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AN EVALUATION OF AIRCRAFT MAINTENANCE PERFORMANCE FACTORS IN THE OBJECTIVE WING

THESIS

Mark A. Gray, Captain, USAF
Margaret M. Ranalli, Captain, USAF

AFIT/GLM/LA/93S-22

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DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY
AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT/GLM/LA/93S-22

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AN EVALUATION OF AIRCRAFT MAINTENANCE PERFORMANCE FACTORS IN THE OBJECTIVE WING

THESIS

Presented to the Faculty of the 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

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September 1993

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Preface

The purpose of our research was to study the effects of the Objective Wing on aircraft maintenance performance. The implementation of this structure raised many doubts and questions in the minds of maintainers Air Force wide. We wanted to study this problem to see if this structural change was really an improvement.

We would like to thank Chief Master Sergeant Russell Presley of the 92nd Wing, Fairchild AFB, WA for his assistance in obtaining the data for this research. His assistance was invaluable to our efforts.

We also want to thank our thesis advisors Lt Col Phil Miller and Major Michael Morabito for their patience, guidance and support throughout this seemingly never ending process.

We also want to thank our families:

From Mark: to Velda Gray, my loving and supportive wife, I would like to extend my greatest thanks and appreciation for your patience and love during this trying period of our marriage. To my precious daughter, Kimberly, who always managed to lift my spirits with a smile and a loving hug, I will always love and adore you.

From Margaret: To my husband, Steve, for your support and love. Not many men would be willing to maintain home, hearth and cats for a year and a half without help. Your support of my goals has always inspired me to achieve. You

can never know how grateful I am for your confidence in me. To my "AFIT family," Lisa Carney and Steve Fiorino, and Roger Quinto, thanks for your friendship and support, and for listening to me complain about being away from my husband. You guys definitely made AFIT a more bearable experience!

Mark A. Gray

Margaret M. Ranalli

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Abstract

Prior to 1992, organizational maintenance was aligned under a separate maintenance organization. In 1992, the Air Force restructured into Objective Wings with organizational maintenance aligned under the flying squadrons. This study looks at the impact of this reorganization on maintenance performance factors.

The researchers developed maintenance performance models using regression and principal component analysis. Mission Capable Rate and Total Not Mission Capable Maintenance Rate are used as dependent variables. A comparison of key maintenance performance indicators and model predictions before and after the reorganization is accomplished.

Based on the results of this analysis, the researchers conclude that there is significant improvement in all dependent variables, model predictions of these dependent variables and improvement in some of the independent variables. Improvement occurred after organizational structure changed, however, other factors not included in the models such as the stand-down of the Alert Force may also contribute to this improvement.

AN EVALUATION OF AIRCRAFT MAINTENANCE PERFORMANCE FACTORS IN THE OBJECTIVE WING

I. Introduction

Background

The United States Air Force (USAF) is operating in an extremely dynamic and ever-changing world. We "are absorbing change on a scale without precedent since the Air Force became a separate service in 1947" (Correll, 1992:4). Many events have occurred in the past few years that will have dramatic and enduring effects on the Air Force and the way we perform our mission. The Union of Soviet Socialist Republics (USSR), our arch enemy for decades, has dissolved into numerous independent states -- each striving for democracy. Germany has been united, disbanding the communist regime that has reigned in East Germany since the end of World War II. Iraq has continuously been a "thorn in the side" of the United States since its invasion of Kuwait in the fall of 1990.

These changes in the world environment do not guarantee an end to threats to our national security. Threats to the United States in the 1990s and beyond include a combination of political instability, serious economic dislocation and widespread military power. This combination of threats presents the Air Force with many new and unique challenges. To meet these threats, the Air Force must maintain flexible, lethal forces with the ability to respond rapidly (Rice, 1990:1-3). In the past, it was a challenge for the USAF to "respond with a tailored, appropriately sized, combat effective force" (Wiswell, 1986:11).

Congressional reductions in the Department of Defense's budget and authorized size also pose a challenge for military managers to do "more with less." In 1991, "Congress voted to trim the 2,000,000-strong US military by one-fifth over five years" (Callander, 1991:36). According to Air Force Chief of Staff, General Merrill A. McPeak, "Our budget this year, in real terms, is about the same size it was in 1981, ten years ago" (Dudney, 1992:20).

These factors have combined to demonstrate the need for a flexible Air Force -- an Air Force with the capability to project its power and influence in a swift, forceful and effective manner. As former Air Force Chief of Staff General Charles A. Gabriel said:

> If we are to deter and, if necessary, respond (to conflict) we must ensure that our forces are flexible, can deploy rapidly anywhere in the world, and can fight effectively in widely ranging conditions. (Wiswell, 1986:14)

This theme was furthered by General McPeak when he stated that a reorganized force will "place a premium on speed, mobility, and lethality" (Dudney, 1992:22). In addition, the Senate Armed Services Committee has stated that "[t]o meet potential force-projection missions, the United States must restructure its forces" (Corddry, 1991:80). As the size of the Air Force decreases, restructuring provides a means to maintain combat capability and effectiveness(Air Force Restructure, 1992:2).

As a result, the Air Force restructured its forces in 1991. Major Command reorganization led to the birth of Air Combat Command and Air Mobility Command. Within Air Combat Command, flying wings were reorganized into the Objective Wing structure. The new organizational alignment was designed to allow the operational units to practice during peacetime the way they operate in wartime scenario. One dimension of this restructuring assigns organizational (flightline) maintenance to its respective flying squadron (Rine, 1992:24).

General Issue

In 1991, the Air Force undertook a major force restructuring. In order to respond to changes in the world today, the Air Force has been guided by the doctrine of Global Reach/Global Power (Air Force Restructure, 1992:2). As the Air Force gets smaller as a result of budget cuts, restructuring is a logical way to maintain combat capability. One of the most significant results of restructuring is placing organizational maintenance under the control of flying squadrons.

Problem Statement

As part of the Air Force restructuring, aircraft organizational maintenance elements were functionally assigned to their respective flying squadrons. However, the effect of the Objective Wing structure on aircraft maintenance performance factors has never been fully researched.

Research Questions

1. What analytical methods have been used in the past to create performance models?

2. What dependent variables best represent aircraft maintenance performance?

3. What independent variables affect aircraft maintenance performance?

4. What problems exist in previous researchers' models and how might these deficiencies be corrected?

5. Which analytical method is the most appropriate to model aircraft maintenance performance?

6. Are regression and principal component models useful for predicting aircraft maintenance performance?

7. Which performance model best predicts aircraft maintenance performance?

8. Do significant statistical differences exist in aircraft maintenance performance in the Objective Wing and pre-1992 organizational structures, and, if so, what are they?

Scope and Limitations

The scope of this research is limited to the effects of the Air Force reorganization at the Wing level; specifically the 92nd Wing at Fairchild AFB, Washington. The researchers consider performance measures for two aircraft, the B-52H and KC-135R. Results of the research may not be applicable for other wings or Air Combat Command or Air Mobility Command as a whole. Additionally, performance data were derived from 92nd Wing Monthly Maintenance Summaries. These data may have some recording accuracy or computational errors.

Summary

In Chapter I, the researchers presented the reasons for the Air Force reorganization. Next, we discussed the need to evaluate the impact of reorganization on aircraft maintenance. We concluded the chapter by presenting the research questions to be explored and the scope and limitations of the research.

Chapter II presents a review of literature on organizational structures and evaluating organizational performance. This chapter provides the answers to research questions one through four.

Chapter III outlines the methodology we use in Chapter IV to analyze our aircraft maintenance data. Once the data have been analyzed, we can then answer the remaining research questions.

Chapter IV provides data analysis and a presentation of our findings. These findings supply the answers to research questions five through eight.

Chapter V demonstrates the significance of the research findings. This chapter also includes our conclusions and recommendations for further research.

II. Literature Review

Introduction

In the past five years, business and industry in the United States have been experiencing a management revolution. Quality, down-sizing, and participative management have been assimilated into the vocabulary of managers. One dimension of these new philosophies is corporate restructuring. Successful companies are moving from a bureaucratic, specialty-oriented organizational structures to lean, product-oriented structures (Peters, 1987:3, 14, 34, 52-4).

The United States Air Force is no different. In 1991, U.S. Air Force flying wings were reorganized. The goals of this reorganization were to decentralize authority, remove unnecessary layers, and finally give field commanders responsibility for all elements necessary for mission accomplishment or "production" (Air Force Restructure, Jan 1992:2).

The focus of this research is to evaluate performance of the organizational maintenance units assigned to flying units after this reorganization. In this literature review, we set the stage for our discussion of the reorganization. We first discuss the types of organizational structures in business and enumerate some of the fundamental differences in these structures. Next, we examine the performance of product-oriented organizations in business. We then examine some of the effects of organizational change. Next is a discussion of the differences between the pre-1992 and Objective Wing structures. We then discuss the methods used by previous researchers to measure performance in aircraft maintenance organizations and evaluate the strengths and weaknesses of this previous research. This part of Chapter II provides us with the answers to our first four research questions. We conclude by examining additional methods of improving aircraft maintenance performance models.

Organizational Structure in Business

Business organizations typically design their organization in some sort of departmentalized structure. Two means of departmentalization are by function or product. In a functionally aligned organization, specialists are grouped together. For example, in a manufacturing firm all engineers are grouped in one department, while production workers are in another. In an organization aligned based on product, all elements needed to design, manufacture, and market a product are assigned to the same department (Gibson, 1991:446-448). Organizational design decisions are based on company needs, size, and priorities (Litterer, 1980:115).

The functional organization consists of two distinct elements: line agencies and staff agencies. Line agencies are, for example, specific product or manufacturing divisions. Staff agencies consist of the functional elements such as personnel, accounting, engineering, etc. Both types of agencies report to the Chief Executive Officer (CEO). Integration of staff and line activities occurs at the top management level (Litterer, 1980:130). A company usually chooses to adopt a functional structure based on the need or perceived need for centralized control of specialized functions, such as accounting or data management (Peters, 1987:427).

In a product-based organizational design, separate units contain all the elements necessary to do business. These units are usually organized by product or manufacturing division (Litterer, 1980:116). Staff elements become a part of line divisions. Here, integration of staff and line functions occurs at the lowest level (Peters, 1987:431).

Both of these structures have merit. However, many companies are replacing large, functional structures with smaller, more flexible product-oriented structures. In the next section, we discuss how organizations that are organized around product lines have performed well in the private sector.

Product Structures in Practice

In the past, American manufacturing firms focused on quantity, not quality. "Bigness" and mass production were the standard for industry. The hierarchical, function-oriented, centralized structure of American companies has, in fact, stalled productivity (Peters, 1987:4). The "bigness" and bureaucracy of American industrial firms has slowed progress and limited rapid response to change. Line divisions often must seek approval from staff bureaucracies prior to carrying out a new project. Taskings, memos, and problems are passed up and down different chains of command before decisions are made (Peters, 1987:257-58).

Creating a product-oriented organization can increase efficiency, responsiveness, and productivity (Peters, 1987:16-17). In *Thriving on Chaos*, Tom Peters gives several anecdotal examples of these, such as Ford's Team Taurus, or the Limited (Peters,1987:637). In addition to Peters, some other researchers have examined the effect of product structures.

In 1986, a group of researchers from the Massachusetts Institute of Technology compared automobile production by a "traditional" centralized company (General Motors) with production by a product-oriented or "lean" producing firm (Toyota). The lean producers clearly had the advantage. Productivity and quality were significantly better. The Toyota plant averaged 16 hours to assemble a car, while

General Motors averaged 31 hours. Toyota had only 45 assembly defects per 100 cars, while General Motors had 130. Although reasons other than structure contributed to this success, a product-oriented structure played an important role (Womack, 1990:77-81).

Another group of researchers studied what they termed "high involvement" companies. One facet of these companies was their organizational structure. High involvement companies were organized around a product or geographical location. The researchers found that productivity and quality in these plants exceeded that of other plants manufacturing the same product (Perkins, 1983:195).

