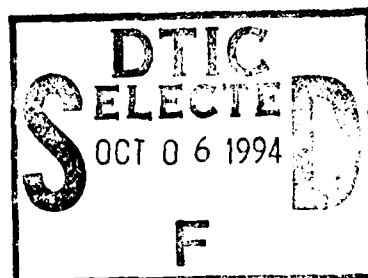


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EVALUATION OF
AIR FORCE AND NAVY DEMAND
FORECASTING SYSTEMS

THESIS

Christian J.H. Dussault, B.S.

AFTT/GLM/LAL/95M-1

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EVALUATION OF AIR FORCE
AND NAVY DEMAND FORECASTING SYSTEMS

THESIS

Presented to the Faculty of the Graduate School of Logistics and Acquisition Management
of the Air Force Institute of Technology

Air University

In Partial Fulfillment of the
Requirements for the Degree of
Master of Science in Logistics Management

Christian J.H. Dussault, B.S.
Captain, Canadian Armed Forces

March 1995

Approved for public release; distribution unlimited

Preface

The purpose of this study was to perform a comparison between the Navy Statistical Demand Forecasting system and the Air Force Requirements Data Bank forecasting system. The results of this research may help the Air Force managers and the Joint Logistics System Center managers to obtain a better understanding of the implications in using one system versus the other.

An extensive search of existing literature was conducted to gain an understanding of the basic algorithms of each system. A simulation model of the Requirements Data Bank system was developed to generate Air Force forecasts. The actual Statistical Demand Forecasting system was used to generate Navy forecasts.

The completion of this research would not have been possible without the help of several people to whom I am deeply indebted. I would like to thank my advisor, Major Terrance Pohlen, for his knowledgeable advice, patience, inspiration and guidance throughout the process.

I would like to thank my other advisor, Dr. Craig Brandt, for his continuing support while I was pursuing my course work as a part time student.

The completion of this thesis is due primarily to Mr. Victor Presutti, Mr. Curt Neumann, and every one of my co-workers who have, in some way or another, provided me with some assistance in completing my thesis.

I would also like to thank my sponsor, Mr. Jean-Guy Mathieu, for believing in me and sending me to the US Air Force Materiel Command as a Canadian Exchange Officer.

Most of all, I am forever grateful to every member of my family for their unwavering love and support.

Christian J.H. Dussault

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Abstract

In March 1993, the JLSC selected the Navy's Statistical Demand Forecasting System as the standard DOD forecasting system. The purpose of this study was to evaluate and compare the performance and accuracy of the Navy Statistical Demand Forecasting system, relative to the Air Force Requirements Data Bank forecasting system in an Air Force environment. To compare the performance of each forecasting system, the research used three different approaches.

The first approach looked at time series components and evaluated how each forecasting system reacted to different data patterns. From this approach, it was found that under the presence of a trending component, the Statistical Demand Forecasting system generated more accurate forecasts than the Requirements Data Bank system did. It was also found that under the presence of outliers, the SDF system computed more accurate forecasts than the RDB system did.

The second approach looked at the actual Air Force data and evaluated the forecast accuracy established by each forecasting technique. The results demonstrated that there was no significant difference in the forecast accuracy between the two forecasting systems.

The third approach looked at how each forecasting system would affect aircraft availability. It was found that under the presence of trending data and outliers, there was a significant difference in aircraft availability between the two forecasting systems. However it was found that under the presence of actual Air Force data, there was no significant difference in aircraft availability between the two forecasting systems.

Contrary to the RDB system, the SDF system performs well in detecting outliers and trending component data. However it was found that with actual Air Force data, the

SDF system and the RDB system generate forecasts with approximately the same level of aircraft availability. These results demonstrate that either system represents a good approach to generate forecasts that will provide relatively the same level of aircraft availability.

EVALUATION OF AIR FORCE AND NAVY DEMAND FORECASTING SYSTEMS

I. Introduction

General Issue

The military services use large inventory systems to manage many items of varying attributes or characteristics. Forecasting demand for and acquiring spare parts is an important facet of inventory systems.

Although results obtained from different forecasting methods may vary slightly, a one percent difference can represent millions of dollars of investment (Roberts, 1991:4). Over 70 percent of the Air Force's computed gross requirement for reparable spares is computed by forecasting the expected number of component failures. Because of the size of the computed demand-based gross requirement (\$43 billion in procurement and \$4 billion in repair), a small percentage error in forecasted demands can translate into a large dollar amount (Bachman, 1993:1). It is important to ensure that the forecasting method selected is the most appropriate and accurate, because overestimated demands will cause the requirements system to drive unnecessary buys and repairs, while items with underestimated demands will cause backorders which translate into bad supply performance (Bachman, 1993:3).

Background

A logistics management information system consists of an extensive network of interrelated sub-systems which manages the procurement, distribution, repair and maintenance of spare parts to support weapon systems (Bond, 1989:1). For many years, the Air Force, the Army, the Navy and the Defense Logistics Agency have each spent millions of dollars to design, develop and maintain logistics systems. Although each service has its own specific logistics system, the objectives of each system remain the

same. For this reason, the Department of Defense gathered that it would be more cost effective to maintain one standard DOD logistics system than to maintain four. On February 13, 1992, the Assistant Secretary of Defense approved the charter for the Joint Logistic System Center (JLSC) (Klugh, 1994a).

The JLSC has been tasked with the highly complex and complicated mission of developing and implementing standard materiel management and depot maintenance automated business systems across the Department of Defense (DOD) (Klugh, 1994b). The JLSC's main mission is to evaluate and select the sub-systems from each service's logistics system to produce a standard DOD logistic system most appropriate to the Air Force, Navy, Army, and DLA (Defense Logistics Agency) (Klugh, 1994b). The difficulty lies in determining which sub-systems DOD should keep for all four organizations, especially when each service has developed different approaches for similar sub-systems. Figure 1-1 illustrates the integration of the sub-systems into a standard DOD Logistic System.

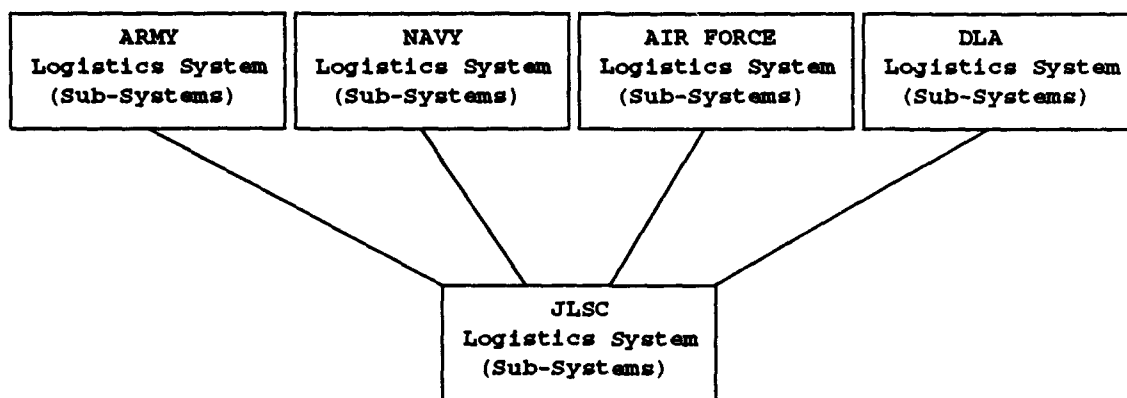


Figure 1-1. Joint Logistic Systems

One of the elements studied by the JLSC is the sub-system which forecasts demand for reparable spare parts. This sub-system determines the worldwide requirements for reparable spare parts to satisfy future operational goals for weapon systems. In November 1992, the JLSC approved the Statistical Demand Forecasting System (SDF) as a near term

initiative to be implemented at the Defense Logistics Agency Inventory Control Points (Moore, 1994). In March 1993, the JLSC selected the Navy's Statistical Demand Forecasting System as the standard DOD forecasting system (Moore, 1994).

Another element studied by the JLSC is the database sub-system which maintains data on consumable and recoverable items. The JLSC selected the Air Force's Requirements Data Bank (RDB) information system as the database sub-system for the standard DOD Logistics System (Moore, 1994). Along with its database capacity, the Requirements Data Bank information system also contains various materiel management processes and functions used to manage the Air Force inventory (Searock, 1992:Ch 1, 2). One of the processes or sub-systems of RDB used to compute recoverable items' requirements is the Recoverable Item Process. The Recoverable Item Process implicitly contains an integrated forecasting approach. Since the RDB information system has already incorporated an integrated forecasting approach, the Air Force Material Command is questioning the adoption of the Navy's Statistical Demand Forecasting System (Gitman, 1994).

The JLSC recently decided to temporarily keep the RDB forecasting component for the Air Force (Moore, 1994). The decision to allow the Air Force to use its RDB forecasting approach is implicitly contained in the JLSC Requirements Determination Business Process Model (Moore, 1994).

Specific Problem

Since the JLSC selected the Navy's Statistical Demand Forecasting System as the standard DOD forecasting system, the Army and the Defense Logistics Agency have both performed analyses to measure the impact of using SDF within their own organization (Wehde, 1994b; Roberts, 1994). The specific problem is that the Air Force has not analyzed or studied how SDF could affect its operational requirements. Therefore the

effect of SDF on USAF requirements determination remains unknown. This is a problem because budget allocation across items depends on solving the statistical problem of forecasting item demand rates (Sherbrooke, 1987: v).

Purpose of the Study

The purpose of this study is to evaluate and compare the performance and accuracy of the Navy forecasting system, Statistical Demand Forecasting, relative to the Air Force forecasting system (Requirements Data Bank Forecasting) in an Air Force environment.

Contributions and Implications for DOD Managers

The purpose of this research is to compare the Air Force forecasting approach to the Navy forecasting approach. This comparison analysis provides the Air Force and the Joint Logistic Systems Center the following contributions:

1. Observations on the forecasting approaches' weaknesses and strengths. The implications associated with this contribution are that the managers will have greater understandings of the forecasting systems and will know the areas where they can concentrate efforts in developing and improving the forecasting systems.
2. Recommendations on which forecasting approach would be most accurate and useful to the Air Force. One of the implications associated with this contribution is that the Air Force managers will be able to decide whether to keep the RDB forecasting approach or accept the SDF forecasting approach. The forecasting approach on which Air Force managers will concentrate their efforts to improve requirements determination accuracy, is another implication associated with this contribution.
3. Information for the JLSC concerning their decision on SDF. JLSC selected SDF as a near term initiative (Moore, 1994). The implication connected with this

contribution is that it will help the JLSC managers decide whether they should invest in the development and improvement of the RDB system versus the development and improvement of the SDF system. The selection of the appropriate forecasting system is also important because requirements determination is based on forecasts of past demands. If the forecasts are not accurate, DOD managers could buy the wrong parts and degrade weapon system availability as a result.

Research Questions

The research questions support the comparison between the Navy forecasting system and the Air Force forecasting system. To address forecasting accuracy and robustness, the following research questions are developed:

1. How does each forecasting system perform with different data pattern components?
 - a) What is the difference between the RDB average forecasting error and the SDF average forecasting error when a trending component is present in the data?
 - b) What is the difference between the RDB average forecasting error and the SDF average forecasting error when a cyclic component is present in the data?
 - c) What is the difference between the RDB average forecasting error and the SDF average forecasting error when a seasonal component is present in the data?
 - d) What is the difference between the RDB average forecasting error and the SDF average forecasting error when a random component is present in the data?
 - e) What is the difference between the RDB average forecasting error and the SDF average forecasting error when an outlier/spike component is present in the data?
2. How accurate are the forecasts computed by each forecasting technique subject to actual Air Force demand data?
 - a) What are the mean, variance and standard error of the forecasting errors?
 - b) Are the forecasts responsive to actual observations?

c) What is the difference between the RDB average forecasting error and the SDF average forecasting error?

3. What effects do the forecasts, computed by each forecasting approach, have on aircraft availability?

a) What is the difference between the aircraft availability achieved with SDF stock levels and the aircraft availability achieved with the RDB stock levels?

Some of the possible moderating variables that may affect the results of the research questions are:

- 1) Two vs. three level maintenance (procedure change).
- 2) Variance in the actual demand data due to new world situations (wartime).
- 3) A reduction in peacetime flying due to budget cuts (less demands).

Research Hypotheses

To answer the first research question, an hypothesis is developed for each time series components. Considering each data pattern component, the null hypothesis to be tested is that the RDB forecasting error mean (μ_1) is equal to the SDF forecasting error mean (μ_2) at the 90% confidence level.

$$H_0: \mu_1 = \mu_2$$

$$H_a: \mu_1 \neq \mu_2$$

To answer the second research question, the null hypothesis to be tested is that the RDB forecasting error mean (μ_1) is equal to the SDF forecasting mean (μ_2) at the 90% confidence level.

$$H_0: \mu_1 = \mu_2$$

$$H_a: \mu_1 \neq \mu_2$$

To answer the third research question, the evaluation of aircraft availability, the null hypothesis to be tested is that the average aircraft availability (μ_1) achieved with the

RDB forecasting approach is equal to the average aircraft availability (μ_2) achieved with the SDF forecasting approach at the 90% confidence level.

$$H_0: \mu_1 = \mu_2$$

$$H_a: \mu_1 \neq \mu_2$$

Research Approach

Three analytical approaches are used to evaluate and compare the Air Force forecasting method (RDB) to the Navy forecasting method (SDF):

1. The first approach measures the performance of the two forecasting techniques in terms of accuracy and stability under the influence of different data pattern components. Forecasting measurement errors are used to measure the stability and accuracy of the forecasts.
2. The second approach measures the performance of the forecasting techniques in terms of accuracy and stability under the influence of real Air Force data. Forecasting measurement errors are used to measure the stability and accuracy of the forecasts.
3. The third approach consists of computing the aircraft availability achieved when demand is estimated by one of the forecasting techniques and the Aircraft Availability Model is constrained by a specific funding level. The Aircraft Availability Model is used to compute the associated aircraft availability.

Scope and Limitations

This research limits its analysis to the range of reparable spare parts. For this reason, the sample size of the reparable spare parts includes items that are specific and common to different weapon systems. Although the Navy Statistical Demand Forecasting approach and the RDB Forecasting approach contain various forecasting techniques, this

study also limits itself to the comparison of the moving average technique used by each system.

Reparable Items. There are two types of spare parts -- consumable spare parts and reparable spare parts. A consumable spare part is an item that is normally expended or used beyond recovery, in the use for which it was designed or intended (Pohlen, 1994; Gluck, 1970:105). A reparable spare part is an item which can be reconditioned or repaired for re-use when it becomes unserviceable. Such items are usually high valued items (Pohlen, 1994; Gluck, 1970:377).

The purpose of the Recoverable Item Process in the Requirements Data Bank System is to manage reparable spare parts (Gitman, 1994). Although RDB will have the capability of managing consumable items in the future, the Air Force currently manages consumable items using the Economic Order Quantity Buy Budget Computation System (D062) (Gitman, 1994). Since a comparison is made to address Air Force concerns, this research only limits its analysis to the range of Air Force reparable spare parts.

Population Size and Sample Size. The population size of the reparable items for the Department of Defense is approximately 600,000 items (Lucas, 1994; Maitland, 1994b; Wehde, 1994a). The population size of the reparable items for the Air Force is approximately 185,000 items (Lucas, 1994). The demands for every item and for every weapon system are totaled from each base and reported as an overall worldwide quantity.

There are two types of items: specific items and common items. Specific items represent items that have application to one weapon system. Common items represent items that have applications to two or more weapon systems. Eighty-five percent of the total reparable items' population are specific to weapons systems while fifteen percent are common to different weapon systems (Lucas, 1994).

The data sample consists of 245 reparable items. Specific items and common items are included in the analysis. Chapter Three of this thesis details the computation of

the sample size. The secondary demand data were gathered from the Recoverable Consumption Item Requirements (D041) System. The demand data cover four years of historical data and are specific or common to different weapon systems. It included quarterly information such as the quantity demanded and the flying program for each item.

Forecasting Techniques. The Navy Statistical Demand Forecasting approach and the RDB Forecasting approach offer a variety of forecasting techniques to predict demands. For example, the Navy Demand Forecasting approach offers various forecasting techniques such as exponential smoothing, double exponential smoothing, moving average, and linear regression (Urban, 1993c). The RDB Forecasting approach uses linear regression, exponential smoothing and moving average as forecasting techniques (Lucas, 1993).

Both forecasting systems have three forecasting techniques in common: moving average, double exponential smoothing and linear regression. The technique most often used by each system, approximately 90% of the time, is the moving average forecasting approach (Searock, 1993:Ch 3, 4; Maitland, 1994a). For this reason, this research limits itself to the comparison of the moving average technique used by each system.

Assumptions

The analysis of this research adopts the following assumptions:

- 1) The reparable spares demands are correlated with flying hours. This assumption is important because the Air Force forecasts demand rates and not actual demands. The demand rates are computed by dividing the number of demands by the number of flying hours.
- 2) The actual spare part demand data are assumed to be specific to one fictitious weapon system. Since the sample size includes items from different weapon systems, it would be difficult to measure a significant aircraft availability for each weapon system. For this reason, it is assumed that all items are part of an imaginary or fictitious weapon system.

- 3) The actual spare part demand data are assumed to be all LRUs (Line Replaceable Units) with a quantity per application equal to one.
- 4) The probability of having x units in resupply follows a negative binomial probability distribution (Rexroad, 1992:6).
- 5) The reparable demand process follows the Palm's Theorem. The Palm's Theorem is described as:

If demand for an item is a Poisson process with annual mean λ and if repair time for each unit is independently and identically distributed according to any distribution with mean T years, then the steady-state probability distribution for the number of units in repair has a Poisson distribution with mean λT .
(Sherbrooke, 1992:21)

- 6) The model structure and its parameters stay the same during the forecast period. This implies that the forecast-generating process is in control and that the forecast errors are normally distributed over time (Abraham and Ledolter, 1983:374).

Chapter Summary and Organization of the Research

This chapter presented the problem of comparing the Air Force's Requirements Data Bank forecasting approach to the Navy's Statistical Demand forecasting approach. This chapter also described the specific problem, reviewed the research questions and delineated the scope of the research. Chapter Two describes the current Air Force Requirements System, the future Air Force Requirements Data Bank System and the Navy's Statistical Demand Forecasting System. Chapter Three discusses the research methodology. Chapter Four presents the results and analysis of the data collected. Finally, Chapter Five provides the conclusions and recommendations derived from the research.

II. Literature Review

Introduction

This chapter discusses the current forecasting concepts and presents different logistics systems implicated in the research. First, the chapter gives a description of the magnitude of the Air Force reparable items inventory. Then, time series components are presented and different forecasting techniques are discussed. Finally an overview of the current Air Force D041 system, the Requirements Data Bank System, and the Statistical Demand Forecasting System is presented.

Magnitude of the Air Force Reparable Items Inventory

The United States Air Force is one of the largest buyers of goods and materials in the world (Sysdek, 1989:5). Approximately 185,000 reparable items are stocked in the Air Force Materiel Command (AFMC) inventory for support of weapon systems (Lucas, 1994). With such large purchasing needs lies the inherent responsibility to manage assets in an "effective and efficient" manner (Department of the Air Force, 1987:Ch 2, 45).

Once an item is purchased, it is either used or held in inventory until needed or deemed in excess to requirements (Sysdek, 1989:5). Too little inventory may harm the Air Force operational needs in both peace and war because of stockouts (Searock, 1992:Ch 1, 1). On the other hand, too much inventory increases operating costs (Sysdek, 1989:5; Ammer, 1980:255-257). As Ammer notes, inventories act as a protection against uncertainties in supply and demand (Sysdek, 1989:5; Ammer, 1980:257). Inventory is an important aspect of efficient materiel management because the major goals of materiel management are to minimize inventory investment, maximize customer service and assure efficient operation of the organization (Tersine, 1988:16). The Air Force currently uses the Recoverable Consumption Item Requirements System (D041) to manage its reparable

items (Department of the Air Force, 1991:32). Because today's technological advances offer opportunities for improvement to the current system, D041 is technically archaic (Searock, 1992:Ch 1, 1-2). In July 1982, the AFMC established the Logistics Management Systems (LMS) Modernization Program. In June 1985, the Secretary of Defense directed the services to strengthen their weapon systems management approach. The new Requirements Determination System (RDB) is one of the Air Force programs that implemented that directive. Since 1985, the Air Force has been developing RDB to manage 807,000 consumable spares, recoverable spares, repair parts, and equipment items with an inventory valued at \$59 billion (Searock, 1992:Ch 1, 1-2). The Air Force plans to replace the current D041 system with the Recoverable Item Process of RDB (Department of the Air Force, 1988:Ch 2, 1).

Time Series Components

A time series component is a pattern produced by a set of time ordered observations found during successive and equal periods (Tersine, 1988: 41). John E. Hanke and Arthur G. Reitsch stipulate that two considerations are involved in producing an accurate and useful forecast of a time series. The first consideration is to collect data that are relevant to the forecasting task. The second consideration is to choose a forecasting technique that will utilize the information contained in the time series components to its fullest (Hanke and Reitsch, 1992:90).

Time series components can be decomposed into patterns such as trend, cycle, seasonality, and randomness known as time series components (Hanke and Reitsch, 1992:91). The four components are illustrated in figure 2-1.

The trend is the long-term component that represents the growth or decline in the time series over an extended period of time. The basic forces that affect and help explain the trend component are population growth, price inflation, technological change, and

productivity increases (Hanke and Reitsch, 1992:92). In a military environment, an increase or a decrease in operational activities could explain the trend component. The cyclical component is the wave-like fluctuation around the trend, usually affected by general economic conditions (Hanke and Reitsch, 1992:92).

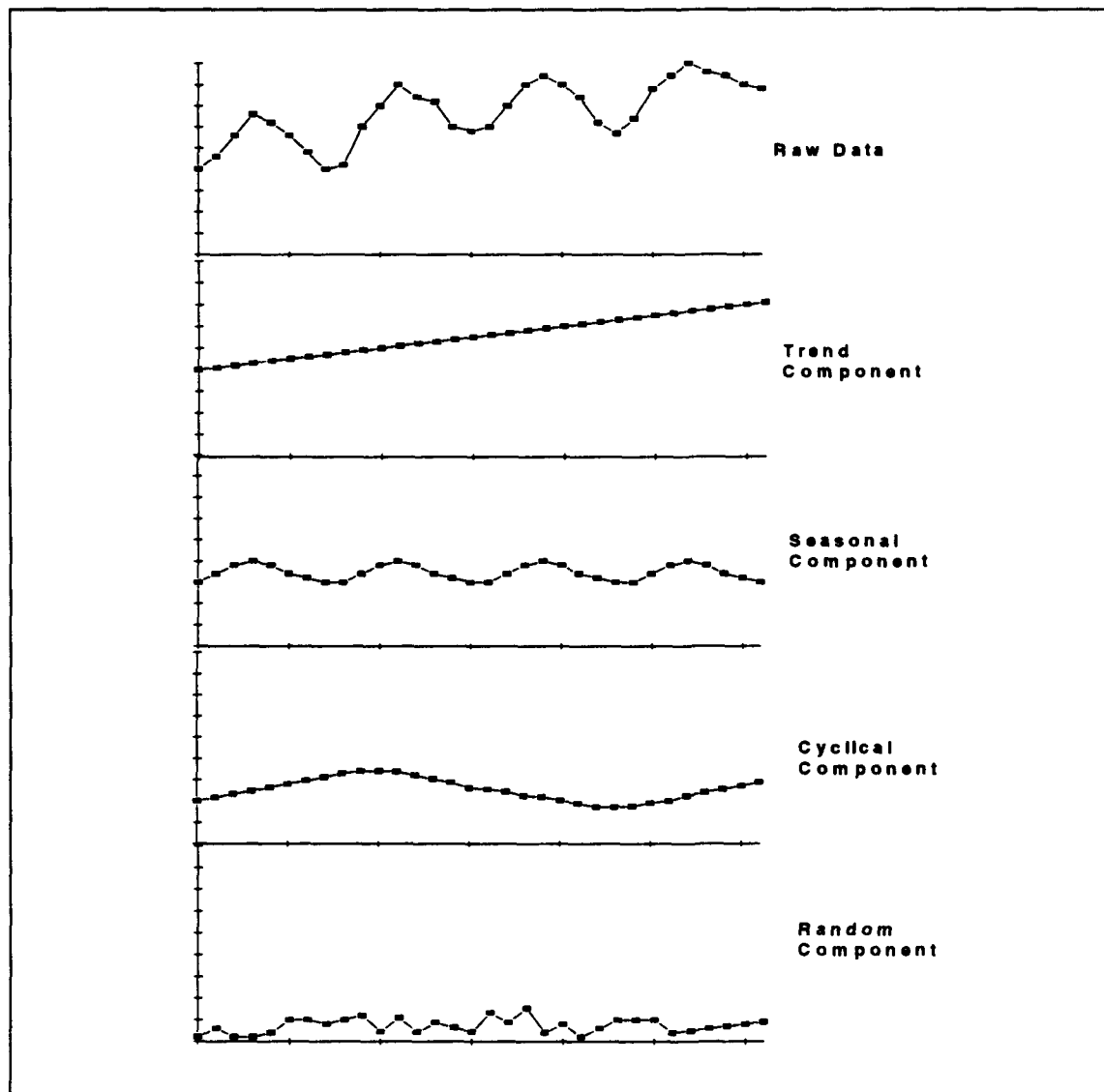


Figure 2-1. Time Series Components (Adapted from Tersine, 1988:42)

The seasonal component is the pattern of change that repeats itself year after year. Seasonal variation may reflect weather conditions, holidays, or length of calendar months

(Hanke and Reitsch, 1992:92). The random component measures the variability of the time series after the other components have been removed (Hanke and Reitsch, 1992:93). Random variations are those in the data which cannot be accounted for otherwise and have no identifiable pattern (Sysdek, 1989:18).

Forecasting Techniques

The Requirements Data Bank System and the Statistical Demand Forecasting System contain alternative forecasting techniques. Item managers may select a certain forecasting technique depending on the pattern projected by the data.

The current Air Force D041 System uses an eight quarter moving average and PRELOG (Predictive Logistics) as forecasting techniques. The USAF decided on the eight quarters moving average technique for two reasons: the users can easily understand the model, and the technique provides stable forecasts under fluctuating demand (Rexroad, 1993a). The USAF decided on Predictive Logistics technique for its capability to detect and respond to a trend (Department of the Air Force, 1991:585).

The Requirements Data Bank System possesses four different forecasting techniques: moving average (four and eight quarters), double exponential smoothing, linear regression known as PRELOG (Predictive Logistics), and manually input estimates (primarily used for new items) (Searock, 1992:Ch 4. 2). These four forecasting techniques were selected to create greater flexibility for the item manager or the equipment specialist to respond to changing demand patterns (Searock, 1992:Ch 4.2).

The Statistical Demand Forecasting System (SDF) has a variety of forecasting techniques for different demand patterns: moving average, exponential smoothing, double exponential smoothing, linear regression, non-parametric, Sen median regression, damped, and composite forecasting (Urban, 1993c). These forecasting techniques were selected to create greater flexibility for the item manager or the equipment specialist to

choose an appropriate technique depending on the demand pattern components (Maitland, 1994b).

Although both forecasting systems have several forecasting techniques, the technique used approximately 90% of the time is the eight quarters moving average forecasting approach (Searock, 1993:Ch 3, 4; Maitland, 1994a).

Moving Average. The moving average is a forecasting technique where a constant number of data points can be specified at the outset and a mean computed for the most recent observations. As each new observation becomes available, a new mean can be computed by dropping the oldest value and including the newest one (Hanke and Reitsch, 1992:134). The moving average technique can be very responsive to big changes in the data pattern if the number of periods in the moving average is small. On the other hand, the technique can be very stable if the number of periods in the moving average is large. The rate of response to changes in the underlying data pattern depends on the number of periods in the technique. The moving average model performs best with stationary data; however, it does not handle trend or seasonality very well (Hanke and Reitsch, 1992:134-135). Equation 1 provides the formula for the moving average forecasting technique (Hanke and Reitsch, 1992:134).

$$F_{t+1} = (Y_t + Y_{t-1} + Y_{t-2} + \dots + Y_{t-n+1}) / n \quad (1)$$

where

Y_t = Actual datum in quarter t

F_{t+1} = Forecast made in quarter t for t+1

n = number of terms in the moving average

Exponential Smoothing. Exponential smoothing is a method based on averaging (smoothing) past values of demands in a decreasing (exponential) manner. The observations are weighted with more weight given to more recent observations (Hanke and Reitsch, 1992:140). One advantage of exponential smoothing is that it is a simple

technique and requires very little historical data (Evans, 1993:740). It is very responsive to changes in data patterns because more weight is given to the most recent observation. Equation 2 demonstrates the exponential smoothing equation (Hanke and Reitsch, 1992:140).

$$F_{t+1} = \alpha Y_t + (1-\alpha) * F_t \quad (2)$$

where

Y_t = Actual datum in month t

F_{t+1} = Forecast made in month t for t+1

F_t = Forecast made in month t

α = Smoothing Constant ($0 < \alpha < 1$)

Double Exponential Smoothing. The double exponential smoothing technique, often referred to as Brown's Method, is used as an exponential smoothing technique for forecasting demand data that have a linear trend (Hanke and Reitsch, 1992:146). A disadvantage with double exponential smoothing is the initialization of the smoothed series variables and the trend adjustment variable. Also, if no trend is present in the data, the forecast may be underestimated or overestimated (Hanke and Reitsch, 1992:150). Equation 3 demonstrates the double exponential smoothing technique (Hanke and Reitsch, 1992:146).

$$A_t = \alpha Y_t + (1-\alpha) * A_{t-1} \quad (3)$$

$$A'_t = \alpha A_t + (1-\alpha) * A'_{t-1}$$

$$a_t = 2A_t + A'_t$$

$$b_t = (\alpha / 1-\alpha) * (A_t - A'_t)$$

$$F_{t+p} = a_t + (b_t * p)$$

where

Y_t = Actual datum in period t

F_{t+1} = Forecast made in period t for t+1

F_t = Forecast made in period t

α = Smoothing Constant ($0 < \alpha < 1$)

A_t = new smoothed value

Linear Regression. Once a linear relationship is established, knowledge of an independent variable can be used to forecast a dependent variable (Hanke and Reitsch, 1992:178). The method used to determine the regression equation is called the method of least squares (Hanke and Reitsch, 1992:180). Although the model is very responsive to any type of trend patterns, one disadvantage with linear regression is that it is complex and not easily understood by the user (Searock, 1992:Ch 3, 2). The mathematical formula for the regression equation is illustrated in Equation 4 (Hanke and Reitsch, 1992:181).

$$Y = a + bX \quad (4)$$

$$a = \bar{Y} - b\bar{X}$$

$$b = (\sum X_i Y_i - n \bar{X} \bar{Y}) / (\sum X_i^2 - n \bar{X}^2)$$

Recoverable Consumption Item Requirements System (D041)

The previous section discussed about a variety of forecasting techniques that can be used to forecast future demands. This section describes the current Air Force requirements system and discuss which forecasting techniques it uses to forecast future demands. The current Air Force requirements system known as the Recoverable Consumption Item Requirements System (D041) has been designed to support the repairable requirements function for the Air Force. It has the following functions (Department of the Air Force, 1992:32):

1. Computes spare parts requirements for recoverable items.
2. Accomplishes the routine clerical, mathematical, and statistical workload involved in computing recoverable item requirements.
3. Forecasts gross and net requirements using past and future programs, usage history, and asset information maintained within this system.
4. Produces reports for management evaluation and action.
5. Produces information for logistics systems.

