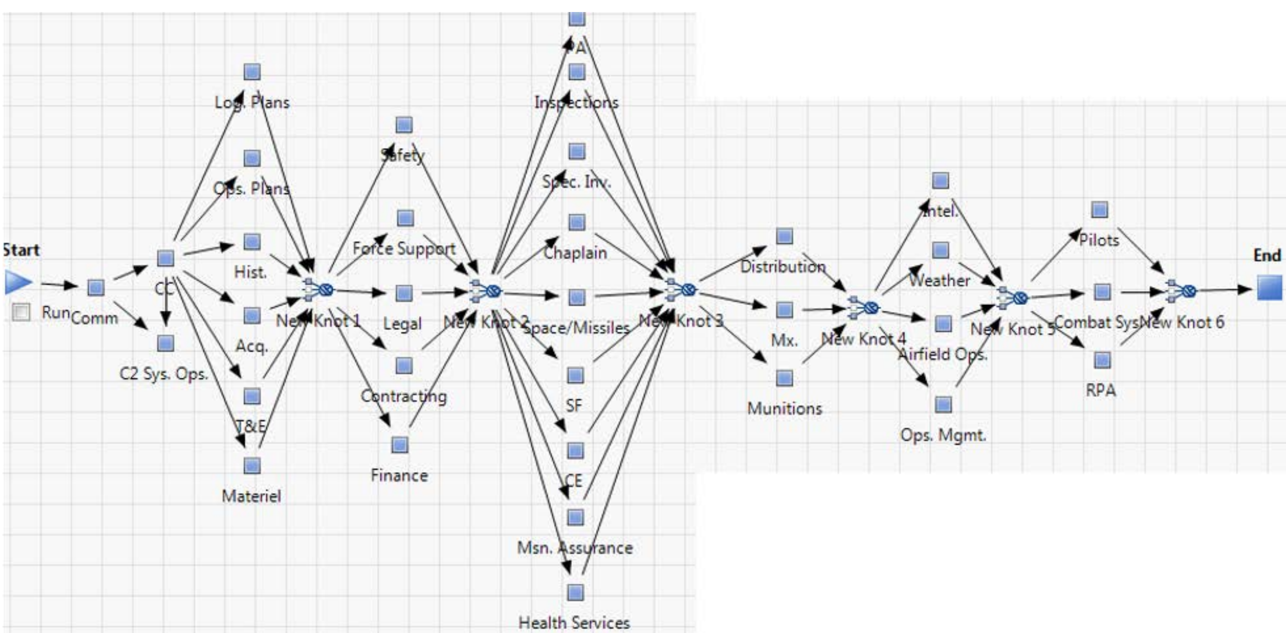


Figure VI-4: Notional USAF Personnel RBD

A major concern with using a system reliability approach to assess the risk of this notional version of a USAF network (i.e. Figure VI-4) is the way by which the risk is propagated. Using the network structure, a bootstrapped demonstration of system reliabilities assigned to each FE ranging from 99 to 100% is performed. Assuming a linear relationship between risk and capability, a bootstrapped sample of 500 yields an average system overall reliability of 0.227 or 22.7% capability, which is analogous to approximately 77% risk. This theoretically means when there exists all but 1% risk in any or all components of the notional USAF enterprise, on average, the organizational ability to achieve a mission is about 25%. Presenting these results to a senior decision leader is ill-advisable, as the results are not credit-worthy and do not depict a realistic representation of risk when personnel capability on average is 99%.

The systems reliability approach is applied to a notional USAF core capability consisting of multiple tasks and subtasks. The USAF has over 40 core capabilities managed by a dozen core functions or enterprise of personnel employed to plan, manage, deliver and execute a given capability. A core capability is an enabling function necessary for the USAF to perform its mission as part of the Department of Defense (DOD). Assessing risk at the core capability is a good start to assessing risk, but is still not comprehensiveness enough. There are lots of missed, unexamined and not well-understood issues that occur below the core capability level particularly as it relates to mission and force risk. Consequently, core capabilities have an activity or task structure as a means to mitigate risk (Pitstick, 2017).

Largely, the ability to accomplish these tasks or subtasks is based on personnel availability rates (McMillie, 2017) in three distinctive timeframes (i.e. Near (0-5 yrs); Mid (6-10 yrs); Far (11-30 yrs)). We use the Installation Mission and Support (I&MS) core capability as an illustration. Provided a serial relationship exists between tasks, notionally, if there are eight tasks to accomplish I&MS and any *one* of the tasks is assessed as 100% risk, then the ability to accomplish this core capability is 0%.

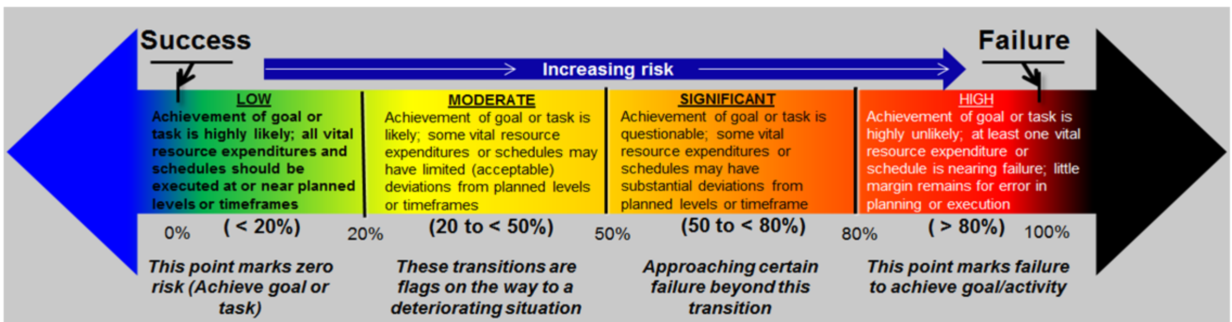
The systems reliability (serial network), weighted (weights arbitrarily chosen) average and average risk results are presented in Figure VI-5 coupled with a legend to identify bands of risk. Another notional outcome of risk is displayed at the far right to illustrate cases where if the systems reliability approach (e.g. serial configuration) is used the overall risk results are overstated.

Core Capability (I&MS)---> Risk

	I&MS approach			Weighted Average			Average			I&MS Examples		
	Timeframe			Timeframe			Timeframe			Timeframe		
	Near	Mid	Far	Near	Mid	Far	Near	Mid	Far	Near	Mid	Far
	100.00	100.00	99.97	38.65	72.80	47.55	20.38	46.50	55.63	100.00	34	83

Task	Description	Near 0-5	Mid 6-10	Far 11-30	Near 0-5	Mid 6-10	Far 11-30	Weight	Near 0-5	Mid 6-10	Far 11-30	Near 0-5	Mid 6-10	Far 11-30
4.1	Provide Command Support	3	4	73	3	4	73	0.05	3	4	73	0	5	20
4.2	Provide Ops Support	5	4	65	5	4	65	0.05	5	4	65	0	5	20
4.3	Provide Health Readiness Support	9	2	90	9	2	90	0.05	9	2	90	0	5	20
4.4	Provide I&MS Protective Services	4	5	29	4	5	29	0.05	4	5	29	0	5	20
4.5	Provide Personnel, Airmen & Family Services	11	92	56	11	92	56	0.05	11	92	56	0	5	20
4.6	Provide Services, Contingency & Resiliency Support	14	76	75	14	76	75	0.2	14	76	75	0	5	20
4.7	Provide I&MS Expeditionary Support	17	89	4	17	89	4	0.25	17	89	4	0	5	20
4.8	Provide Installation Support	100	100	53	100	100	53	0.3	100	100	53	100	5	20

SUCCESS **FAILURE**



ACS risk evaluators currently speculate on how many resources are required to execute scenarios and associated risk.

Figure VI-5: Notional USAF Core Capability Assessment (AFMC/A9A, 2016)

If the tasks are assembled in a parallel configuration, using risk values from IM&S example in Figure VI-5 on the far left, the overall risk results are drastically different. The overall system reliability using a parallel scheme is 100%. Further, using the aforementioned scheme, if we consider the values used in the far right table of Figure VI-5, the result for near term is 99.9999%. This depiction of risk is not organizationally or operationally representative.

If we expand the discussion to include subtasks and sub-subtasks, the results become even more unrealistic. For example, consider a core capability (e.g. IM&S) with 11 tasks, each with 4 subtasks and each subtask has 7 sub-subtasks totaling 308 $(11 * 4 * 7)$ components. Also, each *component reliability* ranges from 99 to 100%. Simulated mean system reliability result for serial configuration is 24%. The results infer a senior leader has an abundance of resources and is still failing to deliver desired capability. For a parallel (at task and subtask level) and serial (sub-subtask level) configuration, the mean is 99.99999%. The latter results appear superficially reasonable, but just because the capability requirement is met, does not eliminate risk. Further, if the lower bound reliability threshold is decreased from 95% to 70%, the combination configuration mean is 99.99999%. From an organizational risk assessment perspective, the risk propagation is incorrectly depicted.

While all possible outcomes of task/sub-task configurations are not explored, the aforementioned results reveal for an organizational risk assessment, the weighted average and average results are more realistic and operationally representative than system reliability approaches. Ideally, an organizational risk assessment should account for mitigated risk actions, whereby if a risk imbalance exists, management actions may be able to rebalance to a certain extent. Weighted average and average techniques appear to provide a more balanced approached to the assessment of organizational risk.

The next section of this manpower strategic assessment research examines an aggregation methodology to compute a core capability risk score using a normalization algorithm. We consider tailoring an algorithm used in Pacific Air Forces Command (PACAF) that used root mean squaring via a weighted *p*-norm (L^p) methodology to assess personnel capability. Several years ago, PACAF adopted a USAF risk-based assessment to become more capability-based. The rationale is when requested by a supported commander during contingency operations, PACAF will provide air power, regardless of risk. As a result, the command's focus shifted fundamentally from a risk-based assessment to a more capability-based assessment.

Methodology

The PACAF shift to a capability-based assessment paved the way for the warfighter capability assessment (WCA), which is a capability-based assessment for the Pacific Commander of Air Forces and/or the Joint Force Air Component Compact Commander on how Air Force resources and assets are postured in terms of providing air power capability to meet operational requirements in the Pacific theater. Capability (in response to a crisis prior to force flow) is based upon eight functional areas (i.e. Aircraft, Munitions, Fuels, Installation, Communications, Personnel, Medical, And Services) spanning across nine air bases. Prior to a revision in 2014, the assessment was highly subjective. Figure VI-6 provides a notional example of the WCA used by PACAF.

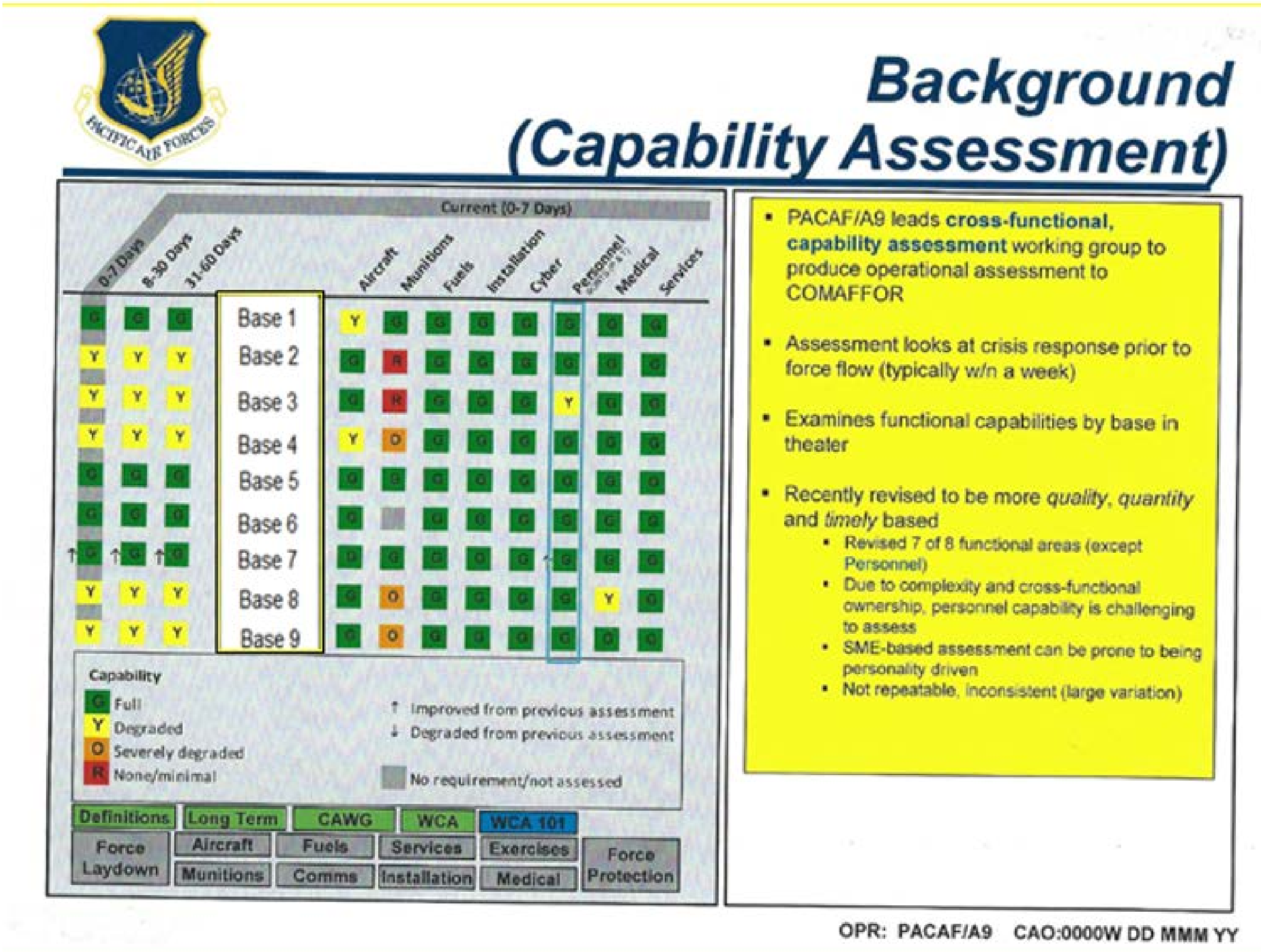


Figure VI-6: Notional example of PACAF Capability Assessment (PACAF A9, 2014).