A product-oriented structure has contributed to success in the private sector. This can be translated into the military. "The same principles of success" can apply to the public sector as well as to the private (Peters, 1987:47).

Structure and Change in Organizations

A great deal of research has been done on the relationship between organizational structure and environment. Factors such as technology, market, product demand and environmental uncertainty have an impact on organizational structure (Gibson, 1991:515-17). Some recent research has focused on organizational change as a result of environmental change, and the performance of organizations who fit their structure to the environment. Reorganizing for the sake of reorganizing does no good. However, reorganization as a response to changes in the environment often enhances performance (Haveman, 1992:49). Research of changes in the savings and loan industry analyzes the connection between organizational change as a response to the changing environment and success and survival of the organizations. The savings and loan industry has experienced environmental change with respect to technology, regulations and the economy. The researcher in this case hypothesizes that when an organization changes in response to environmental changes, organizational performance and survival chances improve because this change "enables organizations to meet new environmental demands." This hypothesis is supported by the results of performance analysis of savings and loans over a ten year period. Performance improved as a result of organizational change (Haveman, 1992:52-71).

Another study attempts to establish causal relationships between change as a result of the environment and performance. Organizational structure is an intervening variable in this relationship. The researchers develop a model that ultimately links change to performance. In the model, transformational change is defined as change that is a response to the external environment that impacts the strategy or mission of the organization. Transactional change is change that involves structure, management practices and climate. Transactional and transformational changes both affect motivation, which in turn, affects performance. The researchers establish a causal relationship between structure and climate: the working conditions and/or level of participation in the company. The researchers, in turn, show a link between climate and motivation, and performance. The most significant aspect of structure that made a difference was if workers saw the structure as useful. If the structure is viewed as one that enhances work team relations, it will have a positive impact on performance (Burke, 1992:523-39).

The "fit" between the environment and organizational structure is also an area of great interest. Contingency Design categorizes organizational design on a spectrum from mechanistic to organic. A mechanistic structure is characterized by centralized, controlling authority and little flexibility. An organic structure is characterized by a decentralized, flexible structure. An organic structure is the best fit in an environment of uncertainty. Fitting an organic structure to an uncertain environment will enhance performance (Gibson, 1991:509).

Changes in structure that are useful and are made to fit environmental conditions most positively impact performance (Haveman, 1992:49). Environmental change has been an impetus for restructuring in the United States Air Force. Air Force leaders have developed the Objective Wing structure in an attempt to fit organizational structure to an uncertain environment (Air Force Restructure,1992:2).

Fitting Structure to Environment: Objective Wings

In 1991, the Objective Wing was born. This new structure was designed to align personnel around a specific "manufacturing division," the operational flying squadron, and a specific product -- aircraft sorties. According to Secretary of the Air Force, Donald Rice, "We've applied modern management principles: delayering, streamlining, ...and pushing power and responsibility down to the talented people who do the day to day work" (Rice, Jan 1992:6). To see how the Objective Wing has changed aircraft maintenance, we must first look at the "old" wing organizational structure.

Prior to the reorganization, flightline aircraft maintenance branches were assigned to the Organizational Maintenance Squadron (OMS). Intermediate or off-equipment maintenance fell under the Field Maintenance Squadron (FMS) and the Avionics Maintenance Squadron (AMS). Maintenance and weapons loading fell under the Munitions Maintenance Squadron (MMS). All of these squadrons were placed under the functional authority of the Deputy Commander for Maintenance (DCM). Flying Squadrons were assigned to the Deputy Commander for Operations (DO). Both the DCM and the DO reported to the Wing Commander (SAC Handbook, 1989:Ch 2, 3-16).

Even under this "old" structure, the flightline branches worked very closely with their associated flying unit. However, the people who planned and produced aircraft sorties in association with the flying squadrons still fell under a wing maintenance hierarchy (Canan, 1992:36). This organization resulted in coordination across two chains of command to make a decision, such as producing the flying schedule. Operations and maintenance concerns were arbitrated at the wing commander level.

In the Objective Wing, this is not the case. The Objective Wing is organized into three groups: the Operations Group, the Logistics Group and the Support Group. Each group "produces" a different product. The Logistics Group includes the Maintenance Squadron. All off-equipment aircraft and munitions maintenance elements are assigned to the Maintenance Squadron. The product of the Maintenance Squadron is aircraft/munition components and major aircraft repairs. The Operations Group produces aircraft sorties. All elements necessary to do this, including weather, base operations and flightline maintenance are assigned to the Operations Group. The flightline maintenance branches are assigned directly to their supported flying squadron. In addition, weapons loaders, previously assigned to the Munitions Maintenance Squadron, are part of the flightline maintenance branch. The branch reports to the squadron maintenance officer, who is co-equal to the squadron operations officer (Air Force Restructure, Jan 1992:5).

The goal of this reorganization is to improve combat capability and increase peacetime effectiveness. The

Objective Wing structure is designed to accelerate reaction time and improve processes by pushing power and authority down to the lowest level (Air Force Restructure, Jan 1992:2). The Air Force has attempted to fit organizational structure to our ever-changing world. However, we do not know how this change has affected maintenance performance.

Performance Models

In order to answer research questions one through four, we analyzed the efforts of previous researchers. Previous research examines the effects of chosen maintenance performance factors on aircraft mission capability and productivity. These research efforts, and the lessons learned from them, are summarized in Table 1 and in following paragraphs.

The first area we examined was the type of methods used in the past. This answers research question one, what analytical methods have been used in the past to create performance models? Previous researchers have developed predictive models of aircraft maintenance performance. This was accomplished primarily through the use of regression analysis of aircraft maintenance performance data. Again, the analysis methods used are summarized in Table 1.

Performance Factor Selection. Once we determine the methods used by previous researchers, our next step is to determine the answers to research questions two and three:

What dependent variables best represent aircraft maintenance performance and what independent variables affect aircraft maintenance performance? In the past, several methods have been employed in selecting the aircraft maintenance performance factors to be examined. Selection methods range from using personal experience, expert opinion, surveys from Deputy Commanders for Maintenance to information from higher headquarters. In all, past researchers have analyzed 53 dependent and independent variables while building various predictive models of aircraft performance. Appendix A provides a comprehensive list of these variables, and specifies which factors were chosen as dependent and independent for each research effort.

TABLE 1

SUMMARY OF AIRCRAFT MAINTENANCE PERFORMANCE MODEL RESEARCH

RESEARCHERS	METHODOLOGY AND TOOLS	VARIABLES	LESSONS LEARNED
DEINER & HOOD(1980)	STEPWISE REGRESSION WILCOX SIGNED RANK TEST CORRELATION ANALYSIS	6 INDEPENDENT 9 DEPENDENT (INCLUDING FMC RATE, MANHOUR PER FLYING HOUR,NMCM RATE)	CANNOT ASSUME MAINTENANCE DATA IS FROM A NORMAL DISTRIBUTION. USE OF NONPARAMETRIC STATISTICAL ANALYSIS.
GILILLAND(1990)	STEPWISE REGRESSION CORRELATION ANALYSIS RESIDUAL ANALYSIS	5 INDEPENDENT 8 DEPENDENT (INCLUDING MC RATE AND MANHOUR PER FLYING HOUR).	TESTED INTERACTION AMONG VARIABLES CONDUCTED RESIDUAL ANALYSIS
JUNG(1991)	STEPWISE REGRESSION CORRELATION ANALYSIS RESIDUAL ANALYSIS	23 INDEPENDENT 3 DEPENDENT (MC RATE, NMCM, NMCS)	DIFFERENT AIRCRAFT PRODUCE DIFFERENT REGRESSION MODELS
DAVIS & WALKER (1992)	STEPWISE REGRESSION PAIRED T-TEST	4 INDEPENDENT 1 DEPENDENT (MC RATE)	TESTED RANDOMNESS BY SPLIT HALF TECHNIQUE

By aggregating the aircraft maintenance performance factors used in the past, we observe that "Mission Capable Rate" stands out as the most commonly chosen (dependent) performance factor. In addition, "Manhours Per Flying Hour" shows up as the most frequently used independent variable. Therefore, for our research, we include these two commonly used and validated variables in our predictive models. In addition, we use several other independent variables that have proven useful in past predictive models. The complete list of variables used in this study are listed and defined in Chapter III. This aggregate list of variables provides the answers to research questions two and three. That is, it reveals which dependent variables best represent aircraft maintenance performance, and which independent variables affect aircraft maintenance performance.

Model Applicability. To answer research question four, we must first evaluate problems previous researchers had in developing their performance models. These are summarized as lessons learned in Table 1. We will discuss some specific problems in greater detail. We also propose some ways to correct model deficiencies.

In 1991, Jung sought to derive predictive models for nine separate mission design series (MDS) aircraft (Jung, 1991). In so doing, he attempted to form an aggregate model of maintenance performance which was applicable across MDS lines. This aggregation of predictive models yielded inconsistent and inconclusive results. In Jung's own words, "future research in this area at the aggregate level may not be appropriate" (Jung, 1991:115, 116).

In 1992, Davis and Walker attempted to determine whether the Air Force's reorganization into the Objective Wing structure resulted in improvements to aircraft maintenance performance factors (Davis & Walker, 1992). Since the reorganization was recent, much of the necessary data were unavailable. To compensate for this lack of data, Davis and Walker attempted to compare the performance factors of Air Force F-15 and F-16 aircraft to the U.S. Navy's F-14 and F/A-18, across MDS lines. They too learned that "the inconsistency of independent variables selected by stepwise regression does not allow direct comparison of different types of aircraft" (Davis & Walker, 1992:60).

These previous researchers has shown that regression model variables differ based on aircraft type. That is, there is no universal aircraft performance model. Our research attempts to avoid this pitfall by analyzing the effects of the Objective Wing structure on two specific aircraft types. Specifically, we analyze KC-135R and B-52H data from the 92nd Wing at Fairchild AFB, Washington.

Overall, regression analysis is a good tool to build performance models. The main shortcoming in previous research is the way data are handled prior to using them for the regression analysis. One problem with previous research is that, in most cases, data were not tested for normality or randomness prior to analysis and model building. There are also no tests for autocorrelation of dependent variables. In our research, we attempt to properly represent the data prior to use in the regression models. We attempt to circumvent this problem by analyzing the raw data and, if necessary, transforming it, using an autoregressive model. Additionally, we will use nonparametric tests if the data do not conform to a normal distribution. The specific methods involved in this data analysis and transformation process are explained in the Chapter III. This section has provided the answer to research question four. That is, what problems exist in previous researchers' models and how might these deficiencies be corrected?

Summary

Since the Air Force became a separate organization, it has undergone numerous changes in both leadership and organizational design. Not since the end of World War II have the changes been as dramatic and pronounced as those made in the last two years. The questions remain: Can the U.S. maintain the same level of national defense with less manpower and a reorganized Air Force? Have we enhanced or degraded our defense capability by reorganizing? Which maintenance factors contribute the most to this defensive capability?

This chapter reviewed literature in subject matter related to these questions. We first reviewed the differences between functional and product organizations. We then gave examples of the successes of product-oriented businesses in the civilian community. A discussion of organizational structure in response to environment followed. Next, we presented the Objective Wing aircraft maintenance structure. Finally, we summarized previous research on aircraft maintenance performance models. This summary furnished us with answers to research questions one, two, three and four. Modelling and comparison techniques, similar to those of previous researchers, are used to determine the answers to our remaining research questions.

III. Methodology

Introduction

This chapter outlines the methodology used by the researchers to answer research questions five through eight. It also includes a description of the population and sample, data collection, and variable definitions. We include a review of the statistical tests and methods used to explore the research questions, and also assumptions and limitations of the research.

Population and Sample

The population for this study is United States Air Force flying units organized under an Objective Wing structure. This population includes, but is not limited to, Air Combat Command bomber units and Air Mobility Command tanker units. The sample for this study is the 92nd Wing's B-52H and KC-135R aircraft. This sample was chosen based on convenience. Data were readily available.

Data Collection and Treatment

Data were obtained from the 92nd Wing in the form of monthly maintenance summaries. The researchers compiled the variables of interest and created data files to use in our analysis.