It uses an eight quarter moving average as a forecasting technique to predict future spare part requirements for weapon systems (Department of the Air Force, 1992:583). D041's eight quarter moving average computes a demand rate known as the Organizational Intermediate Maintenance Demand Rate (Department of the Air Force, 1992:556). The demand rate is then multiplied by planned future flying hours to compute future spare part requirements. The equation for the eight quarter moving average technique in D041 is demonstrated in Equation 5 (Lucas, 1993).

$$F_{t+1} = (\sum D_i / \sum P_i) , \quad i = (t) \text{ to } (t - 7) \quad (5)$$

$$\text{Demand}_{t+1} = (\text{Number projected to fly at } t+1) \times (F_{t+1})$$

F_{t+1} = Forecasted value for quarter $t+1$

D_i = Demand value at quarter i

P_i = Number of flying hours at quarter i

t = Quarter i

To further explain the eight quarter moving average, the following example is considered. A type of aircraft in the Air Force is projected to fly 150 hours in the next quarter. What would be the requirement for landing gears in the next quarter? Table 2-1 gives more information pertaining to past demands on the landing gear.

Table 2-1. Landing Gear Demands

Quarter	Landing Gear Demands	Flying Hours
1	2	100
2	3	100
3	4	75
4	1	125
5	2	75
6	2	100
7	3	150
8	3	75
Total:	20	800
	-----	-----
9	Projected 3.75	Projected 150

$$F_9 = (\sum D_i / \sum P_i)$$

$$= (20 / 800) = 0.025 \text{ Demands per flying hour}$$

$$D_9 = 0.025 \times 150 \text{ flhrs} = 3.75 \text{ landing gears projected for quarter 9}$$

PRELOG (Predictive Logistics) is another forecasting technique incorporated into D041. Although the technique is available for use, it is rarely used to compute factors or rates because of its complexity (Rexroad, 1993a). The technique is discussed in the description of the RDB System.

Deficiencies within the D041 system addressed by the RDB system are (Searock, 1992:Ch3, 2-10):

- 1) Forecasting techniques for recoverable items are limited in scope.
- 2) No capability to recompute requirements to reflect a changing environment.
- 3) Historical data are not readily accessible.
- 4) There is no capability to accommodate surge in processing requirements.
- 5) Stock list changes are not received in a timely manner.
- 6) Access to data is not adequately controlled in current systems.

Requirements Data Bank System

Introduction. Because technological advances offer opportunities for material management improvement, the current AFMC logistics systems, developed in the 1950s and 1960s, are technically archaic. For this reason, the Requirements Data Bank is part of a modernization program known as the Logistics Management Systems (LMS) Modernization Program initiated by AFMC in 1982. RDB is currently being developed by the Air Force and consists of automated and manual functions to forecast and control procurement and repair requirements of assets needed for logistics support of USAF weapon systems (Searock, 1992:Ch 1,1). It is designed to compute requirements for buy and repair for 807,000 consumable spares, recoverable spares, repair parts, and equipment

items with an inventory valued at \$59 billion (Searock, 1992:Ch 1, 1-2). One of the RDB objectives is to improve the accuracy, visibility and timeliness of data, thus reducing paperwork and increase asset visibility (Department of the Air Force, 1988:2-17).

Replacement of Existing Systems by RDB. The Air Force uses many logistics information systems to manage their assets. One of the functions of materiel management is the Materiel Requirements Process. The Air Force Materiel Requirements Process computes procurement requirements for equipment, spares, and repair parts, and determines depot maintenance repair needs. Searock defines requirement as "the function or process of applying available or projected inventory against a forecasted need to determine if a shortage or excess exists, or if the items in an optimum position." (Searock, 1992:Ch3,1). The RDB provides such a system for the Materiel Requirements Process, which is divided into six major functional areas: Recoverable; Equipment; Expense; Finance; Repair; and Support (Searock, 1992:Ch 3, 1). Table 2-2 illustrates the current Air Force systems of the Materiel Requirements Process that RDB will replace (Searock, 1992:Ch 3, 1-2).

RDB Sub-systems. The RDB is being developed using a relational data base management system. A relational data base management system represents the newest technology in data base management (Searock, 1992:Ch 4, 10). The Requirements Data Bank system is made up of multiple physical processes, referred to as sub-systems, or CPCIs (Computer Program Configuration Items). These sub-systems, together, make the RDB system and replace the current Air Force systems illustrated in Table 2-2. Table 2-3 demonstrates the twenty-one CPCIs or sub-systems that compose the RDB system.

RDB Recoverable Item Sub-system. The Recoverable Item Sub-system (D200.A) is one of the processes that compose the RDB system. This study only discusses the RDB Recoverable Item Sub-system because the research focuses on the forecasting aspects of this sub-system. The Recoverable Item Sub-system computes repair, acquisition, and

Table 2-2. Current Air Force Systems Replaced by RDB

System Designation	System Description
CO17	Special Tooling and Special Test Equipment System
D039	Computation of Requirements for Equipment Items
D041	Recoverable Consumption Item Requirements System
D041A	Recoverable Consumption Item Requirements System
D049	Master Material Support Record
D055	Stock Fund War Requirements
D058	Economic Order Quantity (EOQ) Wartime Requirements Computation Gunnery Equipment
D062	Economic Order Quantity (EOQ) Buy/Budget Computation System
D067	Defense Materiel Utilization and Disposition Program Management System
D072	Other War Reserve Materiel Requirements
D073	Repair Requirements Computation System
D085	Air Force Requirements Forecasting System
D141A	Base Consolidation Inventory Status & Transaction Report Table III Items
D141B	AF Consolidated Inventory Status & Transaction Report Table III
G033J	Past Programs Data System
G035B	Central Management of Depot Level Maintenance
G072E	Depot Level Maintenance Requirements and Program Management System
G079	Systems and Equipment Modification/Maintenance Program
K004	Program Data for Input to Consumption Requirements Computation
APIS	Application Program Information System
IRCMIS	Initial Requirements Computation and Management Information System
WARS	Wartime Assessment and Requirements Simulation (WARS) Model

Table 2-3. RDB Sub-systems

Process #	Process or Sub-System	Process #	Process or Sub-System
D200.A	Recoverable Item Process	D200.L	Equipment Item Requirements Inventory Analysis Report
D200.B	Expense Item Process	D200.M	Economic Order Quantity Depot Data Base
D200.C	Equipment Item Process	D200.N	Recoverable Item Stratification
D200.D	Repair Process	D200.O	Economic Order Quantity Item Stratification
D200.E	Requirements Items Identification Data Process	D200.P	Past/Projected Programs Data
D200.F	Application & Programs Indenture Process	D200.1	Administration and Support
D200.G	War Readiness Spares Kit/Base Level self-sufficiency Spares Process	D200.2	Computations Methods Management
D200.H	Initial Requirements Determination Process	D200.5	Data Base Management System
D200.I	Retail Item Stratification	D200.9	Planning, Programming, Budgeting System
D200.J	Special Tooling and Special Test Equipment Process	D200.7	User Problem Report System
D200.K	Disposal Process		

retention requirements for reparable items (Searock, 1992:Ch 1, 10). The major functions of the Recoverable Item Sub-system are (Searock, 1992:Ch1, 11-12):

1. Collect, maintain, and retrieve item data.
2. Collect, maintain, and retrieve weapon system/end item data.
3. Collect, manage financial data.
4. Perform management analysis.
5. Compute item gross/net requirements by forecasting factors.
6. Compute stock levels using Aircraft Availability Model.

The RDB Recoverable Item Sub-system contains four different forecasting techniques: moving average (four & eight quarters), double exponential smoothing, linear regression known as PRELOG (Predictive Logistics), and manually input estimates (primarily used for new items) (Searock, 1992:Ch 4, 2; Lucas, 1993).

RDB Moving Average. The formula for the moving average technique in the Requirements Data Bank System (RDB) is identical to the eight quarter moving average technique presented in the Recoverable Consumption Item Requirements System (D041) (Department of the Air Force, 1988:Ch C, 286). The only difference is that the equipment specialist or the item manager has the flexibility of choosing among a four quarter moving average technique or an eight quarter moving average technique (Department of the Air Force, 1988:Ch C, 272). The eight quarter moving average will compute a more stable forecast and the four quarter moving average will be more responsive to changes in the data pattern.

RDB Double Exponential Smoothing. The double exponential smoothing technique, often referred to as the Brown's method, is used for forecasting demand data that have a linear trend (Hanke and Reitsch, 1992:146). The formula for the double exponential smoothing is illustrated in Equation 6 (Hanke and Reitsch, 1992:147).

$$\begin{aligned}
 F_{t+1} &= a_t + (p)b_t & (6) \\
 a_t &= 2S'_t - S''_t \\
 b_t &= (\alpha/1-\alpha) (S'_t - S''_t) \\
 S'_t &= \alpha(Y_t) + (1-\alpha) (S'_{t-1}) \\
 S''_t &= \alpha(S'_t) + (1-\alpha) (S''_{t-1})
 \end{aligned}$$

where

F_{t+1} = Forecast made for period $t+1$
 a_t = computed value for period t
 b_t = computed value for period t
 p = number of period forecasted ahead
 Y_t = Actual datum in period t
 S'_t = S-Prime
 S''_t = S-Double Prime
 α = Smoothing Coefficient

Contrary to the moving average technique, which sums demand over four or eight quarters, the double exponential smoothing technique uses past Organizational Intermediate Maintenance demand rates as input data (Department of the Air Force, 1988:Ch C, 274). The double exponential smoothing technique in the RDB Recoverable Item Sub-system will compute five different forecasts using five different smoothing coefficients and will retain the forecast having the lowest MAD (Mean Absolute Deviation) value (Department of the Air Force, 1988:Annex C, 274).

RDB Predictive Logistics (PRELOG). Predictive Logistics (PRELOG) is a forecasting system which checks up to twelve quarters of past demand rates for a significant trend and generates regression forecast estimates (Department of the Air Force, 1991:585). The Predictive Logistics technique is a tool to be used by the equipment specialist, along with the advice of an actuary, to forecast future demand rates. Working as a team, the equipment specialist and the actuary apply their experience and knowledge to promote optimal use of the Air Force resources (Department of the Air Force, 1980:Ch 9, 9).

PRELOG uses regression analysis to make a forecast and performs two types of testing (Department of the Air Force, 1991:587):

1. The first test uses the method of least squares to compute the best fit line for data. This test is designed to determine if the slope of the computed line is significantly different from a horizontal line.
2. The second test measures the error involved in using the moving average to forecast the demand rate. Each quarterly demand rate is compared with the immediate preceding moving average.

If the results of either of these tests equals or exceeds the Air Logistic Center determined levels, the item is selected for evaluation. A list of the items selected is provided to the actuary and the equipment specialist for review. They, together, decide

whether demand rates should be changed manually to forecast requirements more accurately (Department of the Air Force, 1991:587).

Statistical Demand Forecasting System

The Statistical Demand Forecasting (SDF) approach was developed in 1992 by the Navy to forecast its recoverable and consumable requirements for program and non-program related items (Urban, 1994a:Ch 2, 1). SDF was developed to reduce wholesale operating cost by improving forecast accuracy and reducing inventory level instability. The SDF approach employs statistical process control charts to detect demand instability and is designed to improve forecast accuracy and to reduce level instability (Wehde, 1994b:1). SDF offers eight different demand forecasting techniques for different types of commodities (Urban, 1994a:Ch 2, 3)

The Statistical Demand Forecasting model forecasts the mean and variance of the net demand during the procurement lead-time and the net demand during the repair turn-around-time (Urban, 1994a:Ch 2, 1). Past observations and current forecasts on each item are entered in the SDF system and both values are compared using statistical tests (Wehde, 1994b:2) When past observations are processed through SDF, the most recent observation will be processed through a series of filters and tests to ensure that it is consistent with the most recent forecast. If the most recent observation is consistent with the most recent forecast, then SDF will not change its current forecast and will keep the same forecast for the next period (Wehde, 1994b:2). However, if a significant difference is found, then a new forecast is calculated for the next period. If a major difference is found between the current forecast and the most recent observation, the SDF system will download the item demand information to a Personal Computer Exception Tool to advise the item manager of the situation. The item manager will then be given the opportunity to evaluate the situation through the Personal Computer Exception Tool (Maitland, 1994b).

It is not unusual for each item or a group of items to have different demand observation patterns. A demand pattern may demonstrate a trending component, a seasonality component, a cyclical component and/or an irregular component (Hanke and Reitsch, 1992:91-93). Different forecasting techniques will perform better than others depending on the data demand pattern. SDF is flexible in that it has a series of forecasting techniques for different demand pattern situations. These include (Urban, 1994a:Ch 2, 1):

- | | |
|---------------------------------|--------------------------|
| 1. Moving Average | 5. Non-Parametric |
| 2. Exponential Smoothing | 6. Linear Regression |
| 3. Double Exponential Smoothing | 7. Sen Median Regression |
| 4. Damped | 8. Composite Forecasting |

In more detail, the Statistical Demand Forecasting System is divided into six modules (Urban 1993c):

1. Module 0: Administrative Lead-time
2. Module 1: Time Forecasts
3. Module 2: Rates Forecasts
4. Module 3: Filters and Trends
5. Module 4: Quantity Forecasts
6. Module 5: Procurement Problem Variable Forecast

The modules are independent of each other and SDF can be run using only one module or a combination of any modules (Urban, 1993c). Each module computes the values for specific variables, which can then be used to feed other modules within the SDF system.

Module 0 - Administrative Lead-time. This module computes the administrative lead-time for each item (Urban, 1994b; Urban, 1994c:3-4). Module 0 takes contract information and computes the administrative lead-time prior to contract initiation (Urban, 1994b; Urban, 1994c:3). This information is computed by item, by group of items or by program. The administrative lead-time depends on the dollar value of the item(s) or the

contract(s) (Urban, 1994a:Ch 3, 5). When the computation is completed, the administrative lead-time is fed to SDF.

Module 1 - Time Forecasts. The purpose of this module is to compute the procurement lead-time and the repair-turn-around lead-time (Urban, 1994b; Urban, 1994c:5).

The Procurement Lead-Time: This variable represents the time necessary to procure an item. The procurement lead-time is computed by adding the Administrative Lead-time (computed in module 0) to the Production Lead-time (Urban, 1994a:Ch 3, 5). The production lead-time is defined as the time necessary to generate an item (Urban, 1994a:Ch 3, 6). It is generally identified and specified by the Navy (Urban, 1994b). The production lead-time is forecasted using an exponential smoothing technique (Urban, 1994a:Ch 3, 6).

The Repair Problem Average: Also known as the Repair Cycle Time, this variable represents the time required to repair an item (Urban, 1994a:Ch 3, 10; Urban 1994b). The repair problem average is computed using the following variables (Urban, 1994a:Ch 3, 4):

1. Remain in Place time. The length of time until a serviceable item is available as a prerequisite for the removal of an unserviceable from the end item as measured from the time the unserviceable item is determined to be beyond the repair capability of an organizational/intermediate maintenance activity (Urban, 1994a:Ch 4, 3).

2. Retrograde time. Time it takes for an item to be shipped from the base to the depot (Urban, 1994a:Ch 3, 4).

3. Overall Retrograde Time. Remain in Place + Retrograde Time (Urban, 1994a:Ch 3, 4).

4. Administrative time. Time to prepare the item for repair (Urban, 1994b).

5. Depot Maintenance time. Repair time (Urban, 1994a:Ch 3, 9).

6. Depot Repair Problem Average Time. Administrative + Depot Maintenance (Urban, 1994a:Ch 3, 10).

7. Depot Repair Cycle time. Overall Retrograde Time + Depot Repair Problem Average time (Urban, 1994a:Ch 3, 4)

Figure 2-2 illustrates these variables.

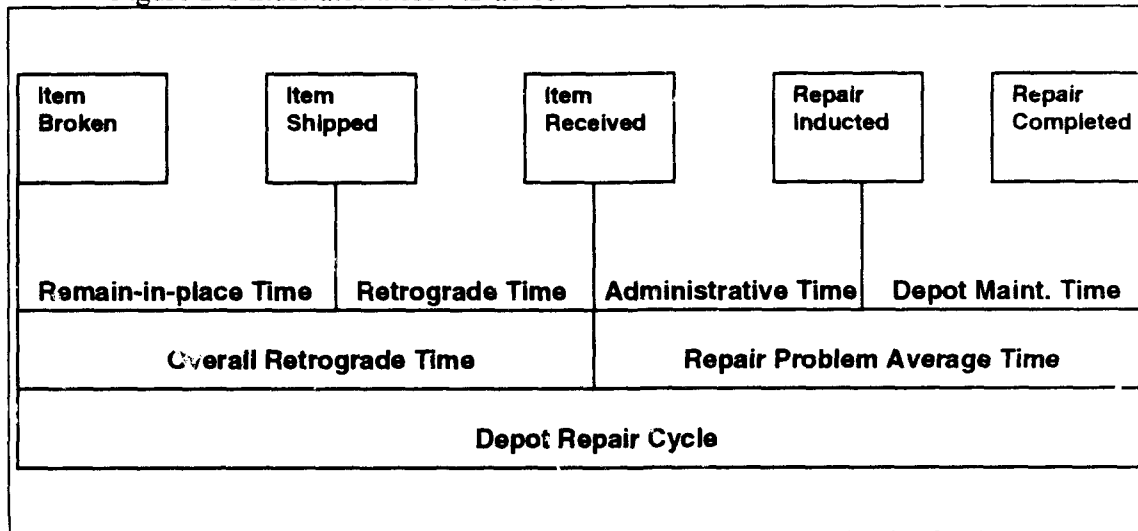


Figure 2-2. Repair Turn-Around-Time

Module 2 - Rates Forecasts. SDF computes the following rates to determine the number of regenerations expected from repair (Urban, 1994a:Ch 3, 11):

1. Final Recovery Rate (FRR). This rate represents the percentage of items inducted into the repair program that can be anticipated to be returned to a usable or serviceable condition.

2. Unserviceable Return Rate (URR). This rate represents the percentage of the total items issued expected to be turned in for repair.

3. The Washout/Condemnation Rate (WCR). It is an expression of the percentage of total items denanded that never return to a reparable condition.

4. Serviceable Return Rate (SRR). This rate represents the percentage of total items which are returned to the supply system in a reparable condition.

5. Nonrecurring Demand Rate (NDR). The NDR is the percentage of nonrecurring demands.

Module 3 - Filters and Trends. This module represents the main component of the Statistical Demand Forecasting system (Urban, 1994b). It consists of five independent statistical process control tests used to measure demand forecast stability (Wehde, 1994b:2; Urban, 1994b). These tests determine whether the most current forecast is still a good demand predictor of the future (Wehde, 1994b).

The main objectives of the five statistical tests within this module are the evaluation of the following elements (Urban, 1994a:Ch 3, 14-15):

1. Stability of the forecast. Determine whether the current forecast is still a good predictor of the future.
2. Possibility of a trend. Determine whether a trend component exists in the demand data even though past observations appear to be stable for several consecutive periods.
3. Possibility of biased demand. Determine if observations have drifted away from the mean forecast even though demands are stable and non-trending.

The most recent observation will be compared to the most recent forecast using the five statistical parametric tests. If one of the statistical tests determines that the forecast is not a good predictor, SDF computes a new forecast. However, if all the tests determine that the current forecast is still a good predictor, the current forecast becomes the next period's forecast (Wehde, 1994b:1-5; Urban, 1994b).

The five independent statistical parametric tests that SDF uses are: The Demand Filters Test, the Trending Test, the Bias Test - Runs Test, the Bias Test - Cumulative Error Tests, and the Bias Test - Student Confidence Interval Test (Urban, 1994c:7-10, Wehde, 1994b:1-5).

Demand Filters Test. To measure the stability of the forecast, SDF uses a statistical control test known as the Demand Filters Test. The purpose of the Demand Filters Test is to determine whether the current forecast is a good predictor of the future. If the test demonstrates that the current forecast is not a good estimation, then it will reforecast the demand data to obtain a new forecast more representative of the demand pattern (Urban, 1994a:Ch 3, 15; Wehde, 1994b:2).

SDF uses a control chart with a mean forecast and regions surrounding the mean. Those regions are known as filters. Figure 2-3 illustrates the control chart.

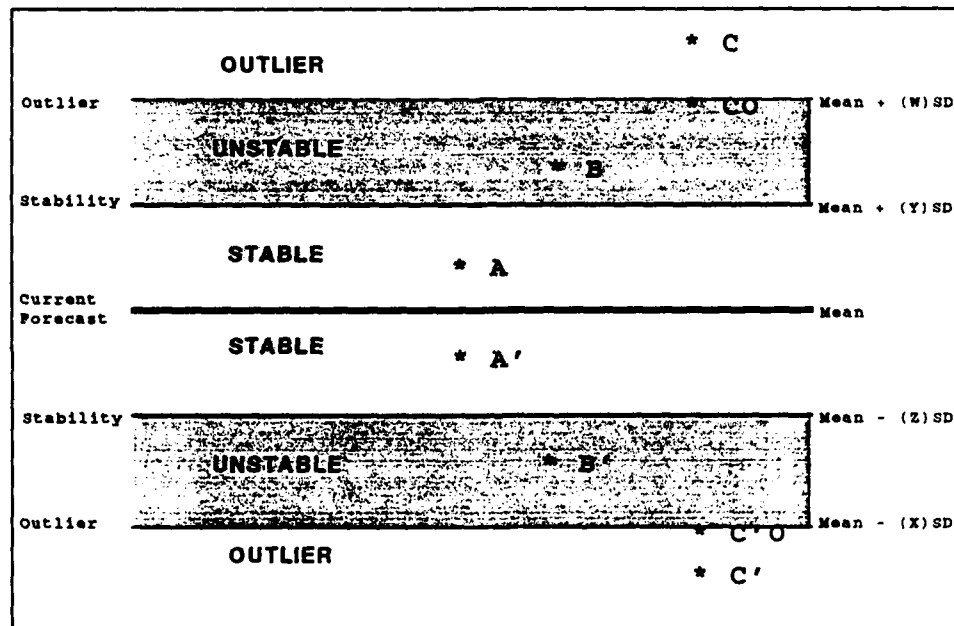


Figure 2-3. SDF Statistical Control Chart - Filters Test

The three regions on the control chart are the stability, instability and outlier regions (Wehde, 1994b:3). The region into which a given demand observation falls determines if a decision is made about whether to reforecast demand at this point or to defer the decision pending the outcome of the four remaining statistical process control tests.

Stability Region. The mean on the control chart (figure 2-3) represents the forecast currently being used to forecast demand. The stability region is the

area around the mean. Its boundaries are defined by $(\text{Mean} + Y \cdot \text{SD})$ and $(\text{Mean} - Z \cdot \text{SD})$ where Y and Z are constant values defined by the item manager and SD is the standard deviation of the forecasted mean (Urban, 1994a:Ch 3, 15; Wehde, 1994b:3). The default value of Y and Z is one (Maitland, 1994a). When the most recent observation falls within the stability region, the current forecast is considered to be a good predictor of the future. The observation passes the Filters test and continues on to the Bias tests (Wehde, 1994b:3). Points A and A' on the control chart are examples of observations falling into the stable region.

Instability Region. The instability region is the region above and below the stability region (Wehde, 1994b:3). The instability region is defined as the region between $(\text{Mean} + Y \cdot \text{SD})$ and $(\text{Mean} + W \cdot \text{SD})$ and the region between $(\text{Mean} - Z \cdot \text{SD})$ and $(\text{Mean} - X \cdot \text{SD})$. Y , W , Z and X are constant values that must be set and SD is the standard deviation of the mean (Urban, 1994a:Ch 3, 15; Wehde, 1994b:3). The default value of X and W is three (Maitland, 1994a). A demand observation falling into the instability region is a signal that the current forecast is unstable with the most recent observation. Therefore, the current forecast is no longer representative of the demand pattern and demand has to be reforecasted using the forecasting technique selected by the item manager (Wehde, 1994b:3). Points B and B' on the control chart in figure 2-3 are examples of observations falling into the instability region.

Outlier Region. The outlier region consists of the region above and below the instability region. The outlier region is defined as the region above the value of $(\text{Mean} + W \cdot \text{SD})$ and the region below the value of $(\text{Mean} - X \cdot \text{SD})$ (Urban, 1994a:Ch 3, 15; Wehde, 1994b:3). When an observation falls within the outlier region, it is considered as an outlier and two options are possible (Maitland, 1994a). One of the two options can be set by the user as a parameter.

In the first option, when a single consecutive observation falls in the outlier region, it is marked high (above mean) or low (below mean). The outlier is dampened or reduced/increased to a value equal to the unstable outer limit. The forecast is updated using the dampened value. Points C and C' on the control chart (figure 2-3) are examples of observations falling into the outlier region. They are dampened to CO and C'O respectively.

In the second option, the first occurrence of an outlier is ignored. When a single consecutive demand observation falls in the outlier region, it is considered to be an error or the result of a series of events or conditions that do not occur with a high probability. They are not likely to occur again in the future at any time soon. Therefore the observation is ignored. The forecast is not updated and the observation will go through the Bias tests.

SDF considers two consecutive demand observations falling in the same outlier region to be strong evidence that the true demand has changed in a significant way. Therefore demand is reforecast when two consecutive outliers on the same side of the current forecast are observed (Wehde, 1994b:5). However, the standard forecasting technique selected by the item manager is not used in this instant. A four quarter moving average step forecast is computed to give more weight to the two outliers. If a set dollar value is met, the item demand information is then downloaded to the PC exception tool for the item manager to review (Maitland, 1994b).

Figure 2-4 illustrates the Demand Filters test. Instability is shown in Zone-1, outliers are found in Zone-2, and stability is displayed in Zone-3. The scenario starts in Zone-1 with a current quantity forecast of 9. Demand observations 11, 8, 10, 7 and 11 fall in the stable region. Demand observations 2 and 16 fall within the outlier region and are ignored because they are not consecutive. Because demand observation 13 falls in the instability region, a new forecast is computed. The new current forecast (Zone-2) takes

the value of $10 = (11+8+10+7+11+13) / 6$. In Zone-2, because of two consecutive outliers, a new forecast is computed using a four quarter moving average. The new current forecast (Zone-3) takes the value of $7 = (10+12+3+3) / 4$.

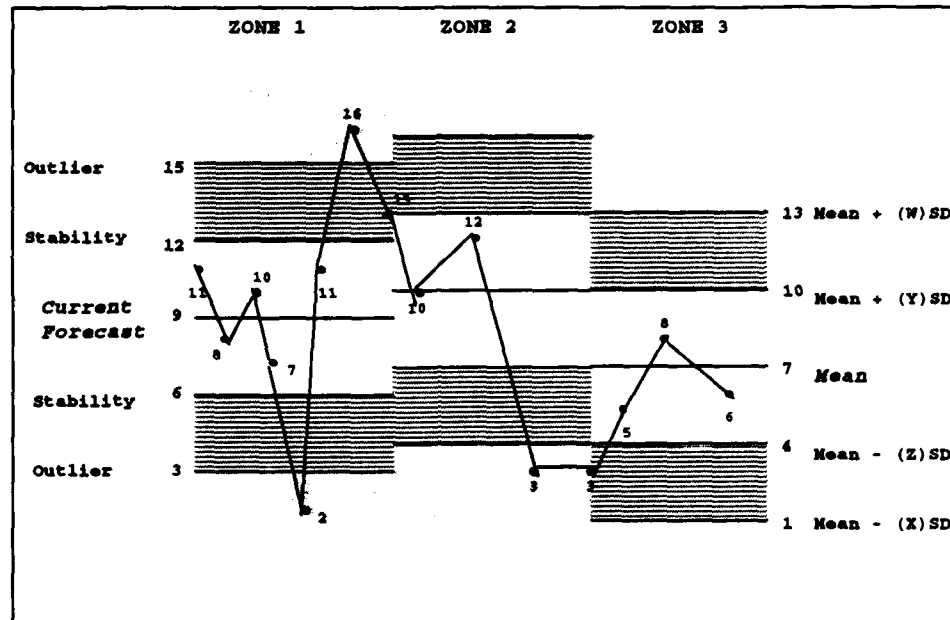


Figure 2-4. Demand Filters Test (Adapted from Wehde, 1994b:5)

Trending Test. The Demand Filters Test is followed by the Trending Test. Observations of demand are tested to determine whether there is a significant trend in the system demand pattern (Urban, 1994a:Ch 3, 16). Although demand displays stability, a trending component in the observations could exist. Figure 2-5 illustrates this situation.