The methodology only worked with consistent subject matter expertise (SME) participation who were engaged with the various functional managers at bases in theater in order to ascertain insight into capability gaps or general unit health. This approach was often not repeatable or consistently defensible. The 2014 revision afforded the opportunity for less subjectivity, and relied more on quality (how capable are we), quantity (how much capability can we provide) and timeliness (how quickly can we provide the capability) metrics by base to support a crisis. All eight functional capability (to include personnel) areas were successfully revised. In the next section we demonstrate a way to effectively assess organizational risk using a norming algorithm.

P-norm

A norm or *p*-norm is typically expressed as a vector which consists of distance and magnitude (Elmore and Richman, 2001). Specifically, a norm is a p^{th} root of all summed elements within a sample space (e.g. career field risk scores) to the p^{th} power. In fact for every real number (to include integers), a norm can be computed. The Euclidean norm or 2-norm is one of the most widely used distance computational algorithms in the field of mathematics. In many instances, the Euclidean norm is used as a component of penalization or loss functioning in order to propagate error in regression and machine learning (ML) (Gentile and Littlestone, 1999). The *p*-norm has also been used in the field of multi-task feature selection, which is a type of ML whereby different tasks share a subset of relevant features to be selected from a larger common space of features (Obozinski et al., 2006). Additionally, the *p*-norm is used in the context of multi-task selection applications to include speech recognition, robotics, and handwriting authenticity (Obozinski et al., 2006).

The 2-norm is a significant application to this work as it mathematically provides more weight to larger risk items, while not dominating the sample size. Essentially, the 2-norm allows numerous organizational tasks to be aggregated such that no one sub-performing task is going to severely degrade the organizational success level. This is appropriate for USAF enterprises that have tens of thousands of personnel performing and enabling a multitude of tasks to ultimately provide a core capability. An additional advantage of the 2-norm is while the risk space generally shrinks for individual tasks, weightier tasks (i.e. tasks with more risk) still have larger impacts on the organizational risk assessment than tasks with not as much risk. If we let

$$x = \begin{pmatrix} x_1 \\ x_2 \\ \cdots \\ x_n \end{pmatrix} \text{ and } x = (x_1, x_2, \ldots, x_n) \text{ be column and row vectors, then}$$

$$\| x \|_2 = \sqrt{(x_1)^2 + (x_2)^2 + \cdots + (x_n)^2} \qquad \textbf{Eq. VI-7}$$

which represents the length of a line segment from the origin to x or 2-norm of x. An USAF application using a 2-norm is discussed in the next section.

2-norm application

A SORTS-based algorithm (at the time referred to as SORTS Base Rollup (SBR)) was used to objectively assess personnel capability by base (Bradshaw and Novak, 2014). AF-IT [22] (formerly known as Status of Resources and Training system (SORTS)) data provides insight to unit health by base. AF-IT is the primary system of record for operational unit health reporting (AFI 10-201, 2019). Notable effort was taken in revising the personnel functional area of the assessment by combining AF-IT reporting and response times from 130 different operational units. This aggregation methodology was presented during the 2014 Air Force Operations Research Symposium (AFORS). The SBR algorithm is adapted and applied to the personnel component of the ACS RA, whereby Air Force Specialties or career field bundle risk scores will replace response time weights and the SORTS vector [23]

[22] AF-IT provides near real-time force readiness and consists of four areas: Personnel, Training, Equipment Condition and Equipment Status.
[23] For more details on the actual procedure, please reference classified AFORS 2014 presentation.

(Bradshaw, 2014) will be replaced with risk scale vectors using the AFRAF. Details of the procedure are what follow.

Assuming a function has a uniquely determined property (i.e. boundary condition) for any vector (distance) within the vector space, using a weighted *p*-norm (Bourbaki, 1987), we can express a task risk score (*TR*) between zero and infinity ([0, ∞) as

$$TR = [\sum_{i=1}^{N} r_j * (\|s_k\|)^p]^{1/p}. \qquad \textbf{Eq. VI-8}$$

The risk score (r_j) is represented as a weighted value within the bounds of 1 and 10 or ($1 \leq r_j \leq 10$). Recall, P_i is the expectation of *probability of failure occurrence* and *consequence of respective impact*. These values are obtained from the normal, Sigmoid and expectation functions discussed in Chapter V. S_k represents a distinctive vector (value) from the AFRAF scale, within the set {1,2…,6}. The *p*-norm ($p \geq 1$) produces a reasonable spread across a span of risk scores. This is the most critical component of the algorithm to account for proper aggregation of the various career field bundle risk scores. In this specific case, we use the 2- norm. *N* represents the total number of career field bundled risk scores within a given task. Similarly, if we normalize the algorithm for a given number of career field bundles for a task, we can achieve an aggregated value or capability risk value (*CR*). We express the minimal (best) and maximum (worst) possible task risk scores as:

$$b_i = Min[TR = (\sum_{i=1}^{N} r_j * (\|1\|)^2)^{1/2}] \qquad \textbf{Eq. VI-9}$$

and

$$w_i = Max[TR = (\sum_{i=1}^{N} r_j * (\|6\|)^2)^{1/2}] \qquad \textbf{Eq. VI-10}$$

Collectively, these parameters are used to express an aggregation risk score or *CR* as:

$$CR = \frac{(TR - b_i)}{(w_i - b_i)}, \ (0 \le CR \le 1). \qquad \textbf{Eq. VI-11}$$

For the personnel risk prioritization in Chapter V, magnitude of impact was a value between 0.01 and 1. Since, the career fields are theoretically equal, this level of magnitude is sufficient in order to compute personnel risk by career field in isolation. However, when career field risk is aggregated or propagated to a task or core capability level, further computations are needed. To prepare the data for 2-norm aggregation, we consider a simple translation of the composite personnel risk scores computed in the methodology section of this Chapter V.

We note the translation of the composite risk score to the AFRAF did not have an additional magnitude to account for weightiness of each career field. We introduce a scale depicted in Table VI-1, which shows bounds for each AFRAF risk level and ordinal ratings, respectively. This measure allows more separation between sub-tasks and tasks as they are computed to ultimately assess aggregated risk within a core capability (i.e. I&MS).

Table VI-1: Risk to AFRAF Translation for Aggregation

Composite Risk boundary	**Risk Rating**
$0 < f(x) \le 0.005$	$i = 1 \rightarrow Success$
$0.005 < f(x) \le 0.20$	$i = 2 \rightarrow Low$
$0.20 < f(x) \le 0.50$	$i = 3 \rightarrow Moderate$
$0.50 < f(x) \le 0.80$	$i = 4 \rightarrow Significant$
$0.80 < f(x) < 1.00$	$i = 5 \rightarrow High$
$f(x) = 1.00$	$i = 6 \rightarrow Failure$

Case Study

The case study uses the prescribed methodology to assess personnel capability shortfalls. The methodology can be applied to a near, mid or far term planning cycle. Tables VI-2-4 provide a visualization of the step-by-step process used to the ACS RA to include subtask association to career field manning rates. Table VI-2 shows overall manning of the I&MS task (4.x) to be 93%. This simple rate assumes personnel are trained and available and does not adequately account for risk. Further, where certain sub-tasks are overmanned in career fields, does not mean these overages can be applied to undermanned career fields as the skillsets and level of expertise differ. Analysis at lower levels of manning echelons are needed in order to more adequately assess personnel capability and risk.

Table VI-2: Notional Core Capability Sub-task Career Field Manning

Career Field	**Core Capability Sub-task**	**Asgn (Actual)**	**Auth (Allocated)**	**Manning Rate**
Airfield Mgmt	4.1.1 Provide Airfield Mgmt	499	499	1.00
Clinical SW	4.1.5 Provide Socially Safe Environment	937	950	0.99
Logistics Plans Officer	4.2.1 Provide Airfield Operations	65	111	0.59
Fuels Specialist	4.2.2 Perform Installation Supply Log.	162	162	1.00
Aero. Medical Service	4.3.1 Provide Emergency Services	77	77	1.00
Security Forces	4.4.1 Provide Protection Services	810	816	0.99
Force Support Officer	4.5.1 Provide Family Services	25	63	0.40
Traffic Mgmt	4.6.1 Command Community Log. Service	265	266	1.00
Services Mgmt	4.6.2 Fitness and Rec. Operations	41	122	0.34
Explosive Ord. Disposal	4.7.1 Provide Combat Support	40	134	0.3
Materiel Mgmt	4.8.3 Sustain Operating Locations	740	744	0.99
Pavement/Construction	4.8.3 Sustain Operating Locations	375	354	1.06
Personnel Mgmt	4.8.4 Operate Facilities	966	970	1.00
Civil Eng. Officer	4.8.5 Maintain/Sustain Infrastructure	654	662	0.99
Civil Eng. (Electrical)	4.8.5 Maintain/Sustain Infrastructure	63	103	0.61
Civil Eng. (Ops Mgmt)	4.8.5 Maintain/Sustain Infrastructure	106	174	0.61
Civil Eng. (HVAC)	4.8.6 Provide Family Housing	0	1	0.00
		5800	6208	**93%**

Table VI-3 applies risk components (probability of failure and impact) to manning rates from Table VI-2 to ultimately compute composite risk scores, which are translated by the AFRAF risk scale into ordinal ratings. A correction procedure is applied to the probability of failure occurrence algorithm computed by the normal cumulative distribution function. If a career field is 33% manned or less, the probability of failure is 100%. This purposefully serves to send a severely degraded personnel capability indicator. We seek to obtain the overall task personnel capability assessment, given the individual subtask assessments. The 2-norm is used to compute an overall core capability risk value.

Table VI-3: Notional Core Capability Sub-task Personnel Risk Assessment

		Normal	**Sigmoid**	$(p^* + i^*)/2$	
Career Field	**Core Capability Sub-sub task**	***Prob. of failure Occurrence (p^*)**	**Impact (i^*)**	**Personnel Comp. Risk (P_i)**	**AFRAF Risk (S_k)**
Airfield Mgmt	4.1.1 Provide Airfield Mgmt	0.49	0.011	0.251	**3**
Clinical SW	4.1.5 Provide Socially Safe Environment	0.50	0.012	0.256	**3**
Logistics Plans Officer	4.2.1 Provide Airfield Operations	0.55	0.308	0.429	**3**
Fuels Specialist	4.2.2 Perform Installation Supply Log.	0.50	0.011	0.256	**3**
Aero. Medical Service	4.3.1 Provide Emergency Services	0.49	0.011	0.251	**3**
Security Forces	4.4.1 Provide Protection Services	0.50	0.012	0.256	**3**
Force Support Officer	4.5.1 Provide Family Services	0.72	0.711	0.716	**4**
Traffic Mgmt	4.6.1 Command Community Log. Service	0.48	0.011	0.246	**3**
Services Mgmt	4.6.2 Fitness and Rec. Operations	0.63	0.808	0.719	**4**
Explosive Ord. Disposal	4.7.1 Provide Combat Support	1.00	0.858	0.929	**5**
Materiel Mgmt	4.8.3 Sustain Operating Locations	0.50	0.012	0.256	**3**
Pavement/Construction	4.8.3 Sustain Operating Locations	0.48	0.0048	0.242	**3**
Personnel Mgmt	4.8.4 Operate Facilities	0.49	0.011	0.251	**3**
Civil Eng. Officer	4.8.5 Maintain/Sustain Infrastructure	0.50	0.012	0.256	**3**
Civil Eng. (Electrical)	4.8.5 Maintain/Sustain Infrastructure	0.57	0.271	0.421	**3**
Civil Eng. (Ops Mgmt)	4.8.5 Maintain/Sustain Infrastructure	0.58	0.271	0.426	**3**
Civil Eng. (HVAC)	4.8.6 Provide Family Housing	1.00	1.00	1.00	**6**

Table VI-4 demonstrates the use of the 2-norm algorithm to compute aggregated risk for a task (e.g. Provide Installation & Mission Support capability). Weights are simply multipliers of the probability of failure rates (i.e. $(10 * P^*)$). Subtask, best subtask and worst subtask scores are computed based on weights and AFRAF vectors. The values are summed and normalized to determine an overall risk score.