Variable Definitions

Our data sets are based upon nine independent and two dependent variables for both the B-52H and KC-135R models. Thirty-seven months of B-52H and twenty-eight months of KC-135R data were available. Variables were selected based on variable choices in previous research and also based on convenience. Significant factors that were consistently reported in the monthly maintenance summaries were used. Table 2 summarizes all the variables and their names in the data set. This section lists and defines these variables.

For each aircraft, we have two dependent variables in our data set:

Mission Capable (MC) Rate: Percentage of total time an aircraft is mission ready. Defined as total MC hours divided by total possessed hours (92 Wing, 1993:19a).

Total Not Mission Capable Maintenance Rate (TNMCM): Percentage of total time an aircraft is not mission ready due to maintenance. Defined as Total Not Mission Capable Maintenance hours divided by possessed hours (92 Wing, 1993:19a).

Both of these rates are based on aggregate hours for the entire aircraft fleet.

There are nine independent variables in each aircraft data set:

Air Abort Rate: Number of Air Aborts divided by total number of sorties flown (SAC Maintenance Officer Handbook, 1989:5-5).

Average Possessed: Average number of each aircraft type possessed by the wing (92 Wing, 1993:10a).

Cannibalization Rate: Number of cannibalization actions divided by number of sorties (92 Wing, 1993:12).

Maintenance Cancellation Rate: Number of sorties cancelled due to maintenance problems divided by the number of sorties scheduled (92 Wing, 1993:13).

Delayed Discrepancy Rate: Average number of maintenance discrepancies awaiting action (92 Wing, 1992:15).

Scheduling Effectiveness Rate: Number of sorties scheduled minus total schedule deviations divided by number of sorties scheduled (92 Wing, 1993:18).

Maintenance Late Takeoff Rate: Number of late sorties due to maintenance divided by total number of sorties flown (92 Wing, 1993:14).

Manhours per Flying Hour: Number of maintenance man hours for each aircraft type expended divided by total hours flown (92 Wing, 1991:14).

Manhours per Sortie: Number of man hours expended divided by the number of sorties (92 Wing, 1991:14).

TABLE 2

LIST OF VARIABLE NAMES IN DATA SET

ABORT	Abort Rate
AVPOS	Average Possessed Aircraft
CANN	Cannibalization Rate
CANX	Maintenance Cancel Rate
DD	Delayed Discrepancy Rate
EFFEC	Scheduling Effectiveness
LTO	Late Takeoff Rate
MC	Mission Capable Rate
MHFH	Man Hours per Flying Hour
MHS	Man Hours per Sortie
NMC	Total Not Mission Capable Maintenance Rate

Data Characteristics

We must first attempt to answer research question five: which analytical method is the most appropriate to model aircraft maintenance performance? In order to do this, we must determine the attributes of our data set. We test for normality, randomness and autocorrelation of the dependent variables in the data set. If data are not from a normal distribution, for example, we must use nonparametric tests to evaluate differences in variables. If dependent variables exhibit autocorrelation, we will be required to use an autoregressive model.

The Wilk-Shapiro test and Rankit plots are tests for normality. The Rankit plot is a plot of rankits, or expected values of a transformed distribution with a mean of zero and standard deviation of one. If the actual values closely approximate these expected values, then the plot produced will be linear. Any departures from this linearity are indications of nonnormality. The Wilk-Shapiro test also produces an approximate Wilk-Shapiro statistic. The value of this statistic is between zero and one. A small value of this statistic coupled with a nonlinear Rankit plot suggests nonnormality (Statistix User's Manual, 1992:246-7). A value below the table value for this statistic also indicates nonnormaility. Based on $\alpha = 0.05$ and sample sizes of 28 and 37, the table values for the KC-135R and B-52H data sets are 0.924 and 0.936 respectively. If the Wilk-Shapiro statistic falls below these values, then the variable being tested is not from a normal distribution.

The runs test determines the randomness of a sample. This test is based on comparing the number of runs in a sample with the hypothesized value for this sample. A run is a set of two or more values either consistently above or below the sample median (Statistix User's Manual, 1992:244). A very small or very large number of runs in a sequence would indicate non-randomness. A rejection region is determined based on the probability of a certain number of runs, total number of values above and below the median and a chosen significance level (Mendenhall, 1986:643-46).

The final initial test of the data set is to test the dependent variables for autocorrelation. Autocorrelation is the tendency of time series residuals to alternatively group into positive and negative clusters (McClave and Benson, 1991:835). The runs test can be used for this as well. If a sample has too few runs, this indicates a small number of very long runs which would suggest positive autocorrelation. Conversely, if a sample has a large number of runs, this indicates many short runs and points to negative autocorrelation (Statistix User's Manual, 1992:245).

Autocorrelation plots also provide a means to determine if autocorrelation is present. The plots include 95 percent confidence intervals for correlation of points with previous points. This interval is based on the assumption that autocorrelation for each subsequent point, or lag, is zero.

The autocorrelation is presented as a horizontal bar. If this bar is beyond the confidence interval, then there is evidence of significant autocorrelation (Statistix User's Manual, 1992:254-55).

Another useful test for autocorrelation is the Durbin-Watson test. This test is based on a regression model and calculates a test statistic based on the number of observations and the difference between successive residual values in a time series. If there is no autocorrelation, the value of this statistic is approximately two. If positive autocorrelation exists, the value approaches zero. If there is negative autocorrelation, the value approaches four (McClave and Benson, 1991:836). We will use the Durbin-Watson test as a confirmation of autocorrelation based on the plots and runs test.

If there is evidence of autocorrelation, we correct for it through the use of an autoregressive model. An autoregressive model corrects for autocorrelation by means of an autoregression coefficient and an independent time series with a mean of zero and constant variance. The value of the autoregression coefficient is based on the degree of autocorrelation. A coefficient of 0.8 indicates strong autocorrelation, 0.5 indicates moderate autocorrelation, and 0.2 indicates weak autocorrelation. The autoregression model uses a modification of least squares approximation to fit a straight line to the corrected data (McClave and Benson, 1991:841-3).

Modelling

We next answer research question six: are regression and principal component models useful for predicting aircraft maintenance performance? We start, of course by building the models. In order to answer this question, we evaluate model usefulness by means of an F test, evaluate residual plots and perform model validation with actual data.

To build our performance models we use two different methodologies: stepwise regression of the independent variables and also stepwise regression of their principal components.

Regression analysis is an iterative process which determines which independent variables contribute the most to the prediction of a dependent variable. This process will "provide a good fit [of an equation] to a set of data," allow the modeler to "give good estimates of the mean value of y [dependent variable]," and finally a model will provide "good predictions of future values of y for given values of the independent variables" (McClave and Benson, 1991:606). Stepwise regression serves as a means to differentiate between important and unimportant independent variables to include in a model. Stepwise regression is a systematic approach which takes into account variable interactions and higher order polynomials. Stepwise regression is an iterative approach which tests all possible combinations of factors and discards insignificant factors. Terms are discarded based on the value of their model parameter. If the parameter value is not significantly different from zero, it is discarded. Terms with significant parameter values will become part of the model (McClave and Benson, 1991:671-3).

The purpose of principal component analysis is to develop successive functions of two or more variables which account for as much of the total variance as possible. These values are called the principal components (Daintith, 1989:262). Principal components are uncorrelated representations of data points. They are based on the eigenvalues of the correlation matrix (SAS User's Guide, 1985:622). The precise mathematical methods used to develop the principal components are beyond the scope of this thesis. Principal components are used to reduce the number of factors in a regression model and minimize the effects of multicollinearity among the independent variables. Multicollinearity may result in large variance of estimated regression coefficients. This may, in turn, result in unstable or misleading model estimates. Principal component regression is one approach that can overcome the problem of multicollinearity. Principal component regression is done by substituting the values of the principal components for the independent variables. If all principal components are included in the model, it is roughly equivalent to the ordinary regression model. However, if some principal components are deleted from the regression equation, variance of the regression coefficients is reduced. Principal components can be eliminated by several methods, including eliminating elements that are essentially equal to zero, the methodology used in stepwise regression (Jolliffe, 1986:129-133). As a result, we use stepwise regression to develop a reduced principal component model.

Analysis and Validation. Once the models are developed, we perform residual analysis. Residual analysis is also a very important part of regression. A residual is the difference between the model prediction and the actual value of an independent variable. In building our model, we assume that the residuals are normally distributed with a mean of zero. If this is not the case, it may be necessary to transform the dependent variables based upon the pattern of the residuals. Transformation techniques allow data to more closely fit a regression line. Logarithmic or exponential transformations are most common transformation techniques (McClave and Benson, 1991:677-81).

Once we have developed, analyzed and transformed the models as needed, we validate the models by using six months of maintenance performance data. We compare the predicted and actual values of the variables in the models.

Model Comparisons

We now move on to research question seven: which performance model best predicts aircraft maintenance performance? To answer this question, we compare the regression and principal component models. We examine the values of model predictions and the average difference in predicted and actual values. We look at model statistics including the adjusted R-square value. The adjusted R-square value, the sample multiple coefficient of determination, represents the amount of variation attributable to the regression model adjusted for the number of terms in the model. An adjusted R-square value of zero implies a complete lack of fit, while an adjusted R-square value of one implies a perfect fit (McClave and Benson, 1991:541). We also evaluate Sum of Squares Error, Root Mean Square Error (RMSE) and the F statistic to determine the usefulness of the models. We determine the values of these factors for each model and select the best model on the basis of these factors.

Comparison of Performance Factors

We next answer research question eight: do significant statistical differences exist in aircraft maintenance performance in the Objective Wing and pre-1992 organizational structures, and, if so, what are they? To answer this question, we perform statistical comparisons of actual performance data and model predictions.

We split our data set into data collected under the pre-1992 maintenance structure and the Objective Wing structure. This cut is made based on a May 1992 implementation of the Objective Wing at Fairchild AFB. We then perform statistical comparisons of the independent variables, dependent variables, and model predictions of dependent variables. If all the data follow a normal distribution, we use a difference in means t-test. In the difference in means test, the t statistic is based on the difference in two sample means and the samples pooled variance. The test of hypothesis determines if there is a significant statistical difference between the means of the two samples. The difference in means tests assumes that the samples are independent and taken from a normal distribution (McClave and Benson, 1991: 403-407).

If the data do not follow a normal distribution, we use a nonparametric test for these comparisons, the Median Test. This method tests to see if there is a difference in the central tendency, or median, of two samples. If the two samples represent populations with the same median, we expect a similar number of values to be above or below the median for all the data. The median test then performs a chi-square approximation based on the number of values expected to be above/below the median. It calculates a p-value based on the hypothesis that the medians are the same. A very low p-value indicates that there are significant differences in the medians (Statistix User's Manual, 1992:119-120).

Based on the results of the difference in means and median tests, we will be able to determine if significant differences exist in performance measures in the pre-1992 structure and the Objective Wing.

To answer our research questions, our data analysis includes tests for normality, randomness, and autocorrelation. We then develop performance models using two different methodologies: principal component analysis and stepwise regression. We validate and evaluate these models, compare model usefulness and select the best predictive model for each dependent variable. Finally, we perform statistical comparisons of performance factors and model predictions under both aircraft maintenance organizational structures. There are, however, some assumptions and limitations in our research.

Assumptions and Limitations

The researchers assume that data received from the 92nd Wing analysis section are accurate and complete. We assume that the data are an accurate representation of actual maintenance performance measures. This study is limited to the effects of the Objective Wing structure at the 92nd Wing.

Summary

This chapter included a discussion of our population and sample, variable definitions, and most importantly covered the methodology the researchers use to investigate research questions five through eight. We gave an outline for our data analysis and background information on the statistical methods used. We also discuss the assumptions and limitations of our research.

Chapter IV presents the results of our analysis based on this research methodology. In Chapter IV, we answer research questions five through eight.