SDF uses the Kendall "S" statistic to make statistical inferences about the presence of a trend. To determine if a trend exists, SDF will compute Kendall "S" statistics for observations falling in either the stability region or the instability region (Urban, 1994a:Ch 3, 16; Urban, 1993c:8-11). Kendall Trend Detection is used to determine the likelihood or probability that a trend exists in a series of demand observations observed during some time period. The Kendall "S" statistics is by design robust, invariant procedures, which together, provide an integrated capability to make realistic and statistically sound

inferences about the presence of a trend and its expected impact or affect on the average or forecast demand (Urban, 1994a:Ch 3, 16; Urban, 1993c:8-11).

If it detects a trend, SDF will use the Sen Median forecast technique or a four quarter moving average technique to adjust the forecast to the demand pattern and then return to the original forecasting technique. The adjustment procedure is known as a step increase or step decrease forecast.

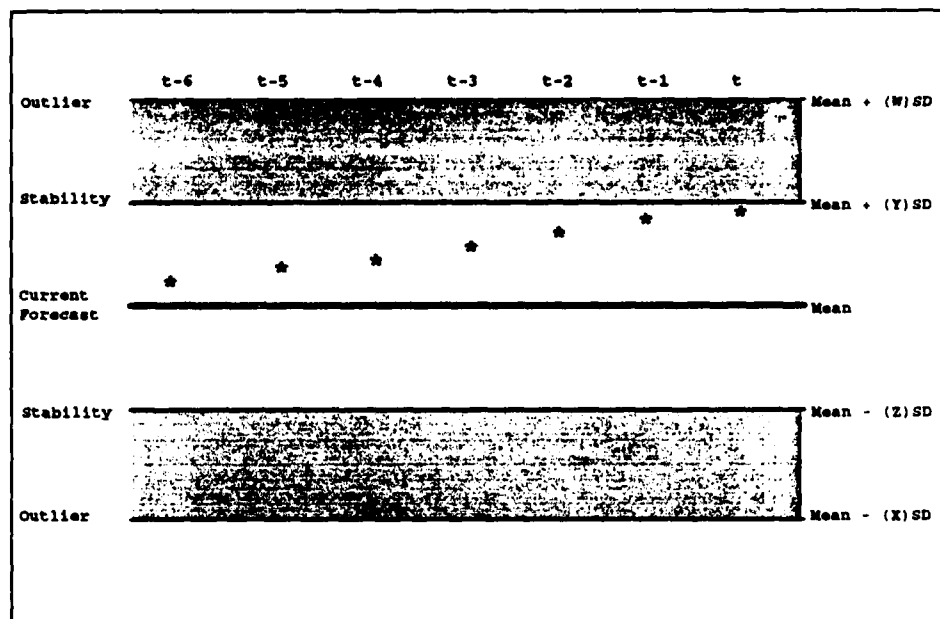


Figure 2-5. Demand Trending

Bias Tests. For stable non-trending items, the forecasting system performs a series of tests to ensure that the observations have not drifted away from the mean forecast. The Bias tests are the Runs Test, the Cumulative Quantity Difference Test or the Cumulative Percentage Difference Test, and the Student Confidence Interval Test (Urban, 1994a: Ch 3, 16). These tests are conducted only if the Filters test has categorized the current forecast as being stable. It is not conducted if the Filters test caused the system to reforecast a new forecast (Wehde, 1994b:6).

The bias tests are conducted because it is possible for demand observations to be stable but still suggest that demand should be reforecast (Wehde, 1994b:6). For example, a series of stable demand observations that fall consecutively above the mean suggests that the forecast is too low. SDF's Bias tests are conducted using an average quarterly demand which is computed over a one or two year period (Wehde, 1994b:6).

Runs Test. If the current forecast is a good estimate of future demand, then it is expected that future demand observations will be uniformly distributed above and below the current forecast serving as the mean. In the Runs Test, for every time period, SDF compares the average quarterly demand (DemCur) to the current demand forecast (DemFor) (Wehde, 1994b:6). If demand observations are consecutively recurring above or below the mean, then the Runs Test is failed. If the Runs Test fails, demand is reforecast (Wehde, 1994b:4).

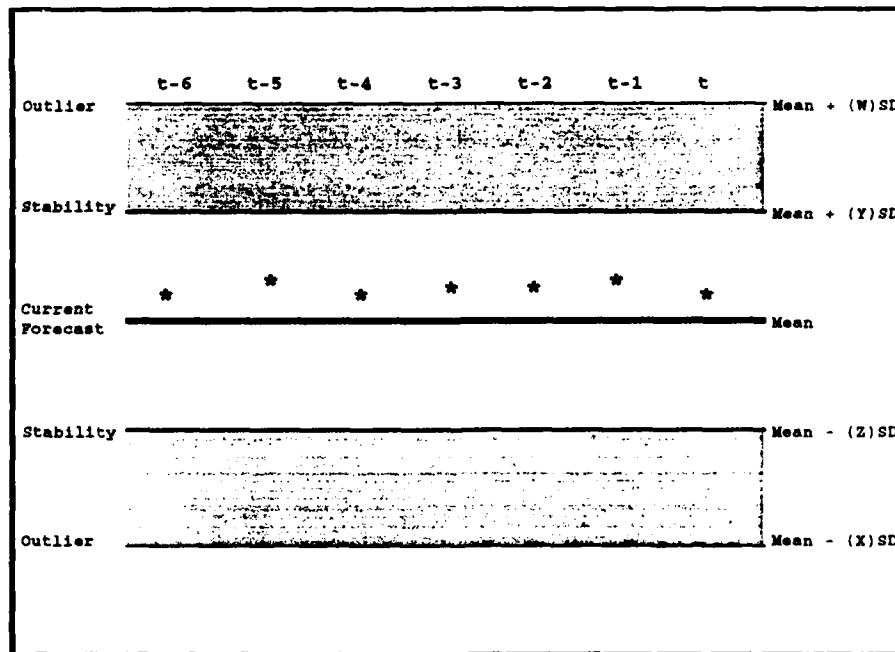


Figure 2-6. Runs Test

Figure 2-6 illustrates such a situation. The length of a run (X) is compared to a parameter value set by the item manager. It is reset to zero when:

1. DemCur equals DemFor.
2. DemCur changes from being less than DemFor to being greater or vice versa.
3. Demand is reforecast.

In the Runs Test , items are also classified as low, medium and high dollar value items. The constant value parameter to which the length of run is compared is set according to the dollar value of the item. A high dollar value item may have a length of run set to four [4] and a low dollar value item may have a length of run set to ten [10]. Figure 2-6 illustrates a situation where the length of run is seven [7].

Cumulative Error Tests. There are two cumulative error tests: the Cumulative Quantity Difference Test and the Cumulative Percentage Difference Test. The Cumulative Quantity Difference Test is used for low demand items. This test is conducted only if the demand originally fell in the Stability Region and then passed the Runs Test . During this test, SDF takes the absolute difference between the current observation and the current forecast. A running total of the errors is kept. When the cumulative sum of the forecast error grows to be larger than some set parameter, then demand is reforecasted (Urban, 1994a:Ch I, 1; Wehde, 1994b:8). The Cumulative Quantity Difference equation is shown below.

$$\text{Cumulative Quantity Difference} = \sum | \text{Obs} (t) - \text{For} (t) | \quad (7)$$

where

Obs(t) = Observation at period t

For (t) = Forecast for period t

The Cumulative Percentage Difference Test is the same as the Cumulative Quantity Difference Test but it is used for high demand items. This test is conducted only if the demand observation originally fell in the Stability Region and then passed the Runs Test . With this test, SDF takes the absolute percentage difference between the current

observation and the current forecast. A running total of the percentage errors is kept. When the cumulative sum of the forecast error grows to be larger than some set parameter, then demand is reforecast (Urban, 1994a:App I, 2; Wehde, 1994b:8). The Cumulative Percentage Difference is shown below.

$$\text{Cumulative Percentage Difference} = \sum \{ | \text{Obs} (t) - \text{For} (t) | / \text{For}(t) \} \quad (8)$$

where

Obs(t) = Observation at period t

For (t) = Forecast for period t

Student Confidence Interval Test. A confidence interval is computed using a Student-t test. The mean current forecast is used to compute the confidence interval. If the average quarterly demand is outside of the confidence interval, the test fails and a new demand forecast is computed (Urban, 1994a:App I, 2).

Module 4: Quantity Forecasts. In this module, SDF performs quantity forecasts for different variables. These variables will help to compute the net procurement lead-time demand and the net demand during repair turn-around-time (Urban, 1993c:18; Urban, 1994b). These variables are:

1. Demand Forecast
2. Program Related Values
3. System Forecasts
4. System Requisition Average
5. Regenerations Forecast
6. Activity Demands and Requisition Average Forecast
7. Fixed Allowance Demand, Repair Completion, and BCM Forecasting (System)

Module 5: Procurement Problem Variable Forecast. The purpose of this module is to aggregate all variables computed in the previous modules to compute the net demand

during lead-time and the net demand during repair turn around time (Urban, 1993c:20; Urban, 1994b).

Chapter Summary

This literature review presented descriptions of the data pattern components, the current Air Force Recoverable Consumption Item Requirements System (D041) forecasting approach, the future Air Force Requirements Data Bank System forecasting approach and the Navy's Statistical Demand Forecasting System.

Data can be decomposed into components known as trend, cycle, seasonality, and randomness. The current Air Force forecasting approach uses an Eight Quarter Moving Average as a forecasting technique to predict future spare part requirements for weapon systems. The future Air Force forecasting approach contains three different forecasting techniques: Four to Eight Quarter Moving Average technique, Double Exponential Smoothing technique, and Predictive Logistics known as the PRELOG technique.

The Statistical Demand Forecasting System was developed by the Navy Aviation Supply Office to forecast its recoverable and consumable requirements for program and non-program related items. The SDF system contains statistical process control charts to detect demand instability and is designed to improve forecast accuracy and to reduce level instability. SDF also contains several forecasting techniques which include Moving Average, Exponential Smoothing, Linear Regression, Dampened, Non-Parametric, and Composite Forecasting techniques. The next chapter discusses how the actual research was conducted. It also describes how the data were obtained and analyzed.

III. Methodology

Introduction

The purpose of this study is to provide a comparison of the performance and accuracy of the Navy forecasting system (SDF) relative to the Air Force forecasting system (RDB) in an Air Force environment.

This chapter describes the type of research design, the research questions, the null hypotheses, and the instruments pursued to do the comparison analysis. The analytical approach, population size, sample size, data collection, and limitations used to perform the study are also discussed. Finally, this chapter highlights the actual research plan.

Type of Research Design

A research design represents the blueprint for the collection, measurement, and analysis of data. It is a structured outline conceived to obtain answers to research questions (Emory and Cooper, 1991:138). The research design may be viewed from different perspectives such as the method of data collection, the design of the research, the purpose of the research, and the topical scope (Emory and Cooper, 1991:139).

The method of data collection depends on whether the research is observational or survey. An observational research refers to the study of activities of a subject or the nature of some material without interacting with the subject or material. The subject or the material is being observed (Emory and Cooper, 1991:140). A survey research refers to the study of responses obtained from questions asked to the subject (Emory and Cooper, 1991:140). This research falls into the category of an observational research. The two forecasting systems are being observed under different scenarios to determine which system is most appropriate to forecast Air Force demand.

The design of the research depends on whether the researcher has control over the variables being studied. The two types of research designs are the experimental design and the ex post facto design. Experimental design is appropriate if the researcher has the ability to manipulate the variables to determine whether the variables affect other variables (Emory and Cooper,1991:140). In the ex post facto design, the investigator has no control over the variables. It is difficult to manipulate the variables because the researcher can only report what happened (Emory and Cooper,1991:140). This thesis research deals with an ex post facto research design. The research design measures and compares the forecasts of the forecasting systems.

The purpose of the study depends on whether the research is descriptive or causal. The purpose of a descriptive study is to answer the questions: what, when, where or how much (Emory and Cooper,1991:141). It deals with a question or hypothesis being stipulated concerning the size, form, distribution or existence of a variable (Emory and Cooper,1991:148). A causal study deals with learning why or how one variable affects another. It tries to explain the relationship that can exist among variables (Emory and Cooper,1991:141). This research is a descriptive study and it answers the following question: What forecasting approach is most accurate to forecast Air Force demand?

The topical scope of the research is defined as the breadth and depth of the study (Emory and Cooper,1991:139). The research may represent a case study or a statistical study. A case study refers to the analysis of a limited number of events or conditions and their interrelations (Emory and Cooper,1991:142). A statistical study deals with capturing the characteristics of a population by making inferences from a sample of items. In general the hypotheses tested are quantitative (Emory and Cooper,1991:142). This thesis research is a statistical study. It tries to determine which forecasting approach is best suited to forecast Air Force recoverable items demands.

The design of this thesis research is described as follow: the method of data collection is observational; the design of the research is ex post facto; the purpose of this study is descriptive; and the topical scope of the study is statistical. The implementation of the research design is described at a later point in this chapter.

Research Questions

To evaluate the forecasting systems and to address forecasting accuracy and robustness, the following research questions are developed:

1. How does each forecasting system perform with different time series components?
2. How accurate are the forecasts computed by each forecasting technique subject to actual Air Force demand data?
3. What effects do the forecasts, computed by each forecasting approach, have on aircraft availability?

Research Question I. The first research question is: How does each forecasting system performs with different data pattern components? The purpose of this research question is to determine how well the forecasting systems react to different times series components. Times series components can be encountered in the demand data and it is important to understand how well the forecasting systems will respond to them. To answer the research question, the following investigative questions are developed:

1. What is the difference between the RDB average forecasting error and the SDF average forecasting error when a trending component is present in the data?
2. What is the difference between the RDB average forecasting error and the SDF average forecasting error when a cyclic component is present in the data?
3. What is the difference between the RDB average forecasting error and the SDF average forecasting error when a seasonal component is present in the data?

4. What is the difference between the RDB average forecasting error and the SDF average forecasting error when a random component is present in the data?
5. What is the difference between the RDB average forecasting error and the SDF average forecasting error when an outlier/spike component is present in the data?

Research Question II. The second research question is: How accurate are the forecasts computed by each forecasting technique subject to actual Air Force demand data? The main purpose of this approach is to verify and evaluate how well each forecasting approach performs when subject to real world data. To answer the research question, the following investigative questions are developed:

1. What are the mean, variance and standard error of the forecasting errors?
2. Are the forecasts responsive to actual observations?
3. What is the difference between the RDB average forecasting error and the SDF average forecasting error?

Research Question III. The third research question is: What effects do the forecasts, computed by each forecasting approach, have on aircraft availability? The main purpose of this approach is to verify and evaluate how each forecasting approach affects the aircraft availability achieved.

1. What is the difference between the aircraft availability achieved with actual demand rates and the aircraft availability achieved with the RDB forecasted values?
2. What is the difference between the aircraft availability achieved with actual demand rates and the aircraft availability goals achieved with the SDF forecasted values?

Research Hypotheses

To answer the research questions, null hypotheses were constructed to make inferences about the forecasting systems. This research hypothesizes that the the Air

Force Requirements Data Bank system's forecasts are as accurate as the Navy Statistical Demand Forecasting system's forecasts.

To answer the first research question, a hypothesis is developed for each time series components. Considering each data pattern component, the null hypothesis to be tested is that the RDB forecasting error mean (μ_1) is equal to the SDF forecasting error mean (μ_2) at the 90% confidence level.

$$H_0: \mu_1 = \mu_2$$

$$H_a: \mu_1 \neq \mu_2$$

The test is a two-tailed test and tries to determine whether there is a significant difference between the forecasting errors generated by the RDB system and the SDF system. The 90% confidence level was selected because if there is no significant difference at 90%, there won't be a significant difference at 95% either.

To answer the second research question, the null hypothesis to be tested is that the RDB forecasting error mean (μ_1) is equal to the SDF forecasting mean (μ_2) at the 90% confidence level.

$$H_0: \mu_1 = \mu_2$$

$$H_a: \mu_1 \neq \mu_2$$

The test is a two-tailed test and tries to determine whether there is a significant difference between the forecasting errors generated by the RDB system and the SDF system. The 90% confidence level was selected because if there is no significant difference at 90%, there won't be a significant difference at 95% either.

To answer the third research question, the evaluation of aircraft availability, the null hypothesis to be tested is that the average aircraft availability (μ_1) achieved with the RDB forecasting approach is equal to the average aircraft availability (μ_2) achieved with the SDF forecasting approach at the 90% confidence level.

$$H_0: \mu_1 = \mu_2$$

$$H_a: \mu_1 \neq \mu_2$$

The test is a two-tailed test and tries to determine whether there is a significant difference between the forecasting errors generated by the RDB system and the SDF system. The 90% confidence level was selected because if there is no significant difference at 90%, there won't be a significant difference at 95% either.

Since the analysis involved two populations, a Paired Difference Test is used to test each of the null hypotheses mentioned above.

Instruments

The forecasts for the Air Force RDB system are computed using a simulation model of the RDB Forecasting approach. The simulation program uses FORTRAN coding and is shown in Appendix C. The forecasts associated with the SDF system are computed using the actual Navy's SDF System.

To compare the SDF forecasting performance to the RDB forecasting performance, three instruments are used: forecasting measurement errors, Paired Difference Test, and Aircraft Sustainability Model.

Forecasting Error Measurements. The purpose of this instrument is to compare the forecasts to the actual observations. The accuracy of forecasting methods is frequently judged by comparing the original observations to the forecast of these observations. Several methods have been devised to summarize the errors generated by a particular forecasting technique (Hanke, 1992:112). Most of these measures involve averaging some function of the difference between an actual observation and its forecast value. These differences between observed values and forecast values are often referred to as residuals (Hanke, 1992:113).

Four methods used to evaluate the forecasting errors associated with each forecasting technique are: Mean Absolute Deviation (MAD), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Percentage Error (MPE).

Mean Absolute Deviation. The Mean Absolute Deviation (MAD) measures forecast accuracy by averaging the magnitudes of the forecast error. MAD is most useful when the analyst wants to measure forecast error in the same units as the original series (Hanke, 1992:113). The MAD formula is presented in Equation 9 (Hanke, 1992:114).

$$MAD = \frac{\sum |Y_t - F_t|}{n} \quad (9)$$

where

Y_t = Actual value at time t

F_t = Forecast at time t

n = number of periods

Mean Square Error. The Mean Square Error (MSE) is an alternative method for evaluating a forecasting technique. Each residual is squared. This approach provides a penalty for large forecasting errors. Equation 10 demonstrates the Mean Square Error formula (Hanke, 1992:114).

$$MSE = \frac{\sum (Y_t - F_t)^2}{n} \quad (10)$$

where

Y_t = Actual value at time t

F_t = Forecast at time t

n = number of periods

Mean Absolute Percentage Error. Sometimes it is more useful to compute the forecasting errors in terms of percentages rather than amounts (Hanke, 1992:114).

The Mean Absolute Percentage Error (MAPE) provides an indication of how large the forecast errors are in comparison to the actual values. In the MAPE equation, the residual

is divided by the actual demand to obtain a percentage. Sometimes, for different items, the true quarterly demand is zero. If the true demand is zero, then the MAPE becomes undefined. For this reason, if the true demand is zero, the demand observation should be ignored (Sherbrooke, 1987:5). Equation 11 demonstrates the Mean Absolute Percentage Error formula (Hanke, 1992:114).

$$MAPE = \frac{\sum \{|Y_t - F_t| / P_t\}}{n} \quad (11)$$

where

Y_t = Actual value at time t

F_t = Forecast at time t

$P_t = Y_t$

n = number of periods

Mean Percentage Error. Sometimes it is necessary to determine whether a forecasting method is biased (consistently forecasting low or high). The Mean Percentage Error (MPE) is used in this case (Hanke, 1992:114). For the purpose of this research, the MPE equation was slightly modified. In the MPE equation, the residual is divided by the actual demand to obtain a percentage. If the true demand is zero, then the MPE becomes undefined. For this reason, if the true demand is zero, the demand observation should be ignored (Sherbrooke, 1987:5). Equation 12 demonstrates the Mean Percentage Error formula (Hanke, 1992:114).

$$MPE = \frac{\sum \{(Y_t - F_t) / P_t\}}{n} \quad (12)$$

where

Y_t = Actual value at time t

F_t = Forecast at time t

$P_t = Y_t$

n = number of periods

Student Paired Difference Test. The purpose of the Student Paired Difference Test is to compare the difference between two population means (McClave and Benson, 1991:421). The assumptions of the test are (McClave and Benson, 1991:424):

1. The relative frequency distribution of the population of differences is normal.
2. The differences are randomly selected from the population of differences.

Table 3-1 illustrates the Paired Difference Test (McClave and Benson, 1991:424).

Aircraft Sustainability Model. Aircraft availability is defined as the percentage of aircraft which are available, or fully mission capable. If an aircraft is not missing a reparable component due to repair, it is considered available (O'Malley, 1983:Ch1, 1). Inventory stockage models, used to optimize the aircraft availability, are: METRIC, Mod-METRIC, Aircraft Availability Model, Vari-METRIC, Dyna-METRIC and Aircraft Sustainability Model (Pohlen, 1994:4-5).

Table 3-1. Paired Difference Test

Two Tailed Test	
Hypotheses	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$
Test Statistic	$t = (\mu_D - D_0) / (S_D - \text{Square Root}(n_D))$ where μ_D = Sample mean of differences S_D = Sample standard deviation of differences n_D = Number of differences
Rejection Region	$t < -t_{\alpha/2}$ or $t > t_{\alpha/2}$ where $t_{\alpha/2}$ has $(n_D - 1)$ df

For the purpose of this study, the Aircraft Sustainability Model was selected to measure the aircraft availability achieved. The reason for selecting this model versus the

other models is because of its simplicity. This model is easier to use than the others and can run quickly on a micro-computer (Klinger, 1994:48).

The Aircraft Sustainability Model is a "two-indenture, two-echelon requirements model for a single weapon system." (Slay and King, 1987:Ch 2, 2). Given the stock levels for the parts being modeled over a period of time, it projects aircraft availability rates. The user can also specify the desired aircraft availability goals and funding constraint (Klinger, 1994:42-43). To compute the aircraft availability rate, the expected backorders must first be calculated. Backorders are defined as unfilled demands. They are the number of holes in an aircraft, or the number of missing items on an aircraft (Klinger, 1994:13). Using a pure Poisson distribution, the expected backorders are computed as follows (Sherbrooke, 1992:25):

$$EBO(S_i) = \sum_{x=S+1}^{\infty} (x-S) p(x|\lambda T) \quad (13)$$

where

S = stock level

$x = S+1$ to ∞

λT = mean number of units in resupply

Using the expected backorders, the aircraft availability is then computed as follows (Sherbrooke, 1992:25):

$$A = 100 \prod_{i=1}^I \{ 1 - EBO_i(s_i)/(NZ_i) \}^{Z_i} \quad (14)$$

where

N = the number of aircraft

Z_i = quantity per application

$EBO_i(s_i)$ = expected backorders

The research assumptions used with the Aircraft Sustainability model are as follows:

1. An aircraft is down upon failure of an LRU for which no spare is available (Klinger, 1994:43).
2. If a part cannot be repaired at the base, it is shipped to the depot for possible repair (Klinger, 1994:43).
3. A replenishment from the depot is requested immediately. Both the base and the depot operate under (s-1, s) inventory policy (Klinger, 1994:43).
4. All failures occur at the base (Klinger, 1994:43).
5. For all items, the quantity per aircraft is equal to one.
6. There are no SRUs.
7. All items belong to a fictitious weapon system.
8. If a part is condemned, a replenishment from an outside source of supply is requested (Slay and King, 1987:Ch 2, 2).

Analytical Approaches

To support the research design, and to answer the research questions cited in Chapter One, three analytical approaches are used to evaluate and compare the Air Force forecasting method (RDB) to the Navy forecasting method (SDF):

Approach One. The first approach measures the performance of the two forecasting systems, subject to the influence of different time series components, in terms of accuracy and stability. The main purpose of this approach is to verify and evaluate how well each forecasting approach reacts when subject to different time series components. A FORTRAN program was built to generate each type of data pattern. The code for the FORTRAN program is contained in Appendix A. Forecasting measurement errors are used to measure the stability and accuracy of the forecasts. Separate scenarios are

constructed for each of the time series components: trend, cycle, seasonal, random and outlier. Under each scenario, forecasting measurement errors (MAD, MSE, MAPE and MPE) are computed to measure the performance of each forecasting system (SDF versus RDB). A Paired Difference Test at the 90% confidence level is conducted for each scenario and for each type of forecasting error. Table 3-2 illustrates the design of each scenario. Considering each data pattern component, the null hypothesis to be tested is that the RDB forecasting error mean (μ_1) is equal to the SDF forecasting mean (μ_2) at the 90% confidence level.

$H_0: \mu_1 = \mu_2$: RDB forecasting error mean = SDF forecasting error mean

$H_a: \mu_1 \neq \mu_2$: RDB forecasting error mean \neq SDF forecasting error mean

Table 3-2. Design of Analytical Approach One

Forecasting Error	Trend Component	Seasonal Component	Cyclical Component	Random Component	Outlier/Spike Component
MAD	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test
MSE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test
MAPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test
MPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test
μ_1 :	Mean forecasting error for RDB				
μ_2 :	Mean forecasting error for SDF				

For each test where a significant difference exists between the two forecasting error means, a One-Tailed Paired Difference Test at the 95% confidence level is conducted. The null hypothesis to be tested is that the RDB forecasting error mean (μ_1) is equal to the SDF forecasting mean (μ_2) at the 95% confidence level.

Ho: $\mu_1 = \mu_2$: RDB forecasting error mean = SDF forecasting error mean

Ha: $\mu_1 > \mu_2$: RDB forecasting error mean > SDF forecasting error mean, or

Ha: $\mu_1 < \mu_2$: RDB forecasting error mean < SDF forecasting error mean

Approach Two. Subject to real Air Force data, the second approach measures the performance of the forecasting techniques in terms of accuracy and stability. The main purpose of this approach is to verify and evaluate how well each forecasting approach performs when subject to real world data. Four years of historical data from the Air Force D041 system was used to feed both forecasting systems. The first three years were used to make forecasts for the fourth year. The forecasts were then compared to the actual demands occurring in the fourth year. This approach measured the performance of the forecasting systems in terms of accuracy and stability subject to the presence of real Air Force data. Forecasting errors (MAD, MSE, MAPE and MPE) were computed to measure the performance of each forecasting approach (SDF versus RDB). A Paired Difference Test at the 90% confidence level is conducted for each forecasting error. Table 3-3 illustrates the design of Approach Two. The null hypothesis to be tested is that the RDB forecasting error mean (μ_1) is equal to the SDF forecasting mean (μ_2) at the 90% confidence level.

Ho: $\mu_1 = \mu_2$: RDB forecasting error mean = SDF forecasting error mean

Ha: $\mu_1 \neq \mu_2$: RDB forecasting error mean \neq SDF forecasting error mean

Table 3-3. Design of Analytical Approach Two

Forecasting Measurement Error	Air Force Data
MAD	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test
MSE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test
MAPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test
MPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$ Paired Difference Test
μ_1 :	Mean forecasting error for RDB
μ_2 :	Mean forecasting error for SDF

For each test where a significant difference exists between the two forecasting error means, a One-Tailed Paired Difference Test at the 95% confidence level is conducted. The null hypothesis to be tested is that the RDB forecasting error mean (μ_1) is equal to the SDF forecasting mean (μ_2) at the 95% confidence level.

$H_0: \mu_1 = \mu_2$: RDB forecasting error mean = SDF forecasting error mean

$H_a: \mu_1 > \mu_2$: RDB forecasting error mean > SDF forecasting error mean, or

$H_a: \mu_1 < \mu_2$: RDB forecasting error mean < SDF forecasting error mean

Approach Three. The main purpose of this approach is to verify and evaluate how each forecasting approach affects the aircraft availability achieved. Accuracy in terms of demand is important. However accuracy in terms of aircraft availability is even more important because the aircraft availability is the Air Force primary measure of system level performance (Sherbrooke, 1992:27). Approach three has five stages:

1. Using the RDB forecasted demand rates and setting a specific funding level, use the Aircraft Sustainability Model to compute stock levels for all items.

2. Using the actual demand rates and the stock levels determined by RDB in stage one, use the Aircraft Sustainability Model to compute the aircraft availability percentage. The model is constrained by a specific funding level. The funding constraint is \$80,000 for times series components and \$700,000 for the real Air Force data. These funding constraints were selected to give a fair aircraft availability for the mixed of items found in the sample data.

3. Using the SDF forecasted demand rates and setting a specific funding level, use the Aircraft Sustainability Model to compute stock levels for all items.

4. Using the actual demand rates and the stock levels determined by SDF in stage three, use the Aircraft Sustainability Model to compute the aircraft availability percentage. The model is constrained by a specific funding level. The funding constraint is \$80,000 for times series components and \$700,000 for the real Air Force data.

5. Compare the aircraft availability achieved in stages two and four with a Paired Difference Test. The null hypothesis to be tested is that the average aircraft availability (μ_1) achieved with the RDB forecasting approach is equal to the average aircraft availability (μ_2) achieved with the SDF forecasting approach at the 90% confidence level.

$H_0: \mu_1 = \mu_2$: RDB average aircraft availability = SDF average aircraft availability

$H_a: \mu_1 \neq \mu_2$: RDB average aircraft availability \neq SDF average aircraft availability

The average aircraft availability achieved is computed over a period of four quarters, using the Aircraft Sustainability Model. This approach is repeated for the time series components' scenarios and the real Air Force data scenario. Table 3-4 illustrates the approach.