Table VI-4: Notional Core Capability Personnel Risk Assessment

Career Field	Core Capability Sub-subtask	P_i	AFRAF vector s_k	Weight r_j	Subtask Score TR_i	Best Task Score b_i	Worst Task Score w_i
Airfield Mgmt	4.1.1 Provide Airfield Mgmt	0.251	3	4.9	14.7	4.9	29.4
Clinical SW	4.1.5 Provide Socially Safe Environment	0.256	3	5	15	5	30
Logistics Plans Ofcr.	4.2.1 Provide Airfield Operations	0.429	3	5.5	16.5	5.5	33
Fuels Specialist	4.2.2 Perform Installation Supply Log.	0.256	3	5	15	5	30
Aero. Med. Service	4.3.1 Provide Emergency Services	0.251	3	4.9	14.7	4.9	29.4
Security Forces	4.4.1 Provide Protection Services	0.256	3	5	15	5	30
Force Support Ofcr.	4.5.1 Provide Family Services	0.716	4	7.2	28.8	7.2	43.2
Traffic Mgmt	4.6.1 Command Community Log. Service	0.246	3	4.8	14.4	4.8	28.8
Services Mgmt	4.6.2 Fitness and Rec. Operations	0.719	4	6.3	25.2	6.3	37.8
EOD	4.7.1 Provide Combat Support	0.929	5	10	50	10	60
Materiel Mgmt	4.8.3 Sustain Operating Locations	0.256	3	5	15	5	30
Pave./Construction	4.8.3 Sustain Operating Locations	0.242	3	4.8	14.4	4.8	28.8
Personnel Mgmt	4.8.4 Operate Facilities	0.251	3	4.9	14.7	4.9	29.4
CE Officer	4.8.5 Maintain/Sustain Infrastructure	0.256	3	5	15	5	30
CE (Electrical)	4.8.5 Maintain/Sustain Infrastructure	0.421	3	5.7	17.1	5.7	34.2
CE (Ops Mgmt)	4.8.5 Maintain/Sustain Infrastructure	0.426	3	5.8	17.4	5.8	34.8
CE (HVAC)	4.8.6 Provide Family Housing	1.000	6	10	60	10	60
				$\Sigma =$	362.9	99.8	598.8

The complement of the overall risk score is the core capability expressed as a rate (e.g. 58%). Thus, the I&MS core capability assessment when considering the potential lack of available and trained professionals, is 42% or 58% risk, which by the AFRAF scale is considered ‘significant risk’.

Limitations and Final Remarks

The analysis is presented under the assumption of maximum resource capacity does not equate to risk eradication. There are several career fields that appear to be overmanned, only when training and availability of personnel are not considered. Only viewing manning from people versus people requirements is a myopic approach to assessing personnel risk. Known mathematical functions are applied via normal probability distributions, sigmoid and expectation functions to account for the lack of available and trained personnel by career field.   Further, a Euclidean norm is applied to objectively propagate risk in an enterprise.

Strengths and limitations of the Agile Combat Support personnel capability assessment methodology are discussed. A strength of the said personnel risk aggregation methodology is the ability to provide an objective, defensible situational awareness procedure for senior leaders to get an enterprise-level personnel capability assessment. The procedure is a proven technique used in Pacific Air Force PACAF command, and is adapted for core function core capabilities. As long as personnel data are available, the procedure is repeatable and can be easily tailored for USAF wide usage. While the strengths outweigh the limitations of the personnel capability assessment procedure, a summary of limitations is provided.

An upfront limitation of the ACS core capability assessment is anecdotal evaluation along with other functional assessments to make accurate assessment of base personnel capability cannot be eliminated. While highly objective, the assessment requires managerial and functional oversight; it is not intended to replace common sense. Another limitation is if the AFRAF model becomes obsolete, the assessment procedure will have to be re-examined as 2-norm vectors will need to be re-established.

VII. Conclusions and Recommendations

Overview

The final chapter provides a comprehensive set of conclusions and recommendations from the body of research presented in Chapters I through VI. First, the chapter begins by drawing conclusions from this research objectives and questions. Second, the chapter discusses this research significance and potential benefits of the various proposed methodologies to meet USAF enterprise risk assessment challenges. Third, recommendations are stated for further research. Fourth, the chapter concludes with a summary of the dissertation contribution.

Research Conclusions

A building block approach of numerous mathematical techniques from logistic regression to linear optimization were used to examine USAF personnel capability. Review of this research suggests several conclusions can be made. Chapters I and II provide the foundation for which the problem is scoped and defined and known mathematical formulae are explored as potential solutions. The literature search (Chapter II) explored several discrete and continuous distributions and concluded the normal distribution is the best known distribution to use to compute probability of personnel failure. The sigmoid function is a well-known function used in numerous risk assessment applications, and thereby is the best candidate for risk impact determination. The coupling of these two mathematical functions yields an operationally representative, objective risk score.

Chapter III presents the use of categorical data analysis techniques to create a repeatable, measureable baseline personnel capability assessment across the 12 USAF core functions. Specifically, logistic fit analyses via logistic odds ratio comparisons and contingency table analyses revealed significant manning shortfalls in all 12 core functions. This work demonstrates how seemingly disparate types of raw data; can be systematically synchronized to produce meaningful insight relating to personnel capability, not only at the core function, but functional equity (career family) level. The methodology can serve as a way to standardize how enterprise-level manning assessments are computed across the USAF.

One of the goals of this research was to examine if efficiency could be examined using personnel data *and* airbase resiliency metrics. Chapter IV demonstrates that fighter pilot manning data and respective sorties can be collected by base to compute efficiency using Data Envelopment Analysis (DEA). The methodology uses a bootstrapping technique to estimate future efficiency trends of the 10 F-16 bases examined. This research identified potential base benchmarks as a means to improve aircraft sortie production with current fighter pilot manning levels. The next portion of this research seeks to examine if there is a statistically significant relationship between efficiency and personnel risk.

Chapter V illustrates four outcomes: 1.) personnel data can be decomposed by career family; 2.) assuming equal equity, personnel capability can be objectively prioritized; 3.) DEA can be used to compute efficiency by career family and; 4.) risk and efficiency can be nonparametrically statistically examined to determine significant relationships. Until this work, none of the these have been studied and published. This research is further expounded to include a use case of how to compute risk in an organizational context.

Chapter VI examines aggregation methodologies to compute a core USAF personnel core capability risk score. This work is a capstone of Chapters I through V, which presents a use case of an organizational risk assessment using career field data by task and subtask. Numerous risk aggregation techniques were surveyed, but the 2-norm root mean squaring function appeared to be the most operationally representative way to depict USAF personnel capability and risk from an organizational perspective. Normal and sigmoid functions are used to compute composite personnel risk values by task/subtask; these values are then codified using an existing USAF risk assessment framework. A 2-norm is used to aggregate the tasks and subtasks to an overall personnel risk or capability score, and an ultimate assessment is developed.

Significance of Research

Currently, each USAF core function independently assesses risk. Some enterprises strongly consider manning shortfalls and overages, while others do not. Until recently, there was no repeatable, measureable way to assess baseline personnel capability assessment across the six enterprises in Agile Combat Support (ACS). Understanding potential personnel shortfalls at the career field level should better inform core capability analysis, and thus increase credibility and defensibility of strategic risk assessments. ACS Planners and programmers no longer have to defend the needs of their programs emotionally or base their arguments on precedence. These experts can use data coupled with mathematical acumen to produce credible, defensible risk/capability assessments. This is needed for improved senior decision making as it relates to resource allocation and prioritization.

ACS enterprises are dependent upon one another to deliver capability in order to achieve a given mission. Not only is this true, but other core functions heavily depend on the success of the ACS mission in order to deliver and execute airpower globally at any given time or place. Deliberately, examining risk by greatest USAF capability asset (i.e. personnel), objectively affords senior decision makers opportunities to advocate for resources when needed.

Examining the relationship between efficiency and risk among USAF career fields has never been fully studied. Using applied statistics and optimization, we discovered there is a statistically significant correlation between personnel manning risk and efficiency. In other words, more people equate to less efficiency. However, more people equate to less risk. More people (to include training) equate to more cost. Additional analysis is needed to ascertain if *competency levels* of various personnel career fields are the real force multipliers in determining personnel capability. If the personnel management community is able to increase personnel competency levels while sustaining current manning levels, this may yield lower risk and higher efficiency.

With the aforementioned, at least a minimum, a level of managerial insight is provided to enhance personnel capability at the enterprise and sub-enterprise level. If a defensible, traceable personnel risk assessment methodology were developed, all ACS enterprises could more easily defend why they need more resources to perform required tasks. Further, the successful implementation of a repeatable, proven process lends credence to other core functions using this approach, which should increase USAF strategic risk assessment confidence at very little or no cost.

Way Forward

Currently, ACS is the only core function with a 'task structured' library. The other core functions have activities aggregrated to their respective core capabilities. With the current ACS construct, this research has created a repeatable process to link enterprise tasks to program element codes (PECs) by career field, thereby increasing risk assessment traceability, defensibility and credibility. If ACS planners and programmers now know the number of airmen required to complete a task at the PEC level, they can better justify why they either need or do not require resources. This makes defending requirements more traceable and credible. If this approach is extended across the USAF, we now have a standardized way to assess personnel risk. In fact, the analysis can be conducted by one organization as the data are centrally managed.

General Ellen Pawlokowski (former commander of Air Force Materiel Command (AFMC) and ACS core function) had four goals for Fiscal Year 2016 and one was to "Bolster Trust and Confidence of those we serve, by meeting our commitments." (AFMC CC FY16 Report, 2017) She planned to achieve this objective by

"…striving to earn and maintain the <u>trust of our partners</u> by delivering the right capabilities at the right time. We want <u>those we serve</u> to value our support and come to us for solutions because <u>they trust</u> that we will deliver what <u>they need</u> when we say we will and at the agreed upon cost or better." –Gen. Ellen Pawlokowski

The former commander of the ACS core function was clearly stakeholder conscious. Dr. Charles Keating, a Systems Engineering professor at Old Dominion University teaches a main systemic error to avoid when complex system problem solving, and that is not considering all stakeholder viewpoints to the problem domain (Keating, 2005). Stakeholder analysis is necessary in order for an enterprise-level risk assessment upgrade is to be successfully implemented.

Stakeholder analysis aims to identify stakeholders and assess how they are likely to be impacted by the project. The primary goal of stakeholder analysis is to develop cooperation between the stakeholder and the project team to assure a successful outcome (Camilleri, 2011). Stakeholder analysis needs bounds in the form of assumptions. We assume all stakeholders share similar worldviews for the ACS risk assessment, otherwise problem resolution is extremely difficult.

After successful identification of the stakeholders, problem resolution needs exploration. In 20 years of experience with enterprise level problem resolution implementations, the success rate percentage is 0% when there are not leadership 'buy in', middle management salesmanship, facilitation expertise and subject matter expertise. If any one of these critical components is absent, the implementation will either not occur or not have the intended impact. Provided those four critical components are present, we can use whatever current organizational staffing solution tools (e.g. Task Management Tool (TMT), Senior Officer Communication Coordination Electronic Resource (SOCCER), etc.) to give key personnel an indication of leadership expectations.

An implementation of this magnitude will take at least a year if inefficiencies are considered before assessing (personnel) risk. Bottom line: scope drives the length of implementation. The more resources (e.g. personnel, infrastructure, equipment, etc.) to consider, equates to more decision space; which means more time and money are needed to ensure all of the elements of the complex problem system are identified first before resolution. For more details on complex problem resolution, please request access to a document entitled 'Keating's Top 10: ten ways to increase complex problem system resolution."

A project charter is needed in order to provide a level of codification/governance to enhance the chances of successfully implementing the new initiative. A charter is a governing document for a new initiative that outlines leadership expectations, identifies the problem, identifies the suppliers, inputs, products, outputs and consumers (SIPOC), key personnel required to tackle the initiative, goals and impact of the initiative if successful.

The analysis could be conducted within the HQ AFMC Strategic Plans, Programs, Requirements, and Analyses Directorate (AFMC A5/8/9), whereby the Analyses and Assessments Division (AFMC A9A) would serve as the lead integrator. The collection of this information requires support from the AFMC 5/8 (Plans, Programs and Requirements Division). If the personnel databases are unavailable, then the proposed framework is void. The personnel capability/risk research is open to other proven methods/approaches with regards to proper portrayal of strategic risk notably as it relates to the ACS core function or AFMC.

Recommendations for Future Research

An interdependency model is needed to examine the interdependencies among USAF *career fields*. As of July 2016, there were over 400,000 active duty military and civil servants in the USAF. Of the 400,000+ (assigned) personnel, 55% are enlisted, 13% are officer and the remaining 32% are civil servants. To date, there is no visual or mathematical representation of how each Air Force Specialty or career field is connected to the other. This research would inform strategic decision making by illustrating multi-order effects of resource constraints on career fields. In other words, senior leaders could visually observe the dependencies between career fields and recognize the potential impact of under/over-filling certain career fields.