IV. Findings and Analysis

Introduction

This chapter presents the findings of the researchers, in particular, we answer research questions five through eight. To answer these questions, we discuss the results of normality, randomness, and autocorrelation tests. Next, we discuss our model building process, including residual analysis and validation. We present comparisons of performance models and select the "best" model. Finally, we discuss the results of comparisons of actual performance data and model predictions.

Data Characteristics

Our first step was to answer research question five: which analytical method is the most appropriate to model aircraft maintenance performance? To do this, we perform analysis of normality and independence among the dependent and independent variable samples. We also test for autocorrelation of the dependent variables. We determine the attributes of our data set to make determinations on how to handle these data in later analysis.

Data Set. We first examine time series plots of our data set. These plots are included in Appendix B. The time series plots give us a graphical representation of our data which we can examine as questions arise in our analysis.

Runs and Wilk-Shapiro Tests. We tested for normality to determine if it would be appropriate to use t-tests or if nonparametric tests are needed. Tables 3 and 4 summarize the results of the Wilk-Shapiro test. Rankit plots are found in Appendix C. For the KC-135R, the table value of the Wilk-Shapiro statistic at $\alpha = 0.05$ is 0.924. Any values that fall below this indicate nonnormality. Based on this, ABORT, AVPOS, CANX and LTO do not exhibit normality.

For the B-52H, the table value based on a sample size of 37 and $\alpha = 0.05$ is 0.936. Based on this value, ABORT, AVPOS, DD, EFFEC and LTO are not from a normal distribution. All other variables appear to conform to a normal distribution.

TABLE 3

RESULTS OF WILK-SHAPIRO TEST FOR NORMALITY (KC-135R)

VARIABLE	STATISTIC	NORMAL?
ABORT	0.5204	NO
AVPOS	0.8467	NO
CANN	0.9592	YES
CANX	0.7669	NO
DD	0.9516	YES
EFFEC	0.9566	YES
LTO	0.8870	NO
MC	0.9574	YES
MHFH	0.9822	YES
MHS	0.9796	YES
NMC	0.9640	YES

TABLE 4

RESULTS OF WILK-SHAPIRO TEST FOR NORMALITY (B-52H)

VARIABLE	STATISTIC	NORMAL?
ABORT	0.4613	NO
AVPOS	0.9061	NO
CANN	0.9731	YES
CANX	0.9453	YES
DD	0.9012	NO
EFFEC	0.7958	NO
LTO	0.9082	NO
MC	0.9769	YES
MHFH	0.9903	YES
MHS	0.9649	YES
NMC	0.9896	YES

We used the runs test to determine if our sample data were random. Tables 5 and 6 summarize the results of the runs test. Six of eleven KC-135R and eight of eleven B-52H variables test within the expected number of runs. For both aircraft types, ABORT and AVPOS have too few runs. In the case of ABORT, the median value was zero. Therefore, all values were either tied with the median or above the median. The result is one long run. This is due to the fact that aborts are rare and the abort rate is often zero. In the case of AVPOS, the average number of B-52H aircraft assigned went down over time due to a steady decrease in authorized aircraft. Conversely, the number of KC-135R aircraft increased steadily over time due to conversion from the KC-135A. This resulted in long runs. Both aircraft delayed discrepancy statistics exhibit too few runs.

TABLE 5

RUNS TEST RESULTS FOR KC-135R

	EXPECTED NUMBER RUNS		ACTUAL NUMBER RUNS
VARIABLE	LOWER	UPPER	
ABORT	*	*	(1)
AVPOS	9	21	(7)
CANN	9	21	13
CANX	9	21	12
DD	9	21	(3)
EFFEC	9	21	(8)
LTO	9	21	12
MC	8	19	8
MHFH	9	21	13
MHS	8	20	11
NMC	3	11	(12)

"*" Not enough values significantly different from median. Runs test requires a minimum of 2 runs.

"()" Actual number of runs is outside expected runs limits.

Source: Langley, 1970: 325

For both weapon systems, the delayed discrepancy rate decreases dramatically beginning in November 1991. This corresponds to the deactivation of the Alert Force in October 1991. This event, in addition to the change in organizational structure, may affect maintenance performance factors. Two other KC-135R variables fall outside the runs parameters. Scheduling Effectiveness (EFFEC) exhibits one too few runs, while Total Not Mission Capable Maintenance (NMC) exhibits one too many. Both of these variables are very close to being within the range.

TABLE 6

RUNS TEST RESULTS FOR B-52H

VARIABLE	EXPECTED NUMBER RUNS LOWER	EXPECTED NUMBER RUNS UPPER	ACTUAL NUMBER RUNS
ABORT	*	*	(1)
AVPOS	12	26	(2)
CANN	11	25	14
CANX	11	25	18
DD	12	26	(6)
EFFEC	12	26	16
LTO	12	26	16
MC	12	26	14
MHFH	12	26	20
MHS	12	26	14
NMC	12	25	12

"*" Not enough values significantly different from median. Runs test requires a minimum of 2 runs.

"()" Actual number of runs is outside expected runs limits.

Source: Langley, 1970: 325

Most of our variables exhibit randomness and normality, however, a few do not. This is vital to later analysis.

Autocorrelation. We test for autocorrelation of the dependent variables (MC, NMC) by means of autocorrelation plots. These plots are found in Appendix D. For the KC-135, the autocorrelation plots of both MC and NMC are within the confidence intervals. For the B-52, MC is within the confidence interval. NMC is within the interval, however, values appear to fluctuate from one end of the interval to the other. This suggests possible autocorrelation. We will use the Durbin-Watson statistic from the regression models to determine if this autocorrelation is significant.

Modelling

To answer research question six, we primarily focused on two types of regression models, one based on regression of the independent variables which we will refer to as the "regression" models, and one based on regression of the principal components of these variables which we refer to as the "principal component" models. We produced full and reduced regression models for all the dependent variables, full and reduced principal component models for all the dependent variables, and one autoregressive model due to evidence of autocorrelation in one model. We based these models on 31 months of B-52H data and 22 months of KC-135R data. Six months of each data set were set aside for model validation.

Regression Models. The first step in modelling involved developing full and reduced regression models for each dependent variable (B-52 MC, B-52 NMC, KC-135 MC and KC-135 NMC). We used the System for Statistical Analysis (SAS) REG and STEPWISE procedures to develop these models. We then compared each reduced model to its full model by means of an F-test. Results of these F-tests are summarized in Table 7.

The Test of Hypothesis took the form of:

Ho: Coefficients of added terms in full model equal zero.

Ha: At least one coefficient does not equal zero.

Test Statistic:

$$F = \frac{SSE(reduced)-SSE(full)/(k-g)}{SSE(full)/(n-(k+1))}$$

k = number of terms in full model
g = number of terms in reduced model
SSE = Sum of squares error
n = sample size

Rejection Region : Test Statistic > Table Value

For all of our regression models (B-52 MC and NMC, KC-135 MC and NMC), none of the full models contributed any significant additional parameters. In all cases, our test statistic was less than the table value at $\alpha = 0.05$ significance level. As a result, we eliminated the full regression models for consideration as our final performance model. However, our stepwise models may be useful as prediction models. Table 8 summarizes the components of these stepwise models.

Principal Component Models. The next step in our analysis was calculation of the principal components based on our nine independent variables. We used the SAS PRINCOMP procedure to calculate the principal components. The principal components and the correlation matrix are included in Appendix F. We created a data set of the principal component values and then used them as independent variables for regression analysis of both dependent variables. We developed full and reduced regression models based on these principal components just as we did for the independent variables. We identified these variables as P1 through P9.

We again compared the full and reduced models for both the dependent variables by means of an F-test. Results of these tests are summarized in Table 9. Once again, in all cases the full models did not provide any additional significant parameter values.

TABLE 7

F-TEST COMPARISON OF FULL AND REDUCED REGRESSION MODELS

KC-135R

VARIABLE	TEST STATISTIC	TABLE VALUES ALPHA = 0.05
MC	0.38	2.85
NMC	0.46	2.91

B-52H

VARIABLE	TEST STATISTIC	TABLE VALUES ALPHA = 0.05
MC	0.29	2.63
NMC	0.95	2.42

Source: McClave and Benson, 1991: 1176 - 1179

TABLE 8

RESULTS OF STEPWISE REGRESSION

AIRCRAFT	DEP. VARIABLE	MODEL EQUATION
B-52H	MC	73.19 + 4.46 ABORT - 0.42 DD + 0.18 MHFH
	NMC	13.2 + 4.6 CANN
KC-135R	MC	95.12 - 0.83 DD
	NMC	8.69 + 0.45 LTO - 0.09 MHFH

TABLE 9

F-TEST COMPARISON OF FULL AND REDUCED PRINCIPAL COMPONENT MODELS

KC-135R

VARIABLE		TEST STATISTIC	TABLE VALUES ALPHA = .05
KC-135R	MC	0.24	3.00
	NMC	0.69	2.91
B-52H	MC	0.90	2.49
	NMC	1.13	2.42

Source: McClave and Benson, 1991: 1176 - 1179

TABLE 10

RESULTS OF STEPWISE REGRESSION OF PRINCIPAL COMPONENTS

AIRCRAFT	DEP. VARIABLE	MODEL EQUATION
B-52H	MC	78.04 - 2.00 P1 - 0.86 P2
	NMC	16.25 + 0.61 P1
KC-135R	MC	88.55 + 0.99 P1 - 1.3 P2 -.38 P4
	NMC	7.77 - 0.71 P1 + 0.27 P4

We eliminated all of the full principal component regression models from consideration for the final performance model. The resulting reduced regression models are summarized in Table 10. Interestingly enough, since the first principal component accounts for the most variance of the independent variables, it is included in all models as expected.

Effects of Autocorrelation. The next step in our analysis was to determine if any of our models displayed autocorrelation. We did this by means of a Durbin-Watson d statistic. The Durbin-Watson Test of Hypothesis took the form of:

Ho: No significant positive or negative autocorrelation exists.

Ha: Significant positive or negative autocorrelation exists.

Rejection Region: $T > d_L$ or $4-T < d_L$, where

TS = d Test statistic
d_L = d lower (from table)

None of the KC-135R models and neither B-52H MC model exhibited significant positive or negative autocorrelation based on the Durbin-Watson statistic at $\alpha = 0.05$. However, the B-52H NMC regression model's d statistic fell between the table's upper and lower limits indicating possible significant autocorrelation. The reduced principal component model's d statistic was less than the lower limit, indicating positive autocorrelation. The d statistic values and table values are summarized in Table 11. Based on the evidence of autocorrelation, we chose to eliminate the principal component and regression models for B-52H NMC and to develop an autoregressive model.

Autoregressive Model. We used the SAS AUTOREG procedure to develop a prediction model for B-52H NMC. We essentially started from scratch on this model. We again developed full and reduced regression and principal component models using autoregression. We based the reduced models on the previous stepwise regression results. Instead of "plugging them into" the SAS REG procedure, we used the AUTOREG procedure. This resulted in autoregressive models based on these same factors. These models are summarized in Table 12. The amount of autocorrelation present can be determined by the value of the autoregression coefficient.

TABLE 11

RESULTS OF THE DURBIN-WATSON TEST FOR AUTOCORRELATION

		TEST STATISTIC	d LOWER	d UPPER
B-52H				
REGRESSION	MC	1.74	1.23	1.65
	NMC	1.45	1.36	1.50
PRIN. COMP	MC	1.89	1.30	1.57
	NMC	1.09	1.36	1.50
KC-135R				
REGRESSION	MC	2.43	1.24	1.43
	NMC	1.78	1.15	1.54
PRIN. COMP	MC	2.22	1.05	1.66
	NMC	2.00	1.15	1.54

Source:McClave and Benson, 1991: 1188.

In the reduced regression model, the coefficient is 0.36, which indicates weak to moderate autocorrelation. For the principal component model, the coefficient is 0.47, indicating moderate autocorrelation. There is definitely evidence of autocorrelation, thus our choice of an autoregressive model seems appropriate.