Table 3-4. Design of Analytical Approach Three

Stage	Trend	Seasonal	Cyclical	Random	Outlier/ Spike	Air Force Data
I. Compute RDB Stock Levels	Stock Levels RDB	Stock Levels RDB	Stock Levels RDB	Stock Levels RDB	Stock Levels RDB	Stock Levels RDB
II. Compute Aircraft Availability with RDB Stock Levels	Average Aircraft Availability (μ_1)	Average Aircraft Availability (μ_1)	Average Aircraft Availability (μ_1)	Average Aircraft Availability (μ_1)	Average Aircraft Availability (μ_1)	Average Aircraft Availability (μ_1)
III. Compute SDF Stock Levels	Stock Levels SDF	Stock Levels SDF	Stock Levels SDF	Stock Levels SDF	Stock Levels SDF	Stock Levels SDF
IV. Compute Aircraft Availability with SDF Stock Levels	Average Aircraft Availability (μ_2)	Average Aircraft Availability (μ_2)	Average Aircraft Availability (μ_2)	Average Aircraft Availability (μ_2)	Average Aircraft Availability (μ_2)	Average Aircraft Availability (μ_2)
V. Compare Aircraft Availability	Ho: $\mu_1 - \mu_2 = 0$ Ha: $\mu_1 - \mu_2 \neq 0$ Paired Difference Test	Ho: $\mu_1 - \mu_2 = 0$ Ha: $\mu_1 - \mu_2 \neq 0$ Paired Difference Test	Ho: $\mu_1 - \mu_2 = 0$ Ha: $\mu_1 - \mu_2 \neq 0$ Paired Difference Test	Ho: $\mu_1 - \mu_2 = 0$ Ha: $\mu_1 - \mu_2 \neq 0$ Paired Difference Test	Ho: $\mu_1 - \mu_2 = 0$ Ha: $\mu_1 - \mu_2 \neq 0$ Paired Difference Test	Ho: $\mu_1 - \mu_2 = 0$ Ha: $\mu_1 - \mu_2 \neq 0$ Paired Difference Test

For each test where a significant difference exists between the two average aircraft availability means, a One-Tailed Paired Difference Test at the 90% confidence level is conducted. The null hypothesis to be tested is that the RDB average aircraft availability (μ_1) is equal to the SDF average aircraft availability (μ_2) at the 95% confidence level.

Ho: $\mu_1 = \mu_2$: RDB average aircraft availability = SDF average aircraft availability

Ha: $\mu_1 \neq \mu_2$: RDB average aircraft availability > SDF average aircraft availability

or Ha: $\mu_1 < \mu_2$: RDB average aircraft availability < SDF average aircraft availability

Population Size

This study is limited to the forecast of repairable items only. As discussed in Chapter One, the purpose of the Recoverable Item Process in the Requirements Data Bank System is to manage repairable spare parts (Gitman, 1994). Although RDB will

have the capability of managing consumable items in the future, the Air Force currently manages consumable items using the Economic Order Quantity Buy Budget Computation System (D062) (Gitman, 1994). Since a comparison is made to address Air Force concerns, this research limits its analysis only to the range of Air Force reparable spare parts. The population size of the reparable items in D041 is approximately 185,000 items (Lucas, 1993). However, about 40,000 of those reparable items are active (items that are used on a regular base) (Rexroad, 1993a).

Sample Size and Data Collection.

This discusses the computation of sample sizes for actual Air Force demand data and time series components demand data. Equation 15 demonstrates the formula used to compute the sample size necessary to estimate the mean to within a bound, with a 90% confidence level (McClave and Benson, 1991:320). Appendix B presents the Excel Spreadsheet that computes the sample sizes.

$$n = [(Z_{\alpha/2})^2 \sigma^2] / B^2 \quad (15)$$

where

n = sample size

$Z_{\alpha/2}$ = Z-value at 90% level confidence = 1.96

σ^2 = Variance of the beginning sample size

B = The bound within the mean

Sample Size for Air Force Data. The data sample consists of 245 reparable items. Specific items and common items are included in the analysis. The secondary demand data were gathered from the Recoverable Consumption Item Requirements (D041) System. The demand data cover four years of historical data and are either specific or common to different weapon systems. The demand data include information

such as Base RTS (Reparable This Station), Base NRTS (Not Reparable This Station), Base Condemnations and Flying Programs.

Variance-to-Mean Ratio. The presence of variability in demand data makes it impossible to forecast future demands without error (McClave and Benson, 1991:810). The VTMR (variance-to-mean ratio) is a measure of the variability, hence the error source of the demand process (Crawford, 1988:3). Since demand variability affects forecasting outputs more than demand mean does, the use of the variance-to-mean ratio becomes an important factor in the computation of a sample size for demand data (Maitland, 1993a). To ensure that the sample size is really representative of the population size, it is essential that the variance-to-mean ratio distribution of the sample size resembles the variance-to-mean ratio distribution of the population size (Abell, 1994). To illustrate the VTMR distribution of the population size, the VTMR was computed across 6500 items of the population size. The mean VTMR was 2.3626 and the median was 1.3267 across the 6500 items. These results were validated by John B. Abell who stipulated that worldwide demands generally have a VTMR approaching 1.5 (Abell, 1994). Figure 3-1 illustrates the VTMR distribution of the population size.

To select an appropriate sample size, a beginning or starting sample size of 600 items is first selected from the population size to compute the mean, variance, and variance-to-mean ratio for each item. The mean and variance are computed by weighting the demand by the number of flying hours. The variance-to-mean ratio is then computed using equation 16 (Crawford, 1988:3).

$$\text{VTMR} = \frac{\text{(the variance of the number of demands per unit time)}}{\text{(the expected number of demands per unit time)}} \quad (16)$$

The overall VTMR mean and overall VTMR standard deviation of the beginning sample size are computed. Using the VTMR standard deviation with equation 15, the final Air Force sample size is computed within a bound, being the VTMR standard

deviation of the population size. Equation 15 demonstrates the formula used to compute the sample size (McClave and Benson, 1991:320). Appendix B presents the Excel Spreadsheet that computes the final sample size.

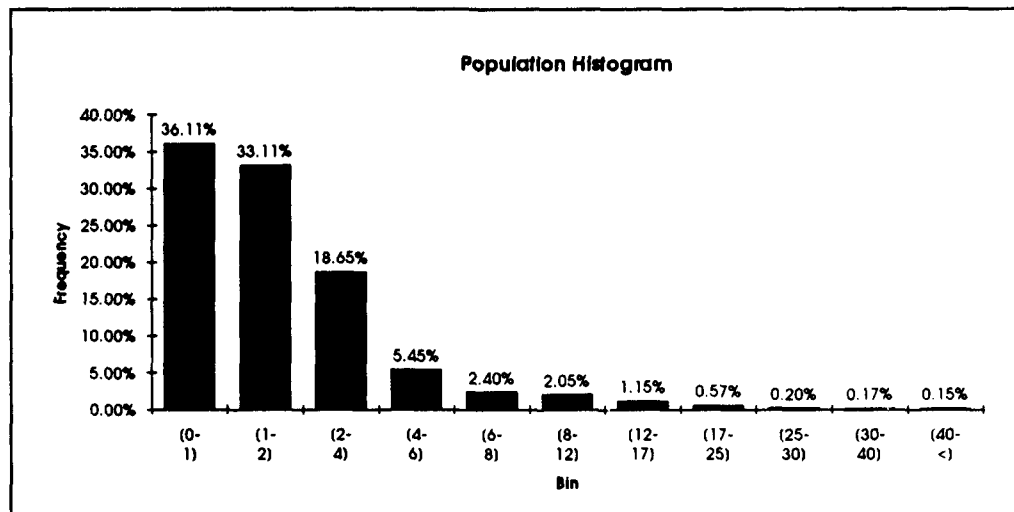


Figure 3-1. Variance-to-Mean Ratio of Recoverable Items Population Size

To illustrate the VTMR distribution, the VTMR was computed across the 245 items of the sample size. Figure 3-2 illustrates the VTMR distribution of the sample size.

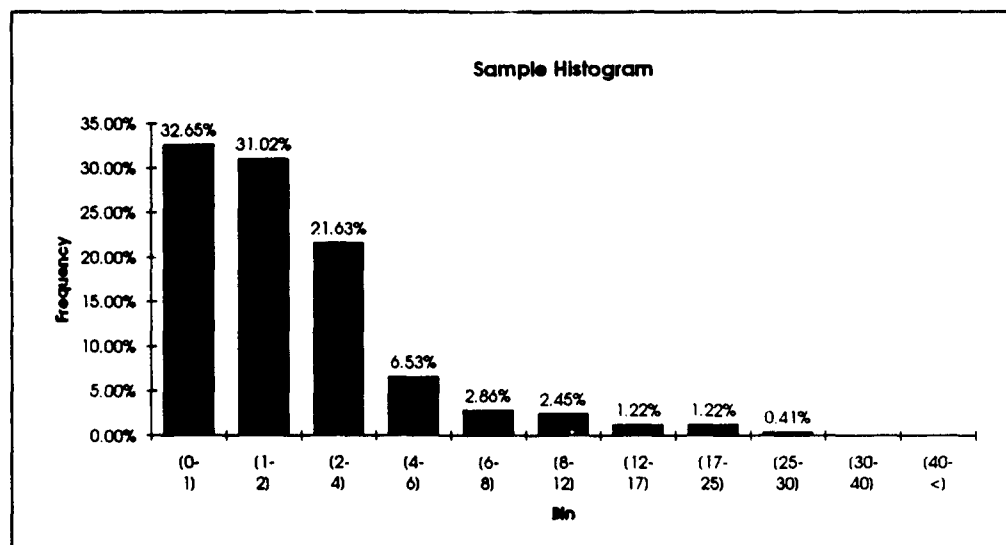


Figure 3-2. Variance-to-Mean Ratio of Recoverable Items Sample Size

Figure 3-1 demonstrates the VTMR of the recoverable items distribution of the population size and figure 3-2 illustrates the VTMR of the recoverable items sample size. Figure 3-1 and figure 3-2 confirm that the sample size is representative of the population size.

Sample Sizes for Time Series Components. The sample size for each time series component's scenario consists of forty items. The time series component data are generated by FORTRAN programs shown in Appendix A. To determine the sample size for each time series component (trend, cycle, seasonal, randomness, and outlier), data is first generated to create a beginning sample size. The mean VTMR and standard deviation VTMR of the beginning sample size are computed to determine the final sample size for each of the time series components. Each time series component sample size computed had a value lower than forty. However to be on the safe side, a sample size of forty was used. Appendix B presents the Excel Spreadsheet that computes the time series components sample sizes.

Implementation of the Research Design

To perform the comparison analysis between the Air Force Requirements Data Bank forecasting approach and the Navy Statistical Demand Forecasting approach, the implementation of the design is divided into three phases. The purpose of each phase is to answer the three research questions.

Phase One. The purpose of this phase is to answer the first research question: How does each forecasting system performs with different time series components? The following steps are used to answer the research question:

1. Build FORTRAN programs that generate time series components. Appendix A demonstrates the coding of the programs.

2. Compute a sample size for each time series component to do the analysis.

Appendix B demonstrates the calculation of each sample size.

3. Build a FORTRAN program that simulates the Requirements Data Bank forecasting approach. Appendix C demonstrates the coding of the program.
4. Use the simulation model to analyze the demand data and to compute forecasts.
5. Compare the observed values to the forecasted values and compute the forecasting error measurements (MAD, MSE, MAPE & MPE) to evaluate the accuracy and the stability of the Air Force RDB Forecasting system. The RDB forecasting measurement errors are computed with the help of the RDB simulation program shown in appendix C.
6. Use the actual SDF system to analyze the demand data and to compute forecasts.
7. Compare the observed values to the forecasted values and compute the forecasting measurement errors (MAD, MSE, MAPE & MPE) to evaluate the accuracy and the stability of the Statistical Demand Forecasting system. The SDF forecasting errors are computed with the help of a FORTRAN program shown in appendix D.
8. Use a Paired Difference Test to test the following hypothesis: Subject to the presence of each data pattern component, the null hypothesis to be tested is that the RDB forecasting error mean (μ_1) is equal to the SDF forecasting error mean (μ_2) at the 90% confidence level.

Phase Two. The purpose of this phase is to answer the second research question: How accurate are the forecasts computed by each forecasting technique, subject to the presence of actual Air Force data? The following steps are used to answer the research question:

1. Compute the sample size necessary to represent the Air Force demand data at the 90% confidence level. Appendix B demonstrates the calculation of the sample size.

2. Collect four years of historical demand data from the D041 system. The items selected are either specific or common to different weapon systems. The time period for the data is from January 1989 to December 1993. Appendix D illustrates the data formats created to run both the RDB system and the SDF system.

3. Use the RDB simulation model to analyze the demand data and compute forecasts.

4. Compare the observed values to the forecasted values and compute the forecasting error measurements (MAD, MSE, MAPE & MPE), to evaluate the accuracy and the stability of the Air Force RDB Forecasting system. The RDB forecasting errors are computed with the help of the RDB simulation program shown in appendix C.

5. Use the actual SDF system to analyze the demand data and to compute forecasts.

6. Compare the observed values to the forecasted values and compute the forecasting measurement errors (MAD, MSE, MAPE & MPE) to evaluate the accuracy and the stability of the Statistical Demand Forecasting system. The SDF forecasting errors are computed with the help of a FORTRAN program shown in appendix D.

7. Use a Paired Difference Test to test the following hypothesis: subject to the presence of actual Air Force data, the null hypothesis to be tested is that the RDB forecasting error mean (μ_1) is equal to the SDF forecasting error mean (μ_2) at the 90% confidence level.

Phase Three. The purpose of this phase is to answer the third research question: What effects do the forecasts, computed by each forecasting approach, have on aircraft availability? The following steps are used to answer the research question:

1. Using the RDB forecasted demand rates and setting a specific funding level, use the Aircraft Sustainability Model to compute stock levels for all items. Stock levels are computed for each time series components' scenarios and the Air Force item sample

scenario. The funding level is \$80,000 for the time series components and \$700,000 for the actual Air Force data.

2. Using the actual demand rates and the stock levels determined by RDB in stage one, use the Aircraft Sustainability Model to compute the aircraft availability percentage. The model is constrained by a specific funding level. The funding level is \$80,000 for the time series components and \$700,000 for the actual Air Force data.

3. Using the SDF forecasted demand rates and setting a specific funding level, use the Aircraft Sustainability Model to compute stock levels for all items. Stock levels are computed for each time series components' scenarios and the Air Force item sample scenario. The funding level is \$80,000 for the time series components and \$700,000 for the actual Air Force data.

4. Using the actual demand rates and the stock levels determined by SDF in stage three, use the Aircraft Sustainability Model to compute the aircraft availability percentage. The model is constrained by a specific funding level. The funding level is \$80,000 for the time series components and \$700,000 for the actual Air Force data.

5. Compare the aircraft availability achieved in stages two and four with a Paired Difference Test. The null hypothesis to be tested is that the average aircraft availability (μ_1) achieved with the RDB forecasting approach is equal to the average aircraft availability (μ_2) achieved with the SDF forecasting approach at the 90% confidence level.

Chapter Summary

This chapter discussed the approach used to compare the Air Force forecasting system to the Navy forecasting system. Three analytical approaches are used:

1. The first approach consists of measuring the performance of the two forecasting systems, subject to different time series components, in terms of accuracy and stability.

2. The second approach consists of measuring the performance of the two forecasting systems, subject to historical Air Force demand data, in terms of accuracy and stability.

3. The third approach consists of measuring the effects of the two forecasting systems on Air Force aircraft availability.

This chapter gives a description on the type of research design, the research questions, the null hypotheses, and the instruments used to do the comparison analysis. It also presents the analytical approach, population size, sample size, data collection, and limitations used to perform the study. Finally the chapter highlights and explains the implementation of the research plan. The next chapter presents the results and analysis of implementing the research methodology.

IV. Results and Analysis

Introduction

This chapter presents the results and analysis of this comparison research. The chapter is separated into three sections. The first section discusses the forecasting measurement errors associated with the time series components. The forecasting errors are computed for each forecasting system. The second section discusses the forecasting measurement errors associated with actual Air Force data. The forecasting errors are computed for each forecasting system. Finally, the third section presents the aircraft availability results achieved with each forecasting system.

Approach One - Time Series Components Results

This section presents the results obtained to answer the first research question: How does each forecasting system perform with different time series components? The purpose of this research question is to determine how well the forecasting systems react to different time series components. To answer the research question, time series component data sets are generated. The forecasting error results obtained explain how the RDB forecasting system and the SDF system react to different time series components. However the errors computed are not representative of how the RDB system or the SDF system generally performs with real world data. The results demonstrate that when there is a trending component in the data, the SDF system provides more accurate forecasts at 95% level confidence than the RDB system does. The results also demonstrate that when there are outliers in the data, the SDF system generates more accurate forecasts than the RDB system. However the results illustrate that with the remaining time series component, there is not enough evidence at 90% level confidence to show that there is a significant difference between the SDF system and the RDB system.

This section is divided into three parts. The first part presents the forecasting measurement errors obtained with the Requirements Data Bank system for each time series component. The second part presents the forecasting measurement errors obtained with the Statistical Demand Forecasting system for each time series component. Finally the third part provides the comparison findings between the two forecasting systems.

Requirements Data Bank Results. Table 4-1 illustrates the mean and variance of the forecasting measurement errors for each time series component. Appendix F presents an Excel spreadsheet which demonstrates the mean and variance computations.

Table 4-1. RDB Forecasting Errors With Time Series Components

	Trend	Seasonal	Cyclical	Random	Outlier
Observations	40	40	40	40	36
Average MAD	13.1625	1.5969	3.1938	2.4844	17.9514
Variance MAD	44.0178	0.3057	1.2227	0.6184	82.8150
Observations	40	40	40	40	36
Average MSE	216.17	3.9641	15.3563	8.5395	915.12
Variance MSE	35042.21	6.0671	97.0734	18.9599	480952.83
Observations	40	39	40	40	36
Average MPE	4.33%	-0.0065%	-1.32%	0.069%	2.57%
Variance MPE	6.46%	0.0001%	0.62%	0.310%	3.63%
Observations	40	39	40	40	36
Average MAPE	4.33%	0.6021%	1.32%	0.98%	5.27%
Variance MAPE	6.46%	0.1363%	0.62%	0.31%	19.40%

Trend. With a sample made of trending component data, the Requirements Data Bank obtained a Mean Absolute Deviation of 13.16 and a Mean Square Error of 216.17. This demonstrates that the forecasting errors are very stable since the MSE approach provides very little penalty for individual errors. The Mean Percentage Error of 4.33% demonstrates that the RDB system over-estimated the trending component demands by 4.33%. The Mean Absolute Percentage Error demonstrates that the RDB

system creates an average error of 4.33%. The positive MPE indicates that the stronger trends in the data set are going upward.

Seasonal. With a sample made of seasonal component data, the Requirements Data Bank obtained a Mean Absolute Deviation of 1.59 and a Mean Square Error of 3.96. This demonstrates that the forecasting errors are very stable since the MSE approach provides very little penalty for individual errors. The Mean Percentage Error of -0.0065% demonstrates that the RDB system under-estimated demands by 0.0065%. The Mean Absolute Percentage Error demonstrates that the RDB system provides an average error of 0.6021%. The small percentage error indicates that the demand is large and that the errors are minor compared to the actual demands.

Cyclical. With a sample made of cyclical component data, the Requirements Data Bank obtained a Mean Absolute Deviation of 3.19 and a Mean Square Error of 15.35. This demonstrates that the forecasting errors are very stable since the MSE approach provides very little penalty for individual errors. The Mean Percentage Error of -1.32% demonstrates that the RDB system under-estimated the seasonal data set demands by 1.32%. The Mean Absolute Percentage Error demonstrates that the RDB system provides an average error of 1.32%. The small percentage error indicates that demand is large and that the errors are minor compared to the actual demands.

Random. With a sample made of random component data, the Requirements Data Bank obtained a Mean Absolute Deviation of 2.48 and a Mean Square Error of 8.53. This demonstrates that the RDB system and the forecasting errors are very stable since the MSE approach provides very little penalty for individual errors. The Mean Percentage Error of 0.069% demonstrates that the RDB system over-estimated the seasonal data set demands by 0.069%. The Mean Absolute Percentage Error demonstrates that the RDB system provides an average error of 0.98%. The small

percentage error indicates that demand is large and that the errors are minor compared to the actual demands.

Outlier. With a sample made of data with outliers, the Requirements Data Bank obtained a Mean Absolute Deviation of 17.95 and a Mean Square Error of 915.12. This demonstrates that the forecasting errors are not very stable since the MSE approach provides a large penalty for large individual errors. The Mean Percentage Error of 2.57% demonstrates that the RDB system over-estimated the seasonal data set demands by 2.57%. The Mean Absolute Percentage Error demonstrates that the RDB system provides an average error of 5.27%.

Statistical Demand Forecasting Results. Table 4-2 illustrates the mean and variance of the forecasting measurement errors for each time series component. Appendix F presents an Excel spreadsheet which demonstrates the mean and variance computations.

Table 4-2. SDF Forecasting Errors With Time Series Components

	Trend	Seasonal	Cyclical	Random	Outlier
Observations	40	40	40	40	36
Average MAD	7.3125	1.6025	3.3113	2.5600	14.3750
Variance MAD	13.5857	0.3120	2.1501	0.7739	59.0625
Observations	40	40	40	40	36
Average MSE	66.72	3.9653	17.0248	9.5103	897.92
Variance MSE	3338.17	6.0688	259.4047	31.6613	484870.54
Observations	40	39	40	40	36
Average MPE	2.41%	-0.0036%	-1.35%	0.036%	4.01%
Variance MPE	1.99%	0.0003%	0.72%	0.598%	10.99%
Observations	40	39	40	40	36
Average MAPE	2.41%	0.6036%	-1.35%	0.988%	4.01%
Variance MAPE	1.99%	0.1359%	0.72%	0.312%	10.99%

Trend. With a sample made of trend component data, the Requirements Data Bank obtained a Mean Absolute Deviation of 7.31 and a Mean Square Error of 66.72. This demonstrates that the forecasting errors are very stable since the MSE

approach provides very little penalty for individual errors. The Mean Percentage Error of 2.41% demonstrates that the SDF system over-estimated the trend data set demands by 2.41%. The Mean Absolute Percentage Error demonstrates that the SDF system provides an average error of 2.41%. The positive percentage error indicates the stronger trends in the data set are going upward.

Seasonal. Using the seasonal component data set generated, the Requirements Data Bank obtained a Mean Absolute Deviation of 1.60 and a Mean Square Error of 3.96. This demonstrates that the forecasting errors are very stable since the MSE approach provides very little penalty for individual errors. The Mean Percentage Error of -0.0036% demonstrates that the SDF system under-estimated the seasonal data set demands by 0.0036%. The Mean Absolute Percentage Error demonstrates that the SDF system provides an average error of 0.6036%. The small percentage error indicates that the demand is large and that the errors are minor compared to the actual demands.

Cyclical. Using the cyclical component data set generated, the Requirements Data Bank obtained a Mean Absolute Deviation of 3.31 and a Mean Square Error of 17.02. This demonstrates that the forecasting errors are very stable since the MSE approach provides very little penalty for individual errors. The Mean Percentage Error of -1.35% demonstrates that the SDF system under-estimated the seasonal data set demands by 1.35%. The Mean Absolute Percentage Error demonstrates that the SDF system provides an average error of 1.35%. The small percentage error indicates that demand is large and that the errors are small compared to the actual demands.

Random. Using the random component data set generated, the Requirements Data Bank obtained a Mean Absolute Deviation of 2.56 and a Mean Square Error of 9.51. This demonstrates that the SDF system and the forecasting errors are very stable since the MSE approach provides very little penalty for individual errors. The Mean Percentage Error of 0.036% demonstrates that the SDF system over-estimated the

seasonal data set demands by 0.036%. The Mean Absolute Percentage Error demonstrates that the SDF system provides an average error of 0.98%. The small percentage error indicates that demand is large and that the errors are minor compared to the actual demands.

Outlier. Using the outlier component data set generated, the Requirements Data Bank obtained a Mean Absolute Deviation of 14.37 and a Mean Square Error of 897.92. This demonstrates that the forecasting errors are not very stable since the MSE approach provides very large penalty for individual errors. The Mean Percentage Error of 4.01% demonstrates that the SDF system over-estimated the seasonal data set demands by 4.01%. The Mean Absolute Percentage Error demonstrates that the SDF system provides an average error of 4.01%.

Comparative Results of Approach One. The Comparative results demonstrate that when there is a trending component in the data, the SDF system gives a more accurate forecast than the RDB system does at 95% level confidence. The results also demonstrate that when there are outliers in the data, the SDF system gives a more accurate forecast than the RDB system does at 95% level confidence. However the results show that for the remaining time series components, there is not enough evidence at 90% level confidence to present a significant difference in terms of accuracy between the SDF system and the RDB system.

Trend. Table 4-3 illustrates the results obtained with the paired difference test when the forecasts were made with data containing a trending component. Appendix F demonstrates the results of the paired difference test at a higher level of detail. The results demonstrate that there is enough evidence at 90% level confidence (two-tailed test) and at 95% level confidence (one-tailed test) that when there is a trending component in the data, the SDF system gives a more accurate forecast than the RDB system does. This demonstrates that the RDB system is more stable when a trending component is found in

demand observations. It also demonstrates that the SDF system is more responsive than the RDB system. The reason for this is that the SDF system uses a four quarter moving average technique to make forecasts when a trend exists in the data. Therefore it is more responsive to a trending component.

Table 4-3. Trend Paired Difference Test

Forecasting Error	Hypothesis	Mean RDB	Mean SDF	Z-Value	Two-Tail Z at 90%	One-Tail Z at 95%	Results
MAD	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	13.16	7.31	4.8749	1.6450	1.6450	Enough Evidence to Reject H_0
MSE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	216.17	66.72	4.8247	1.6450	1.6450	Enough Evidence to Reject H_0
MPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	4.33%	2.41%	4.1891	1.6450	1.6450	Enough Evidence to Reject H_0
MAPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	4.33%	2.41%	4.1891	1.6450	1.6450	Enough Evidence to Reject H_0

Seasonal. Table 4-4 illustrates the results obtained with the paired difference test when the forecasts were made with data containing a seasonal component. Appendix F demonstrates the results of the paired difference test at a higher level of detail. The results demonstrate that there is not enough evidence at 90% level confidence to show that there is a significant difference in the level of accuracy provided by each

Table 4-4. Seasonal Paired Difference Test

Forecasting Error	Hypothesis	Mean RDB	Mean SDF	Z-Value	Two-Tail Z at 90%	One-Tail Z at 95%	Results
MAD	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	1.59	1.60	-0.0453	1.6450	1.6450	Not enough evidence to Reject H_0
MSE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	3.96	3.96	-0.0022	1.6450	1.6450	Not enough evidence to Reject H_0
MPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	-0.006%	-0.004%	-0.9210	1.6450	1.6450	Not enough evidence to Reject H_0
MAPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	0.602%	0.603%	-0.0176	1.6450	1.6450	Not enough evidence to Reject H_0

forecasting system. In other words, the SDF system and the RDB system provide approximately the same level of accuracy, when seasonal component demand observations exist in the data set.

Cyclical. Table 4-5 illustrates the results obtained with the paired difference test when the forecasts were made with data containing a cyclical component. Appendix F demonstrates the results of the paired difference test at a higher level of detail. The results demonstrate that there is not enough evidence at 90% level confidence to show that there is a significant difference in the level of accuracy provided by each forecasting system. In other words, the SDF system and the RDB system provide approximately the same level of accuracy, when cyclical component demand observations exist in the data set.

Table 4-5. Cyclical Paired Difference Test

Forecasting Error	Hypothesis	Mean RDB	Mean SDF	Z-Value	Two-Tail Z at 90%	One-Tail Z at 95%	Results
MAD	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	3.19	3.31	-0.4046	1.6450	1.6450	Not enough evidence to Reject H_0
MSE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	15.36	17.02	-0.5589	1.6450	1.6450	Not enough evidence to Reject H_0
MPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	-1.32%	-1.35%	-0.2213	1.6450	1.6450	Not enough evidence to Reject H_0
MAPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	1.32%	1.35%	-0.2213	1.6450	1.6450	Not enough evidence to Reject H_0

Random. Table 4-6 illustrates the results obtained with the paired difference test when the forecasts were made with data containing a random component. Appendix F demonstrates the results of the paired difference test at a higher level of detail. The results demonstrate that there is not enough evidence at 90% level confidence to show that there is a significant difference in the level of accuracy provided by each forecasting technique. In other words, the SDF system and the RDB system provide

approximately the same level of accuracy, when random component demand observations exist in the data set.

Table 4-6. Random Paired Difference Test

Forecasting Error	Hypothesis	Mean RDB	Mean SDF	Z-Value	Two-Tail Z at 98%	One-Tail Z at 95%	Results
MAD	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	2.48	2.56	-0.4052	1.6450	1.6450	Not enough evidence to Reject H_0
MSE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	8.54	9.51	-0.8630	1.6450	1.6450	Not enough evidence to Reject H_0
MPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	0.068%	0.036%	0.2173	1.6450	1.6450	Not enough evidence to Reject H_0
MAPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	0.99%	1.01%	-0.1952	1.6450	1.6450	Not enough evidence to Reject H_0

Outlier. Table 4-7 illustrates the results obtained with the paired difference test when the forecasts were made with data containing outliers. Appendix F demonstrates the results of the paired difference test at a higher level of detail. Table 4-7 illustrates that when comparing the MAD means, the SDF system is more accurate at 95% level confidence. However, when comparing the MPE means, the paired difference test demonstrates that the RDB system is more accurate. Also, when comparing the MSE means and the MAPE means, there is not enough evidence to demonstrate that there is a significant difference between the error means.

To explain these results, it is important to understand that outliers usually create large variances around the forecasting error means. The paired difference test takes into consideration the size of the variance. The insignificant results of the paired difference test for the MAPE and the MSE can be explained by the fact that there are large variances around the MAPE means and the MSE means.