The dependency model could be explored in the context of aircraft sortie generation. The model would make several assumptions. The model should assume an inherent level of dependency among functional communities (i.e. rated operations, maintenance, communications, intelligence, medical, finance, acquisitions and resiliency support (e.g. chaplain, legal, force support, etc.)). For example, the safety function is something equivalent to the legal or chaplain career field. That is to say, the safety functional service or some career field equivalent, is required for most operational career fields. This infers there is a level (albeit not exactly known) of safety career field dependency in order for the operational career fields to accomplish a mission. This research should also seek to identify a mathematical way to use the career field dependency model to assess risk.

Summary

Procedurally and wisely using mathematical application coupled with SME insight are proven ways to inform strategic decision making. Applied statistics and optimization (to suggest a few) are ways to increase rigor, traceability, defensibility, repeatability and better inform strategic decision making. If used correctly, hard data (e.g. personnel current and historical manning rates) can provide substantiating insight to help quantify risk. These added analytical insights foster better strategic decision making by identifying capability gaps, and provide an increased level of objectivity to support personnel resource allocation. The results of the analysis contribute to better inform the USAF Strategic, Planning & Programming Process (SP3).

Appendix A. Joint Model from Chapter III

2.00205380064806 + *Match*(: ***SCF***,
"*ACS*", −0.169625541949248, "*AS*", 0.382773594328361, "*C2*", 0.598187339531182, "*CS*", −0.340458443926399,

"*GISR*", 0.840216482139152, "*GM*", −0.959983538960857, "*GPA*", 0.382773594328361,

"*NDO*", 0.598187339531182,

"*P & T*", −0.335101203204821, "*PR*", −1.3124077302221, "*SO*", 1.1217617567933, "*SS*", −0.806323648388117) +
Match(: ***Functional Equity***,
"*Acquisition*", −1.50895901227517, "*Airfield Operations*", −0.774050445307, "*C2 Systems Ops*",

−1.22630715465715, "*CE*", −1.22630715465715, "*Chaplaincy*", −0.485653424612526, "*Combat Systems* (12*X*)",

−0.215625028117114, "*Commander/Sr Leader*", −2.78780240085377, "*Contracting*", −1.6287434114286,

"*Distribution*", −1.6287434114286, "*Finance*", 0.620987265633101, "*Force Support*", −0.215625028117114,

"*Health Services*", −0.215625028117114, "*Historian*", −1.50895901227517, "*Inspections*", 0.620987265633101,

"*Intelligence*", −1.6287434114286, "*Legal*", −0.215625028117114, "*Logistics Plans*", 0.620987265633102,

"*Maintenance*", −1.22630715465715, "*Materiel*", −0.215625028117114, "*Mission Assurance*",

−1.22630715465715, "*Munitions*", −1.22630715465715, "*Ops Mgt*", −0.774050445307, "*Ops Planning*",

−1.6287434114286, "*PA*", −2.00975916866181, "*Pilot*", −1.40608660852006, "*RPA*", −2.25311850963814,

"*S&T*", 15.3930762469828, "*Safety*", −1.50895901227517, "*SF*", 15.3930762472812,

"*Space/Nuke/Missile Ops*", −0.774050445307, "*Special Invest.* ", −1.40608660852006,

"*Weather*", −1.72694463802467).

Appendix B. SCF and FE Assigned Manning levels by Demographic

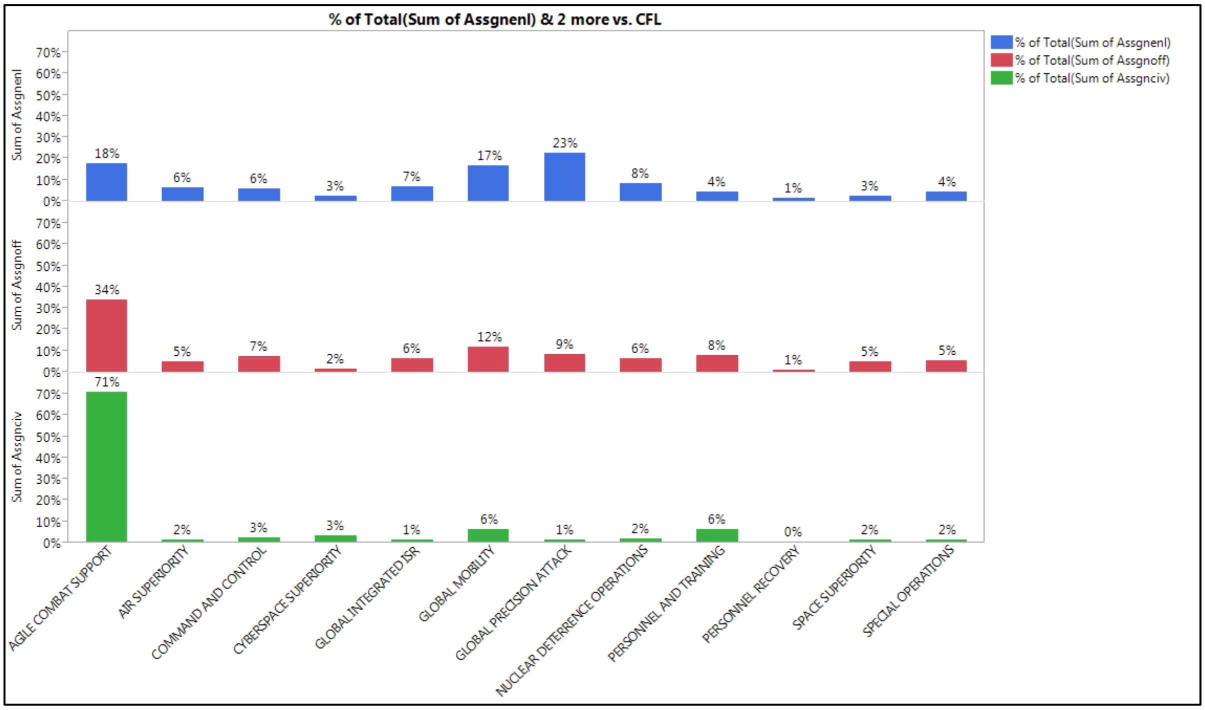
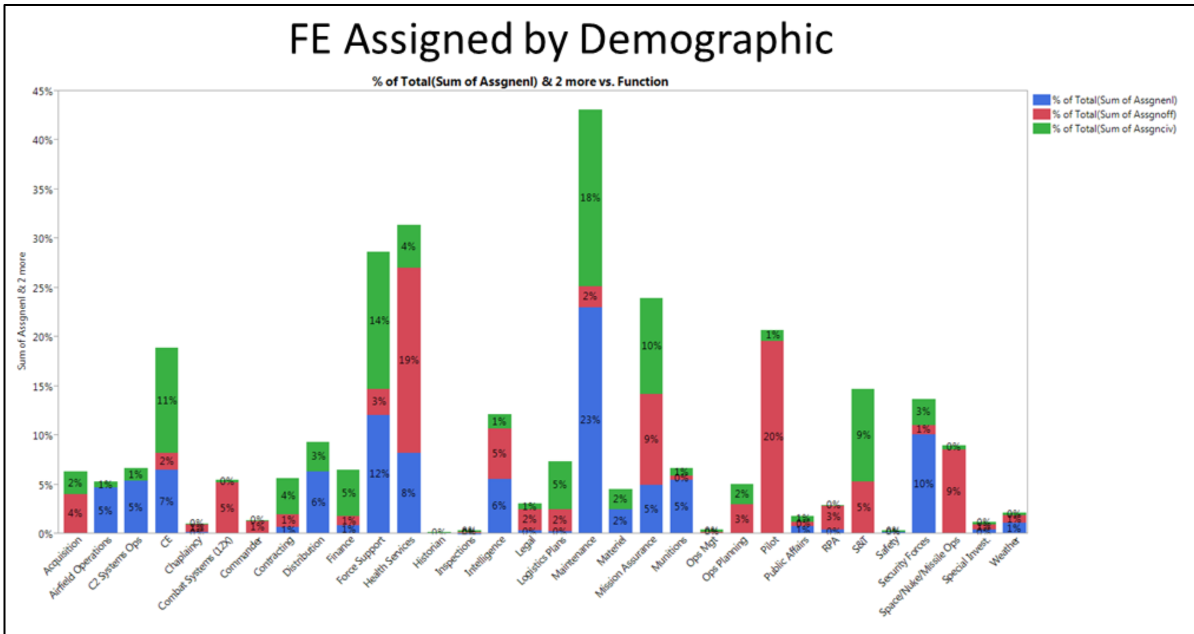


Figure B-1: SCF Assigned Manning Levels by Demographic



$$\% \text{ of Total} = \frac{\text{Sum of Assigned of Demographic Functional Area}}{\text{Total Assigned of Functional Area}}$$

Figure B-2: FE Assigned Manning Levels by Demographic

Appendix C. (FE Manning Odds Ratio Analyses)