We next evaluate the usefulness of the models. We once again compared both full and reduced significant additional

TABLE 12

AUTOREGRESSION MODEL RESULTS, B-52H NMC

MODEL	MODEL EQUATION
REGRESSION	23.015 - 2.61 ABORT - 0.00014 DD - 0.105 MHFH
PRINCIPAL COMPONENT REGRESSION	17.4043 + 0.345 P1

parameters at $\alpha = 0.05$. Results of the F-test are summarized in Table 13. Based on the results of this analysis, we included the reduced and principal component autoregressive models for consideration as the final models to predict B-52H NMC.

Model Testing

Residual Analysis. We examined the residual plots for each model to determine if error distributions warranted transformation in any of our models. Residual plots are included in Appendix G. All of the residual plots appear to exhibit constant error variance. There are no obvious quadratic, cubic, or exponential patterns which would warrant any transformations. Based on these residual plots, we determined that transformations were not necessary.

TABLE 13

F-TEST COMPARISON OF FULL AND REDUCED AUTOREGRESSION MODELS

B-52H REGRESSION MODEL

VARIABLE	TEST STATISTIC	TABLE VALUE ALPHA = 0.05
NMC	0.76	2.57

B-52H PRINCIPAL COMPONENT MODEL

VARIABLE	TEST STATISTIC	TABLE VALUE ALPHA = 0.05
NMC	0.64	2.42

Source: McClave and Benson, 1991: 1176 - 1179

Model Validation. The next step in our analysis was model validation. As mentioned earlier, we left six months of data out of our models for the purpose of validation. For the "regular" regression and principal component models, we selected six random months based on random number table values. This choice avoids the selection of consecutive months for model validation however it may mask effects of autocorrelation. For the B-52H, we used the first two digits of the random numbers down the first column of the table. For the KC-135R, we used the last two digits of the random numbers across the first row of the table. As a result, months 7, 9, 10, 22, 24 and 28 were removed from the B-52H data set, and months 2, 5, 7, 11, 15 and 27 were removed from the KC-135R data set. For the B-52H NMC autoregressive model, we removed the first and last three months of data: months 1, 2, 3, 35, 36, and 37.

In order to validate the models, we compared the 95 and 99 percent model prediction intervals for each dependent variable with actual values. A summary of validation results is found in Table 14, and the specific prediction intervals for each model are found in Appendix I.

For the KC-135R MC regression and principal component models, five of the six actual values are within the 95 percent interval. At the 99 percent interval, all six values were within the prediction interval for the regression model. In the case of the principal component model, one value was still outside the prediction interval at 99 percent. This value was for month 2, November 1991. The actual MC rate was 80.2, below the lower prediction limit (99 percent interval) of 81.63. However, the MC rate in November 1991 was the lowest value in our data set. It was not used to formulate regression models, but was used only for validation. It seems reasonable that this actual value could be outside model prediction intervals.

Validation of the KC-135R NMC models was a little better. For both the regression and principal component models, five of six values were within the prediction interval at 95 percent, and all six values were within the prediction interval at 99 percent. Once again, the only value ever outside the prediction interval was month 2, which also had the highest NMC rate in our data set.

The B-52H MC models produced identical validation results. Both the regression and principal component models had five of six values within the prediction interval at 95

TABLE 14

RESULTS OF MODEL VALIDATIONS

		VALUES WITHIN PREDICTION INTERVAL	
KC-135R		95%	99%
REGRESSION	MC	5	6
	NMC	5	6
PRIN. COMP	MC	5	5
	NMC	5	6
B-52H			
REGRESSION	MC	5	5
	NMC*	6	6
PRIN. COMP	MC	5	5
	NMC*	6	6

"*" PERFORMED VALIDATION OF AUTOREGRESSION MODELS ONLY and 99 percent. This is due to the fact that we once again randomly selected our "worst" month to use for validation. Month 24, December 1991, had a MC rate of 64.9 percent, once again the lowest in our data set.

The B-52H NMC models used a different set of months for validation. Because we used an autoregressive model to predict NMC rate, we needed to draw our validation data points in such a way as to not disrupt the time series. Thus, we chose the first and last three data points in the set for validation. Using these points, both the regression and principal component models had six of six points within the prediction interval at 95 and 99 percent.

Overall, the models appear to be useful in predicting MC and NMC rates. The only actual values outside the prediction interval represent the "worst" months for both aircraft. In all cases, both the regression and principal component models are useful. However, we must determine which of these is the best predictive model.

Comparison of Models

We now turn to research question seven: Which performance model best predicts aircraft maintenance performance? To answer this question, we perform a comparison of our aircraft models. For each dependent variable, we still needed to consider a regression and principal component model. We based our comparison of these models on several factors. These included maximum adjusted R-square, minimum average prediction error, minimum root mean square error (RMSE), and minimum probability of the F statistic being in the rejection region when testing the usefulness of the model. These factors and model values are summarized in Tables 15-18. As a result of this analysis, we chose the regression models as the "best" predictor of KC-135R MC and NMC rates, and B-52H MC rate. All of these models had the highest adjusted R-square, lowest average prediction error, lowest RMSE and the lowest F statistic. In the case of B-52H NMC, the principal component model is the best. For this model, we looked at adjusted R-square, prediction accuracy and RMSE. The principal component model was slightly better than the regression model in all of these areas. The adjusted R-square values are less than one percentage point apart. SSE, RMSE and average prediction error are all very close. However, overall the principal component model is slightly better. Based on this, we chose the principal component model as our "best" model of B-52H NMC.

Comparison of Performance Factors

Once we determined which model was best, we then needed to determine if maintenance performance had actually improved since the implementation of the Objective Wing

TABLE 15

COMPARISON OF KC-135R REGRESSION AND REDUCED PRINCIPAL COMPONENT MODELS (MC)

STATISTIC	REGRESSION	REDUCED PC
F-STATISTIC	0.0014	0.0083
R-SQUARE	0.4080	0.4705
ADJ. R-SQUARE	0.3784	0.3822
SSE	168.0	284.0
ROOT MSE	2.9	2.9
AVG PREDICTION ERROR (ABS VALUE)	2.45	3.27

TABLE 16

COMPARISON OF KC-135R REGRESSION AND REDUCED PRINCIPAL COMPONENT MODELS (NMC)

STATISTIC	REGRESSION	REDUCED PC
F-STATISTIC	0.0329	0.0873
R-SQUARE	0.3020	0.2264
ADJ. R-SQUARE	0.2285	0.1450
SSE	89.36	99.04
ROOT MSE	2.17	2.28
AVG PREDICTION ERROR (ABS VALUE)	2.75	3.33

TABLE 17

COMPARISON OF B-52H REGRESSION AND REDUCED PRINCIPAL COMPONENT MODELS (MC)

STATISTIC	REGRESSION	REDUCED PC
F-STATISTIC	0.0002	0.0005
R-SQUARE	0.5	0.42
ADJ. R-SQUARE	0.4600	0.3803
SSE	513.58	611.14
ROOT MSE	4.36	4.67
AVG PREDICTION ERROR (ABS VALUE)	6.03	6.76

TABLE 18

COMPARISON OF B-52H REGRESSION AND REDUCED PRINCIPAL COMPONENT (AUTOREGRESSION) MODELS (NMC)

STATISTIC	REDUCED REG.	REDUCED PC
R-SQUARE	0.07	0.05
ADJ. R-SQUARE	0.2708	0.2720
SSE	366.86	366.24
ROOT MSE	3.76	3.62
AVG PREDICTION ERROR (ABS VALUE)	4.54	4.38

structure; research question eight. To evaluate this we first test the independent variables that appear in the stepwise models. For the B-52H, this includes ABORT, DD, MHFH and CANN. For the KC-135R, we must test DD, LTO, and MHFH. Based on the results of normality testing, B-52H DD, MHFH and CANN are normally distributed. ABORT is not normally distributed. KC-135R MHFH is normally distributed, however DD and LTO are not. We will use a difference in means t-test to evaluate differences in the normally distributed variables and a median test for those that are not normally distributed.

For both aircraft, the dependent variables (MC, NMC) are normally distributed, so we use a t-test to evaluate differences in these variables and model predictions. For the normally distributed variables, we first compared the difference in means of the actual maintenance data, then we compared model predictions based on these data. We used a difference in means t-test with pooled variance. For all variables, our test of hypotheses took the form of :

Ho: No significant difference in means.
Ha: Significant difference in means.

$$\text{Test Statistic } t = \frac{\text{Mean (new)} - \text{Mean (old)}}{[s^2_p(1/n_{new} + 1/n_{old})]^{1/2}}$$

Where,

n_{new}, n_{old} = sample size of new and old samples

s^2_p = Pooled variance
$= [((s^2_{new} * n_{new}) + (s^2_{old} * n_{old})) / (n_{old} + n_{new} - 2)]^{1/2}$

Rejection Region : $|T| > T_{Table}$

We based the cutoff for our 2 samples on the May 1992 implementation of the Objective Wing. We divided our data set and produced summary statistics for each section. We then used these statistics to perform the tests of hypotheses.

The test of actual data revealed that there were significant improvements at $\alpha = 0.1$ for B-52H CANN (decreased), B-52H DD (decreased), B-52H and KC-135R MC (increased) and NMC (decreased). Results and test statistics for these tests are summarized in Tables 19 and 22.

For the non-normal variables we used a median test to determine differences in the samples. However, we chose not to test the abort rate (ABORT). ABORT was not normally distributed, thus we could not perform a t-test. Although ABORT was included in the B-52H MC model, the rarity of aborts make it impossible to perform a meaningful analysis of any differences. Further analysis would yield inconclusive and inconsistent results. As a result, our median test was limited to KC-135R DD and LTO. Results of these tests are summarized in Table 20, and the complete test results are included in Appendix J. For DD, there is a

TABLE 19

RESULTS OF DIFFERENCE IN MEANS t-TEST (FROM ACTUAL DATA)

(KC-135R)

VARIABLE	TEST STAT.	TABLE VALUE, ALPHA/2 = 0.05	RESULT
MC	3.1844	"	DIFFERENCE
MHFH	-0.1484	"	NO DIFFERENCE
NMC	-1.7134	"	DIFFERENCE

Source: McClave and Benson, 1991: 1175

significant difference. The p-value associated with the chi-square test is 0.0005. This indicates that it is very unlikely that the samples have the same median. Data under the pre-1992 structure have 18 values above the median, while data from the Objective Wing structure have no values above the median. This leads to the conclusion that the median for delayed discrepancies has decreased in the Objective Wing. For LTO, the p-value is 0.6857, indicating that there are no significant differences in the medians.

We next performed a difference in means t-test of model predictions based on actual maintenance data. We input the actual values of the independent variables and used model predictions of MC and NMC rates to perform a difference in means analysis. The results of these analyses are in Tables 20, 22, and 23. In all cases, there was significant improvement in MC and NMC rates at $\alpha = 0.1$.

TABLE 20

RESULTS OF MEDIAN TEST (FROM ACTUAL DATA)

(KC-135R)

VARIABLE	CHI-SQUARE VALUE	P-VALUE	RESULT
DD	12.00	0.0005	DIFF
LTO	0.16	0.6857	NO DIFF

TABLE 21

RESULTS OF DIFFERENCE IN MEANS t-TEST BASED ON PREDICTED VALUES FROM REDUCED REGRESSION MODEL

(KC-135R)

VARIABLE	TEST STATISTIC	TABLE VALUE, ALPHA/2 = .05
MC	4.42	1.706
NMC	-3.36	1.706

Source: McClave and Benson, 1991: 1175

TABLE 22

RESULTS OF DIFFERENCE IN MEANS t-TEST (FROM ACTUAL DATA)
(B-52H)

VARIABLE	TEST STAT.	TABLE VALUE, ALPHA/2 = 0.05	RESULT
CANN	-3.4586	1.690	DIFFERENCE
DD	-4.6759	"	DIFFERENCE
MC	2.9861	"	DIFFERENCE
MHFH	1.3659	"	NO DIFFERENCE
NMC	-2.1983	"	DIFFERENCE

Source: McClave and Benson, 1991: 1175

TABLE 23

RESULTS OF DIFFERENCE IN MEANS t-TEST BASED ON PREDICTED VALUES FROM REDUCED REGRESSION MODELS
(B-52H)

VARIABLE	TEST STATISTIC	TABLE VALUE, ALPHA/2 = 0.05
MC	3.50	1.690

Source: McClave and Benson, 1991: 1175

TABLE 24

RESULTS OF DIFFERENCE IN MEANS t-TEST BASED ON PREDICTED VALUES FROM REDUCED PRINCIPAL COMPONENT (AUTOREGRESSION) MODEL (B-52H)

VARIABLE	TEST STATISTIC	TABLE VALUE, ALPHA/2 = 0.05
NMC	3.36	1.690

Source: McClave and Benson, 1991: 1175

Summary

This chapter presented the results of our research methodology to answer research questions five through eight. To answer research question five, we discussed the attributes of our data set including the results of tests for normality and randomness and their implications. To answer research question six, we presented the process we used to develop our performance models and criteria for model evaluation and validation. We performed a comparison of the performance models to answer question seven and chose a best model for each dependent variable. Finally, we answered research question eight by discussing the results of comparisons of actual performance data from both organizational structures and model predictions based on these data.