The results obtained with the paired difference test for the MPE can also be explained. Demand outliers in the data set were either larger than the average forecast or lower than the average demand. The average size of forecasting errors for RDB were

larger than the average size of forecasting errors in SDF. The direction of the error, negative or positive, canceled each other to create a small MPE. The MAPE is larger than the MPE because it takes the absolute percentage instead of the actual percentage. Therefore the MAD demonstrates that there is enough evidence at 90% level confidence (two-tailed test) and at 95% level confidence (one-tailed test) to show that the SDF system gives more accurate forecast than the RDB system. This demonstrates that the SDF system is more stable when outliers are found in the observations. The reason for this is that the SDF system ignores outliers on the first occurrence, making it more stable.

Table 4-7. Outlier Paired Difference Test

Forecasting Error	Hypothesis	Mean RDB	Mean SDF	Z-Value	Two-Tail Z at 90%	One-Tail Z at 95%	Results
MAD	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	17.95	14.38	1.8015	1.6450	1.6450	Enough evidence to Reject H_0
MSE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	915.16	897.92	0.1051	1.6450	1.6450	Not enough evidence to Reject H_0
MPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	2.57%	4.004%	-2.2574	1.6450	1.6450	Enough evidence to Reject H_0
MAPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	5.27%	4.004%	1.3740	1.6450	1.6450	Not enough evidence to Reject H_0

Approach Two - Actual Air Force Data Results

This section presents the results obtained to answer research question two: How accurate are the forecasts computed by each forecasting technique subject to actual Air Force demand data? The main purpose of this approach is to verify and evaluate how well each forecasting system performs when subject to real world data. The results demonstrate that there is not enough evidence at 90% level confidence to show that there is a significance difference in the level of accuracy between the SDF system and the RDB system.

This section is divided into three parts. The first part presents the forecasting measurement errors obtained with the Requirements Data Bank system. The second part presents the forecasting measurement errors obtained with the Statistical Demand Forecasting system. Finally the third part provides the comparison findings between the two forecasting systems.

Requirements Data Bank Results. Table 4-8 illustrates the mean and variance of the forecasting measurement errors obtained with Air Force sample data set. Appendix F presents an Excel spreadsheet report which demonstrates all the mean and variance computations.

Table 4-8. RDB Forecasting Errors
With Air Force Data

	Air Force Data
Observations	245
Average MAD	6.88
Variance MAD	141.53
Observations	245
Average MSE	246.75
Variance MSE	1229284.67
Observations	245
Average MPE	-26.39%
Variance MPE	4922.41%
Observations	245
Average MAPE	61.99%
Variance MAPE	3151.37%

The Requirements Data Bank obtained a Mean Absolute Deviation of 6.88 and a Mean Square Error of 246.75. This demonstrates that the forecasting errors are not very stable since the MSE approach provides a large penalty for individual errors. The Mean Percentage Error of -26.39% demonstrates that the RDB system under-estimated the

seasonal data set demands by 26.39%. The Mean Absolute Percentage Error demonstrates that the RDB system creates an average percentage error of 61.99%.

Statistical Demand Forecasting Results. Table 4-9 illustrates the mean and variance of the forecasting measurement errors obtained with the Air Force sample data set. Appendix F presents an Excel spreadsheet which demonstrates the mean and variance computations.

The Requirements Data Bank obtained a Mean Absolute Deviation of 7.36 and a Mean Square Error of 312.69. This demonstrates the forecasting errors are not very stable since the MSE approach provides a large penalty for individual errors. The Mean Percentage Error of -23.31% demonstrates that the RDB system under-estimated the seasonal data set demands by 23.31%. The Mean Absolute Percentage Error demonstrates that the SDF system provides an average percentage error of 61.04%.

Table 4-9. SDF Forecasting Errors
With Air Force Data

	Air Force Data
Observations	245
Average MAD	7.36
Variance MAD	198.22
Observations	245
Average MSE	312.69
Variance MSE	1923245.47
Observations	245
Average MPE	-23.30%
Variance MPE	5851.61%
Observations	245
Average MAPE	61.04%
Variance MAPE	3829.83%

Comparative Results of Approach Two. Table 4-10 illustrates the results obtained with the paired difference test when the forecasts were made with the actual Air Force

data. Appendix F demonstrates the results of the paired difference test at a higher level of detail. The results demonstrate that there is not enough evidence at 90% level confidence to show that there is a significant difference in the level of accuracy provided by both the SDF system and the RDB system. In other words, when using actual Air Force data, the SDF system and the RDB system provide approximately the same level of accuracy.

Table 4-10. Air Force Data Paired Difference Test

Forecasting Error	Hypothesis	Mean RDB	Mean SDF	Z-Value	Two-Tail Z at 90%	One-Tail Z at 95%	Results
MAD	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	6.88	7.36	-0.4072	1.6450	1.6450	Not enough evidence to Reject H_0
MSE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	246.75	312.69	-0.5813	1.6450	1.6450	Not enough evidence to Reject H_0
MPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	-26.39%	-23.31%	-0.4662	1.6450	1.6450	Not enough evidence to Reject H_0
MAPE	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	61.99%	61.04%	0.1791	1.6450	1.6450	Not enough evidence to Reject H_0

Approach Three - Aircraft Availability Results

This section presents the results obtained to answer research question three: What effects do the forecasts, computed by each forecasting approach, have on aircraft availability? The main purpose of this approach is to verify and evaluate how each forecasting approach affects the aircraft availability achieved. The results demonstrate that when there is a trending component in the data, the SDF system achieves a higher aircraft availability at 95% level confidence than the RDB system does. The results also demonstrate that when there are outliers in the data, the SDF system achieves a higher aircraft availability than the RDB system does. However the results illustrate that with the remaining time series component and the real Air Force data, there is not enough evidence at 90% level confidence to show that there is a significant difference between the SDF system and the RDB system. This section is divided into three parts. The first part

presents the aircraft availability achieved with the Requirements Data Bank system. The second part presents the aircraft availability achieved with the Statistical Demand Forecasting system. Finally, the third part provides the comparison findings between the two forecasting systems.

Requirements Data Bank Results. Table 4-11 illustrates the average aircraft availability achieved when forecasts are made by the RDB system. The aircraft availability is shown for four different quarters under each of the time series components and the actual Air Force data. Aircraft Availability is computed with the Aircraft Sustainability Model with funding constraint of \$80,000 for times series components and \$700,000 for the real Air Force data. Appendix G presents an Excel spreadsheet which demonstrates the results.

Table 4-11. RDB Aircraft Availability

	Trend	Seasonal	Cyclical	Outlier	Random	Air Force
Average Aircraft Availability -Quarter 1	74.30%	78.93%	86.98%	83.25%	91.88%	79.84%
Average Aircraft Availability -Quarter 2	74.27%	78.71%	86.63%	82.99%	88.36%	80.28%
Average Aircraft Availability -Quarter 3	74.10%	78.92%	86.64%	83.15%	91.00%	80.36%
Average Aircraft Availability -Quarter 4	74.12%	78.90%	86.90%	82.85%	90.77%	80.59%

Statistical Demand Forecasting Results. Table 4-12 illustrates the average aircraft availability achieved when forecasts are made by the SDF system. The aircraft availability is shown for four different quarters under each of the time series components and the actual Air Force data. Aircraft Availability is computed with the Aircraft Sustainability Model with funding constraint of \$80,000 for times series components and \$700,000 for the real Air Force data. Appendix G presents an Excel spreadsheet which demonstrates the results.

Table 4-12. SDF Aircraft Availability

	Trend	Seasonal	Cyclical	Outlier	Random	Air Force
Average Aircraft Availability -Quarter 1	75.08%	80.93%	87.25%	84.05%	90.63%	78.73%
Average Aircraft Availability -Quarter 2	74.98%	79.13%	86.57%	83.97%	90.55%	80.50%
Average Aircraft Availability -Quarter 3	74.95%	78.97%	87.23%	83.98%	90.45%	80.66%
Average Aircraft Availability -Quarter 4	74.90%	80.31%	86.83%	84.04%	90.51%	80.33%

Comparative Results of Approach Three. Table 4-13 illustrates the results obtained with the paired difference test used to compare the aircraft availability achieved with each forecasting system. Appendix G demonstrates the results of the paired difference test at a higher level of detail. The results demonstrate that when there is a trending component in the data, the SDF system achieves a higher aircraft availability at 95% level confidence than the RDB

Table 4-13. Aircraft Availability Paired Difference Test

Data	Hypothesis	Mean RDB	Mean SDF	t-Value	Two-Tail t at 90%	One-Tail t at 95%	Results
Trend	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	74.20%	74.98%	-26.6226	3.1824	3.1824	Enough evidence to Reject H_0
Seasonal	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	78.87%	79.83%	-2.1723	3.1824	3.1824	Not enough evidence to Reject H_0
Cyclical	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	86.79%	86.97%	-1.1481	3.1824	3.1824	Not enough evidence to Reject H_0
Random	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	90.50%	90.54%	-0.0449	3.1824	3.1824	Not enough evidence to Reject H_0
Outlier	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	83.06%	84.01%	-10.6221	3.1824	3.1824	Enough evidence to Reject H_0
Air Force	$H_0: \mu_1 - \mu_2 = 0$ $H_a: \mu_1 - \mu_2 \neq 0$	80.27%	80.06%	0.6514	3.1824	3.1824	Not enough evidence to Reject H_0

system does. The results also demonstrate that when there are outliers in the data, the SDF system achieves a higher aircraft availability than the RDB system does. However the results illustrate that with the remaining time series component and the real Air Force data, there is not enough evidence at 90% level confidence to show that there is a significant difference between the SDF system and the RDB system.

Chapter Summary

This chapter discussed the results obtained for each of the analytical approaches to answer the three research questions. In the case of time series components, it was found that the SDF system provided more accurate forecasts than the RDB system, when there was a trend component or an outlier component in the data. It was also found that was no significant difference in the level of accuracy between the two forecasting systems when there was a seasonal component, a cyclical component or a random component in the data. In the case of actual Air Force data, it was found that was no significant difference in the level of accuracy between the two forecasting systems.

Finally, in the case of aircraft availability, it was found that the SDF system generated higher aircraft availability percentage than the RDB system, when there was a trend component or an outlier component in the data. However it was found that there was no significant difference in the aircraft availability achieved by each forecasting system with seasonal component data, cyclical component data, random component data or actual Air Force data. The next chapter presents the conclusions and recommendations of this forecasting comparison research.

V. Conclusion and Recommendation

Introduction

The purpose of this chapter is to present the conclusions and recommendations of this research. First the chapter restates the specific problem, the purpose of the research and the research questions. Then, for each research question, the chapter summarizes the results and presents an interpretation of their management implications. Some observations made regarding the forecasting systems during the research are then presented. A section on recommendations for future studies and analyses is then provided. Finally the chapter gives a conclusion and a summary of the research.

Specific Problem

Since the JLSC selected the Navy's Statistical Demand Forecasting System as the standard DOD forecasting system, the Army and the Defense Logistics Agency have both performed analyses to measure the impact of using SDF within their own organizations. The specific problem is that the Air Force has not analyzed or studied how SDF could affect its operational requirements. Therefore the effect of SDF on USAF requirements determination remains unknown. This is a problem because budget allocation across items depends on solving the statistical problem of forecasting item demand rates (Sherbrooke, 1987: v).

Purpose of the Study

The purpose of this study is to evaluate and compare the performance and accuracy of the Navy forecasting system, Statistical Demand Forecasting, relative to the Air Force forecasting system, Requirements Data Bank Forecasting, in an Air Force environment.

Research Questions

The research questions support the comparison between the Navy forecasting system and the Air Force forecasting system. To address forecasting accuracy and robustness, the following research questions are developed:

1. How does each forecasting system perform with different data pattern components?
2. How accurate are the forecasts computed by each forecasting technique subject to actual Air Force demand data?
3. What effects do the forecasts, computed by each forecasting approach, have on aircraft availability?

Results and Management Implication for Research Question One

This section summarizes the results obtained from the analysis of time series components and explains the management implications that they may have for the Air Force.

Forecast Accuracy Results for Time Series Components. The results demonstrate that when there is a trending component in the data, the SDF system provides more accurate forecasts at 95% level confidence than the RDB system does. The reason why the SDF system performs so well when there is a trend in the data is that it has the capability of detecting the trend when it exists in the data. When a trend is found in the data, the system will either use a regression technique or a four quarter moving average to react to the change in the data. The RDB system does use a technique known as PRELOG to detect a trend, but the system does not do use a different forecasting technique to account for the trend unless specified by the item managers or the equipment specialist.

The results also demonstrate that when there are outliers in the data, the SDF system generates more accurate forecasts than the RDB system. The reason why the SDF system performs so well when there are outliers in the data is because of the filters test. If the filters test detects an outlier, it will either ignore it or reduce it to a lower value. Therefore the forecast generated by the SDF system will remain stable with the actual future demand. The RDB system does not have any measure to detect outliers. Therefore the full value of the outlier is taken into account to compute a forecast. This causes the forecast to be unstable.

The results illustrate that with the remaining time series component, there is not enough evidence at 90% level confidence to show that there is a significant difference between the SDF system and the RDB system. Both forecasting systems generate forecasts with approximately the same level of forecasting error.

Management Implication. Occasionally Air Force data include time series components such as trend or outliers. An increasing program data will cause the demand data to increase also. An unexpected and short operational exercise may cause the occurrence of many demands for some items. The first situation demonstrates an example of a trending component. In that example the forecasting technique is required to be very responsive to the increase in the demand. The second situation illustrates an example of an outlier. Since it is a one-time occurrence, the forecasting technique is required to be very stable. The RDB system can be responsive to the trending component through PRELOG, but the process is complex and requires the assistance of an item manager or equipment specialist. Contrary to the RDB system, the SDF system is autonomous. It does not require the help of an item manager or equipment specialist to respond to the trend. The SDF system is also very good in detecting outliers and generating stable forecasts. The RDB system cannot detect outliers and a bad forecast may cause the system to think that there is an increase in the demand data. For USAF item managers.

this aspect becomes very important when the time comes to determine what items to buy to maintain good aircraft availability.

Results and Management Implication for Research Question Two

This section summarizes the results obtained from the analysis of actual Air Force data and explains the management implications that they may have for the Air Force.

Forecast Accuracy Results for Actual Air Force Data. The results demonstrate that there is not enough evidence at 90% level confidence to show that there is a significant difference in the level of accuracy between the SDF system and the RDB system. The data includes one major time series component known as the random component. Although there may be outliers and trending components in the data, they are very minimal compared to the random component. Since the RDB system and the SDF system generate relatively the same level of accuracy when a random component exists in the data, the results are not surprising with the actual Air Force data.

Management Implication. The SDF system and the RDB system generate forecasts with approximately the same level of accuracy with actual Air Force data. These results demonstrate that either system represents a good approach to generate forecasts with a fair level of accuracy. The Air Force requires a forecasting system that will generate forecasts that are relatively stable. The question becomes which forecasting is more cost effective to implement and easiest to understand.

Results and Management Implication for Research Question Three

This section summarizes the results obtained from the analysis of aircraft availability and explains the management implications that they may have for the Air Force.

Aircraft Availability Results. The results demonstrate that when there is a trending component in the data, the SDF system achieves a higher aircraft availability at 95% level confidence than the RDB system does. The results also demonstrate that when there are outliers in the data, the SDF system achieves a higher aircraft availability than the RDB system does. However the results illustrate that with the remaining time series component and the real Air Force data, there is not enough evidence at 90% level confidence to show that there is a significant difference between the SDF system and the RDB system.

These results demonstrate that the more accurate the forecast is, the greater is the aircraft availability. In the case of outliers and trending components, a higher aircraft availability is achieved.

Management Implication. The SDF system performs well in detecting outliers and trending component data. The RDB system cannot detect outliers and a bad forecast may cause the system to think that there is an increase in the demand data. For USAF item managers, this aspect becomes very important when the time comes to determine what mix of items to buy to maintain a high aircraft availability.

With actual Air Force data, the SDF system and the RDB system generate forecasts with approximately the same level of aircraft availability. These results demonstrate that either system represents a good approach to generate forecasts that will provide relatively the same level of aircraft availability. The Air Force basically requires a forecasting system that will generate forecasts that are relatively stable. The question becomes which forecasting system is more cost effective to implement and easiest to understand.

Observations on the Forecasting Systems

The purpose of this section is to illustrate some of the advantages and disadvantages of each forecasting technique observed during the analysis study. This

section first discusses the advantages and disadvantages of the Requirements Data Bank system and then discusses the advantages and disadvantages of the Statistical Demand Forecasting system.

Requirements Data Bank System. The Requirements Data Bank system is designed to compute requirements for buy and repair for 807,000 consumable spares, recoverable spares, repair parts, and equipment items. The Requirements Data Bank system is made up of multiple sub-systems which interface through a relational database.

Some of the observed advantages associated with the Requirements Data Bank are:

1. The Requirements Data Bank is being developed using a relational database management system. The relational database creates more efficient data management and a better interface between the sub-systems. Therefore, data access and retrieval are easier for the system's users.

2. The eight quarter moving average used by the RDB system is simple and easy to understand. Since item managers deal with forecasts on a day to day basis, an understanding of what makes the forecasts leads to better decisions.

3. The double exponential smoothing method used by the RDB system produces a forecast with five different alpha values. A mean absolute deviation associated with each forecast produced is also computed. This helps the item managers to make a better decision as to which forecasting technique could be used.

Some of the disadvantages observed on the Requirements Data Bank system are:

1. The double exponential smoothing, planned to be used by the RDB system, is a forecasting technique that performs well when there is a trend in the data. However this technique has to be selected by the item manager or the equipment specialist to perform a forecast. Once selected, it will remain the forecasting technique until the item manager or the equipment specialist switches the forecasting technique back to the original forecasting

technique. The double exponential technique will perform poorly with any other type of time series components. The disadvantage is that the RDB system already uses a forecasting technique known as PRELOG for trending components. Therefore the double exponential technique is not really required for the RDB system. As Sherbrooke mentioned in his technical report, the Evaluation of Demand Prediction Techniques, the single exponential smoothing is a good technique to forecast recoverable items (Sherbrooke, 1987: 17). The use of a single exponential smoothing technique instead of a double exponential technique would be more appropriate.

2. The Requirements Data Bank system uses a technique known as Predictive Logistics to depict trending in the data observations. Although the method is a good technique, it is not user friendly and very complex. Therefore, the technique is rarely chosen by item managers or equipment specialists to make forecasts with trending data.

3. The development of the Requirements Data Bank system started in 1985. To this day, there are still some processes or sections of the RDB system that have not been developed. An example of this is the double exponential technique.

4. The concept of the RDB system is very complex. It involves many algorithms and sub-systems. Although the RDB system has its own functional description documents, very few reports and analyses exist on the description and purpose of the RDB system. A descriptive paper on the RDB system would help to clarify and strengthen the position of the RDB system in the DOD environment.

Statistical Demand Forecasting System. The Statistical Demand Forecasting system is a forecasting system designed by the Navy to forecast both consumable and recoverable item demands. It is a system which includes a series of statistical control tests to detect whether the data observations are changing radically or not over time. Some of the advantages of the SDF system are:

1. The SDF system consists of a variety of forecasting techniques that can be selected by item managers depending on the demand data pattern. Such techniques are single exponential smoothing, double exponential smoothing, regression, moving average, naive method and composite forecasting

2. The SDF system consists of a series of statistical control tests that can depict observations that are statistically inconsistent with previous observations. These inconsistencies could be: a trend in the data; the existence of outliers; bias forecasts; or unstable observations. This gives the SDF system and the item managers the flexibility to make a stable forecast when necessary or make a responsive forecast when required.

3. The SDF system possesses an interface with the item manager's personal computer known as the PC Exception tool. When SDF finds some inconsistencies with the data such as outliers, the system downloads the information to the item managers to review. At that point, the item manager has the flexibility to determine whether the observations are valid and decide if he / she should choose a different forecasting technique.

Some of the observed disadvantages associated with the SDF system are:

1. The program related items entered into the SDF system are not processed through all the statistical control tests. For example the trend test is not currently used for program related items. The Navy intends to change the SDF system in the future so that program related items can be processed through the trend test (Maitland, 1992a).

2. The SDF system is a complex system. The system consists of many statistical functions and algorithms. Unless item managers have a statistical background, it may be difficult for them to understand the functions of the SDF system.

3. The SDF system contains a multiple of parameters that must be set for the system to operate. Although default values exist, these parameters can be set by item managers. The values of these parameters greatly affect the forecast that will be generated

by the system. Therefore, parameter setting becomes important. There is no method or approach that exists at this point to evaluate an optimal parameter setting.

Recommendations For Future Studies and Analyses

As discussed above, the research demonstrates that there is no significant difference between the two forecasting systems. The question on whether the Joint Logistics System Center should maintain its decision on using the Statistical Demand Forecasting system as the DOD standard forecasting system does not depend on forecasting accuracy, but on the costs involved in integrating one system versus the other and the flexibility of implementing the forecasting system.

It is recommended that a cost analysis of integrating and implementing one system versus the other be done. Factors such as system interface, system maintenance, system flexibility and system complexity should also be considered. Perhaps, the integration of some of the SDF algorithms into the RDB system would be an ideal solution.

Studies or analyses related to this research that could be done are:

1. SDF possesses other forecasting techniques other than the moving average technique to generate forecasts. A comparison on comparing the SDF exponential smoothing technique to the RDB moving average would be interesting.
2. The RDB system does not have any statistical control tests to detect data patterns. An analysis on using statistical control tests with the RDB algorithm is an area which could improve RDB forecasting.
3. The RDB forecasting system uses the Mean Absolute Deviation as a measure of forecasting performance. A study on using aircraft availability as a forecasting performance instead of the MAD could improve aircraft availability.

Conclusions

Dealing with forecasting remains a very complicated matter because no one can predict the future and be one hundred percent accurate. As the French author Eugene InonESCO says: "You can only predict things after they have happened" (Augarde, 1991:110). Many factors can affect demand such as economic conditions, political decisions, weather conditions, number of flying hours, number of sorties and so on. For this reason, a level of uncertainty exists. To reduce the level of uncertainty, one forecasting technique may be good at one point and another forecasting technique may be better at another point in time.

The results of this research demonstrate that in general there is no significant difference in the forecasts provided by the RDB system versus the forecasts provided by the SDF system. However the SDF system did provide more accurate forecasts than the RDB system did in the case of data that included trending components or outliers.

Research Summary

This research presented the problem of comparing the Air Force's Requirements Data Bank forecasting approach to the Navy's Statistical Demand Forecasting approach. The research consisted of five chapters. The first chapter introduced the purpose of the research and the background surrounding it. The second chapter presented some of the concepts discussed throughout the research. The third chapter illustrated the methodology used for the research. Chapter four provided the results and analysis of the study. Finally, this chapter made some recommendations for future studies.

Appendix A: Times Series Components Generator Programs

1) Trend Times Series Component

```
*****
** The purpose of this program is to generate trend times series **
** component data. **
*****

PROGRAM TREND

** Variables **

CHARACTER LINE*190, NSN*17
INTEGER RECORD, X, J, I, VALUE(16), FLH(16), PROG(25)
X=100
J=2
Y=1

** Format **

1000 FORMAT(I2, A190)
1001 FORMAT (A17)
1002 FORMAT(A2, A17, 4X, I5, 15(2X, I5))
1003 FORMAT(A2, A17, 4X, I5, 24(2X, I5))
1004 FORMAT(A2, A190)

** Opening Files **

OPEN(1, file='SDFRDB1.TXT', form='formatted', status='UNKNOWN')
OPEN(2, file='TREND.TXT', form='formatted', status='UNKNOWN')

** Reading Input File for NSNs information only **

10 READ (1, 1000, end=999) RECORD, LINE

IF (RECORD.EQ.01) THEN
WRITE (2, 1004) '01', LINE
ENDIF

** Generating Demand **

IF (RECORD.EQ.02) THEN
READ (LINE, 1001) NSN
DO 20 I=1, 16
VALUE(I)=X+J
J=J+Y
20 CONTINUE
X=X+10
J=INT(RND()*10)
Y=INT(RND()*10)
25 IF ((Y.LT.1).OR.(Y.GT.5)) THEN
GOTO 25
ENDIF

** Writing Demand **

WRITE(2, 1002) '02', NSN, VALUE(1), VALUE(2), VALUE(3), VALUE(4),
& VALUE(5), VALUE(6), VALUE(7), VALUE(8), VALUE(9), VALUE(10),
& VALUE(11), VALUE(12), VALUE(13), VALUE(14), VALUE(15),
& VALUE(16)
ENDIF
```

** Generating Flying Program **

```
      IF (RECORD.EQ.03) THEN
        READ (LINE,1001) NSN
        DO 30 I=1,16
          FLH(I)=2000+X
30      CONTINUE
        WRITE(2,1002) '03',NSN,FLH(1),FLH(2),FLH(3),FLH(4),FLH(5),
&          FLH(6),FLH(7),FLH(8),FLH(9),FLH(10),FLH(11),
&          FLH(12),FLH(13),FLH(14),FLH(15),FLH(16)
      ENDIF

      IF (RECORD.EQ.04) THEN
        READ (LINE,1001) NSN
        DO 40 I=1,25
          PROG(I)=2500
40      CONTINUE
```

** Writing Flying Program **

```
      WRITE(2,1003) '04',NSN,PROG(1),PROG(2),PROG(3),PROG(4),
&          PROG(5),
&          PROG(6),PROG(7),PROG(8),PROG(9),PROG(10),PROG(11),
&          PROG(12),PROG(13),PROG(14),PROG(15),PROG(16),
&          PROG(17),PROG(18),PROG(19),PROG(20),PROG(21),
&          PROG(22),PROG(23),PROG(24),PROG(25)
      ENDIF

      GOTO 10
999    CLOSE(1)
      CLOSE(2)
      STOP
      END
```

2) Seasonal Times Series Component

```
*****
** The purpose of this program is to generate seasonal times series **
** component data. **
*****
```

```
PROGRAM SEASONAL
```

```
** Variables **
```

```
CHARACTER LINE*190,NSN*17
INTEGER RECORD,X,J,I,VALUE(16),FLH(16),PROG(25)
X=100
J=2
Z=1
```

```
** Format **
```

```
1000 FORMAT(I2,A190)
1001 FORMAT (A17)
1002 FORMAT(A2,A17,4X,I5,15(2X,I5))
1003 FORMAT(A2,A17,4X,I5,24(2X,I5))
1004 FORMAT(A2,A190)
```

```
** Opening Files **
```

```
OPEN(1,file='SDFRDB2.TXT',form='formatted',status='UNKNOWN')
OPEN(2,file='SEASONAL.TXT',form='formatted',status='UNKNOWN')
```

```
** Reading Input File for NSNs information only **
```

```
10 READ (1,1000,end=999) RECORD,LINE
   IF (RECORD.EQ.01) THEN
       WRITE (2,1004) '01',LINE
   ENDIF
```

```
** Generating Demand **
```

```
   IF (RECORD.EQ.02) THEN
       READ (LINE,1001) NSN
       VALUE(1)=X+J
       VALUE(2)=X+J+1+Z
       VALUE(3)=X+J+2+Z
       VALUE(4)=X+J+1+Z
       VALUE(5)=X+J
       VALUE(6)=X+J+1+Z
       VALUE(7)=X+J+2+Z
       VALUE(8)=X+J+1+Z
       VALUE(9)=X+J
       VALUE(10)=X+J+1+Z
       VALUE(11)=X+J+2+Z
       VALUE(12)=X+J+1+Z
       VALUE(13)=X+J
       VALUE(14)=X+J+1+Z
       VALUE(15)=X+J+2+Z
       VALUE(16)=X+J+1+Z
       X=X+10
25  J=INT(RND()*10)
     Z=INT(RND()*10)
     IF ((Z.LT.1).OR.(Z.GT.5)) THEN
         GOTO 25
     ENDIF
```

** Writing Demand **

```
        WRITE(2,1002) '02',NSN,VALUE(1),VALUE(2),VALUE(3),VALUE(4),
&          VALUE(5),VALUE(6),VALUE(7),VALUE(8),VALUE(9),VALUE(10),
&          VALUE(11),VALUE(12),VALUE(13),VALUE(14),VALUE(15),
&          VALUE(16)
        ENDIF
```

** Generating Flying Program **

```
        IF (RECORD.EQ.03) THEN
          READ (LINE,1001) NSN
          DO 30 I=1,16
            FLH(I)=2000+X
30      CONTINUE
```

** Writing Flying Program **

```
        WRITE(2,1002) '03',NSN,FLH(1),FLH(2),FLH(3),FLH(4),FLH(5),
&          FLH(6),FLH(7),FLH(8),FLH(9),FLH(10),FLH(11),
&          FLH(12),FLH(13),FLH(14),FLH(15),FLH(16)
        ENDIF

        IF (RECORD.EQ.04) THEN
          READ (LINE,1001) NSN
          DO 40 I=1,25
            PROG(I)=2500
40      CONTINUE
          WRITE(2,1003) '04',NSN,PROG(1),PROG(2),PROG(3),PROG(4),
&          PROG(5),
&          PROG(6),PROG(7),PROG(8),PROG(9),PROG(10),PROG(11),
&          PROG(12),PROG(13),PROG(14),PROG(15),PROG(16),
&          PROG(17),PROG(18),PROG(19),PROG(20),PROG(21),
&          PROG(22),PROG(23),PROG(24),PROG(25)
        ENDIF
```

```
        GOTO 10
999     CLOSE(1)
        CLOSE(2)
        STOP
        END
```