Rank		Acq	irfld Op	2 Sys O	CE	Chap.	Navs	CC/SL	Contr.	Dist.	Fin.	orce Su	ealth Sr	Hist.	Insp.	Intel.	LE	G Plan	Mx	Mat'l	Isn Ass	Muns	Dps Mg	ps Plar	Pilot	PA	RPA	S&T	SE	SF	e/Nuke	SI	Wx
19	Acq	-	0.48	0.754	0.754	0.359	0.274	3.592	1.127	1.127	0.119	0.274	0.274	1	0.119	1.127	0.274	0.119	0.754	0.274	0.754	0.754	0.48	1.127	0.902	1.65	2.105	0	1	0	0.48	0.902	1.244
14	Airfld Ops	2.085	-	1.572	1.572	0.749	0.572	7.491	2.351	2.351	0.248	0.572	0.572	2.085	0.248	2.351	0.572	0.248	1.572	0.572	1.572	1.572	1	2.351	1.881	3.441	4.389	0	2.085	0	1	1.881	2.593
7	C2 Sys Ops	1.327	0.64	-	1	0.477	0.364	4.766	1.495	1.495	0.158	0.364	0.364	1.327	0.158	1.495	0.364	0.158	1	0.364	1	1	0.636	1.495	1.197	2.189	2.792	0	1.327	0	0.636	1.197	1.65
21	CE	1.327	0.64	1	-	0.477	0.364	4.766	1.495	1.495	0.158	0.364	0.364	1.327	0.158	1.495	0.364	0.158	1	0.364	1	1	0.636	1.495	1.197	2.189	2.792	0	1.327	0	0.636	1.197	1.65
25	Chap.	2.782	1.33	2.097	2.097	-	0.763	9.996	3.136	3.136	0.331	0.763	0.763	2.782	0.331	3.136	0.763	0.331	2.097	0.763	2.097	2.097	1.334	3.136	2.51	4.591	5.856	0	2.782	0	1.334	2.51	3.46
26	Navs	3.645	1.75	2.747	2.747	1.31	-	13.09	4.109	4.109	0.433	1	1	3.645	0.433	4.109	1	0.433	2.747	1	2.747	2.747	1.748	4.109	3.289	6.014	7.671	0	3.645	0	1.748	3.289	4.533
1	CC/SL	0.278	0.13	0.21	0.21	0.1	0.076	-	0.314	0.314	0.033	0.076	0.076	0.278	0.033	0.314	0.076	0.033	0.21	0.076	0.21	0.21	0.133	0.314	0.251	0.459	0.586	0	0.278	0	0.133	0.251	0.346
4	Contr.	0.887	0.43	0.669	0.669	0.319	0.243	3.187	-	1	0.105	0.243	0.243	0.887	0.105	1	0.243	0.105	0.669	0.243	0.669	0.669	0.425	1	0.8	1.464	1.867	0	0.887	0	0.425	0.8	1.103
13	Dist.	0.887	0.43	0.669	0.669	0.319	0.243	3.187	1	-	0.105	0.243	0.243	0.887	0.105	1	0.243	0.105	0.669	0.243	0.669	0.669	0.425	1	0.8	1.464	1.867	0	0.887	0	0.425	0.8	1.103
24	Fin.	8.414	4.04	6.343	6.343	3.024	2.309	30.23	9.485	9.485	-	2.309	2.309	8.414	1	9.485	2.309	1	6.343	2.309	6.343	6.343	4.035	9.485	7.592	13.88	17.71	0	8.414	0	4.035	7.592	10.46
17	Force Supt	3.645	1.75	2.747	2.747	1.31	1	13.09	4.109	4.109	0.433	-	1	3.645	0.433	4.109	1	0.433	2.747	1	2.747	2.747	1.748	4.109	3.289	6.014	7.671	0	3.645	0	1.748	3.289	4.533
18	Health Srvs	3.645	1.75	2.747	2.747	1.31	1	13.09	4.109	4.109	0.433	1	-	3.645	0.433	4.109	1	0.433	2.747	1	2.747	2.747	1.748	4.109	3.289	6.014	7.671	0	3.645	0	1.748	3.289	4.533
8	Hist.	1	0.48	0.754	0.754	0.359	0.274	3.592	1.127	1.127	0.119	0.274	0.274	-	0.119	1.127	0.274	0.119	0.754	0.274	0.754	0.754	0.48	1.127	0.902	1.65	2.105	0	1	0	0.48	0.902	1.244
30	Insp.	8.414	4.04	6.343	6.343	3.024	2.309	30.23	9.485	9.485	1	2.309	2.309	8.414	-	9.485	2.309	1	6.343	2.309	6.343	6.343	4.035	9.485	7.592	13.88	17.71	0	8.414	0	4.035	7.592	10.46
11	Intel.	0.887	0.43	0.669	0.669	0.319	0.243	3.187	1	1	0.105	0.243	0.243	0.887	0.105	-	0.243	0.105	0.669	0.243	0.669	0.669	0.425	1	0.8	1.464	1.867	0	0.887	0	0.425	0.8	1.103
28	LE	3.645	1.75	2.747	2.747	1.31	1	13.09	4.109	4.109	0.433	1	1	3.645	0.433	4.109	-	0.433	2.747	1	2.747	2.747	1.748	4.109	3.289	6.014	7.671	0	3.645	0	1.748	3.289	4.533
27	LG Plans	8.414	4.04	6.343	6.343	3.024	2.309	30.23	9.485	9.485	1	2.309	2.309	8.414	1	9.485	2.309	-	6.343	2.309	6.343	6.343	4.035	9.485	7.592	13.88	17.71	0	8.414	0	4.035	7.592	10.46
9	Mx	1.327	0.64	1	1	0.477	0.364	4.766	1.495	1.495	0.158	0.364	0.364	1.327	0.158	1.495	0.364	0.158	-	0.364	1	1	0.636	1.495	1.197	2.189	2.792	0	1.327	0	0.636	1.197	1.65
29	Mat'l	3.645	1.75	2.747	2.747	1.31	1	13.09	4.109	4.109	0.433	1	1	3.645	0.433	4.109	1	0.433	2.747	-	2.747	2.747	1.748	4.109	3.289	6.014	7.671	0	3.645	0	1.748	3.289	4.533
10	Msn Assr.	1.327	0.64	1	1	0.477	0.364	4.766	1.495	1.495	0.158	0.364	0.364	1.327	0.158	1.495	0.364	0.158	1	0.364	-	1	0.636	1.495	1.197	2.189	2.792	0	1.327	0	0.636	1.197	1.65
23	Muns	1.327	0.64	1	1	0.477	0.364	4.766	1.495	1.495	0.158	0.364	0.364	1.327	0.158	1.495	0.364	0.158	1	0.364	1	-	0.636	1.495	1.197	2.189	2.792	0	1.327	0	0.636	1.197	1.65
20	Ops Mgt	2.085	1	1.572	1.572	0.749	0.572	7.491	2.351	2.351	0.248	0.572	0.572	2.085	0.248	2.351	0.572	0.248	1.572	0.572	1.572	1.572	-	2.351	1.881	3.441	4.389	0	2.085	0	1	1.881	2.593
12	Ops Plans	0.887	0.43	0.669	0.669	0.319	0.243	3.187	1	1	0.105	0.243	0.243	0.887	0.105	1	0.243	0.105	0.669	0.243	0.669	0.669	0.425	-	0.8	1.464	1.867	0	0.887	0	0.425	0.8	1.103
15	Pilot	1.108	0.53	0.835	0.835	0.398	0.304	3.982	1.249	1.249	0.132	0.304	0.304	1.108	0.132	1.249	0.304	0.132	0.835	0.304	0.835	0.835	0.532	1.249	-	1.829	2.333	0	1.108	0	0.532	1	1.378
2	PA	0.606	0.29	0.457	0.457	0.218	0.166	2.177	0.683	0.683	0.072	0.166	0.166	0.606	0.072	0.683	0.166	0.072	0.457	0.166	0.457	0.457	0.291	0.683	0.547	-	1.276	0	0.606	0	0.291	0.547	0.754
5	RPA	0.475	0.23	0.358	0.358	0.171	0.13	1.707	0.536	0.536	0.056	0.13	0.13	0.475	0.056	0.536	0.13	0.056	0.358	0.13	0.358	0.358	0.228	0.536	0.429	0.784	-	0	0.475	0	0.228	0.429	0.591
31	S&T	2E+07	1E+07	2E+07	2E+07	8E+06	6E+06	8E+07	2E+07	2E+07	3E+06	6E+06	6E+06	2E+07	3E+06	2E+07	6E+06	3E+06	2E+07	6E+06	2E+07	2E+07	1E+07	2E+07	2E+07	4E+07	5E+07	-	2E+07	1	1E+07	2E+07	3E+07
6	SE	1	0.48	0.754	0.754	0.359	0.274	3.592	1.127	1.127	0.119	0.274	0.274	1	0.119	1.127	0.274	0.119	0.754	0.274	0.754	0.754	0.48	1.127	0.902	1.65	2.105	0	-	0	0.48	0.902	1.244
32	SF	2E+07	1E+07	2E+07	2E+07	8E+06	6E+06	8E+07	2E+07	2E+07	3E+06	6E+06	6E+06	2E+07	3E+06	2E+07	6E+06	3E+06	2E+07	6E+06	2E+07	2E+07	1E+07	2E+07	2E+07	4E+07	5E+07	1	2E+07	-	1E+07	2E+07	3E+07
22	Space/Nuke/M.O.	2.085	1	1.572	1.572	0.749	0.572	7.491	2.351	2.351	0.248	0.572	0.572	2.085	0.248	2.351	0.572	0.248	1.572	0.572	1.572	1.572	1	2.351	1.881	3.441	4.389	0	2.085	0	-	1.881	2.593
16	SI	1.108	0.53	0.835	0.835	0.398	0.304	3.982	1.249	1.249	0.132	0.304	0.304	1.108	0.132	1.249	0.304	0.132	0.835	0.304	0.835	0.835	0.532	1.249	1	1.829	2.333	0	1.108	0	0.532	-	1.378
3	Wx	0.804	0.39	0.606	0.606	0.289	0.221	2.889	0.906	0.906	0.096	0.221	0.221	0.804	0.096	0.906	0.221	0.096	0.606	0.221	0.606	0.606	0.386	0.906	0.726	1.327	1.692	0	0.804	0	0.386	0.726	-

FE odds of not being fully manned

x ≥ 1000 High

1000 > x ≥ 100 Sig

100 > x ≥ 1 Mod

1 > x ≥ 0 Low

Figure C-1: FE Manning Odds Ration Analyses

Appendix D. FE Significant Difference in Manning Odds Ratio Analyses

	Acq	irfld Op	2 Sys O	CE	Chap.	Navs	CC/SL	Contr.	Dist.	Fin.	orce Su	ealth Sr	Hist.	Insp.	Intel.	LE	G Plan	Mx	Mat'l	Isn Ass	Muns	Ops Mg	ps Plar	Pilot	PA	RPA	S&T	SE	SF	e/Nuke	SI	Wx
Acq	-	0.48	0.754	0.754	0.359	0.274	3.592	1.127	1.127	0.119	0.274	0.274	1	0.119	1.127	0.274	0.119	0.754	0.274	0.754	0.754	0.48	1.127	0.902	1.65	2.105	0	1	0	0.48	0.902	1.244
Airfld Ops	2.085	-	1.572	1.572	0.749	0.572	7.491	2.351	2.351	0.248	0.572	0.572	2.085	0.248	2.351	0.572	0.248	1.572	0.572	1.572	1.572	1	2.351	1.881	3.441	4.389	0	2.085	0	1	1.881	2.593
C2 Sys Ops	1.327	0.64	-	1	0.477	0.364	4.766	1.495	1.495	0.158	0.364	0.364	1.327	0.158	1.495	0.364	0.158	1	0.364	1	1	0.636	1.495	1.197	2.189	2.792	0	1.327	0	0.636	1.197	1.65
CE	1.327	0.64	1	-	0.477	0.364	4.766	1.495	1.495	0.158	0.364	0.364	1.327	0.158	1.495	0.364	0.158	1	0.364	1	1	0.636	1.495	1.197	2.189	2.792	0	1.327	0	0.636	1.197	1.65
Chap.	2.782	1.33	2.097	2.097	-	0.763	9.996	3.136	3.136	0.331	0.763	0.763	2.782	0.331	3.136	0.763	0.331	2.097	0.763	2.097	2.097	1.334	3.136	2.51	4.591	5.856	0	2.782	0	1.334	2.51	3.46
Navs	3.645	1.75	2.747	2.747	1.31	-	13.09	4.109	4.109	0.433	1	1	3.645	0.433	4.109	1	0.433	2.747	1	2.747	2.747	1.748	4.109	3.289	6.014	7.671	0	3.645	0	1.748	3.289	4.533
CC/SL	0.278	0.13	0.21	0.21	0.1	0.076	-	0.314	0.314	0.033	0.076	0.076	0.278	0.033	0.314	0.076	0.033	0.21	0.076	0.21	0.21	0.133	0.314	0.251	0.459	0.586	0	0.278	0	0.133	0.251	0.346
Contr.	0.887	0.43	0.669	0.669	0.319	0.243	3.187	-	1	0.105	0.243	0.243	0.887	0.105	1	0.243	0.105	0.669	0.243	0.669	0.669	0.425	1	0.8	1.464	1.867	0	0.887	0	0.425	0.8	1.103
Dist.	0.887	0.43	0.669	0.669	0.319	0.243	3.187	1	-	0.105	0.243	0.243	0.887	0.105	1	0.243	0.105	0.669	0.243	0.669	0.669	0.425	1	0.8	1.464	1.867	0	0.887	0	0.425	0.8	1.103
Fin.	8.414	4.04	6.343	6.343	3.024	2.309	30.23	9.485	9.485	-	2.309	2.309	8.414	1	9.485	2.309	1	6.343	2.309	6.343	6.343	4.035	9.485	7.592	13.88	17.71	0	8.414	0	4.035	7.592	10.46
Force Supt	3.645	1.75	2.747	2.747	1.31	1	13.09	4.109	4.109	0.433	-	1	3.645	0.433	4.109	1	0.433	2.747	1	2.747	2.747	1.748	4.109	3.289	6.014	7.671	0	3.645	0	1.748	3.289	4.533
Health Srvs	3.645	1.75	2.747	2.747	1.31	1	13.09	4.109	4.109	0.433	1	-	3.645	0.433	4.109	1	0.433	2.747	1	2.747	2.747	1.748	4.109	3.289	6.014	7.671	0	3.645	0	1.748	3.289	4.533
Hist.	1	0.48	0.754	0.754	0.359	0.274	3.592	1.127	1.127	0.119	0.274	0.274	-	0.119	1.127	0.274	0.119	0.754	0.274	0.754	0.754	0.48	1.127	0.902	1.65	2.105	0	1	0	0.48	0.902	1.244
Insp.	8.414	4.04	6.343	6.343	3.024	2.309	30.23	9.485	9.485	1	2.309	2.309	8.414	-	9.485	2.309	1	6.343	2.309	6.343	6.343	4.035	9.485	7.592	13.88	17.71	0	8.414	0	4.035	7.592	10.46
Intel.	0.887	0.43	0.669	0.669	0.319	0.243	3.187	1	1	0.105	0.243	0.243	0.887	0.105	-	0.243	0.105	0.669	0.243	0.669	0.669	0.425	1	0.8	1.464	1.867	0	0.887	0	0.425	0.8	1.103
LE	3.645	1.75	2.747	2.747	1.31	1	13.09	4.109	4.109	0.433	1	1	3.645	0.433	4.109	-	0.433	2.747	1	2.747	2.747	1.748	4.109	3.289	6.014	7.671	0	3.645	0	1.748	3.289	4.533
LG Plans	8.414	4.04	6.343	6.343	3.024	2.309	30.23	9.485	9.485	1	2.309	2.309	8.414	1	9.485	2.309	-	6.343	2.309	6.343	6.343	4.035	9.485	7.592	13.88	17.71	0	8.414	0	4.035	7.592	10.46
Mx	1.327	0.64	1	1	0.477	0.364	4.766	1.495	1.495	0.158	0.364	0.364	1.327	0.158	1.495	0.364	0.158	-	0.364	1	1	0.636	1.495	1.197	2.189	2.792	0	1.327	0	0.636	1.197	1.65
Mat'l	3.645	1.75	2.747	2.747	1.31	1	13.09	4.109	4.109	0.433	1	1	3.645	0.433	4.109	1	0.433	2.747	-	2.747	2.747	1.748	4.109	3.289	6.014	7.671	0	3.645	0	1.748	3.289	4.533
Msn Assr.	1.327	0.64	1	1	0.477	0.364	4.766	1.495	1.495	0.158	0.364	0.364	1.327	0.158	1.495	0.364	0.158	1	0.364	-	1	0.636	1.495	1.197	2.189	2.792	0	1.327	0	0.636	1.197	1.65
Muns	1.327	0.64	1	1	0.477	0.364	4.766	1.495	1.495	0.158	0.364	0.364	1.327	0.158	1.495	0.364	0.158	1	0.364	1	-	0.636	1.495	1.197	2.189	2.792	0	1.327	0	0.636	1.197	1.65
Ops Mgt	2.085	1	1.572	1.572	0.749	0.572	7.491	2.351	2.351	0.248	0.572	0.572	2.085	0.248	2.351	0.572	0.248	1.572	0.572	1.572	1.572	-	2.351	1.881	3.441	4.389	0	2.085	0	1	1.881	2.593
Ops Plans	0.887	0.43	0.669	0.669	0.319	0.243	3.187	1	1	0.105	0.243	0.243	0.887	0.105	1	0.243	0.105	0.669	0.243	0.669	0.669	0.425	-	0.8	1.464	1.867	0	0.887	0	0.425	0.8	1.103
Pilot	1.108	0.53	0.835	0.835	0.398	0.304	3.982	1.249	1.249	0.132	0.304	0.304	1.108	0.132	1.249	0.304	0.132	0.835	0.304	0.835	0.835	0.532	1.249	-	1.829	2.333	0	1.108	0	0.532	1	1.378
PA	0.606	0.29	0.457	0.457	0.218	0.166	2.177	0.683	0.683	0.072	0.166	0.166	0.606	0.072	0.683	0.166	0.072	0.457	0.166	0.457	0.457	0.291	0.683	0.547	-	1.276	0	0.606	0	0.291	0.547	0.754
RPA	0.475	0.23	0.358	0.358	0.171	0.13	1.707	0.536	0.536	0.056	0.13	0.13	0.475	0.056	0.536	0.13	0.056	0.358	0.13	0.358	0.358	0.228	0.536	0.429	0.784	-	0	0.475	0	0.228	0.429	0.591
S&T	2E+07	1E+07	2E+07	2E+07	8E+06	6E+06	8E+07	2E+07	2E+07	3E+06	6E+06	6E+06	2E+07	3E+06	2E+07	6E+06	3E+06	2E+07	6E+06	2E+07	2E+07	1E+07	2E+07	2E+07	4E+07	5E+07	-	2E+07	1	1E+07	2E+07	3E+07
SE	1	0.48	0.754	0.754	0.359	0.274	3.592	1.127	1.127	0.119	0.274	0.274	1	0.119	1.127	0.274	0.119	0.754	0.274	0.754	0.754	0.48	1.127	0.902	1.65	2.105	0	-	0	0.48	0.902	1.244
SF	2E+07	1E+07	2E+07	2E+07	8E+06	6E+06	8E+07	2E+07	2E+07	3E+06	6E+06	6E+06	2E+07	3E+06	2E+07	6E+06	3E+06	2E+07	6E+06	2E+07	2E+07	1E+07	2E+07	2E+07	4E+07	5E+07	1	2E+07	-	1E+07	2E+07	3E+07
Space/Nuke/M.O.	2.085	1	1.572	1.572	0.749	0.572	7.491	2.351	2.351	0.248	0.572	0.572	2.085	0.248	2.351	0.572	0.248	1.572	0.572	1.572	1.572	1	2.351	1.881	3.441	4.389	0	2.085	0	-	1.881	2.593
SI	1.108	0.53	0.835	0.835	0.398	0.304	3.982	1.249	1.249	0.132	0.304	0.304	1.108	0.132	1.249	0.304	0.132	0.835	0.304	0.835	0.835	0.532	1.249	1	1.829	2.333	0	1.108	0	0.532	-	1.378
Wx	0.804	0.39	0.606	0.606	0.289	0.221	2.889	0.906	0.906	0.096	0.221	0.221	0.804	0.096	0.906	0.221	0.096	0.606	0.221	0.606	0.606	0.386	0.906	0.726	1.327	1.692	0	0.804	0	0.386	0.726	-