In Chapter V we will discuss conclusions based on our research effort, further elaborate on the implications of our results, and provide some recommendations for further research.

V. Conclusions and Recommendations

Introduction

This chapter discusses conclusions and recommendations based on the research effort. We provide answers to the research questions, including a discussion of conclusions and implications of our research. Finally, we give some recommendations for future research.

Results

In this section we provide answers to our research questions and discuss the implications of our research.

Research Question 1. *What analytical methods have been used in the past to create performance models?*

A literature review unearthed several previous theses that included development of aircraft maintenance performance models. Table 1, page 17 summarizes these research efforts. The most often used method was regression analysis.

Research Question 2. *What dependent variables best represent aircraft maintenance performance?*

We answered this question based on our literature review. Previous researchers used methods such as surveys (Gililland), regulations (Jung), expert opinions and personal experience to determine the most meaningful dependent variables. We reviewed the factors most often used (Appendix A) and determined that Mission Capable Rate and Total Not Mission Capable Maintenance Rate were the most widely used dependent variables.

Research Question 3. *What independent variables affect aircraft maintenance performance?*

Again, we answered this question based on our literature review. Based on the variables used by previous researchers and variables reported in the monthly maintenance summaries, we chose nine independent variables for our analysis. Stepwise regression further narrowed these down. Each aircraft model had different variables. Delayed discrepancy rate (DD) appeared in both aircraft MC models, however, the B-52 model also included the abort rate and manhour per flying hour (MHFH). The NMC models included totally different variables. The B-52 model included cannibalization rate (CANN) while the KC-135 model included the late takeoff rate (LTO) and MHFH. Once again, each aircraft type displayed different variable relationships. There is no one universal aircraft maintenance performance model.

Research Question 4. *What problems exist in previous researchers' models and how might these deficiencies be corrected?*

The main problems exhibited in previous models were seasonality or autocorrelation, nonnormality, and correlation of variables. We tested all variables for normality, and tested the dependent variables for autocorrelation. We used nonparametric tests to evaluate nonnormal variables, and used an autoregressive model to correct for autocorrelation in the dependent variable, B-52H NMC. We performed regression of principal components in an attempt to eliminate correlation of independent variables.

Research Question 5. *Which analytical method is the most appropriate to model aircraft maintenance performance?*

We expanded the use of regression models to include a regression model based upon the principal components of the independent variables. In most cases, the principal component model was not a better predictor of performance than regression models. In the case of B-52H Total Not Mission Capable Maintenance Rate (NMC), the principal component regression model was only a slightly better predictor than the regression model. Additionally, we saw that an autoregressive model was more useful for this variable. In general, it seems that the answer to this question is "it depends." The attributes of the data set dictate which type of model is best. Autocorrelation leads to an autoregressive model, while high correlation between independent variables may warrant use of principal components. There is no universal "one best method."

Research Question 6. *Are regression and principal component models useful for predicting aircraft maintenance performance?*

Our analysis of both types of models shows that both can be considered useful. Adjusted R-square values for our performance models ranged from 0.14 to 0.46. We did not have a perfect fit of our performance data, but we saw a moderate to good fit of the models to the data. Residual plots were as expected, with no obvious quadratic, exponential or cubic patterns. Validation results for all models indicate that with the exception of extremely low MC rates, the model predictions closely approximated actual performance measures.

Research Question 7. *Which performance model best predicts aircraft maintenance performance?*

We focused on regression models, specifically regression of maintenance independent variables, regression of their principal components and autoregressive models. For B-52 MC, KC-135 MC and NMC, reduced regression models of the independent variables were the best predictors. For B-52 NMC, an autoregression of principal components was best. Once again, the data themselves are going to dictate the type of model that is appropriate.

Research Question 8. *Do significant statistical differences exist in aircraft maintenance performance in the Objective Wing and pre-1992 organizational structures, and, if so, what are they?*

In our analysis, we looked at a difference in means of eight of the independent variables, both dependent variables and the model predictions of the dependent variables. We found significant improvement in five variables: cannibalization rate (CANN), delayed discrepancy rate (DD), scheduling effectiveness (EFFEC), mission capable rate (MC) and Total Not Mission Capable Maintenance Rate (NMC). For both aircraft types CANN, DD and NMC decreased, while EFFEC and MC increased. Model predictions were also significantly different. Model predictions for MC and NMC showed significant improvement.

Conclusions and Implications

The most significant conclusion of our research is that performance has in fact improved since the Objective Wing structure was implemented at Fairchild AFB. For both aircraft types, dependent variables MC and NMC improved. However, other factors such as the stand-down of the Alert Force in October 1991 may also have influenced these performance factors.

Another important conclusion concerns model building. Performance models are always a function of the data set used to build them. It is vitally important to evaluate the attributes of the data set to build a good model. There are many "statistical pitfalls" that a researcher must correct for, such as autocorrelation and correlation of independent variables. Each data set will exhibit different characteristics. There is no universal performance model.

The results of this research support the view that reorganization of Air Force Wings into a more organic, decentralized structure may have in fact improved performance, just as it has in the business world. The Air Force has responded to a changing environment by reorganizing into a more flexible structure. It seems we have enhanced defense capability despite less manpower and other resources.

Recommendations for Further Research

There are several aspects of this topic that may warrant further research. These areas include:

1. The effect of other events such as the Alert Force stand-down on maintenance performance. This event occurred just before the implementation of the Objective Wing. A study comparing wings with and without alert commitments or a study solely based on aircraft without an alert commitment may be worthwhile.

2. Sample size under the Objective Wing: further research could encompass two maintenance performance models, one based on the "old" structure and another based on the Objective Wing. We had only nine months of Objective Wing data available for our analysis. With time, a larger data set will be available and more extensive analysis could be performed.

3. A study of other aircraft types: we focused solely on B-52H and KC-135R aircraft. Has the Objective Wing structure improved performance in fighter wings, for example? Or conversely, has performance improved in wings that have not adopted the Objective Wing structure such as Air National Guard units or former Military Airlift Command units? Will different performance models and data sets produce different results?

4. A study that incorporates the effects of Operations Desert Shield and Desert Storm. How did these events affect performance prior to Objective Wing implementation? Did Desert Shield/Storm skew pre-1992 data?

5. A study on the effects of the Objective Wing on other base agencies, such as the maintenance, operations or weather squadrons. Has performance improved in these units?

6. A qualitative study of the behavioral aspects of Objective Wing implementation. For example, has job satisfaction increased for maintenance personnel assigned to the flying squadrons?

7. A study on maintenance data as a time series. We brushed the surface of time series analysis with this thesis. Are there more powerful and or more appropriate time series techniques that will build a better model?

Summary

This research explored the effects of the Objective Wing structure on aircraft maintenance performance. We reviewed literature on organizational change and on performance modelling, developed performance models based on regression and principal component analysis, and performed comparisons of actual performance data and model predictions with a difference of means t-test. We found that there were significant improvements in maintenance performance since the implementation of the Objective Wing structure. We presented our conclusions and some implications of our research. We provide recommendations for further research to better analyze the true effects of the Objective Wing on wing performance.

Appendix A: Aircraft Maintenance Performance Factors

(INDEPENDENT (I) FACTORS USED IN PREDICTING DEPENDENT (D) FACTORS)

Aircraft Maintenance Performance Factor	Researcher(s)			
	Davis & Walker (1992)	Jung (1991)	Gililland (1990)	Diener & Hood (1980)
Air Aborts / Maintenance Air Aborts		I /	/ D	
Air Abort Rate	I	I		
Aircraft Breaks		I		
Aircraft Break Rate		I		
Aircraft Fix Rate		I		
Aircraft Hourly Utilization Rate	I			
Aircraft Sortie Utilization Rate	I	I		
Aircraft Sortie Duration		I		
Average Hours Per Inspection				D
Average Turn Time				D
Awaiting Maintenance Discrepancies			I	
Awaiting Parts Discrepancies			I	
Base Self Sufficiency			I	
Cancellations		I		
Cancellation Rate		I		
Cannibalizations		I		
Cannibalization Rate		I		
Direct Labor Rate				D
Enroute Labor Rate			D	
Full Mission Capable Rate / MC Rate	/ D	I / D	/ D	D /
Ground Abort Rate				D
Home Station Reliability			D	
(Flying) Hours Allocated				I
Hours Flown		I		I
Hours Flown vs. Allocated				I
Late Take-Offs		I		I
Late Take-Off Rate		I		

Appendix A: Aircraft Maintenance Performance Factors

(Continued)

(INDEPENDENT (I) FACTORS USED IN PREDICTING DEPENDENT (D) FACTORS)

Aircraft Maintenance Performance Factor	Researcher(s)			
	Davis & Walker (1992)	Jung (1991)	Gililland (1990)	Diener & Hood (1980)
Maintenance Scheduling Effectiveness			D	
Manhours Expended		I		
Manhours Per Sortie		I		
Maintenance Manhours Per Flying Hour	I	I	D	D
Mean Skill Level of Maintenance Personnel				I
Not Mission Capable Rate / NMC Both Rate	I / I	I / I		
NMC Maintenance Rate / (1/NMCM)	I /	I /		D /
NMC Supply Rate / (1/NMCS)	I /	I /		
Number of Aircraft Fixed in 18 Hours		I		
Number of Maintenance Personnel Assigned				I
Number of Personnel Authorized Per Aircraft	I			
Number of Personnel Assigned vs. Authorized				I
Partial Mission Capable Rate		I		
Partial Mission Capable Both Rate		I		
Partial Mission Capable Maintenance Rate		I		
Partial Mission Capable Supply Rate		I		
Possessed Aircraft / Avg. Possessed Aircraft		I /	/ I	
Possessed Hours		I		
Repeat Discrepancy Rate			D	D
Scheduling Effectiveness Rate				D
Sorties Attempted		I		
Sorties Flown		I		
Sorties Scheduled		I		
Training Reliability			D	
Total NMCM Rate		D		
Total NMCS Rate		D		