3) Cyclical Times Series Component

```
*****
** The purpose of this program is to generate cyclical times series **
** component data. **
*****
```

```
PROGRAM CYCLICAL
```

```
** Variables **
```

```
CHARACTER LINE*190,NSN*17
INTEGER RECORD,X,J,I,VALUE(16),FLH(16),PROG(25)
X=100
J=2
Z=1
```

```
** Format **
```

```
1000 FORMAT(I2,A190)
1001 FORMAT (A17)
1002 FORMAT(A2,A17,4X,I5,15(2X,I5))
1003 FORMAT(A2,A17,4X,I5,24(2X,I5))
1004 FORMAT(A2,A190)
```

```
** Opening Files **
```

```
OPEN(1,file='SDFRDB3.TXT',form='formatted',status='UNKNOWN')
OPEN(2,file='CYCLICAL.TXT',form='formatted',status='UNKNOWN')
```

```
** Reading Input File for NSNs information only **
```

```
10 READ (1,1000,end=999) RECORD,LINE
   IF (RECORD.EQ.01) THEN
       WRITE (2,1004) '01',LINE
   ENDIF
```

```
** Generating Demand **
```

```
   IF (RECORD.EQ.02) THEN
       READ (LINE,1001) NSN
       VALUE(1)=X+J
       VALUE(2)=X+J+1+Z
       VALUE(3)=X+J+2+Z
       VALUE(4)=X+J+1+Z
       VALUE(5)=X+J
       VALUE(6)=X+J-1-Z
       VALUE(7)=X+J-2-Z
       VALUE(8)=X+J-1-Z
       VALUE(9)=X+J
       VALUE(10)=X+J+1+Z
       VALUE(11)=X+J+2+Z
       VALUE(12)=X+J+1+Z
       VALUE(13)=X+J
       VALUE(14)=X+J-1-Z
       VALUE(15)=X+J-2-Z
       VALUE(16)=X+J-1-Z
       X=X+10
       J=INT(RND()*10)
25      Z=INT(RND()*10)
       IF ((Z.LT.1).OR.(Z.GT.5)) THEN
           GOTO 25
       ENDIF
```

** Writing Demand **

```
        WRITE(2,1002) '02',NSN,VALUE(1),VALUE(2),VALUE(3),VALUE(4),
&          VALUE(5),VALUE(6),VALUE(7),VALUE(8),VALUE(9),VALUE(10),
&          VALUE(11),VALUE(12),VALUE(13),VALUE(14),VALUE(15),
&          VALUE(16)
      ENDIF
```

** Generating Flying Program **

```
      IF (RECORD.EQ.03) THEN
        READ (LINE,1001) NSN
        DO 30 I=1,16
          FLH(I)=2000+X
30      CONTINUE
```

** Writing Flying Program **

```
        WRITE(2,1002) '03',NSN,FLH(1),FLH(2),FLH(3),FLH(4),FLH(5),
&          FLH(6),FLH(7),FLH(8),FLH(9),FLH(10),FLH(11),
&          FLH(12),FLH(13),FLH(14),FLH(15),FLH(16)
      ENDIF

      IF (RECORD.EQ.04) THEN
        READ (LINE,1001) NSN
        DO 40 I=1,25
          PROG(I)=2500
40      CONTINUE
        WRITE(2,1003) '04',NSN,PROG(1),PROG(2),PROG(3),PROG(4),
&          PROG(5),
&          PROG(6),PROG(7),PROG(8),PROG(9),PROG(10),PROG(11),
&          PROG(12),PROG(13),PROG(14),PROG(15),PROG(16),
&          PROG(17),PROG(18),PROG(19),PROG(20),PROG(21),
&          PROG(22),PROG(23),PROG(24),PROG(25)
      ENDIF
```

```
999    GOTO 10
        CLOSE(1)
        CLOSE(2)
        STOP
        END
```

4) Random Times Series Component

```
*****
**  The purpose of this program is to generate random times series  **
**  component data.                                                 **
*****
```

```
PROGRAM RANDOM
```

```
** Variables **
```

```
CHARACTER LINE*190,NSN*17
INTEGER RECORD,X,J,I,VALUE(16),FLH(16),PROG(25)
X=100
J=2
Y=1
```

```
** Format **
```

```
1000 FORMAT(I2,A190)
1001 FORMAT (A17)
1002 FORMAT(A2,A17,4X,I5,15(2X,I5))
1003 FORMAT(A2,A17,4X,I5,24(2X,I5))
1004 FORMAT(A2,A190)
```

```
** Opening Files **
```

```
OPEN(1,file='SDFRDB5.'XT',form='formatted',status='UNKNOWN')
OPEN(2,file='RANDOM.TXT',form='formatted',status='UNKNOWN')
```

```
** Reading Input File for NSNs information only **
```

```
10 READ (1,1000,end=999) RECORD,LINE
   IF (RECORD.EQ.01) THEN
       WRITE (2,1004) '01',LINE
   ENDIF
```

```
** Generating Demand **
```

```
   IF (RECORD.EQ.02) THEN
       READ (LINE,1001) NSN
       DO 20 I=1,16
           VALUE(I)=X+INT(RND()*10)
20    CONTINUE
       X=X+10
```

```
** Writing Demand **
```

```
       WRITE(2,1002) '02',NSN,VALUE(1),VALUE(2),VALUE(3),VALUE(4),
&          VALUE(5),VALUE(6),VALUE(7),VALUE(8),VALUE(9),VALUE(10),
&          VALUE(11),VALUE(12),VALUE(13),VALUE(14),VALUE(15),
&          VALUE(16)
   ENDIF
```

```
** Generating Flying Program **
```

```
   IF (RECORD.EQ.03) THEN
       READ (LINE,1001) NSN
       DO 30 I=1,16
           FLH(I)=2000+X
30    CONTINUE
```

** Writing Flying Program **

```
      WRITE(2,1002) '03',NSN,FLH(1),FLH(2),FLH(3),FLH(4),FLH(5),
&      FLH(6),FLH(7),FLH(8),FLH(9),FLH(10),FLH(11),
&      FLH(12),FLH(13),FLH(14),FLH(15),FLH(16)
      ENDIF

      IF (RECORD.EQ.04) THEN
        READ (LINE,1001) NSN
        DO 40 I=1,25
          PROG(I)=2500
40      CONTINUE
        WRITE(2,1003) '04',NSN,PROG(1),PROG(2),PROG(3),PROG(4),
&      PROG(5),
&      PROG(6),PROG(7),PROG(8),PROG(9),PROG(10),PROG(11),
&      PROG(12),PROG(13),PROG(14),PROG(15),PROG(16),
&      PROG(17),PROG(18),PROG(19),PROG(20),PROG(21),
&      PROG(22),PROG(23),PROG(24),PROG(25)
      ENDIF

      GOTO 10
999    CLOSE(1)
      CLOSE(2)
      STOP
      END
```

5) Outlier Times Series Component

```
*****
** The purpose of this program is to generate outlier times series **
** component data. **
*****
```

PROGRAM OUTLIER

** Variables **

```
CHARACTER LINE*190,NSN*17
INTEGER RECORD,X,J,G,Z,F,I,VALUE(16),FLH(16),PROG(25)
X=100
J=2
F=0
G=0
Z=50
```

** Format **

```
1000 FORMAT(I2,A190)
1001 FORMAT (A17)
1002 FORMAT (A2,A17,4X,I5,15(2X,I5))
1003 FORMAT (A2,A17,4X,I5,24(2X,I5))
1004 FORMAT (A2,A190)
```

** Opening Files **

```
OPEN(1,file='SDFRDB4.TXT',form='formatted',status='UNKNOWN')
OPEN(2,file='OUTLIER.TXT',form='formatted',status='UNKNOWN')
```

** Reading Input File for NSNs information only **

```
10 READ (1,1000,end=999) RECORD,LINE

IF (RECORD.EQ.01) THEN
  WRITE (2,1004) '01',LINE
ENDIF
```

** Generating Demand **

```
IF (RECORD.EQ.02) THEN
  READ (LINE,1001) NSN
  VALUE(1)=X+J
  VALUE(2)=X+J
  VALUE(3)=X+J
  VALUE(4)=X+J
  VALUE(5)=X+J
  VALUE(6)=X+J
  VALUE(7)=X+J
  VALUE(8)=X+J
  VALUE(9)=X+J
  VALUE(10)=X+J
  VALUE(11)=X+J
  VALUE(12)=X+J
  VALUE(13)=X+J+F
  VALUE(14)=X+J+G
  VALUE(15)=X+J+Z
  VALUE(16)=X+J
  X=X+10
```

```

J=J+INT(RND()*10)
IF (Z.GT.0) THEN
  G=10*INT(RND()*10)
  F=10*INT(RND()*10)
  Z=0
ELSE
  IF (F.GT.0) THEN
    G=10*INT(RND()*10)
    F=0
    Z=0
  ELSE
    IF (G.GT.0) THEN
      G=0
      F=10*INT(RND()*10)
      Z=0
    ELSE
      G=0
      F=0
      Z=10*INT(RND()*10)
    ENDIF
  ENDIF
ENDIF
ENDIF

** Writing Demand **

      WRITE(2,1002) '02',NSN,VALUE(1),VALUE(2),VALUE(3),VALUE(4),
&      VALUE(5),VALUE(6),VALUE(7),VALUE(8),VALUE(9),VALUE(10),
&      VALUE(11),VALUE(12),VALUE(13),VALUE(14),VALUE(15),
&      VALUE(16)
      ENDIF

** Generating Flying Program **

      IF (RECORD.EQ.03) THEN
        READ (LINE,1001) NSN
        DO 30 I=1,16
          FLH(I)=2000+X
30      CONTINUE

** Writing Flying Program **

      WRITE(2,1002) '03',NSN,FLH(1),FLH(2),FLH(3),FLH(4),FLH(5),
&      FLH(6),FLH(7),FLH(8),FLH(9),FLH(10),FLH(11),
&      FLH(12),FLH(13),FLH(14),FLH(15),FLH(16)
      ENDIF

      IF (RECORD.EQ.04) THEN
        READ (LINE,1001) NSN
        DO 40 I=1,25
          PROG(I)=2500
40      CONTINUE
        WRITE(2,1003) '04',NSN,PROG(1),PROG(2),PROG(3),PROG(4),
&      PROG(5),
&      PROG(6),PROG(7),PROG(8),PROG(9),PROG(10),PROG(11),
&      PROG(12),PROG(13),PROG(14),PROG(15),PROG(16),
&      PROG(17),PROG(18),PROG(19),PROG(20),PROG(21),
&      PROG(22),PROG(23),PROG(24),PROG(25)
      ENDIF

      GOTO 10
999  CLOSE(1)
      CLOSE(2)
      STOP
      END

```

Appendix B: Sample Sizes Computation

1) Air Force Data - VTMR

Descriptive Statistics

Population	
<i>Mean</i>	2.3626
<i>Standard Error</i>	0.0480
<i>Median</i>	1.3267
<i>Mode</i>	0.8750
<i>Standard Dev.</i>	3.8715
<i>Variance</i>	14.9886
<i>Kurtosis</i>	120.9590
<i>Skewness</i>	8.5627
<i>Range</i>	90.4566
<i>Minimum</i>	0.0000
<i>Maximum</i>	90.4566
<i>Sum</i>	15354.7025
<i>Count</i>	6499.0000

Sample	
<i>Mean</i>	4.9175
<i>Standard Error</i>	0.2921
<i>Median</i>	2.5071
<i>Mode</i>	0.8755
<i>Standard Dev.</i>	6.8701
<i>Variance</i>	47.1984
<i>Kurtosis</i>	15.5797
<i>Skewness</i>	3.4689
<i>Range</i>	60.6485
<i>Minimum</i>	0.2954
<i>Maximum</i>	60.9439
<i>Sum</i>	2719.3509
<i>Count</i>	553.0000

Computing Sample Size with 99% Confidence

Sample Size = [(2.575) (Sample Standard Dev) / (Value within Mean)]^2

	DATA
Mean	4.9175
Beginning Sample Std. Dev.	0.2921
Value within Mean	0.0480
Sample size=	245.3817

2) Trend Data - VTMR

Descriptive Statistics

Sample	
<i>Mean</i>	0.7905
<i>Standard Error</i>	0.1128
<i>Median</i>	0.4416
<i>Mode</i>	#N/A
<i>Standard Dev.</i>	0.7135
<i>Variance</i>	0.5091
<i>Kurtosis</i>	-0.6359
<i>Skewness</i>	0.7693
<i>Range</i>	2.3191
<i>Minimum</i>	0.0420
<i>Maximum</i>	2.3611
<i>Sum</i>	31.6218
<i>Count</i>	40.0000

Computing Sample Size with 99% Confidence

Sample Size = $[(2.575) (\text{Sample Standard Dev}) / (\text{Value within Mean})]^2$

	DATA
Mean	0.7905
Beginning Sample Std. Dev.	0.1128
Value within	0.0480
Mean	
Sample size=	36.59026

3) Cyclic Data - VTMR

Descriptive Statistics

Sample	
<i>Mean</i>	0.0613
<i>Standard Error</i>	0.0075
<i>Median</i>	0.0465
<i>Mode</i>	#N/A
<i>Standard Dev.</i>	0.0476
<i>Variance</i>	0.0023
<i>Kurtosis</i>	0.4166
<i>Skewness</i>	1.0528
<i>Range</i>	0.1801
<i>Minimum</i>	0.0085
<i>Maximum</i>	0.1886
<i>Sum</i>	2.4538
<i>Count</i>	40.0000

Computing Sample Size with 99% Confidence

Sample Size = [(2.575) (Sample Standard Dev) / (Value within Mean)]^2

	DATA
Mean	0.0613
Beginning Sample Std. Dev.	0.0075
Value within	0.0480
Mean	
Sample size=	0.163108

4) Seasonal Data - VTMR

Descriptive Statistics

Sample	
<i>Mean</i>	0.0156
<i>Standard Error</i>	0.0018
<i>Median</i>	0.0124
<i>Mode</i>	0.0257
<i>Standard Dev.</i>	0.0117
<i>Variance</i>	0.0001
<i>Kurtosis</i>	0.3812
<i>Skewness</i>	1.0331
<i>Range</i>	0.0442
<i>Minimum</i>	0.0024
<i>Maximum</i>	0.0466
<i>Sum</i>	0.6223
<i>Count</i>	40.0000

Computing Sample Size with 99% Confidence

Sample Size = $[(2.575) (\text{Sample Standard Dev}) / (\text{Value within Mean})]^2$

	DATA
Mean	0.0156
Beginning Sample Std. Dev.	0.0018
Value within Mean	0.0480
Sample size=	0.009829

5) Outlier Data - VTMR

Descriptive Statistics

Sample	
<i>Mean</i>	0.6746
<i>Standard Error</i>	0.1112
<i>Median</i>	0.3918
<i>Mode</i>	0.0000
<i>Standard Dev.</i>	0.8585
<i>Variance</i>	0.7369
<i>Kurtosis</i>	7.8937
<i>Skewness</i>	2.4544
<i>Range</i>	4.3523
<i>Minimum</i>	0.0000
<i>Maximum</i>	4.3523
<i>Sum</i>	26.9820
<i>Count</i>	40.0000

Computing Sample Size with 99% Confidence

Sample Size = [(2.575) (Sample Standard Dev) / (Value within Mean)]²

	DATA
Mean	0.6746
Beginning Sample Std. Dev.	0.1112
Value within	0.0480
Mean	
Sample size=	35.55079

6) Random Data - VTMR

Descriptive Statistics

Sample	
Mean	0.0307
Standard Error	0.0024
Median	0.0274
Mode	0.0481
Standard Dev.	0.0149
Variance	0.0002
Kurtosis	-0.1467
Skewness	0.7709
Range	0.0582
Minimum	0.0087
Maximum	0.0669
Sum	1.2267
Count	40.0000

Computing Sample Size with 99% Confidence

Sample Size = [(2.575) (Sample Standard Dev) / (Value within Mean)]²

	DATA
Mean	0.0307
Beginning Sample Std. Dev.	0.0024
Value within	0.0480
Mean	
Sample size=	0.016007

Appendix C: RDB Eight Quarter Moving Average

```
*****
***  THIS PROGRAM IS TO SIMULATE THE RDB EIGHT QUARTER MOVING      ***
***  AVERAGE FORECASTING TECHNIQUE.                               ***
***  FORECASTING TECHNIQUE TO FORECAST OIM DEMAND.                 ***
*****
***  SIMULATION PROGRAM DEVELOPED BY CAPT CHRISTIAN DUSSAULT.      ***
*****
```

PROGRAM MOVAVE

*** VARIABLES DECLARATION

```
INTEGER TYPE,COUNT/0/,TOTALCOUNT/0/
CHARACTER * 15 NSN
CHARACTER * 9 NIIN
CHARACTER * 200 LINE
REAL FORECAST(16), DEMAND(16), PROGRAM(16), OIMDEMANDRATE(16),
&   MAD, MSE, MPE, MAPE, TOTALPROGRAM/0.0/, TOTALDEMAND/0.0/,
&   ERROR(4),
&   COUNTERROR/0.0/, COUNTMAPE/0.0/,
&   MAPETOTAL/0.0/, COUNTMAD/0.0/, MADTOTAL/0.0/,
&   COUNTMSE/0.0/, MSETOTAL/0.0/, COUNTMPE/0.0/, MPETOTAL/0.0/
```

*** FILES

```
OPEN (1,FILE='trend.TXT',FORM='FORMATTED',STATUS='UNKNOWN')
OPEN (2,FILE='trend.RDB',FORM='FORMATTED',STATUS='UNKNOWN')
```

*** FORMATS

```
1000 FORMAT(2X,A15,2X,16I7)
2000 FORMAT(I2,A200)
3000 FORMAT(A2,2X,A15,2X,4(2X,F8.2))
4000 FORMAT(A2,2X,A9,4(2X,F10.4))
5000 FORMAT('+NSN COUNT: ',I5)
8000 FORMAT(4X,A9)
```

*** READING INPUT FILE

```
DO
```

```
READ(1,2000,END=110) TYPE, LINE
```

```
IF (TYPE.EQ.1) THEN
```

```
  COUNT=COUNT+1
```

```
  TOTALCOUNT=0
```

```
  GOTO 100
```

```
ENDIF
```

```
IF (TYPE.EQ.2) THEN
```

```
  READ(LINE,1000) NSN,DEMAND(1),DEMAND(2),DEMAND(3),
```

```
&   DEMAND(4),DEMAND(5),DEMAND(6),DEMAND(7),DEMAND(8),
```

```
&   DEMAND(9),DEMAND(10),DEMAND(11),DEMAND(12),DEMAND(13),
```

```
&   DEMAND(14),DEMAND(15),DEMAND(16)
```

```
  GOTO 100
```

```
ENDIF
```

```

      IF (TYPE.EQ.3) THEN
        READ(LINE,1000) NSN, PROGRAM(1), PROGRAM(2), PROGRAM(3),
&      PROGRAM(4), PROGRAM(5), PROGRAM(6), PROGRAM(7), PROGRAM(8),
&      PROGRAM(9), PROGRAM(10), PROGRAM(11), PROGRAM(12),
&      PROGRAM(13), PROGRAM(14), PROGRAM(15), PROGRAM(16)
      ENDIF

      IF (TYPE.EQ.4) THEN
        GOTO 100
      ENDIF

*** FORECAST FOR PERIOD 9 USING THE PREVIOUS 8 QUARTERS

      TOTALDEMAND=DEMAND(1)+DEMAND(2)+DEMAND(3)+DEMAND(4)+
&      DEMAND(5)+DEMAND(6)+DEMAND(7)+DEMAND(8)
      TOTALPROGRAM=PROGRAM(1)+PROGRAM(2)+PROGRAM(3)+PROGRAM(4)+
&      PROGRAM(5)+PROGRAM(6)+PROGRAM(7)+PROGRAM(8)
      IF (TOTALPROGRAM.EQ.0) THEN
        FORECAST(9)=0.0
        GOTO 10
      ELSE
        OIMDEMANDRATE(9)=TOTALDEMAND/TOTALPROGRAM
        FORECAST(9)=OIMDEMANDRATE(9)*PROGRAM(9)
      ENDIF

*** FORECAST FOR PERIOD 10 USING THE PREVIOUS 8 QUARTERS

10    TOTALDEMAND=DEMAND(2)+DEMAND(3)+DEMAND(4)+DEMAND(5)+
&      DEMAND(6)+DEMAND(7)+DEMAND(8)+DEMAND(9)
      TOTALPROGRAM=PROGRAM(2)+PROGRAM(3)+PROGRAM(4)+PROGRAM(5)+
&      PROGRAM(6)+PROGRAM(7)+PROGRAM(8)+PROGRAM(9)
      IF (TOTALPROGRAM.EQ.0) THEN
        FORECAST(10)=0.0
        GOTO 20
      ELSE
        OIMDEMANDRATE(10)=TOTALDEMAND/TOTALPROGRAM
        FORECAST(10)=OIMDEMANDRATE(10)*PROGRAM(10)
        TOTALCOUNT=TOTALCOUNT+1
      ENDIF

*** FORECAST FOR PERIOD 11 USING THE PREVIOUS 8 QUARTERS

20    TOTALDEMAND=DEMAND(3)+DEMAND(4)+DEMAND(5)+DEMAND(6)+
&      DEMAND(7)+DEMAND(8)+DEMAND(9)+DEMAND(10)
      TOTALPROGRAM=PROGRAM(3)+PROGRAM(4)+PROGRAM(5)+PROGRAM(6)+
&      PROGRAM(7)+PROGRAM(8)+PROGRAM(9)+PROGRAM(10)
      IF (TOTALPROGRAM.EQ.0) THEN
        FORECAST(11)=0.0
        GOTO 30
      ELSE
        OIMDEMANDRATE(11)=TOTALDEMAND/TOTALPROGRAM
        FORECAST(11)=OIMDEMANDRATE(11)*PROGRAM(11)
        TOTALCOUNT=TOTALCOUNT+1
      ENDIF

```

*** FORECAST FOR PERIOD 12 USING THE PREVIOUS 8 QUARTERS

```
30  TOTALDEMAND=DEMAND(4)+DEMAND(5)+DEMAND(6)+DEMAND(7)+
    & DEMAND(8)+DEMAND(9)+DEMAND(10)+DEMAND(11)
    TOTALPROGRAM=PROGRAM(4)+PROGRAM(5)+PROGRAM(6)+PROGRAM(7)+
    & PROGRAM(8)+PROGRAM(9)+PROGRAM(10)+PROGRAM(11)
    IF (TOTALPROGRAM.EQ.0) THEN
        FORECAST(12)=0.0
        GOTO 40
    ELSE
        OIMDEMANDRATE(12)=TOTALDEMAND/TOTALPROGRAM
        FORECAST(12)=OIMDEMANDRATE(12)*PROGRAM(12)
        TOTALCOUNT=TOTALCOUNT+1
    ENDIF
```

*** FORECAST FOR PERIOD 13 USING THE PREVIOUS 8 QUARTERS

```
40  TOTALDEMAND=DEMAND(5)+DEMAND(6)+DEMAND(7)+DEMAND(8)+
    & DEMAND(9)+DEMAND(10)+DEMAND(11)+DEMAND(12)
    TOTALPROGRAM=PROGRAM(5)+PROGRAM(6)+PROGRAM(7)+PROGRAM(8)+
    & PROGRAM(9)+PROGRAM(10)+PROGRAM(11)+PROGRAM(12)
    IF (TOTALPROGRAM.EQ.0) THEN
        FORECAST(13)=0.0
        GOTO 50
    ELSE
        OIMDEMANDRATE(13)=TOTALDEMAND/TOTALPROGRAM
        FORECAST(13)=OIMDEMANDRATE(13)*PROGRAM(13)
        TOTALCOUNT=TOTALCOUNT+1
    ENDIF
```

*** FORECAST FOR PERIOD 14 USING THE PREVIOUS 8 QUARTERS

```
50  TOTALDEMAND=DEMAND(6)+DEMAND(7)+DEMAND(8)+DEMAND(9)+
    & DEMAND(10)+DEMAND(11)+DEMAND(12)+DEMAND(13)
    TOTALPROGRAM=PROGRAM(6)+PROGRAM(7)+PROGRAM(8)+PROGRAM(9)+
    & PROGRAM(10)+PROGRAM(11)+PROGRAM(12)+PROGRAM(13)
    IF (TOTALPROGRAM.EQ.0) THEN
        FORECAST(14)=0.0
        GOTO 60
    ELSE
        OIMDEMANDRATE(14)=TOTALDEMAND/TOTALPROGRAM
        FORECAST(14)=OIMDEMANDRATE(14)*PROGRAM(14)
        TOTALCOUNT=TOTALCOUNT+1
    ENDIF
```

*** FORECAST FOR PERIOD 15 USING THE PREVIOUS 8 QUARTERS

```
60  TOTALDEMAND=DEMAND(7)+DEMAND(8)+DEMAND(9)+DEMAND(10)+
    & DEMAND(11)+DEMAND(12)+DEMAND(13)+DEMAND(14)
    TOTALPROGRAM=PROGRAM(7)+PROGRAM(8)+PROGRAM(9)+PROGRAM(10)+
    & PROGRAM(11)+PROGRAM(12)+PROGRAM(13)+PROGRAM(14)
    IF (TOTALPROGRAM.EQ.0) THEN
        FORECAST(15)=0.0
        GOTO 70
    ELSE
        OIMDEMANDRATE(15)=TOTALDEMAND/TOTALPROGRAM
        FORECAST(15)=OIMDEMANDRATE(15)*PROGRAM(15)
        TOTALCOUNT=TOTALCOUNT+1
    ENDIF
```

*** FORECAST FOR PERIOD 16 USING THE PREVIOUS 8 QUARTERS

```

70  TOTALDEMAND=DEMAND(8)+DEMAND(9)+DEMAND(10)+DEMAND(11)+
&      DEMAND(12)+DEMAND(13)+DEMAND(14)+DEMAND(15)
    TOTALPROGRAM=PROGRAM(8)+PROGRAM(9)+PROGRAM(10)+PROGRAM(11)+
&      PROGRAM(12)+PROGRAM(13)+PROGRAM(14)+PROGRAM(15)
    IF (TOTALPROGRAM.EQ.0) THEN
        FORECAST(16)=0.0
        GOTO 80
    ELSE
        OIMDEMANDRATE(16)=TOTALDEMAND/TOTALPROGRAM
        FORECAST(16)=OIMDEMANDRATE(16)*PROGRAM(16)
        TOTALCOUNT=TOTALCOUNT+1
    ENDIF

```

*** MAD & MSE

```

80  MAD=(ABS(FORECAST(13)-DEMAND(13))+ABS(FORECAST(14)-DEMAND(14))+
&      ABS(FORECAST(15)-DEMAND(15))+ABS(FORECAST(16)-DEMAND(16))
&      )/4.0
    MSE=((FORECAST(13)-DEMAND(13))**2+(FORECAST(14)-DEMAND(14))**2
&      +(FORECAST(15)-DEMAND(15))**2+(FORECAST(16)-DEMAND(16))**2
&      )/4.0
    MADTOTAL=MADTOTAL+MAD
    COUNTMAD=COUNTMAD+1

    MSETOTAL=MSETOTAL+MSE
    COUNTMSE=COUNTMSE+1

```

*** MPE & MAPE

```

    COUNTERERROR=0

82  IF (DEMAND(13).EQ.0) THEN
    ERROR(13)=0.0
    GOTO 84
    ELSE
    COUNTERERROR=COUNTERERROR+1.0
    ERROR(13)=(DEMAND(13)-FORECAST(13))/DEMAND(13)
    ENDIF

84  IF (DEMAND(14).EQ.0) THEN
    ERROR(14)=0.0
    GOTO 86
    ELSE
    COUNTERERROR=COUNTERERROR+1.0
    ERROR(14)=(DEMAND(14)-FORECAST(14))/DEMAND(14)
    ENDIF

86  IF (DEMAND(15).EQ.0) THEN
    ERROR(15)=0.0
    GOTO 88
    ELSE
    COUNTERERROR=COUNTERERROR+1.0
    ERROR(15)=(DEMAND(15)-FORECAST(15))/DEMAND(15)
    ENDIF

```



```

88  IF (DEMAND(16).EQ.0) THEN
      ERROR(16)=0.0
      GOTO 90
    ELSE
      COUNTERERROR=COUNTERERROR+1.0
      ERROR(16)=(DEMAND(16)-FORECAST(16))/DEMAND(16)
    ENDIF

90  IF (COUNTERERROR.EQ.(0.0)) THEN
      MPE=0.0
      MAPE=0.0
      GOTO 95
    ENDIF
    WRITE(*,5000) 1

    MPE=( (ERROR(13)+ERROR(14)+ERROR(15)+ERROR(16))/COUNTERERROR)*100.0
    MAPE=( (ABS(ERROR(13))+ABS(ERROR(14))+ABS(ERROR(15))+ABS(ERROR(16))
&         )/COUNTERERROR)*100.0

    MAPETOTAL=MAPETOTAL+MAPE
    COUNTMAPE=COUNTMAPE+1
    MPETOTAL=MPETOTAL+MPE
    COUNTMPE=COUNTMPE+1

**  WRITING OUTPUT FILE. IT INCLUDES THE FORECASTS AND FORECASTING **
**  ERRORS **

95  WRITE(2,3000) '01',NSN,DEMAND(13),
&      DEMAND(14),DEMAND(15),DEMAND(16)
    WRITE(2,3000) '02',NSN,FORECAST(13),
&      FORECAST(14),FORECAST(15),FORECAST(16)
    READ(NSN,8000) NIIN
    WRITE(2,4000) '03',NIIN,MAD, MSE, MPE, MAPE

100  WRITE(*,5000) COUNT
      ENDDO

110  PRINT, MADTOTAL/COUNTMAD
      PRINT, MSETOTAL/COUNTMSE
      PRINT, MPETOTAL/COUNTMPE
      PRINT, MAPETOTAL/COUNTMAPE

      CLOSE(1)
      CLOSE(2)

      END

```

Appendix D: Data Elements for SDF and RDB

Record #1 - Data Information

<i>Data Element</i>	<i>Position</i>	<i>Length</i>	<i>Comment</i>
Data Type	1-2	2	
Air Logistic Center	3-4	2	
NSN	5-19	15	
Blank	20-22	3	
Item Name	23-32	10	
Blank	33-34	2	
Cost	35-41	7	Dollar Value = integer
Blank	42-43	2	
Consumable/Reparable Code	44-44	1	All items are reparable = R
Blank	45-46	2	
Previous Demand Average	47-53	7	Determined by Navy
Blank	54-55	2	
Previous Demand Variance	56-62	7	Determined by Navy
Blank	63-64	2	
Previous Demand Forecast	65-71	7	Determined by Navy
Blank	72-73	2	
Previous Demand Leadtime	74-80	7	Determined by Navy

Record #2 - Demands

<u>Data Element</u>	<u>Position</u>	<u>Length</u>	<u>Comment</u>
Data Type	1-2	2	
Air Logistic Center	3-4	2	
NSN	5-19	15	
Blank	20-21	2	
Demands	22-133	16 * 7	Qtr 1(1989) - Qtr 4(1993)

Record #3 - Past Programs

<u>Data Element</u>	<u>Position</u>	<u>Length</u>	<u>Comment</u>
Data Type	1-2	2	
Air Logistic Center	3-4	2	
NSN	5-19	15	
Blank	20-21	2	
Past programs	22-133	16 * 7	Qtr 1(1989) - Qtr 4(1993)

Record #4 - Future Programs

<u>Data Element</u>	<u>Position</u>	<u>Length</u>	<u>Comment</u>
Data Type	1-2	2	
Air Logistic Center	3-4	2	
NSN	5-19	15	
Blank	20-21	2	
Future programs	22-189	24 * 7	Qtr 1(1994) - Qtr 4(1999)

Appendix E: Aircraft Sustainability Data Values

LRU COMPONENT DATA FILE - prefix. 1

Each line replaceable unit (LRU) component will have a corresponding series of seven records in this file. These are read as FORTRAN free-format records with fields separated by a blank space and column positioning is insignificant.