Appendix Figure 4

Considered statistically different

Bibliography

Ackoff, R., (2001), "A Brief Guide to Interactive Planning and Idealized Design," Unpulished Paper, Interact Consulting.

AcqNotes.com (2017). "Defense Acquisitions Made Easy (Defense Planning Guidance)." Accessed 8/20/2017, Retrieved from http://acqnotes.com/acqnote/acquisitions/defense-planning-guidance-dpg

AcqNotes.com (2017). "Defense Acquisitions Made Easy (Program Objective Memorandum)." Accessed 5/5/2017, Retrieved from http://acqnotes.com/acqnote/acquisitions/program-objective-memorandum-pom

Adams, Kevin (2006). "Systems Thinking and Systems Theory," (Technical Paper). Engineering Management 715 Course (Module 4). Norfolk, VA: Old Dominion Univ.

Air Combat Command, (2019). "Best in the world…," Accessed 4/27/2019, Retrieved from https://www.acc.af.mil

Air Education and Training Command (AETC CI 90-1101) (2016), "Special Management to SP3", Accessed 9/26/2017, p. 24

Air Force Instruction Force Readiness Reporting (AFI 10-201), (2019). Air Combat Command Supplement Accessed 02/19/2019, Retrieved from https://static.e-publishing.af.mil/production/1/acc/publication/afi10-201_accsup/afi10-201_accsup.pdf

Air Force Instruction Flying Hour Management (AFI 11-102), (2011). Accessed 02/13/2019, Retrieved from https://static.e-publishing.af.mil/production/1/af_a3_5/publication/afi11-102/afi11-102.pdf

Air Force Instruction Aviation Management (AFI 11-401), (2013). Accessed 11/22/2017, Retrieved from https://static.e-publishing.af.mil/production/1/acc/publication/afi11-401_accsup_i/afi11-401_accsup_i.pdf

Air Force Materiel Command Commander Fiscal Year Report (2016). Accessed 8/13/2017, Retrieved internally

Air Force Materiel Command, Plans, Programs and Analysis Directorate (HQ AFMC 5/8/9) (2016). "2016 Annual Training," Accessed 10/26/2016, Retrieved internally

Air Force Materiel Command, Analysis Division (HQ AFMC A9A) (2016). "2016 Annual Training," Accessed 10/26/2016, Retrieved internally

Air Force Materiel Command website (2017). "Units." Accessed 8/19/2017, Retrieved from http://www.afmc.af.mil/Units/

Air Force Policy Directive (DRAFT) (AFPD Studies, Analyses and Assessments) (2018). Accessed 2/05/2018, p. 9, Retrieved from internal sources within AFMC/A9A

Air Force Officer Classification Directory (AFOCD), (2007). Accessed 1/05/2018, Retrieved from https://www.uc.edu/content/dam/uc/afrotc/docs/Documents/AFOCD.pdf

Air Force Strategic Planning Process (AFGM 2016-90-1101) (2016). Accessed 8/20/2017, p. 32, Retrieved from http://static.e-publishing.af.mil/production/1/af_a5_8/publication/afgm2016-90-1101/afgm2016-90-1101.pdf

Air University (2017). "Core Competency: Agile Combat Support." (AWC), Accessed 8/20/2017, Retrieved from http://www.au.af.mil/au/awc/awcgate/global/competencies/agile.htm

Agile Combat Support (ACS) Risk Assessment Framework, (2017)."Instructions on the Risk Assessment Framework (RAF) in Support of ACS Planning," Accessed 5/15/2017, Retrieved internally

Alvarez, I.C., Barbero, J., & Zofio, J.L., (2016). "A Data Envelopment Analysis Toolbox for MATLAB." Economic Analysis Working Paper Series, Univ. of Madrid, Dept. of Economics, pp. 1-39.

American Heritage College Dictionary, (1993) "Enterprise definition," 3rd Edition. New York: Houghton Mifflin Company.

Andersen, P., & Petersen., N.C., (1993). "A procedure for ranking efficient units in Data Envelopment Analysis." Journal of Management Science, Vol. 39, pp. 1261-1264

Agresti, Alan (2010). "Analysis of Ordinal Categorical Data," (2nd ed.). Wiley Series in Probability and Statistics. Hoboken, New Jersey: John Wiley & Sons, Inc.

Agresti, Alan (2013). "Categorical Data Analysis" (3rd ed.). p. 119-122. Hoboken, New Jersey: John Wiley & Sons, Inc.

Aven, T., (2003). "Foundations of Risk Analysis: A Knowledge and Decision-Oriented Perspective," (pp. 20-103). Hoboken, NJ: John Wiley & Sons, Ltd

Aven, T., (2011)."On some recent definitions and analysis frameworks for risk, vulnerability and resilience." Risk Analysis, Vol. 31, pp. 515–22

Aven, T., & Renn., O., (2009). "On risk defined as an event where the outcome is uncertain." Journal of Risk Research, Vol. 12, No. 1, pp. 1-11

Banker, R. D., Charnes, A. & Cooper, W. W. (1984). "Some models for estimating technical and scale inefficiencies in data envelopment analysis." Management Science, Vol. 30, No. 1, 1078-1092.

Bayne, I., and Friesen, S.K., (2016)."Risk Assessment Framework: Seamless Border Pilot Project," Defence Research and Development Canada, pp. 1-25

Bauer, P.W. (1990). "Recent developments in the econometric estimation of frontiers." Journal of Econometrics, Vol. 46, No. 1-2, pp. 39-56.

Bell, J.L., (2005). "The Continuous and the Infinitesimal in Mathematics and Philosophy," Milan: Polimetrica S.A.

Benjamini, Y., and Hochberg, Y., (1995). "Controlling the false discovery rate: a practical and powerful approach to multiple testing." Journal of the Royal Statistical Society, Series B. Vol. 57, No. 1, pp. 289–300.

Bhatta, G., (2003)."Intent, Risks and Capability: some considerations on rethinking organizational capability". International Review of Administrative Sciences. Vol. 69, No. 3, pp. 401-18.

Black, R., (1997). "Risk assesssments of 264 organisms for Tanzania." New Zealand Biosecurity presentation, p. 17.

Blanchard, B.S., & Fabrycky, W.J., (2006). "Systems Engineering and Analysis." Fourth Edition, Pearson Prentice Hall, Upper Saddle River, NJ pp. 380-390.

Blitzstein, J.K., and Hwang, J., (2014). "Introduction to Probability. Chapman & Hall/Crc Texts in Statistical Science." Accessed 4/27/2019, Retrieved from https://books.google.com/books?id=z2POBQAAQBAJ. CRC Press.

Bogetoft, P., & L., Otto, (2011). "Benchmarking with DEA, SFA and R." Springer, New York, NY.

Boehmke, B.C. (2015),"Grabbing the Air Force by the Tail: Applying Strategic Cost Analytics to Understand and Manage Indirect Cost Behavior." Dissertation, Air Force Institute of Technology.

Bourbaki, N., (1987)."Topological vector spaces, Elements of mathematics." Springer-Verlag, Berlin, Germany.

Bowlin, W.F., (1987), "Evaluating the Efficiency of US Air Force Real-Property Maintenance Activities." Journal of the Operational Research Society, Vol. 38, No. 2, pp. 127-135.

Bowlin, W.F., (1995), "A Characterization of the Financial Condition of the United States Aerospace Defense Industrial Base." Journal of the Operational Research Society, Vol. 38, No. 2, pp. 539-555.

Bowlin, W.F., (1999), "An Analysis of the Financial Performance of Defense Business Segments Using Data Envelopment Analysis." Journal of Accounting and Public Policy, Vol.18, No. 4/5, pp. 287-310.

Bowlin, W.F., (2004), "Financial Analysis of Civil Reserve Air Fleet Participants Using Data Envelopment Analysis." European Journal of Operations Research, Vol.154, No. 3, pp. 691-709.

Bradshaw, C. J., (2017). "Examining Manning Relationships Between Us Air Force Service Core Functions And Functional Area Equities." Paper presented at the AFORS Conference, May 2017, Air Force Institute of Technology (AFIT): WPAFB, OH.

Bradshaw, C. J., & Novak, K.A., (2014). "Using SORTS data and response times to assess a base's operational capability to respond to a crisis." Paper presented at the Virtual AFORS Conference, May 2014, Pentagon, VA.

Bryan, J.D., Caliva, R.M., & Murphy, J.A., (2010). "Enterprise Capability Assessment and Prioritization." Idaho National Laboratory; INCOSE., pp. 1-16.

Brown, P., and Hyer, N.L., (2010). "Managing Project-A Team-based Approach Paperback," Accessed 9/30/2017., McGraw-Hill Higher Education, Ltd.

Camilleri, E., (2011). "Project Success: Critical Factors and Behaviours," p. 107, Burlington, VT: Gower Publishing Company, Ltd.

Chambers, R.G., Chung Y., & Fare, R., (1996). "Benet and Distance Functions." Journal of Economic Theory, Vol. 70, No. 2, pp. 407-419.

Charnes, A., Cooper, W. W., & Rhodes, E., (1978), "Measuring the efficiency of decision making units," European Journal of Operations Research, Vol. 2, No. 6, pp. 429–444.

Charnes, A. T., Clark, C. W., Cooper, W., & Golany, B., (1984). "A developmental study of data envelopment analysis in measuring the efficiency of maintenance units in the U.S. air forces." Annals of Operations Research, Vol. 2, 95-112.

Charnes, A., Cooper, W. W., Golany, B., Seiford, L. M., & Stutz, J. (1985). "Foundations of data envelopment analysis for Pareto-Koopman's efficient empirical production functions." Journal of Econometrics, 30, 1–17.

Charnes, A., Cooper, W.W., Lewin, A.Y., & Seiford, L.M., (1994). "Data Envelopment Analysis: theory, methodology and application." Boston: Kluwer Academic Publishers.