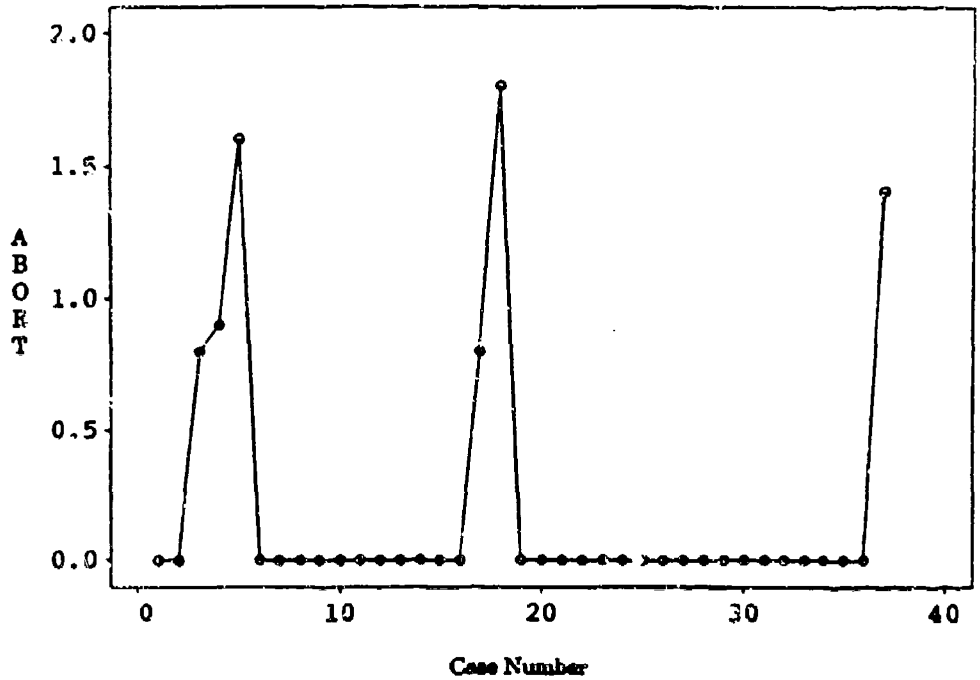
Sources. Davis and Hood, 1980; Gililland, 1990, Jung, 1991; Davis and Walker, 1992

Appendix B: Data Sets and Time Series Plots

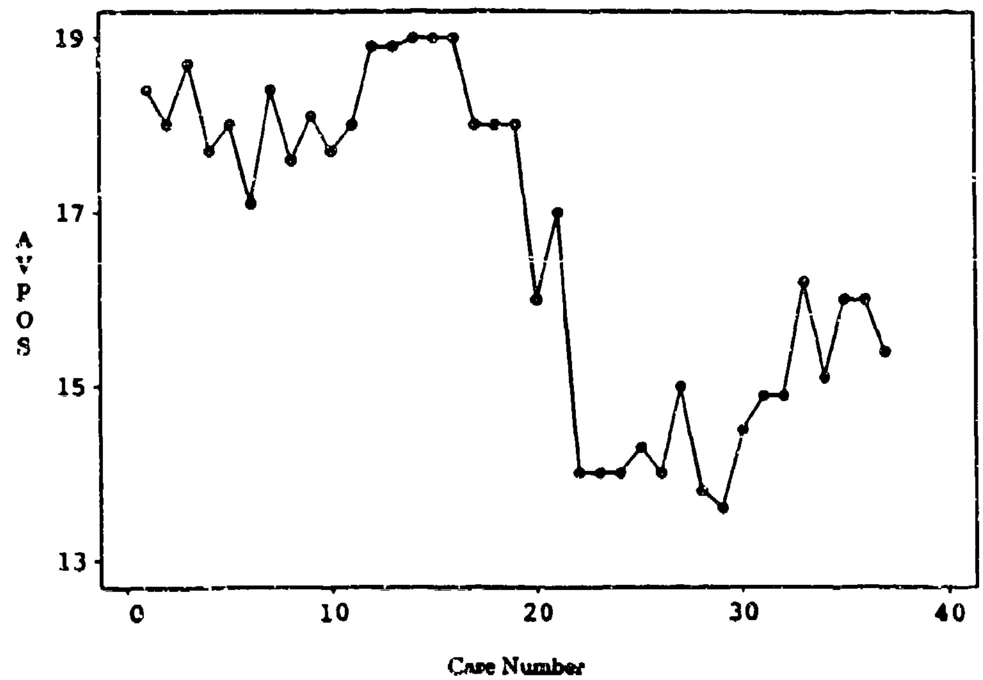
1. B-52H

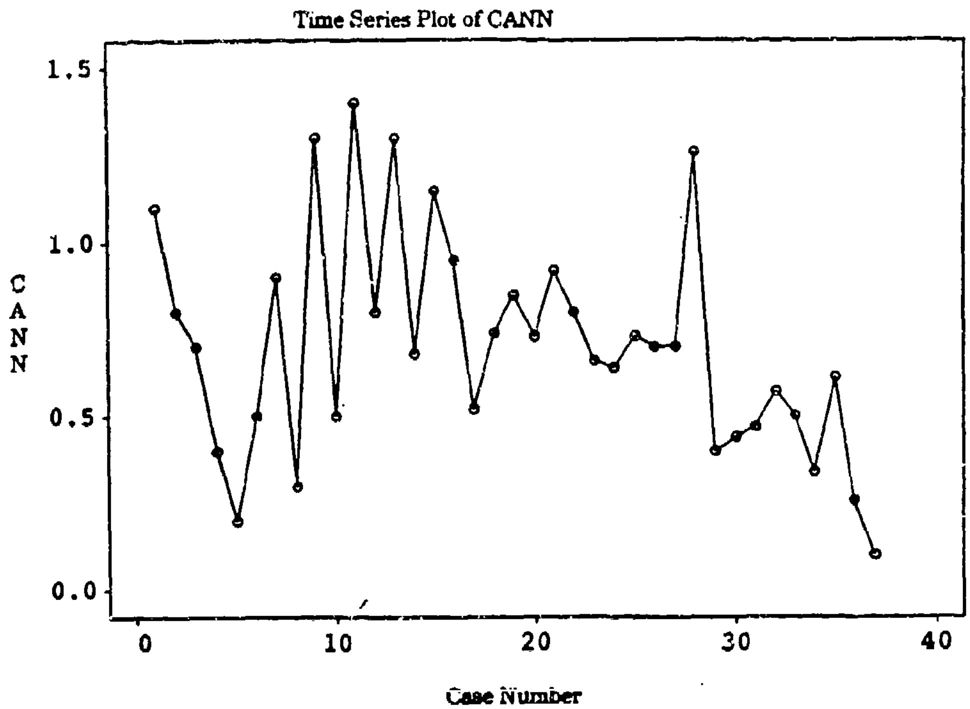
Month	CANN	LTO	DD	CANX	MHFH	MHS	AVPOS	ABORT	EFFEC	MC	NMC
Jan 90	1.1	4.8	18.2	1.5	76.2	444.3	18.4	0	96.7	76.6	21.7
Feb 90	0.8	8.8	17.3	2.6	60.5	392.9	18.0	0	97.7	78.4	19.7
Mar 90	0.7	8.3	15.1	2.6	49.0	262.2	18.7	0.8	95.4	82.3	13.7
Apr 90	0.4	10.4	16.8	1.8	49.6	306.3	17.7	0.9	98.2	77.3	17.8
May 90	0.2	12.0	15.7	1.0	44.7	277.8	18	1.6	98.4	83.8	12.7
Jun 90	0.5	5.2	19.6	1.8	54.3	305.4	17.1	0	99.1	79.9	15.9
Jul 90	0.9	18	18.4	5.7	77.5	393.8	18.4	0	97.6	77.0	18.1
Aug 90	.3	5.9	20.5	4.1	29.8	182.6	17.6	0	96.0	72.1	21.2
Sep 90	1.3	6.0	20.0	0.0	67.5	434.5	18.1	0	98.4	79.3	16.2
Oct 90	.5	6.8	22.4	3.8	46.9	255.9	17.7	0	97.4	79.5	16.2
Nov 90	1.4	20.5	21.9	3.4	39.4	239.2	18.0	0	97.2	74.3	19.1
Dec 90	.8	25.3	18.8	2.4	34.4	177.6	18.9	0	94.1	67.2	23.5
Jan 91	1.3	17.6	21.5	8.8	53.2	282.3	18.9	0	96.9	73.6	18.1
Feb 91	.68	15.1	22.5	1.1	36.4	204.2	19.0	0	99.1	62.4	15.3
Mar 91	1.15	9.3	21.8	4.4	52.3	282.1	19.0	0	95.6	70.1	15.6
Apr 91	.95	6.5	18.9	2	49.6	292.2	19.0	0	93.1	81.7	12.9
May 91	.52	5.0	13.8	1.6	46.3	239.3	18.0	0.8	98.5	80.6	13.6
Jun 91	.74	4.4	15.3	3.4	45.6	278.5	18.0	1.8	96.7	78.3	14.7
Jul 91	.85	12.3	17.8	4	54.9	287.3	18.0	0	96.1	72.2	12.7
Aug 91	.73	16.2	18.4	5.3	46.0	271.1	16.0	0	95.0	76.6	18.9
Sep 91	.92	13.2	16.4	7.4	55.0	303.1	17.0	0	92.9	77.7	19.6
Oct 91	.8	6.5	12.6	3.2	44.5	296.7	14.0	0	96.9	73.6	22.1
Nov 91	.66	3.3	11.1	0	41.1	270.2	14.0	0	100	71.4	23.7
Dec 91	.64	11.4	9.9	2.5	63.4	322.5	14.0	0	97.6	64.9	27.1
Jan 92	.73	7.1	4.6	2.9	65.1	390.2	14.3	0	90.8	75.3	17.5
Feb 92	.7	12.6	4.9	5.3	50.3	289.0	14.0	0	83.2	80.0	14.6
Mar 92	.7	7.7	4.6	0	59.2	277.1	15.0	0	92.6	78.4	17.0
Apr 92	1.26	6.0	4.9	2.4	60.5	300.0	13.8	0	92.3	73.9	10.8
May 92	.4	6.0	6.5	0	51.8	356.5	13.6	0	93.4	88.3	10.6
Jun 92	.44	2.0	7.2	0	52.9	293.4	14.5	0	97.0	78.4	20.7
Jul 92	.47	12.9	4.8	6.9	50.0	342.1	14.9	0	82.2	76.3	22.3
Aug 92	.57	2.8	7.5	1	70.4	411.8	14.9	0	96.4	79.5	16.4
Sep 92	.5	7.1	6.3	1.2	68.5	396.6	16.2	0	91.7	84.6	13.0
Oct 92	.34	6.6	6.5	4.5	59.9	326.1	15.1	0	91.0	84.1	11.5
Nov 92	.61	4.8	6.2	1.2	62.2	348.1	16.0	0	94.1	88.2	8.5
Dec 92	.26	18.2	6.6	2.6	63.2	321.4	16.0	0	78.2	83.0	12.0
Jan 93	.1	7.2	7.1	4	42.8	243.2	15.4	1.4	90.3	86.7	9.5