Record No. 1

NSN	=	National stock number of the component.
COST	=	Unit cost.
IQPA	=	Quantity installed per aircraft. Assumed that all items had a IQPA of one.
FAP	=	Future application fraction: the fraction of aircraft that will be configured with this NSN. Assumed that all items had a FAP of 100%.
PLTT	=	Procurement lead-time in months. Assumed that all items had a PLTT of zero. As soon as we buy the item, we get the item.
ITASSE	=	The starting asset position for the NSN before any buys are made by the Aircraft Sustainability Model (ASM). Assumed that all items had a ITASSE of 0.
NHANSN	=	NSN of the next higher assembly (NHA); the next higher assembly for LRUs will be the weapon system, in this case FCA1 (Fictitious Canadian Aircraft One).
IBUDCODE	=	A budget code integer from 1 to 9 that permits cost subtotals to be generated by budget code. Currently, a value of 1 denotes an LRU

with shop replaceable units (SRUs) and 2 denotes an LRU without SRUs. Assumed that all items had a value of two.

NEGLV = Negotiated level for this NSN. Sometimes, requirements levels are set without regard for optimization. If **NEGFLAG** [in the parameters (PARAMS) file] is set to true, the model will buy up from ITASSE to NEGLV sacrosanct. Assumed that all items had a value of zero.

MAINTCON = Specifies whether the LRU is remove and replace (RR) or remove, repair, and replace (RRR). This affects when (if ever) wartime LRU base repair begins. Assumed that all items had a value of RRR.

ITEMPBUY = Fraction of the pipeline to be bought sacrosanct for this component. This value is used only if the **PBUYA** field on the PARAMS file is coded "ITEM". Assumed that all items had a value of 0.00.

CANNFLAG = A value of "N" indicates this item may not be cannibalized, a value of "Y" indicates that it can. This value is only used if the **CANN** field of the PARAMS file is coded "P" for partial cannibalization. Assumed that all items had a value of N.

NOPFLAG = Applicable only to data drawn from the Air Force's WRSK/BLSS. A value of "NOP" indicates that the item is non-optimized (NOPed). However, NOPed items are still a factor in constrained budget analysis. Processing of NOPed items is currently being developed. Assumed that all items had a value of AAA.

NRTSDEC = Decision to ship this component to the next higher servicing facility is made before attempting repair (1) or after repair (0).

Assumed that all items had a value of one.

Record No. 2

IBRTP = Peacetime base repair time in days for this component. Assumed that all items had a value of four.

IBRTW = Wartime base repair time in days for this component. Assumed that all items had a value of four.

Record No. 3

IOSTP = Peacetime order and ship time in days for this component. Assumed that all items had a value of 17.

IOSTW = Wartime order and ship time in days for this component. Assumed that all items had a value of 17.

Record No. 4

IDRTP = Peacetime depot repair time in days for this component. Assumed that all items had a value of 30.

IDRTW = Wartime depot repair in days for this component. Assumed that all items had a value of 30.

Record No. 5

TOIMDRP = Peacetime demand per flying hour for this component.

TOIMDRW = Wartime demand per flying hour for this component.

Record No. 6

BNRTSP = Base not reparable this station rate - peacetime percentage of demands that are either condemned or sent to the depot for repair (overhaul) for this component. Assumed that all items had a value

of 40%.

BNRTSW = Base not reparable this station rate - wartime percentage of demands that are either condemned or sent to the depot for repair (overhaul) for this component. Assumed that all items had a value of 40%.

Record No. 7

CONPCTP = Peacetime condemnation fraction for this component. Assumed that all items had a value of 1%.

CONPCTW = Wartime condemnation fraction for this component. Assumed that all items had a value of 1%

SRU COMPONENT DATA FILE - prefix. 2

No SRU file was used since items were considered as LRUs.

PARAMETERS FILE - prefix.PRM

The parameters file contains all the processing options for a particular ASM run such as the weapon system name, the flying program for the scenario, the day to be analyzed, the direct support objective (DSO), the first day that base repair of LRUs is permitted, and the type of computer on which the model run is being made (PC for personal computer, or HON for Honeywell). The ddd in the file name is the day(s) in the days of analysis card. The parameters in each file are determined on the ENMCS objectives on the Option 25 card.

These are read as FORTRAN free-format records. In this file, each field must be on a separate line.

ITODAY = The day to be analyzed. Must be between 0 and 99. Took the

value of zero.

- DATADIR** = The drive/directory that contains the ASM input data. For example, C:\ASM\DATA or \ASM\F111\DATA\ . Note the trailing backslash (\) that is required.
- OUTPDIR** = The drive/directory that contains the ASM output. For example, \ASM\OUTPUT\F111\.
- DEBUGER** = Specifies the extent to which debug output should be printed. Must be FULL, SOME, NONE, or NSNS; defaults to NONE.
- PIPEFLAG** = Specifies whether the computed pipeline quantities will be written to the OUTPIPE file. Must be T or F; defaults to T.
- CANN** = Specifies the type of cannibalization allowed. A value of "F" means all items, a value of "N" means no items, and a value of "P" means those items coded "Y" in the CANNFLAG of the component data files may be cannibalized. Took the value of N.
- NSNFILE** = If DEBUGER is set to NSNS, it specifies the file where a list of NSNS is stored. This file must be in the DATADIR directory and must contain one NSN per record. The ASM will then print debug output for each NSN in that list.
- NEGFLAG** = Specifies whether the model is to treat NEGLV as a sacrosanct level. Must be T or F. T indicates purchase of NEGLV quantity as a floor. Took the value of F.
- EXPRESUP** = Specifies that resupply is exponential rather than deterministic. Must be T for exponential or F for deterministic. Took the value of F.

OPTMTHD = A value of C indicates confidence-level optimization; a value of E indicates ENMCs optimization; a value of M indicates the interim (ENMCS/EBOs optimization) method. Took the value of E.

BUYPEAK = Specifies whether the peak pipelines for the whole scenario (T), the peak pipe pipelines through a specified day (for example, 30), or the pipelines on the day to be analyzed (F) are to be bought sacrosanct to the level specified by PBUY (see below). Took the value of T.

COMPUTER = Identifies host computer for the ASM. Should be set to "PC" for any microcomputer. Took the value of PC.

VMOPTION = Specifies how the variance-to-mean ratio (VMR) computation is to be performed. May be 1, 2, 3, or 4 but anything greater than 1 (*fixed VMR*) is highly experimental. Took the value of one.

Q = For VMOPTION=1, specifies the constant VMR. Must be at least 1.0. Took the value of 1.5.

PBUYA = Specifies the percentage of the pipeline to be bought sacrosanct: either peak or for ITODAY, see BUYPEAK. A value of 1.0 would specify buy the whole pipeline, 0.5 would buy half, 0.0 would buy none. PBUYA consists of two numbers: the first is the value for LRUs, the second for SRUs. A value of "ITEM" may also be used to indicate that the percentage coded in ITEMPBUY on the component data files will be bought sacrosanct. A value of "QPA" overrides the ITEMPBUY field and buys the floor quantity for items with QPA > 2. Took the value of 0.0.

WSNAME = Weapon system name (e.g., F111, F004, etc.). Took the value of FCA1.

NUNITS = Number of units of the weapon system at each base (PAA). Took the value of 24.

NBASES = Number of bases. Took the value of one.

NFIRSTBR = The first day base repair is allowed. Base component repair is suspended for days 1 through NFIRSTBR-1. NFIRSTBR is an array of three numbers: NFIRSTBR(1) is the first day that RR LRUs are repaired, NFIRSTBR(2) is the first day that RRR LRUs are repaired, NFIRSTBR(3) is the first day that SRUs are repaired. Took the value of one.

NFIRSTDR = The first day depot repair is allowed. Depot component repair is suspended for days 1 through NFIRSTDR-1. NFIRSTDR is an array of three numbers: NFIRSTDR(1) is the first day that RR LRUs are repaired, NFIRSTDR(2) is the first day that RRR LRUs are repaired, NFIRSTDR(3) is the first day that SRUs are repaired. Took the value of one.

NFIRSTOS = The first day that shipment from the depot becomes available. Took the value of one.

DSO = The number of not mission capable for supply (NMCS) aircraft allowed. The model optimizes the probability that the number NMCS is not greater than the DSO. Took the value of 7.2.

FNAME = The name (without extension) of the files containing the LRU and SRU component data.

NDAYS = The last day for which the component data will change. The component data is specified for day 0 through day NDAYS (in the COMPDATA file). The component data on days before day 0 are assumed identical to day 0. The component data on days after day

NDAYSFH are assumed to be identical to day NDAYSFH. For now, NDAYS is set to 1 -- i.e., resupply times, failure rates -- are assumed to be constant for each day of the war. Took the value of zero.

NDAYWARN= The number of days warning before the start of the scenario (normally set to 0). Allows the resupply times to shift to the wartime values before the start of the scenario. Took the value of zero.

COMMENT = Up to 60 characters of notes. This is a separate record in the file and may contain blanks.

SCENARIO FILE - prefix. SC

The scenario file contains specific items about the flying-hour program for an ASM run. These are read as FORTRAN free-format records.

NDAYSFH = The last day for which the flying program will change. The flying program is specified for day 0 through day NDAYSFH. (See the next field, FHP.) The flying programs on days before day 0 are assumed identical to day 0. The flying programs on days after day NDAYSFH are assumed to be identical to day NDAYSFH. Took the value of zero.

FHP = The array of the flying-hour program in hours per day, for days 0 through NDAYSFH. Took the value of 10.

Appendix E: Results Forecasting Measurements Errors

TREND

RMSE	RMSE	DIFFERENCE	RMSE	RMSE	DIFFERENCE	RMSE	RMSE	DIFFERENCE	RMSE	RMSE	DIFFERENCE
MAO	MAO		MAO	MAO		MAO	MAO		MAO	MAO	
22.5000	12.5000	10.0000	506.2500	156.2500	350.0000	7.0224	3.9013	3.1211	7.0224	3.9013	3.1211
18.0000	10.0000	8.0000	324.0000	100.0000	224.0000	5.6794	3.1552	2.5242	5.6794	3.1552	2.5242
4.5000	2.5000	2.0000	20.2500	6.2500	14.0000	1.5817	0.8787	0.7030	1.5817	0.8787	0.7030
4.5000	2.5000	2.0000	20.2500	6.2500	14.0000	3.8965	2.1647	1.7318	3.8965	2.1647	1.7318
18.0000	10.0000	8.0000	324.0000	100.0000	224.0000	10.7219	5.9566	4.7653	10.7219	5.9566	4.7653
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	3.5717	1.9843	1.5874	3.5717	1.9843	1.5874
22.5000	12.5000	10.0000	506.2500	156.2500	350.0000	6.4394	3.5775	2.8619	6.4394	3.5775	2.8619
22.5000	12.5000	10.0000	506.2500	156.2500	350.0000	6.2256	3.4586	2.7670	6.2256	3.4586	2.7670
18.0000	10.0000	8.0000	324.0000	100.0000	224.0000	2.7192	1.5106	1.2086	2.7192	1.5106	1.2086
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	4.0954	2.2752	1.8202	4.0954	2.2752	1.8202
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	2.5938	1.4410	1.1528	2.5938	1.4410	1.1528
18.0000	10.0000	8.0000	324.0000	100.0000	224.0000	9.8419	5.4677	4.3742	9.8419	5.4677	4.3742
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	2.5141	1.3967	1.1174	2.5141	1.3967	1.1174
22.5000	12.5000	10.0000	506.2500	156.2500	350.0000	5.4688	3.0382	2.4306	5.4688	3.0382	2.4306
22.5000	12.5000	10.0000	506.2500	156.2500	350.0000	5.3390	2.9661	2.3729	5.3390	2.9661	2.3729
4.5000	2.5000	2.0000	20.2500	6.2500	14.0000	5.2152	2.8974	2.3178	5.2152	2.8974	2.3178
4.5000	2.5000	2.0000	20.2500	6.2500	14.0000	1.1524	0.6402	0.5122	1.1524	0.6402	0.5122
22.5000	12.5000	10.0000	506.2500	156.2500	350.0000	5.0063	2.7813	2.2250	5.0063	2.7813	2.2250
18.0000	10.0000	8.0000	324.0000	100.0000	224.0000	4.0363	2.2424	1.7939	4.0363	2.2424	1.7939
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	3.4618	1.9232	1.5386	3.4618	1.9232	1.5386
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	2.0643	1.1468	0.9175	2.0643	1.1468	0.9175
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	2.0180	1.1211	0.8969	2.0180	1.1211	0.8969
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	1.9848	1.1038	0.8830	1.9848	1.1038	0.8830
13.5000	7.5000	6.0000	182.2500	56.2500	126.0000	1.9566	1.0870	0.8696	1.9566	1.0870	0.8696
4.5000	2.5000	2.0000	20.2500	6.2500	14.0000	0.9667	0.5371	0.4296	0.9667	0.5371	0.4296
22.5000	12.5000	10.0000	506.2500	156.2500	350.0000	1.8146	1.0081	0.8005	1.8146	1.0081	0.8005
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	4.1633	2.3129	1.8504	4.1633	2.3129	1.8504
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	1.7544	0.9747	0.7797	1.7544	0.9747	0.7797
13.5000	7.5000	6.0000	182.2500	56.2500	126.0000	6.2084	3.4491	2.7593	6.2084	3.4491	2.7593
4.5000	2.5000	2.0000	20.2500	6.2500	14.0000	0.8781	0.4878	0.3903	0.8781	0.4878	0.3903
18.0000	10.0000	8.0000	324.0000	100.0000	224.0000	9.4293	5.2385	4.1908	9.4293	5.2385	4.1908
13.5000	7.5000	6.0000	182.2500	56.2500	126.0000	7.4818	4.1566	3.3252	7.4818	4.1566	3.3252
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	2.2786	1.2659	1.0127	2.2786	1.2659	1.0127
18.0000	10.0000	8.0000	324.0000	100.0000	224.0000	4.8920	2.7178	2.1742	4.8920	2.7178	2.1742
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	6.1031	3.3906	2.7125	6.1031	3.3906	2.7125
22.5000	12.5000	10.0000	506.2500	156.2500	350.0000	3.7348	2.0735	1.6599	3.7348	2.0735	1.6599
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	8.6412	4.8877	3.8405	8.6412	4.8877	3.8405
4.5000	2.5000	2.0000	20.2500	6.2500	14.0000	4.6638	2.5671	2.0728	4.6638	2.5671	2.0728
9.0000	5.0000	4.0000	81.0000	25.0000	56.0000	2.0596	1.1442	0.9154	2.0596	1.1442	0.9154
13.1625	7.3125	5.8500	216.1688	66.1688	149.4500	4.3324	2.4069	1.9255	4.3324	2.4069	1.9255
44.0178	13.5857	8.6549	3542.2064	338.1160	1679.3308	6.4581	1.9932	1.2757	6.4581	1.9932	1.2757

z-Test: Two-Sample for Means

Mean	Known variance	Observed	Hypothesized Mean Difference	z	z Critical two-tail 90%	z Critical one-tail 95%
13.1625	7.3125	44.0178	13.5857	40.0000	40.0000	40.0000
44.0178	13.5857	40.0000	40.0000	0.0000	0.0000	0.0000
40.0000	40.0000	0.0000	0.0000	4.8147	4.8147	4.8147
0.0000	0.0000	4.8147	4.8147	1.6450	1.6450	1.6450
4.8147	1.6450	1.6450	1.6450	1.6450	1.6450	1.6450

z-Test: Two-Sample for Means

Mean	Known variance	Observed	Hypothesized Mean Difference	z	z Critical two-tail 90%	z Critical one-tail 95%
216.1688	66.1688	3542.2064	338.1160	40.0000	40.0000	40.0000
3542.2064	338.1160	40.0000	40.0000	0.0000	0.0000	0.0000
40.0000	40.0000	0.0000	0.0000	4.8147	4.8147	4.8147
0.0000	0.0000	4.8147	4.8147	1.6450	1.6450	1.6450
4.8147	1.6450	1.6450	1.6450	1.6450	1.6450	1.6450

z-Test: Two-Sample for Means

Mean	Known variance	Observed	Hypothesized Mean Difference	z	z Critical two-tail 90%	z Critical one-tail 95%
7.0224	3.9013	4.3324	2.4069	40.0000	40.0000	40.0000
4.3324	2.4069	6.4581	1.9932	40.0000	40.0000	40.0000
6.4581	1.9932	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	4.8147	4.8147	1.6450	1.6450	1.6450
4.8147	1.6450	1.6450	1.6450	1.6450	1.6450	1.6450

z-Test: Two-Sample for Means

Mean	Known variance	Observed	Hypothesized Mean Difference	z	z Critical two-tail 90%	z Critical one-tail 95%
4.3324	2.4069	6.4581	1.9932	40.0000	40.0000	40.0000
6.4581	1.9932	0.0000	0.0000	0.0000	0.0000	0.0000
0.0000	0.0000	4.8147	4.8147	1.6450	1.6450	1.6450
4.8147	1.6450	1.6450	1.6450	1.6450	1.6450	1.6450

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ID	RMS MAE		DIFFERENCE	SDV MAE		DIFFERENCE	RMS MAE		DIFFERENCE	SDV MAE		DIFFERENCE
	MAE	MAE		MAE	MAE		MAE	MAE				
0	0.8750	0.8500	0.0250	1.1875	1.1900	-0.0025	-0.0111	-0.0593	0.0482	0.8447	0.8230	0.0217
1	2.0000	2.0000	0.0000	5.5000	5.5000	0.0000	-0.0404	-0.0404	0.0000	1.7140	1.7140	0.0000
2	2.0000	2.0000	0.0000	5.5000	5.5000	0.0000	-0.0317	-0.0317	0.0000	1.5187	1.5187	0.0000
3	2.0000	2.0000	0.0000	5.5000	5.5000	0.0000	-0.0282	-0.0282	0.0000	1.4317	1.4317	0.0000
4	1.6250	1.6500	-0.0250	3.6875	3.6900	-0.0025	-0.0182	0.0167	-0.0349	1.4425	1.4366	0.0059
5	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0089	-0.0089	0.0000	0.7873	0.7873	0.0000
6	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0080	-0.0080	0.0000	0.7450	0.7450	0.0000
7	1.6250	1.6000	0.0250	3.6875	3.6900	-0.0025	-0.0115	-0.0392	0.0277	0.9066	0.8930	0.0136
8	0.8750	0.8500	0.0250	1.1875	1.1900	-0.0025	-0.0035	-0.0304	0.0269	0.4721	0.4588	0.0133
9	2.1750	2.3500	0.0250	7.6875	7.6900	-0.0025	-0.0020	-0.0453	0.0253	1.2106	1.1943	0.0163
10	0.8750	0.8500	0.0250	1.1875	1.1900	-0.0025	-0.0028	0.0270	0.0242	0.4240	0.4121	0.0119
11	2.2500	2.2500	0.0000	2.2500	2.2500	0.0000	-0.0048	-0.0048	0.0000	0.5793	0.5793	0.0000
12	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0044	-0.0044	0.0000	0.5512	0.5512	0.0000
13	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0041	-0.0041	0.0000	0.5324	0.5324	0.0000
14	2.0000	2.0000	0.0000	5.5000	5.5000	0.0000	-0.0093	-0.0093	0.0000	0.8206	0.8206	0.0000
15	2.1750	2.4000	-0.0250	7.6875	7.6900	-0.0025	-0.0117	0.0077	-0.0164	0.9270	0.9365	-0.0095
16	2.0000	2.0000	0.0000	5.5000	5.5000	0.0000	-0.0078	-0.0078	0.0000	0.7527	0.7527	0.0000
17	0.8750	0.9000	-0.0250	1.1875	1.1900	-0.0025	-0.0016	0.0167	-0.0183	0.3213	0.3204	0.0009
18	2.1750	2.4000	-0.0250	7.6875	7.6900	-0.0025	-0.0094	0.0080	-0.0174	0.8327	0.8413	-0.0086
19	2.1750	2.4000	-0.0250	7.6875	7.6900	-0.0025	-0.0087	0.0080	-0.0167	0.7991	0.8074	-0.0083
20	1.2500	1.2500	0.0000	5.5000	5.5000	0.0000	-0.0024	-0.0024	0.0000	0.4088	0.4088	0.0000
21	2.0000	2.0000	0.0000	5.5000	5.5000	0.0000	-0.0055	-0.0055	0.0000	0.6335	0.6335	0.0000
22	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0022	-0.0022	0.0000	0.3885	0.3885	0.0000
23	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0020	-0.0020	0.0000	0.3756	0.3756	0.0000
24	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0034	0.0080	-0.0144	0.4840	0.4911	-0.0071
25	2.1750	2.4000	-0.0250	7.6875	7.6900	-0.0025	-0.0040	0.0079	-0.0130	0.6646	0.6718	-0.0072
26	0.8750	0.8500	0.0250	1.1875	1.1900	-0.0025	-0.0057	0.0079	-0.0136	0.4448	0.4535	-0.0086
27	2.3750	2.4000	-0.0250	7.6875	7.6900	-0.0025	-0.0088	0.0124	-0.0132	0.2313	0.2318	-0.0005
28	2.3750	2.4000	-0.0250	7.6875	7.6900	-0.0025	-0.0052	0.0077	-0.0129	0.8165	0.8229	-0.0064
29	2.0000	2.0000	0.0000	5.5000	5.5000	0.0000	-0.0035	-0.0035	0.0000	0.5067	0.5067	0.0000
30	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0013	-0.0013	0.0000	0.3043	0.3043	0.0000
31	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0013	-0.0013	0.0000	0.2971	0.2971	0.0000
32	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0012	-0.0012	0.0000	0.2922	0.2922	0.0000
33	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0012	-0.0012	0.0000	0.2875	0.2875	0.0000
34	1.6250	1.6500	-0.0250	3.6875	3.6900	-0.0025	-0.0019	0.0094	-0.0113	0.3674	0.3730	-0.0056
35	0.8750	0.9000	-0.0250	1.1875	1.1900	-0.0025	-0.0006	0.0104	-0.0110	0.1930	0.1985	-0.0055
36	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0010	0.0010	0.0000	0.2655	0.2655	0.0000
37	2.1750	2.4000	-0.0250	7.6875	7.6900	-0.0025	-0.0034	0.0071	-0.0105	0.4987	0.5039	-0.0052
38	1.2500	1.2500	0.0000	2.2500	2.2500	0.0000	-0.0009	-0.0009	0.0000	0.2563	0.2563	0.0000
39	0.8750	0.9000	-0.0250	1.1875	1.1900	-0.0025	-0.0005	0.0095	-0.0100	0.1749	0.1799	-0.0050
40	1.5949	1.6025	-0.0006	3.9641	3.9653	-0.0012	-0.0075	0.0058	-0.0016	0.6352	0.6360	-0.0008
41	0.3057	0.3120	-0.0063	6.0671	6.0688	0.0000	0.0001	0.0053	0.0002	0.1363	0.1359	0.0004

z-Test: Two-Sample for Means			z-Test: Two-Sample for Means			z-Test: Two-Sample for Means		
variable 1	variable 2		variable 1	variable 2		variable 1	variable 2	
Mean	1.5065	1.6025	Mean	3.9651	3.96536	Mean	0.0065	-0.0036
Known variance	0.305	0.3120	Known variance	6.067	6.0488	Known variance	0.0001	0.0003
Observations	40.0000	40.0000	Observations	40.0000	40.0000	Observations	39.0000	39.0000
Hypothesized Mean Difference	0.0000	0.0000	Hypothesized Mean Difference	0.0000	0.0000	Hypothesized Mean Difference	0.0000	0.0000
z	-0.0453	-0.0072	z	-0.0022	-0.0022	z	-0.9210	-0.9210
Critical two-tail 90%	1.6450	1.6450	Critical two-tail 90%	1.6450	1.6450	Critical two-tail 90%	1.6450	1.6450
Critical one-tail 95%	1.6450	1.6450	Critical one-tail 95%	1.6450	1.6450	Critical one-tail 95%	1.6450	1.6450

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	variable 1	variable 2	variable 1	variable 2	variable 1	variable 2		
Mean	2.4844	2.5600	Mean	0.5395	0.5103	Mean	0.0878	0.1024
Maximal variance	0.6184	0.7331	Maximal variance	18.9599	31.6613	Maximal variance	0.3119	0.3739
Cross-correlation	-0.0000	-0.0000	Cross-correlation	-0.0000	-0.0000	Cross-correlation	-0.0000	-0.0000
Hypothesized Mean Difference	0.0000	0.0000	Hypothesized Mean Difference	0.0000	0.0000	Hypothesized Mean Difference	0.0000	0.0000
t	-0.0952	0.0630	t	-0.6330	0.2173	t	-0.1952	0.1952
2-tailed t-test	90%	90%	2-tailed t-test	90%	90%	2-tailed t-test	90%	90%
Critical t-value	1.6450	1.6450	Critical t-value	1.6450	1.6450	Critical t-value	1.6450	1.6450
Critical z-value	95%	95%	Critical z-value	95%	95%	Critical z-value	95%	95%

Variable	Mean	Standard Deviation	Minimum	Maximum
Age	30.0000	10.0000	18	45
Gender	1.0000	0.0000	1	1
Marital status	1.0000	0.0000	1	1
Education	12.0000	1.0000	10	14
Occupation	1.0000	0.0000	1	1
Income	1.0000	0.0000	1	1
Health	1.0000	0.0000	1	1
Religion	1.0000	0.0000	1	1
Political	1.0000	0.0000	1	1
Family size	1.0000	0.0000	1	1
Household	1.0000	0.0000	1	1
Neighborhood	1.0000	0.0000	1	1
Community	1.0000	0.0000	1	1
Society	1.0000	0.0000	1	1
World	1.0000	0.0000	1	1
Universe	1.0000	0.0000	1	1
Population	1.0000	0.0000	1	1
Sample	1.0000	0.0000	1	1
Survey	1.0000	0.0000	1	1
Study	1.0000	0.0000	1	1
Research	1.0000	0.0000	1	1
Analysis	1.0000	0.0000	1	1
Interpretation	1.0000	0.0000	1	1
Conclusion	1.0000	0.0000	1	1
Recommendation	1.0000	0.0000	1	1
Final report	1.0000	0.0000	1	1
Publication	1.0000	0.0000	1	1
Archiving	1.0000	0.0000	1	1
Preservation	1.0000	0.0000	1	1
Access	1.0000	0.0000	1	1
Use	1.0000	0.0000	1	1
Impact	1.0000	0.0000	1	1
Legacy	1.0000	0.0000	1	1
Future	1.0000	0.0000	1	1
History	1.0000	0.0000	1	1
Present	1.0000	0.0000	1	1
Past	1.0000	0.0000	1	1
Time	1.0000	0.0000	1	1
Space	1.0000	0.0000	1	1
Place	1.0000	0.0000	1	1
Location	1.0000	0.0000	1	1
Address	1.0000	0.0000	1	1
Home	1.0000	0.0000	1	1
Work	1.0000	0.0000	1	1
School	1.0000	0.0000	1	1
Church	1.0000	0.0000	1	1
Government	1.0000	0.0000	1	1
Business	1.0000	0.0000	1	1
Industry	1.0000	0.0000	1	1
Service	1.0000	0.0000	1	1
Healthcare	1.0000	0.0000	1	1
Education	1.0000	0.0000	1	1
Research	1.0000	0.0000	1	1
Development	1.0000	0.0000	1	1
Innovation	1.0000	0.0000	1	1
Progress	1.0000	0.0000	1	1
Change	1.0000	0.0000	1	1
Growth	1.0000	0.0000	1	1
Expansion	1.0000	0.0000	1	1
Contraction	1.0000	0.0000	1	1
Stagnation	1.0000	0.0000	1	1
Regression	1.0000	0.0000	1	1
Decline	1.0000	0.0000	1	1
Disaster	1.0000	0.0000	1	1
Crisis	1.0000	0.0000	1	1
Emergency	1.0000	0.0000	1	1
Conflict	1.0000	0.0000	1	1
War	1.0000	0.0000	1	1
Peace	1.0000	0.0000	1	1
Stability	1.0000	0.0000	1	1
Instability	1.0000	0.0000	1	1
Order	1.0000	0.0000	1	1
Disorder	1.0000	0.0000	1	1
Control	1.0000	0.0000	1	1
Loss of control	1.0000	0.0000	1	1
Freedom	1.0000	0.0000	1	1
Restriction	1.0000	0.0000	1	1

Variable	Value
000000	10124
000000	03239
000000	400000
000000	00000
000000	01952
000000	10450
000000	10450