Chatterjee, D. and Chatterjee, A., (2010), "Binary Logistic Regression Using Survival Analysis", Elsevier, http://ssrn.com/abstract=1672759, Accessed 3/18/2018.

Cheng, G., & Panagiotis, Z., (2012). "A generalized directional distance function in data envelopment analysis and its application to a cross-country measurement of health efficiency." Munich Personal RePEc Archive (MPRA) Paper No. 42068, pp. 1-22.

Chu, X.H., Fielding, G.J., & Lamar, B.W., (1992). "Measuring Transit Performance Using Data Envelopment Analysis." Journal of Transportation Research Part A-Policy and Practice, Vol. 26, pp. 223-230.

Clark, M., (2011). "A Comparison of Correlation Measures." Center for Social Research, University of Notre Dame, pp. 1-16.

Colbert, A., Levary, R. R., & Shaner, M. C., (2000), "Determining the relative efficiency of MBA programs using DEA," European Journal of Operations Research, Vol. 125, No. 3, pp. 656–669.

Conover, W.J. (1980). "Practical Nonparametric Statistics," 2nd Edition, pp. 99-150, John Wiley & Sons, New York.

Cook, W. D., & Zhu, J., (2005). "Modeling Performance Measurement: Applications and Implementations Issues in DEA." Springer, New York, NY.

Cooper, W.W., Seiford, L.M., & Tone, K., (2000)."Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software." Boston: Kluwer Academic Publishers., pp. 21-39.

Covello, V.T. and Mumpower, J. L., (1985). "Risk Analysis and Risk Management: An Historical Perspective" Society for Risk Analysis, Vol. 5, No. 2, pp. 103-123.

Cummings, J., Elzer, S., & Zoppetti, G., (2008). "Bayesian networks in video games," Technical Proceeding: Pennsylvania Associataion of Computer and Information Science Educators, pp. 1-5.

Daraio, C., & Simar, L., (2007). "Advanced Robust and Nonparametric Methods in Efficiency Analysis: Methodology and Applications." New York, NY, Springer, pp. 1-166.

Debreu, G. (1951), "The Coefficient of Resource Utilization," Econometrica, Vol. 19, No. 3, pp. 273-292.

De Laurentis, G., Maino, R., and Molteni, L., (2010). "Developing, Validating and Using Internal Ratings." Methodologies and Case Studies, SI, December, pp. 82-116, Wiley, Hoboken, NJ.

Denis, D.J., (2016). "Analysis of Variance: Fixed Effects Models," Applied Univariate, Bivariate and Multivariate Statistics," John Wiley & Sons, Hoboken, NJ.

Department of the Air Force. (2009)."Technical Order 00-20-2 Maintenance Data Documentation."

Despotis, D. K., (2002). "Improving the Discriminating Power of DEA: Focus on Globally Efficient Units." The Journal of the Operational Research Society Vol. 53, No. 3, pp. 314-323.

DOD Strategic Sustainability Performance Plan, (2012). "LIMS-EV database." Office of Security Review, pp. 114-123.

Dumbrava, V., and Iacob, S., (2013). "Using Probability-Impact Matrix in Analysis and Risk Assessment Projects." Journal of Knowledge Management, Economics and Information Technology, December, p. 82.

Efron, B., and Tibsirani, R., (1993). "The accuracy of a sample mean," An Introduction to the Bootstrap, pp. 1-30, Chapman & Hall/CRC, Boca Raton, FL,

Elmore, K.L., & Richman, M.B., (2001). "Euclidean Distance as a Similarity Metric for Principal Component Analysis." American Meterological Society Journal, Accessed 03/01/2019, Retrieved from https://journals.ametsoc.org/doi/full/10.1175/1520-0493(2001)129%3C0540%3AEDAASM%3E2.0.CO%3B2.

Emerson, C., (2017). "How to Identify the Right Project Management Strategy, Area of Study: Leadership & Management; Northeastern University," Accessed 8/7/2017. Retrieved from https://www.northeastern.edu/graduate/blog/area-of-study/leadership-management/.

Farell, M. J., (1957), "The Measurement of Productive Efficiency," Journal of the Royal Statistical Society, Vol. 120, No. 3, pp. 253-290.

Favero, C.A., & Papi, L. (1995). "Technical efficiency and scale efficiency in the Italian banking sector: A nonparametric approach." Applied Economics Journal, Vol. 27, pp. 385-395.

Fraser, I., & Cordina, D. (1999). "An application of data envelopment analysis to irrigated dairy farms in Northern Victoria, Australia," Journal of Agricultural Systems, Vol. 59, pp. 267-282.

Gentile, C., & Littlestone, N. (1999). "The robustness of the p-norm algorithms." In Proc. 12th Annu. Conf. on Comput. Learning Theory, University of Michigan (pp. 1–11). Association for Computing Machinery.

Hamming, R.W., (1991),"Random variables, mean and the expected value," The art of probability for scientists and engineers, pp. 64-70, Addison-Wesley, Boston, MA.

Han, H. K. & Sohn, S. Y., (2011), "DEA application to grouping military airbases," Military Operations Research, Vol. 16, No. 2, pp. 31–40.

Hansson, Sven Ove; Zalta, Edward N. (Spring 2014). "Risk". The Stanford Encyclopedia of Philosophy. Retrieved 9 May 2014.

Haug, (2009). "Measure of association," Encyclopedia Britannica, Vol 2, pp. 65-93.

Hays, W. L., (1981). "Statistics," Appendix B, Expectation Table, Delmar, Chilton, WI.

Hecht-Nelson, (1992). "Theory of the backpropagation neural network". Accessed 2/5/2019 Retrieved from https://www.britannica.com/topic/measure-of-association.

Heylighen, F., Joslyn, C., (1992). "What is Systems Theory." Accessed 9/25/2017. Retrieved from http://pespmc1.vub.ac.be/SYSTHEOR.html Cambridge University: Principia Cybernetica.

Hoeffding, W., (1948) "A nonparametric test for independence." The Annals of Mathematical Statistics,19, Vol. 4, pp. 546–557.

Hollander, M., and Wolfe , D.A., (1999). "Hoeffding's Test of Independence in R" Nonparametric Statistical Methods, Section 8.6, Wiley, Chicester, U.K.

Howell, D.C, (2007). "Multiple Comparisons Among Treatment Means," Systems Research and Behavioral Science, 6e, pp. 343-388, Thomson Wadsworth, Belmont, CA.

Huguenin, J.M., (2012). "Data Envelopment Analysis (DEA): A pedagogical guide for decision makers in the public sector," Vol. 276 of Cahiers de l'IDHEAP. pp. 1-84.

Jackson, M., (2006). "Creative Holism: A Critical Systems Approach to Complex Problem Situations," Statistical Methods for Psychology, Vol. 23, No. 5, pp. 647-657.

Jarzebowski, S., & Berat- Jarzebowski, A., (2014). "Efficiency of Milk Processing Companies Parametric and Nonparametric Approaches." International European Forum on System Dynamics and Innovation in Food Networks, Feb. 17-21, Innsburck-lgls, Austria.

Jensen, F., (2001). “Bayesian networks and decision graphs," Systems Research and New York, NY: Springer-Verlag,, pp. 26-50.

Kantor, J., & Maital, S. (1999). “Measuring efficiency by product group: integrating DEA with activity-based accounting in a large Mideast bank,” Interfaces, Vol. 29, No. 1-3,pp. 27-36.

Keating, C. B., (2005). “Paradox and Creativity in Systems Analysis," Engineering Management 715 Course (Excursion 2). Norfolk, VA: Old Dominion University.

JMP, (2015). “Specialized Model User Manual,” Version 11. SAS Institute Inc. pp. 167-200, SAS® Pub., Cary, NC.

JMP, (2017). “Mulivariate Methods”, Version 13. SAS Institute Inc. 2e, SAS® Pub., Cary, NC

JMP, (2018). “Mulivariate Methods”, Version 14. SAS Institute Inc. 2e, SAS® Pub., Cary, NC.

Johnes, J. (2006). “Measuring teaching efficiency in higher education: An application of data envelopment analysis to economics graduates from UK universities 1993,” European Journal of Operational Research, Vol. 174, pp. 443-456.

Kalla, S., (2019). “Normal Probability Distribution” Accessed 3/07/2019, Retrieved from https://explorable.com/normal-probability-distribution.

Karimollah, H. T., (2013). “Receiver Operating Characteristic (ROC) Curve Analysis for Medical Diagnostic Test Evaluation.” Caspian Journal of Internal Medicine. Spring; Vol. 4, No. 2, pp. 627–635.

Kendall, M. (1938). “A New Measure of Rank Correlation,” Biometrika Journal. Vol. 30, No. 1–2, pp. 81–89.

Kenton, W., (2018). “Financial Analysis: What is an Event Risk,” Accessed 11/15/2018, Retrieved from https://www.investopedia.com/terms/e/eventrisk.asp

Kusumasari, B., Alam, Q., & Siddiqui, K., (2010). “Resource capability for local government in managing disaster”, Disaster Prevention and Management: An International Journal, Vol. 19 Issue: 4, pp. 438-451.

Lane, D. M., (2019). “Shapes of Distributions.” Accessed 4/17/2019, Retrieved from http://onlinestatbook.com/2/summarizing_distributions/shapes.html.

LaMorte, W. W., (2016). “The Binomial Distribution: A Probability Model for a Discrete Outcome.” Accessed 1/25/2018, Retrieved from http://sphweb.bumc.bu.edu/otlt/mph-modules/bs/bs704_probability/bs704_probability7.html.

Lindbom, H., Tehler, H., Eriksson, K., & Terje, A., (2015). “The capability concept – On how to define and describe capability in relation to risk, vulnerability and resilience.” Reliability Engineering and System Safety, Vol. 135, pp. 45-54.

Liu, J.S., Lu, L.Y., Lu, W.M., & Lin, B.Y., (2013). “Data envelopment analysis 1978-2010: A citation-based literature survey, Omega, Vol. 41, No. 1, pp. 3-15.

Lovell, C.K. & Pastor, J.T., (1995). “Units invariant and translation invariant (DEA) models." Operations Research Letters, Vol. 18, No. 3, pp. 147-151.

Lovell, C.K. & Pastor, J.T., (1999). “Radial DEA models without inputs or without outputs.” European Journal of Operations Research, Vol. 118, No. 3, pp. 46-51.

Lu, S., (2010). “Benchmarking management in military organizations: A non-parametric frontier approach.” African Journal of Business Management, Vol. 5, No. 3, pp. 915-923.

Lu, Y., & Fang, J., (2003). “Advanced Medical Statistics.” River Edge, NJ, World Scientific, pp. 84-100.

Mahalingam, P., R., & Vivek, S., (2016). “Predicting financial savings decisions using sigmoid function and information gain ratio.” Procedia Computer Science Journal, Vol. 93, pp. 19-25.

Manning, B., (2017). “PPBE Process: Program Objective Memorandum (POM)." Accessed 9/16/2017, Retrieved from http://acqnotes.com/acqnote/acquisitions/program-objective-memorandum-pom.

Masiye, F., (2007). “Investigating health system performance: An application of data envelopment analysis to Zambian hospitals." BMC Health Services Research, Vol 7, No. 58, Accessed 1/11/2018, Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1878476/.

McDonald, J.H., (2014). “Handbook of Biological Statistics,” 3ed. Sparky House Publishing, Baltimore,” Maryland. pp. 145-156.

McMillie, M., (2017). “Installation & Mission Support Risk Assessment Discussion,” FOUO Email, April of 2017, Air Force Installation & Mission Support Center: Joint-Base San Antonio, TX .

Mehdiloozad, M., & Roshdi, I., (2019). “Analyzing the concept of super-efficiency in data envelopment analysis: A directional distance function approach.” Department of Mathematics, Science and Research Branch, Islamic Azad University, Tehran, Iran, pp. 1-27 .

Mendenhall, W., & Sincich, T., (2007). “Statistics for Engineering and the Sciences.” 5ed., Pearson, New Jersey.

Menon, A., Mehrotra, K., Mohan, C.K., & Ranka, S., (1996). “Characterization of a Class of Sigmoid Functions with Applications to Neural Networks.” Neural Networks Journal, Vol. 9, No. 5, pp. 819-835.

Merriam Webster Dictionary (2017). “Definition of risk.” Accessed 8/20/2017, Retrieved from https://www.merriam-webster.com/dictionary/risk.

Metters R.C., Frei, F.X., & Vargas, V.A., (1999). “Measurement of multiple sites in service firms with data envelopment analysis.” Production and Operations Management, Vol.8, No. 3; pg. 264-281.

Minitab Support, (2018). “What are parameters, parameter estimates, and sampling distributions?” Accessed 5/1/2019, Retrieved from https://support.minitab.com/en-us/minitab/18/help-and-how-to/statistics/basic-statistics/supporting-topics/data-concepts/what-are-parameters-parameter-estimates-and-sampling-distributions/.

Mitchell, V.W., Davies, F., Moutinho, L., & Vassos, V., (1999). “Using Neural Networks to Understand Service Risk in the Holiday Product.” Journal of Business Research, Vol. 46, pp. 167-180.