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z-Test: Two-Sample for Means		z-Test: Two-Sample for Means		z-Test: Two-Sample for Means	
variable 1	variable 2	variable 1	variable 2	variable 1	variable 2
Mean	1795.14	Mean	915.7250	Mean	2560.3
Standard deviation	88.8150	Standard deviation	40.9167	Standard deviation	10.6888
Number of observations	36	Number of observations	36	Number of observations	36
Hypothesized mean difference	0.0000	Hypothesized mean difference	0.0000	Hypothesized mean difference	0.0000
t-Statistic	180.15	t-Statistic	0.1051	t-Statistic	2.2574
Critical t-value, two-tail, 95%	1.9450	Critical t-value, two-tail, 95%	1.9450	Critical t-value, two-tail, 95%	1.9450
Critical t-value, one-tail, 95%	1.6450	Critical t-value, one-tail, 95%	1.6450	Critical t-value, one-tail, 95%	1.6450
Probability (t-stat > t-critical two-tail)	0.0000	Probability (t-stat > t-critical two-tail)	0.9190	Probability (t-stat > t-critical two-tail)	0.0286
Probability (t-stat > t-critical one-tail)	0.0000	Probability (t-stat > t-critical one-tail)	0.9595	Probability (t-stat > t-critical one-tail)	0.0143
p-Value	0.0000	p-Value	0.9190	p-Value	0.0286
z-Statistic	180.15	z-Statistic	0.1051	z-Statistic	2.2574
Critical z-value, two-tail, 95%	1.96	Critical z-value, two-tail, 95%	1.96	Critical z-value, two-tail, 95%	1.96
Critical z-value, one-tail, 95%	1.645	Critical z-value, one-tail, 95%	1.645	Critical z-value, one-tail, 95%	1.645
Probability (z-stat > z-critical two-tail)	0.0000	Probability (z-stat > z-critical two-tail)	0.9190	Probability (z-stat > z-critical two-tail)	0.0286
Probability (z-stat > z-critical one-tail)	0.0000	Probability (z-stat > z-critical one-tail)	0.9595	Probability (z-stat > z-critical one-tail)	0.0143
p-Value	0.0000	p-Value	0.9190	p-Value	0.0286

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0.5270	0.5750	0.1480	0.3911	0.5375	0.1464	39.1489	30.0000	9.1489
2.1201	2.5750	0.8539	14.0095	20.7775	-6.7880	4.0669	17.0833	-12.3604
1.1995	1.2550	0.0285	3.6554	3.5475	0.1079	27.2645	27.5000	-0.2355
8.4700	7.5500	0.7000	137.6450	111.3900	26.2700	50.5387	45.0780	5.4607
24.7226	41.3250	16.8024	649.8447	1956.4126	1308.5679	34.7155	59.2954	25.1939
3.4031	3.1250	0.2781	14.6250	12.4175	2.2075	40.0416	42.8333	-2.7817
1.9259	1.8000	0.1259	4.7358	3.9650	0.7708	9.0265	11.6875	-2.6510
3.6758	3.5750	0.1008	17.9910	17.1825	0.8085	-136.6335	148.4848	-11.8513
2.2633	2.5500	0.0133	7.2008	7.2850	-0.0842	154.4433	154.6667	-0.2234
9.8445	8.5500	1.2945	119.3983	89.8100	29.5883	-21.0002	13.0649	8.0353
3.6180	2.8250	0.7930	13.3951	11.0375	2.3576	-1.4026	8.1753	9.5779
1.7235	1.5500	0.2235	3.4126	2.5200	0.8926	-58.6551	-40.2500	-18.4051
6.7128	6.8500	0.1172	66.2028	80.2050	-14.0022	9.5099	10.0226	3.5127
5.5601	5.5500	0.0517	42.0158	40.4650	1.5492	-55.8309	60.5100	-4.6791
4.2774	4.1000	0.1774	28.7039	26.7000	1.9739	-33.1649	29.4861	3.6780
4.9994	4.7500	0.1594	35.6584	32.6950	2.9644	-18.1876	-22.0678	3.6702
10.3913	8.1750	2.2163	109.1836	71.7025	37.4811	-46.1426	29.5588	-15.5838
3.4428	4.1250	0.6822	32.0850	33.8375	-1.7525	-66.4030	-79.4162	13.0132
4.2912	4.3000	-0.0088	25.2333	23.8950	1.3383	-65.1568	-58.6310	-6.5268
1.5544	1.4500	0.1044	7.4894	7.2150	0.2744	-156.8389	126.6667	30.1722
5.0373	4.9250	0.1123	28.8344	28.1875	0.6469	-141.9159	143.3333	1.4174
10.4500	15.6250	-5.1750	191.0505	285.9675	-94.9170	19.5083	38.0614	-18.5531
3.5992	3.7250	-0.1258	15.9034	16.9425	-1.0391	-28.6396	-25.9239	-2.7157
7.6533	7.3250	0.3283	62.3134	58.2075	4.1059	-27.1956	-13.4842	-13.7114
7.8820	7.7500	0.6070	76.2106	60.7125	15.4981	-32.2967	-19.8686	-12.4281
2.3672	2.2000	0.1672	5.9926	5.1950	0.7976	-48.4440	-40.2381	-8.2059
4.5038	4.1500	0.4338	44.0020	28.9900	15.0220	-0.4018	-12.1964	12.5982
1.9900	1.9000	0.0900	4.8690	4.7350	0.0730	-115.1298	-96.6667	-18.6631
1.9594	0.6750	0.4834	2.1171	0.5025	1.6146	-107.9202	-26.6667	-81.2535
1.7295	1.8620	-0.1085	3.0568	3.4250	-0.3732	57.7245	61.6667	-4.3922
1.3446	1.3750	-0.0304	3.2428	3.2525	-0.0097	9.1641	9.3333	-0.1472
42.3013	39.5000	2.8013	2130.7893	1882.1953	248.5940	-7.4317	-6.7322	-0.7075
48.5412	62.5500	-14.0088	2868.1082	4060.0449	-3017.9387	12.7500	20.4530	-7.6940
44.5568	47.1000	-2.5432	2935.2039	3331.4456	-396.2417	-7.6140	-7.9728	0.3588
8.5257	8.6250	-0.0993	81.1131	110.0250	-28.9894	-4.1302	12.5845	-16.7147
17.1351	23.1000	-5.9649	375.8703	561.0650	-185.1947	31.0606	43.7157	-12.6551
2.7271	2.5500	0.1771	10.6653	9.6450	1.0201	14.9218	21.0430	-6.1212
26.9472	20.8000	6.1472	1195.9343	1260.8402	64.0959	0.8420	5.5337	4.6917
3.9068	3.4500	-0.4566	18.0414	14.1050	3.9364	-88.6528	-35.2557	-53.3971
2.9560	3.2000	-0.2440	9.4188	11.3250	-1.9062	-1.8549	1.5675	3.4224
15.2913	15.3250	-0.0337	616.3079	655.4326	-39.1247	-22.5872	23.1445	0.5573
8.6478	9.4750	-0.1778	107.8054	85.5575	22.2479	-46.2526	35.4765	-10.7761
0.7968	0.8000	-0.0032	0.8702	0.7750	0.0952	32.4890	40.0000	-7.5110
1.1868	1.3000	-0.1134	1.8752	2.7250	-0.8488	-22.8483	57.5000	34.6517
9.0747	9.5000	-0.4253	64.5591	110.3250	-15.8659	2.8116	7.3085	-4.4869
1.6028	1.8500	-0.2472	4.4935	6.3700	-1.4443	-21.5741	17.3810	4.1931
2.7083	3.5500	-0.8312	8.5820	16.2900	-7.7080	-72.7083	99.5000	26.7917
2.2934	2.5500	0.0134	73.4713	100.0025	26.5312	10.6471	29.3995	-18.7524
27.4761	27.3000	0.0761	31.0911	10.9200	0.1711	36.7018	36.8750	-0.1732
1.9718	3.0250	0.0761	1213.6606	1405.4950	-191.8341	2.6858	7.5620	-4.8762
4.7594	4.7000	0.0594	3.9563	9.2625	-5.3062	0.0000	0.0000	0.0000
2.0957	1.7500	0.3957	44.9025	40.4700	4.4329	-101.5626	104.3553	2.7927
0.9574	0.9500	0.0074	6.0489	4.9150	1.1339	-67.2141	25.3125	-41.9016
4.0248	4.9500	-0.8252	20.7617	28.4850	-7.5233	-46.1360	54.6074	8.4714
4.0598	4.9000	-0.8402	28.1386	39.0500	-10.9520	21.7110	29.6667	-7.9557
3.2901	3.6250	0.3376	12.6489	17.2275	-4.5886	15.1930	39.4875	-24.4945
5.6229	5.2250	0.3977	8.4655	2.4450	0.0295	19.6201	1.5850	21.2051
1.6047	1.1750	-0.0449	37.7705	3.4425	0.3260	-0.6904	3.8917	4.5821
2.5396	2.7250	-0.1851	1.6681	1.8325	0.1684	85.3600	90.0000	-4.6400
5.0044	6.6500	-1.6454	3.6498	3.3500	0.3002	-100.2424	107.7778	7.5354
1.8759	1.5750	0.3019	11.1455	12.4925	-1.3470	-24.2283	19.3750	4.8533
3.3176	3.7750	-0.0431	89.0358	46.5750	42.4608	-16.2086	4.6519	11.5567
3.2268	3.1000	0.0431	4.5946	3.6475	0.9474	107.7326	70.0000	37.7426
5.2603	5.3500	-0.1474	15.1964	18.7075	0.2889	-55.3395	40.7379	14.5756
4.1701	4.2275	1.2564	11.0458	9.8650	1.1608	-88.2325	75.0000	13.2325
4.1557	5.4575	-1.2664	31.9975	37.0450	-5.0475	3.4924	14.0753	10.5829
2.3112	4.2500	-0.0389	22.5659	22.1375	0.4233	47.5405	39.5000	8.2392
			22.1444	19.5350	16.3406	-22.8624	38.6679	8.8015
			5.1430	9.1050	0.0190	-24.0351	26.2560	2.2108

6.3170	6.5500	2.1130	52.4225	86.3300	-33.0075	14.2985	44.3646	58.6631	14.2985
2.1242	1.2650	0.0992	6.6958	5.3675	0.2383	-9.4772	32.2952	27.4351	4.8641
3.2551	3.1000	0.1251	12.6718	12.3750	0.2968	-3.6758	68.1745	63.2407	4.9338
1.1127	1.2350	0.0133	1.8955	1.5825	0.3170	9.9304	77.3040	82.9167	5.6137
1.1019	1.0800	0.2197	130.2784	134.9194	-4.6366	6.8740	48.4001	46.7673	1.6372
1.1152	0.9750	0.1402	1.7286	1.6425	-0.0869	-7.4693	65.8640	73.3333	-7.4693
9.3807	10.7250	-1.3443	102.2685	142.7675	-40.4990	-2.1535	16.2955	18.2771	-2.0116
1.0214	1.6750	-0.6547	4.7000	4.0025	0.7065	5.1853	57.7074	58.7500	1.0428
14.9422	10.8750	4.0672	240.2615	165.3025	83.9590	-14.0351	42.7379	28.7332	14.0027
0.5418	0.0168	0.5250	0.3397	0.4175	-0.0778	43.1961	38.1961	15.0000	23.1961
2.1034	1.5750	0.5282	7.9591	4.8475	3.1116	-43.9434	152.2695	115.9762	36.2933
0.9034	1.0000	-0.0966	1.1024	1.0000	0.1024	-27.2360	58.7855	53.0000	5.7855
1.7789	1.5250	0.2539	5.0322	4.9125	0.1197	-27.2360	57.6438	63.0000	-5.3562
1.8995	1.5000	-0.6005	3.6157	3.8550	-0.2393	0.6360	84.3640	85.0000	-0.6360
2.7635	2.3500	0.4135	7.8978	5.9150	1.9828	-13.5487	40.1621	30.7500	9.4121
0.8637	0.7250	0.1387	0.0344	0.0275	0.0069	17.6153	39.8633	33.3333	6.5500
6.5689	5.9000	0.6689	52.4818	43.2750	9.2068	-32.8799	151.0459	122.2321	28.8138
12.6049	11.3500	1.2549	178.0645	142.1700	35.8945	-13.4892	89.3690	74.9235	12.4255
2.8000	3.0500	-0.2500	-2.2137	13.1550	-5.9433	-23.6559	22.8105	24.9151	-4.1046
2.1580	1.7250	0.4330	5.2094	3.7475	1.4619	-8.6136	37.3352	28.5139	8.8213
1.1038	1.1750	0.0442	126.9449	140.7525	-11.8078	-2.5800	54.6020	57.3820	-2.5800
1.5116	1.2750	0.2366	2.8666	2.2175	0.6291	16.6211	45.5100	28.8889	16.6211
0.7702	0.9750	0.2048	1.1532	1.4675	-0.3143	-15.6197	34.5564	39.3750	-4.8186
6.8031	4.5750	2.2281	51.2890	22.7025	28.5865	-54.4007	126.9901	11.2868	55.3033
0.3346	0.6500	-0.0151	0.5744	0.6300	-0.0556	44.1666	24.1686	20.0000	4.1666
6.0132	3.8000	0.2668	40.7154	50.1550	-9.4376	-44.1666	16.6436	16.8445	-0.2009
1.5927	1.3500	0.2427	3.2806	2.4500	0.8306	-7.1591	30.8452	23.3333	7.5119
1.1568	1.1500	0.0068	1.9332	1.8450	0.0882	-6.5132	61.3704	58.8889	2.4815
1.0850	1.1500	-0.0650	1.5696	2.2300	-0.6604	11.2868	52.5146	53.3333	-0.8167
0.7369	0.7500	0.0089	0.7323	0.6650	0.0673	-8.6353	11.3647	20.0000	-8.6353
4.5346	4.1750	0.3596	27.1271	22.8525	4.2746	-2.7438	47.3790	44.4103	2.9687
1.2456	1.1500	0.0956	1.8826	1.5650	0.3176	0.6948	36.9243	40.0000	-3.0757
0.9837	1.0000	-0.0163	0.9820	1.0150	-0.0330	1.0714	41.0714	40.0000	1.0714
0.5485	0.5500	-0.0015	0.3132	0.3100	0.0032	-4.1892	35.8108	40.0000	-4.1892
2.5504	2.5500	0.0004	7.3036	6.9650	0.3386	-0.9844	24.7481	24.3333	0.4108
1.8708	1.7250	0.1458	5.2673	4.7725	0.4948	-0.2644	53.4182	46.9048	6.5134
1.0358	0.9750	0.0608	1.1285	1.4775	-0.3490	-21.6178	63.8222	65.0000	-21.6178
23.1436	31.3250	-8.1804	558.0660	1038.5875	-480.5815	135.7705	468.1184	603.8889	-135.7705
1.1983	0.9250	0.2733	2.2377	1.2625	0.9752	-24.2454	55.3379	36.6667	18.6712
34.8482	33.3500	1.4982	1533.5568	1421.8650	110.6918	25.9289	25.9289	22.5662	3.3627
0.8122	0.5750	0.0372	0.4066	0.3675	0.0391	76.1077	76.1077	75.0000	1.1077
1.5991	2.1750	-0.5759	3.7784	-1.4775	3.3491	-45.6612	54.0085	75.1100	-21.1105
1.8672	1.9500	-0.0828	6.2100	6.2300	-0.0200	29.4578	24.7563	25.5341	-0.7778
5.4687	7.5250	-2.0563	46.4387	65.4775	-19.0388	-1.0049	69.1732	89.4209	-20.2477
0.6588	0.6000	0.0588	1.2539	0.9900	0.2639	20.2477	73.9983	74.5833	-0.6250
13.6849	13.4250	0.2599	210.0237	201.9875	8.0362	-1.1378	61.3005	60.1627	1.1378
16.8799	16.8000	0.0799	477.4272	411.0051	66.4221	-9.7884	20.0004	25.4516	3.6286
18.0477	20.8000	-2.7523	334.8364	612.1400	-277.3036	-16.1432	13.6447	14.8762	-1.2315
7.7520	6.7750	0.9000	89.1567	68.0525	20.7042	-10.4466	125.4781	153.6285	-21.8494
1.0267	0.2250	0.8017	1.3173	1.1175	0.1998	-21.8079	75.0460	68.7500	6.2960
0.6142	0.6250	-0.0162	105.3917	89.1825	16.2092	-3.9474	44.7004	40.8430	3.8474
0.0389	0.1250	0.1139	0.2284	0.2175	0.0109	-15.0008	74.9992	90.0000	-15.0008
4.5936	6.6750	-2.0814	31.8283	49.0725	-17.2442	16.1663	61.1663	67.4206	-26.2547
2.7257	2.8000	-0.0743	8.4559	8.2750	0.1819	-16.1669	88.8008	72.6339	10.4615
5.3495	5.7000	-0.3505	33.8628	40.1150	-6.3122	-2.4968	40.6549	43.1515	-2.4968
2.4860	2.3000	0.1860	7.4241	6.6550	0.7691	-37.2715	126.5575	100.2381	26.3194
4.1277	2.9500	1.1777	4.2241	6.6550	0.7691	-22.4257	52.1397	29.7576	22.3421
3.6365	4.3000	-0.6695	23.9104	7.6450	16.0654	4.3131	43.0676	46.5808	3.5082
1.4661	1.1500	0.3161	24.5782	24.3350	0.2432	16.2850	62.7034	67.1678	16.2850
5.7011	5.6750	0.0261	2.5130	2.2450	0.2680	-0.5580	39.9106	33.7500	6.1606
1.6484	1.5500	0.0984	42.1661	42.1425	0.0236	16.2850	34.0628	1.1778	6.1606
0.7750	0.7250	0.0000	3.2600	2.9300	0.3300	16.2850	34.0628	1.1778	6.1606
3.8805	4.8750	-0.9445	0.6719	0.7175	-0.0456	0.0411	18.3031	27.8449	-3.6026
1.1632	1.2500	-0.0868	23.1463	32.9975	10.8512	-4.5091	48.0041	51.6267	-4.5091
3.6564	4.4750	-0.8206	1.6434	2.2560	-0.4666	21.7573	47.0126	58.1333	-11.3207
2.7711	3.0500	-0.2789	22.0822	30.9425	-8.8603	44.4071	229.9348	67.4447	37.5037
1.1273	1.2550	0.8777	183.8026	167.1425	1.6599	121.2016	121.2016	131.5000	11.2984
1.1543	1.2250	0.9077	1.9903	2.2625	0.2722	-8.0017	45.3854	43.6161	20.4527
1.4253	1.5750	0.9055	4.8408	5.1975	-0.3567	5.9482	41.4161	41.1750	1.3831
						27.0859	31.358	3.7167	1.5580

4.236	3.9256	0.3146	21.8951	18.4675	3.4276	8.1956	-5.6972	-2.4964	14.7070	13.5473	1.1597
3.766	3.0000	0.7166	17.242	15.0150	2.2592	-21.5069	-14.4947	-7.0122	27.1838	22.3519	4.8319
2.7243	24.750	2.9693	1016.0378	885.5876	130.4502	-35.9570	-32.2860	-3.6710	40.5060	36.8512	3.6568
0.8811	0.7000	0.0189	0.5551	0.6150	-0.0599	16.0315	10.0000	6.0315	16.0315	10.0000	6.0315
0.6158	0.6500	-0.0342	0.4902	0.5300	-0.0398	10.0000	10.0000	0.0000	10.0000	10.0000	0.0000
4.1017	4.0250	0.0767	21.6587	20.8125	0.8462	-63.6853	-65.3704	1.6851	73.8165	75.3407	-1.5242
19.6782	18.0950	1.6532	509.8928	535.0124	-25.1196	7.0652	12.6002	-5.5350	17.1091	15.0660	2.0231
2.1897	2.3000	-0.1103	5.5434	7.8950	-2.3516	-51.5408	-60.0952	17.5526	62.0001	71.2081	-9.2080
11.0649	11.7000	-2.6351	165.6478	214.1050	-48.4572	29.2770	37.3976	-8.1206	29.2770	37.3976	-8.1206
2.3048	2.2750	0.0298	7.7448	8.1025	-0.3577	-12.2225	1.1667	-13.3902	44.6660	39.0500	5.6160
3.0945	3.1750	-0.0805	19.9547	11.8575	8.0972	-32.7516	-15.6250	-17.1266	35.0549	30.6250	4.4299
1.4348	1.4750	-0.0402	8.8488	4.1175	-4.7313	-11.7514	-11.4286	-0.3228	37.8315	38.5714	-0.7399
10.0200	9.9250	0.0970	1.5516	1.0425	0.5093	52.1105	55.8333	-3.7228	52.1105	55.8333	-3.7228
1.7729	1.6000	0.1729	4.7214	4.4050	0.3164	-54.6112	-47.1429	-7.4683	80.2622	72.8671	7.3951
2.0349	1.8750	0.1599	4.1294	3.6075	0.5219	55.6649	52.5000	3.1649	55.6649	52.5000	3.1649
0.7004	0.7000	0.0004	0.9337	0.5650	0.3687	-2.0588	1.2917	-3.3505	17.6775	15.0417	2.6358
1.0096	0.6000	0.4096	1.2111	0.5300	0.6811	-48.4116	-4.3333	-40.0783	66.7910	36.6667	30.1243
3.1273	4.2750	-1.1477	12.2554	20.6475	-8.3921	15.3785	20.8950	-5.5165	15.3785	20.8950	-5.5165
2.3660	3.7500	-1.3840	8.9547	3.0225	5.9321	-8.3868	7.5000	-15.8868	29.0641	27.5000	1.5641
5.0482	4.4000	-0.6482	34.5087	45.1650	-10.6563	14.4574	17.4000	-3.2826	14.4574	17.4000	-3.2826
1.2227	1.0500	0.1727	8.5406	13.8947	-5.3541	0.0000	0.0000	0.0000	64.4330	90.8193	-26.4063
0.3271	0.3500	-0.0229	1.5113	1.1100	0.4013	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2.7784	2.9500	-0.1716	10.6414	12.6550	-2.0136	11.4688	20.0000	-8.5312	11.7605	20.0000	-8.2395
22.6543	22.6250	0.0293	582.3968	685.9275	-103.5307	2.9291	6.5576	-3.6285	14.1102	14.3701	-0.2599
8.0795	5.6750	2.4045	67.2697	38.5225	28.7472	-116.7702	-132.7693	15.9991	124.4507	132.7693	-8.3186
4.8858	3.7500	1.1358	34.2600	30.3125	3.9475	-205.9005	-154.3155	-51.5850	205.9005	154.3155	51.5850
7.8179	11.4500	-3.6321	96.6147	142.1100	-45.4953	-5.9200	3.3144	-9.2434	28.0982	20.5871	7.5111
0.2575	0.7500	0.0025	1.0524	1.0100	0.0424	-152.6588	-185.2500	32.5912	152.6588	185.2500	-32.5912
1.9157	1.7500	0.1607	4.5993	1.9125	2.6868	97.3118	95.0000	2.3118	97.3118	95.0000	2.3118
2.6757	3.0500	-0.3743	8.6009	12.1150	-3.5141	-44.7454	-28.0000	16.7454	82.1112	65.3333	16.7779
5.3913	4.2750	1.1163	33.3532	27.6225	5.7307	-8.0819	8.2883	-16.2902	39.7884	27.5417	12.2467
9.7054	9.9500	-0.2446	112.5511	119.8150	-7.2639	77.7053	80.0000	-2.2947	77.7053	80.0000	-2.2947
8.8834	7.5500	1.3334	95.7641	80.0950	15.6691	35.2687	36.1677	-0.8990	35.2687	36.1677	-0.8990
16.9573	17.5000	-0.5427	413.5897	486.2750	-72.6853	8.8951	9.9189	-1.0238	17.3003	14.7295	2.5708
10.0348	17.7500	-6.8152	196.8643	410.5950	-213.7307	4.8622	17.8132	-12.9510	27.3191	24.5632	2.7559
4.0330	4.4250	-0.3920	18.8466	27.5425	-8.6956	-176.2546	-231.6667	55.4121	201.3186	248.3333	-47.0147
6.7586	5.7500	1.0036	51.9415	36.7075	15.2340	-153.0548	-128.6071	-24.4477	153.0548	128.6071	24.4477
2.9751	3.0750	-0.0999	12.9679	16.6675	-3.7296	-0.7470	5.0685	-5.8155	35.1392	34.0685	1.0707
1.2101	1.1000	0.1101	1.6386	1.4700	0.1686	12.1545	36.6667	-24.5122	63.6896	56.6667	7.0229
1.4124	2.1250	-0.7126	2.6483	6.3375	-3.6842	25.1696	-36.6667	61.8363	27.5479	36.6667	-9.1191
4.1360	5.7500	-1.6140	17.7043	37.2450	-19.4507	-109.8081	-160.3167	50.6086	109.8081	160.3167	-50.6086
Mean	6.8844	7.3839	248.7516	312.6951	-45.9435	26.3983	-23.3070	-3.9013	61.9971	61.0411	0.9560
Variance	141.5291	198.2214	3.5003	487.3457	487.3457	21.2979	21.2979	21.2979	21.2979	21.2979	21.2979

t-Test Two-Sample for Means

Mean	Known variance	Observed	Hypothesized Mean Difference	t	Critical t, one-tail, 90%	Critical t, one-tail, 95%
6.8844	7.3839	248.7516	312.6951	0.5813	1.6450	1.6450
141.5291	198.2214	245.0000	245.0000	0.0000	0.0000	0.0000
245.0000	245.0000	245.0000	245.0000	0.0000	0.0000	0.0000
0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
0.4672	1.6450	1.6450	1.6450	1.6450	1.6450	1.6450
0.4672	1.6450	1.6450	1.6450	1.6450	1.6450	1.6450

Appendix G: Aircraft Availability Results

TREND - % AVAILABLE AIRCRAFT			
	RDB	SDF	
QUARTER 1	74.30%	75.08%	
QUARTER 2	74.27%	74.98%	
QUARTER 3	74.10%	74.95%	
QUARTER 4	74.12%	74.90%	
t-Test: Paired Two-Sample for Means			
	Variable 1	Variable 2	
Mean	0.7420	0.7498	
Variance	1.05E-06	5.86E-07	
Observations	4.0000	4.0000	
Pearson Correlation	0.8216		
Pooled Variance	0.0000		
Hypothesized Mean Difference	0.0000		
df	3.0000		
t	-26.6226		
t Critical two-tail -90%	3.1824		
t Critical one-tail - 95%	3.1824		

SEASONAL - % AVAILABLE AIRCRAFT			
	RDB	SDF	
QUARTER 1	78.93%	80.93%	
QUARTER 2	78.71%	79.13%	
QUARTER 3	78.92%	78.97%	
QUARTER 4	78.90%	80.31%	
t-Test: Paired Two-Sample for Means			
	Variable 1	Variable 2	
Mean	0.7887	0.7983	
Variance	1.05E-06	8.84E-05	
Observations	4.0000	4.0000	
Pearson Correlation	0.5339		
Pooled Variance	0.0000		
Hypothesized Mean Difference	0.0000		
df	3.0000		
t	-2.1723		
t Critical two-tail -90%	3.1824		
t Critical one-tail - 95%	3.1824		

CYCLICAL - % AVAILABLE AIRCRAFT			
	RDB	SDF	
QUARTER 1	86.98%	87.25%	
QUARTER 2	86.63%	86.57%	
QUARTER 3	86.64%	87.23%	
QUARTER 4	86.90%	86.83%	
t-Test: Paired Two-Sample for Means			
	Variable 1	Variable 2	
Mean	0.8679	0.8697	
Variance	3.06E-06	1.11E-05	
Observations	4.0000	4.0000	
Pearson Correlation	0.3547		
Pooled Variance	0.0000		
Hypothesized Mean Difference	0.0000		
df	3.0000		
t	-1.1481		
t Critical two-tail -90%	3.1824		
t Critical one-tail - 95%	3.1824		

OUTLIER - % AVAILABLE AIRCRAFT			
	RDB	SDF	
QUARTER 1	83.25%	84.05%	
QUARTER 2	82.99%	83.97%	
QUARTER 3	83.15%	83.98%	
QUARTER 4	82.85%	84.04%	
t-Test: Paired Two-Sample for Means			
	Variable 1	Variable 2	
Mean	0.8306	0.8401	
Variance	3.08E-06	1.47E-07	
Observations	4.0000	4.0000	
Pearson Correlation	0.0159		
Pooled Variance	0.0000		
Hypothesized Mean Difference	0.0000		
df	3.0000		
t	-10.6221		
t Critical two-tail -90%	3.1824		
t Critical one-tail - 95%	3.1824		

RANDOM - % AVAILABLE AIRCRAFT			
	RDB	SDF	
QUARTER 1	91.88%	90.63%	
QUARTER 2	88.36%	90.55%	
QUARTER 3	91.00%	90.45%	
QUARTER 4	90.77%	90.51%	
t-Test: Paired Two-Sample for Means			
	Variable 1	Variable 2	
Mean	0.9050	0.9054	
Variance	2.27E-04	5.63E-07	
Observations	4.0000	4.0000	
Pearson Correlation	0.1171		
Pooled Variance	0.0000		
Hypothesized Mean Difference	0.0000		
df	3.0000		
t	-0.0449		
t Critical two-tail -90%	3.1824		
t Critical one-tail - 95%	3.1824		

REAL DATA - % AVAILABLE AIRCRAFT			
	RDB	SDF	
QUARTER 1	79.84%	78.73%	
QUARTER 2	80.28%	80.50%	
QUARTER 3	80.36%	80.66%	
QUARTER 4	80.59%	80.33%	
t-Test: Paired Two-Sample for Means			
	Variable 1	Variable 2	
Mean	0.8027	0.8006	
Variance	9.95E-06	7.98E-05	
Observations	4.0000	4.0000	
Pearson Correlation	0.8514		
Pooled Variance	0.0000		
Hypothesized Mean Difference	0.0000		
df	3.0000		
t	0.6514		
t Critical two-tail -90%	3.1824		
t Critical one-tail - 95%	3.1824		

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Vita

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