Mogha, S. K., Yadav, S. P., & Singh, S. P., (2015). “Slack based measure of efficiencies of public sector hospitals in Uttarakhand, India.” Benchmarking: An International Journal, Vol. 22, No. 7, pp. 1229–1246.

Montgomery, D. C., (2013). “Comparing Pairs of Treatment Means.” Design and Analysis of Experiments (8e.), Section 3.5.7, Wiley, Hoboken, NJ.

Narkhede, S., (2018). “Understanding AUC - ROC Curve.” Towards Data Science Online, Accessed 4/2/2019. Retrieved from https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5?gi=8cbf5449657a.

Neuhaus, B.K., (1990). “Evaluating Manpower and Manning Measurement in CE: Do Current Practices Reflect Actual Capability." Air Force Institute of Technology, Wright-Patterson AFB, OH.

National Institute of Standards and Technology (NIST), “7.4.7.1 Tukey’s method,” http://www.itl.nist.gov/div898/handbook/prc/section4/prc471.htm,” accessed 11 Nov 2015.

Obozinksi, G., Taskar, B., & Jordan, M., (2006), “Multi-task feature selection.” Technical Report, Department of Statistics; University of California, Berkeley, pp. 1-15.

Osman, I. H., Anouze, A. L., & Emrouznejad, A., (2014), "Handbook of Research on Strategic Performance and Measurement and Measurement using Data Envelopment Analysis." Advances in Logistics, Operations and Management Science (ALOMS), pp. 256-275.

Ozcan, Y.A., (2014). "Health Care Benchmarking and Performance Evaluation an Assessment using Data Envelopment Analysis." International Series in Operations Research and Management Science, 2ed., pp. 15-47.

Ozcan, Y.A., & Luke, R.D. (1993). "A national study of the efficiency of hospitals in urban markets," Journal of Health Services Research, Vol. 27, pp. 719-739.

Organisation for Economic Co-operation and Development (OECD), (2001). Accessed link 5/14/2018, https://stats.oecd.org/glossary/detail.asp?ID=2350.

Park, K. II, (2018). "Fundamentals of Probability and Stochastic Processes with Applications to Communications." 1e, pp. 51-107, Springer, Switzerland.

Parra, R., & Garrido, L., (2012). "Bayesian Networks for Micromanagement Decision Imitation in the RTS Game Starcraft," Mexican International Conference on Artificial Intelligence (MICAI), pp. 433-443.

Pisupati, S., (2018). "Efficiency of Energy Conversion Devices." Accessed 5/31/2019. Retrieved from EGEE 102: Energy Conservation and Environmental Protection Dept of Energy & Mineral Sciences' OER Initiative, Penn State University, PA.

Pitstick, J., (2017). "Installation & Mission Support Risk Assessment Discussion," FOUO Email, April of 2017, HQ AFMC 5/8/9: WPAFB, OH.

Pitstick, J., Huelsman J., May, T., & Bradshaw, C., (2016)."Agile Combat Support Gap Identification Training," Briefing presented at annual ACS Risk Assessment training conference (Nov 2016), slides 5, HQ AFMC 5/8/9: WPAFB, OH.

Planning, Programming, Budgeting and Execution System (PPBES) Training Program (Reference Manual) (2016). Accessed 7/30/2017.

PSU College of Science, (2019). "Lesson 15: Exponential, Gamma and Chi-Square Distributions." Accessed 4/23/2019. Retrieved from https://newonlinecourses.science.psu.edu/stat414/node/89/.

Prados, J., (1996). "The Reader's Companion to Military History." Accessed 10/7/2017. Retrieved from http://www.history.com/topics/world-war-ii/battle-of-midway Houghton Mifflin Harcourt Publishing Company: Boston, MA.

Renn, O., (2008). “White Paper on Risk Governance: Toward an Integrative Framework.” In: Renn O., Walker K.D. (eds) Global Risk Governance. International Risk Governance Council Bookseries, Vol 1. Springer, Dordrecht.

Rowe, C., Zadeh, H. S., Garanovich, L. J., Jiang, L., Bilusich, D., Nunes-Vaz, R., & Ween, A., (2017). “Prioritizing investment in military cyber capability using risk analysis,” Journal of Defense Modeling and Simulation: Applications, Methodology, Technology; Vol. 16, No. 3, pp. 321–333.

Rumelhart, D.E., Hinton, G.E., & Williams, R.J., (1986). “Learning representations by back-propagating errors.” Nature International Journal of Science, Vol. 323, pp. 533-536.

Schefczyk, M. (1993). “Operational performance of airlines - an extension of traditional measurement paradigms,” Strategic Management Journal, Vol. 14, pp. 301-317.

Schiefer, M., Robbert, A., Galway, L., Stanton, R., & San, C., (2007). “Air Force enlisted force management system interactions and synchronization strategies.” RAND Project: Air Force Enlisted Force Management, pp. 29-31.

Seiford, M.L., (1994). “A DEA Bibliography (1978–1992) in Data Envelopment Analysis: Theory, Methodology and Applications, A. Charnes, W.W. Cooper, Arie Y. Lewin, and Lawrence M. Seiford editors.” Kluwer Academic Press, Boston.

Shapiro S.S., and Wilk, M.B., (1965). “An analysis of variance test for normality (complete samples),” Biometrika Vol. 52, pp. 591-611.

Sherman G., & Gold, F., (1985). “Bank branch operating efficiency - evaluation with data envelopment analysis,” Journal of Banking & Finance, Vol. 9, pp. 297-315.

Shephard, R.W., (1953). “Cost and production functions.” Princeton: Princeton University Press.

Shockey, J., (2012). “Fatality Prevention in this workplace Forum: Effective Hazard Controls for High Risk Tasks Breakout,” Proceedings from Indiana University of PA, Safety Sciences Department, Alcoa Foundation Princeton.

Simar L., & Wilson, P., (2002). “Non-parametric tests to returns to scale,” European Journal of Operational Research., Vol. 139, No.1, pp. 115-132.

Sinuanystern, Z., Mehrez, A., & Barboy, A. (1994). “Academic departments efficiency via DEA,” Computers & Operations Research, Vol. 21, pp. 543-556.

SOCR, (2017). “AP Statistics Curriculum 2007 Gamma,” Accessed 4/28/2019, Retrieved from http://wiki.stat.ucla.edu/socr/index.php/AP_Statistics_Curriculum_2007_Gamma

Specificity and Sensitivity, (2018). “Definition of sensitivity, specificity, and predictive value.” Accessed 12/09/2018, Retrieved from http://gim.unmc.edu/dxtests/reviewof.htm.

Stanford Logistic Regression Tutorial, (2018), “Logistic Regression Tutorial”, Stanford Univ. Psych 252, https://web.stanford.edu/class/psych252/tutorials/Tutorial_LogisticRegression.html, Accessed 3/18/2018.

Stat Trek.com, (2019), “Probability Distributions: Discrete vs. Continuous”, Accessed 4/25/2019. Retrieved from https://stattrek.com/probability-distributions/discrete-continuous.aspx.

Subhash, C. R., (2004). “The Directional Distance Function and Measurement of Super-Efficiency: An Application to Airlines Data.” University of Connecticut Economics Working Papers, pp. 1-16.

Subhash, C. R., (2004). “Theory and Techniques for Economics and Operations Research.” University of Connecticut Economics Working Papers, pp. 29-40.

Sun, S., (2004). “Assessing Joint Maintenance Shops in the Taiwanese Army Using Data Envelopment Analysis.” Journal of Operations Management, No. 22, pp. 233-245.

Szumilas, M. (2010). “Explaining Odds Ratios.” Journal of the Canadian Academy of Child and Adolescent Psychiatry. Vol.19, No. 3, pp. 227–229.

Toloo, M., & Tavana M., (2017). “A novel method for selecting a single efficient unit in data envelopment analysis without explicit inputs/outputs.” Annals of Operations Research., Vol. 253, pp. 657-681.

Trochim, M.K, (2006). “Types of Reliability.” This research Methods Knowledge Base, Accessed 5/6/2019, Retrieved from https://socialresearchmethods.net/kb/reliable.php.

Tukey, J., (1949). “Comparing Individual Means in the Analysis of Variance". Biometrics. No. 5, Vol 2, pp. 99–114.

U.K. Cabinet Office Glossary (2014). “Revision to Emergency Preparedness,” Accessed 10/20/2018, Retrieved from https:// www.gov.uk/government/uploads/system/uploads/attachment_data/file/ 61046/EP_Glossary_amends_18042012_0.pdf.

Vasilev, I. (2019), “A Deep Learning Tutorial: From Perceptrons to Deep Networks,” Accessed 2/01/2019, Retrieved from https://www.toptal.com/machine-learning/an-introduction-to-deep-learning-from-perceptrons-to-deep-networks.

Vasudev, R. (2018), “Continuous vs Discrete Variables in the context of Machine Learning,” Accessed 4/30/2019, Retrieved from https://hackernoon.com/continuous-vs-discrete-variables-in-the-context-of-machine-learning-15d9005e2525?gi=6f6cc7168717.

Vescovi, T., & Favaretto, D., (2002), “Competitive analysis in the Web, Marketing in a Changing World,” 31st EMAC Conference Proceeding, Braga, Portugal.

Watkins, T. (2018), “Suboptimization Defined”, Accessed 7/19/2018, Retrieved from http://www.sjsu.edu/faculty/watkins/suboptimum.htm.

Wikipedia.com, (2019), “Air Force Specialty Code,” Accessed 2/01/2019, Retrieved from https://en.wikipedia.org/wiki/Air_Force_Specialty_Code

Wen, M. (2015). “Uncertain Data Envelopment Analysis.” Introduction to DEA, pp. 45-57. Springer-Verlag Berlin Heidelberg, Germany.

Zunker, C., & Howard, K., (2018), “DEA Military Literature Search,” Advanced Logistics Managements Seminar, Air Force Institute of Technology, Wright Patterson Air Force Base, OH.

Zhu, L., Holt, J, & Black, R., (2005; 2000). “Incorporating weighting into risk assessment: can this make an overall risk rating more meaningful?” New Zealand Pest Risk Assessment, Presented from National Resources Institute of U.K., pp. 1-32.

REPORT DOCUMENTATION PAGE		*Form Approved* *OMB No. 0704–0188*

1. REPORT DATE (DD–MM–YYYY)	2. REPORT TYPE	3. DATES COVERED (*From — To*)
06-15-2019	Dissertation	Jun 2016 – Jun 2019

4. TITLE AND SUBTITLE
Using Manpower to Assess USAF Strategic Risk

5a. CONTRACT NUMBER
5b. GRANT NUMBER
5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Bradshaw, Calvin J., Major, USAF

5d. PROJECT NUMBER
5e. TASK NUMBER
5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Air Force Institute of Technology
Graduate School of Engineering and Management (AFIT/EN)
2950 Hobson Way, Building 640
WPAFB OH 45433-7765

8. PERFORMING ORGANIZATION REPORT NUMBER
AFIT-ENS-DS-19-J-021

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
HQ Air Force Material Command
Analysis & Assessments Division
4375 Chidlaw Road
WPAFB OH 45433
POC: Intentionally left blank

10. SPONSOR/MONITOR'S ACRONYM(S)
HQ AFMC/A9A

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT
Distribution Statement A. Approved For Public Release; Distribution Unlimited.

13. SUPPLEMENTARY NOTES
This material is declared a work of the U.S. Government and is not subject to copyright protection in the United States.

14. ABSTRACT
With limited personnel resource funding availability, senior US Air Force (USAF) decision makers struggle to base enterprise resource allocation from rigorous analytical traceability. There are over 240 career fields in the USAF spanning 12 enterprises. Each enterprise develops annual risk assessments by distinctive core capabilities.

A core capability (e.g. Research and Development) is an enabling function necessary for the USAF to perform its mission as part of the Department of Defense (DOD). Assessing risk at the core capability is a good start to assessing risk, but is still not comprehensiveness enough. One of the twelve enterprises has linked its task structure to Program Element Codes (PECs).

Planners and programmers use amount of funding per PEC to assess tasks needed to address a desired capability. For the first time, a linkage between core functions, core capabilities, PECs, tasks and manpower has been developed. We now can provide an objective nomenclatured way to compute personnel risk.

All resources planned are not programmed (i.e. resource allocated and budgeted); the delta between the two translate into capability gaps and a level of strategic risk. A USAF career field risk demonstration is performed using normal, sigmoid and Euclidean-norm functions. Understanding potential personnel shortfalls at the career field level should better inform core capability analysis, and thus increase credibility and defensibility of strategic risk assessments.

15. SUBJECT TERMS
DEA, Risk Assessment, Personnel, Logistics, Enterprise, Human Resources, Methodology, Strategic, USAF, Military, Defense, Core Capability, Core Function, Career Field, AFS, AFSC, Sigmoid, Normal

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
U	U	U	UU	225	Alan Johnson, AFIT/ENS

19b. TELEPHONE NUMBER (Include Area Code)
(937) 255-6565, ext. 7469
Raymond.Hill@afit.edu

Standard Form 298 (Rev. 8–98)
Prescribed by ANSI Std. Z39.18