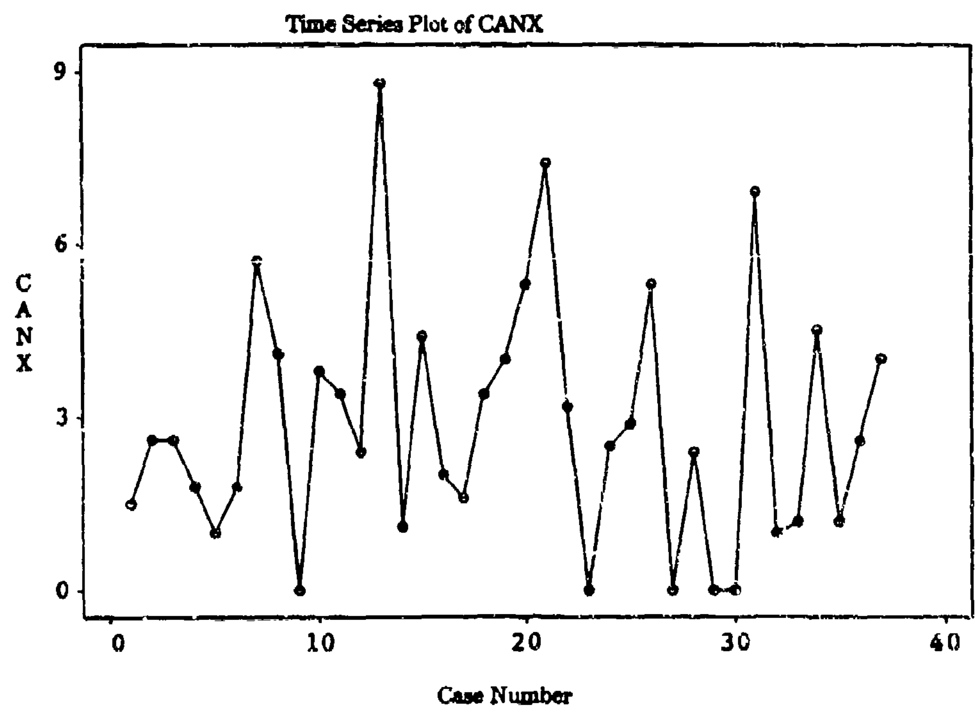
Time Series Plot of ABORT

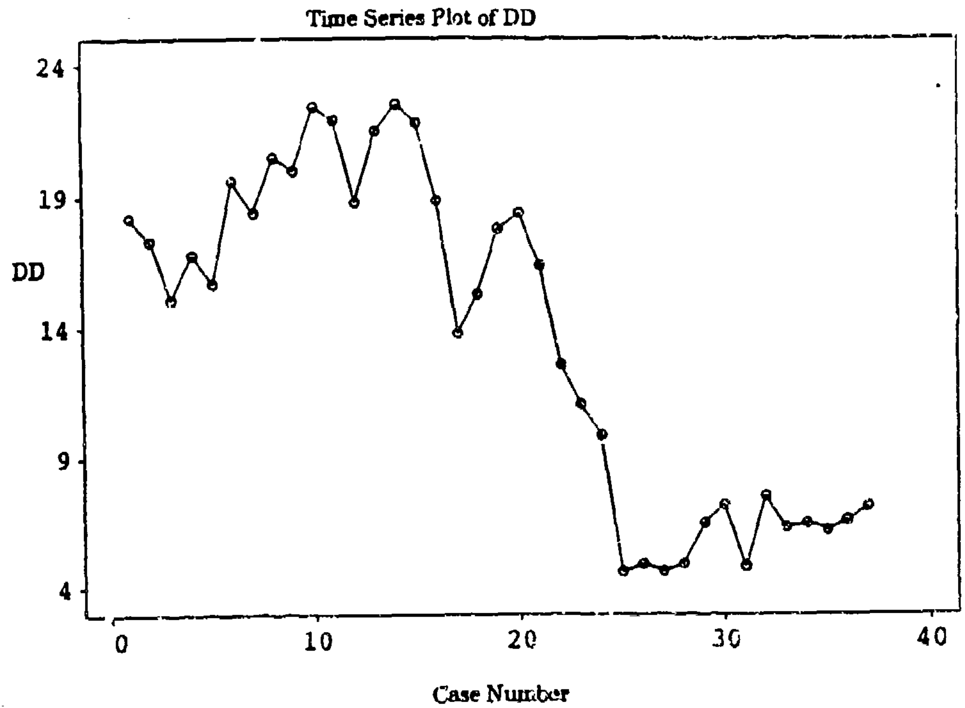


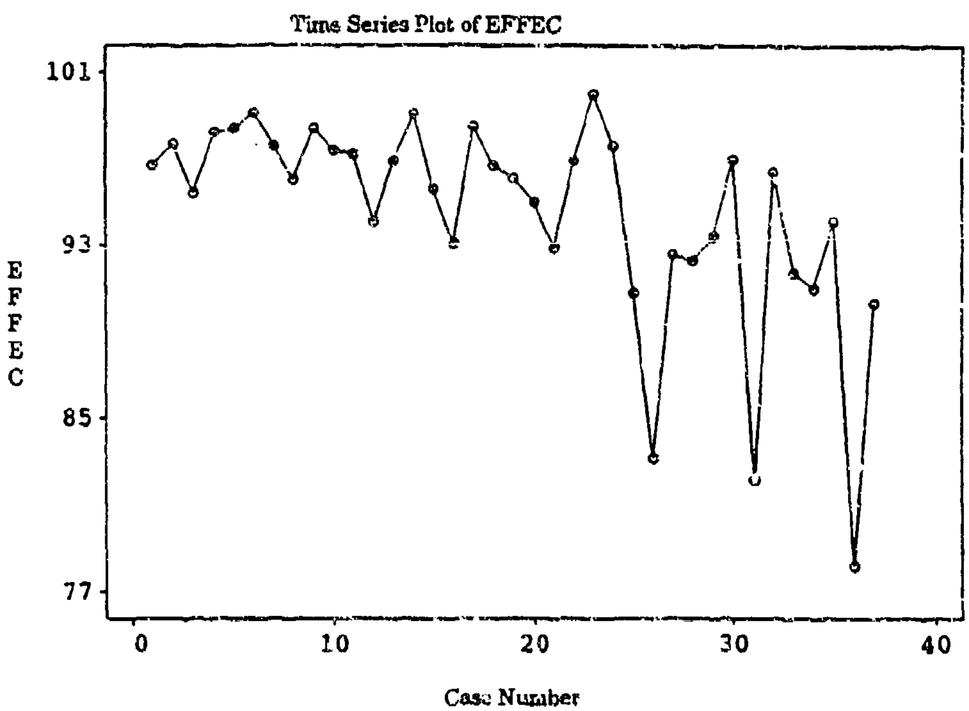
Time Series Plot of AVPOS

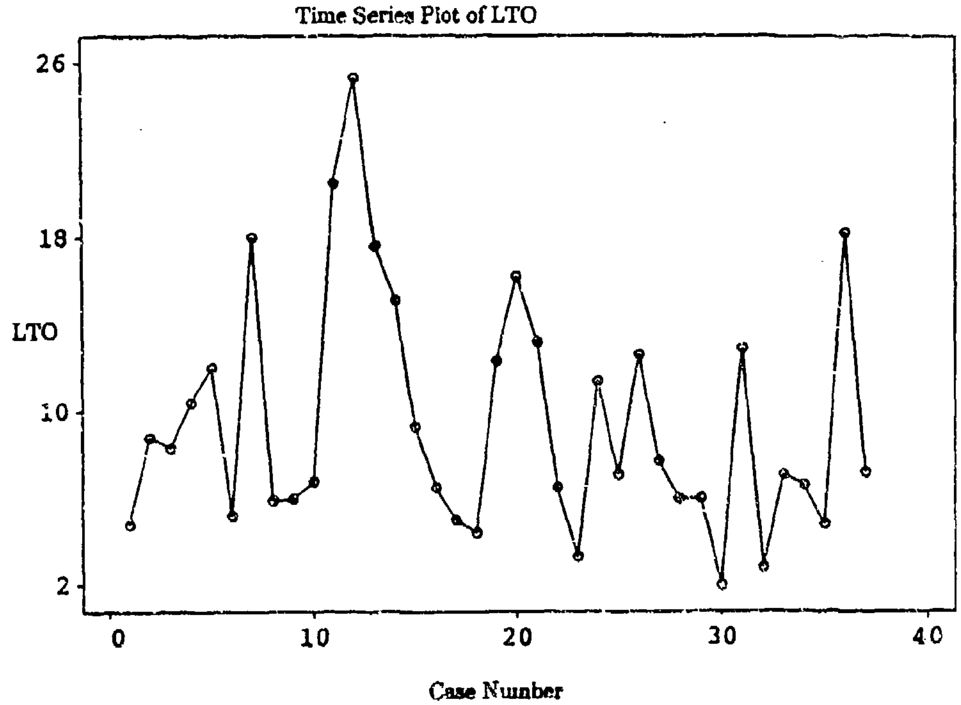


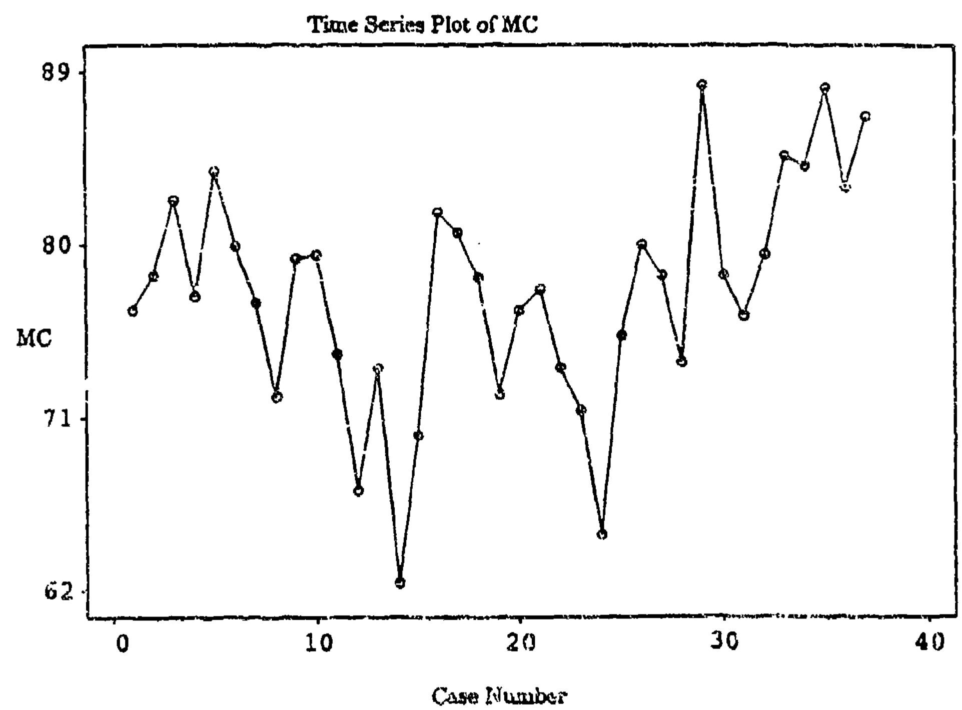

Time Series Plot of CANN
1.5
1.0
0.5
0.0
CANN
0
10
20
30
40
Case Number


Time Series Plot of CANX
9
6
3
0
CANX
0
10
20
30
40
Case Number

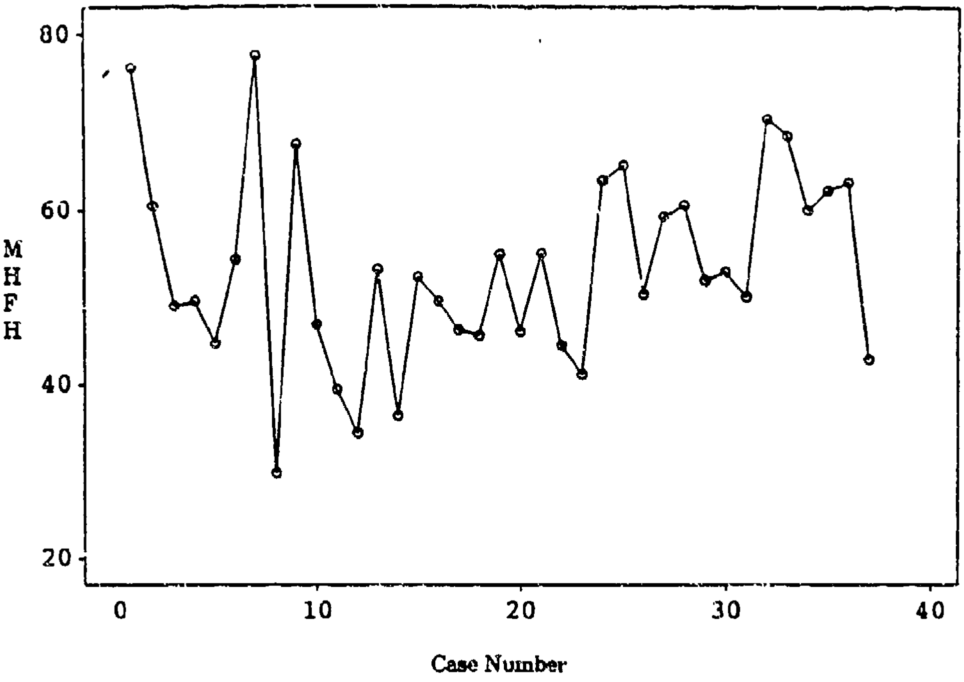

Time Series Plot of DD
24
19
DD
14
9
4
0
10
20
30
40
Case Number


Time Series Plot of EFFEC
101
93
EFFEC
85
77
0
10
20
30
40
Case Number

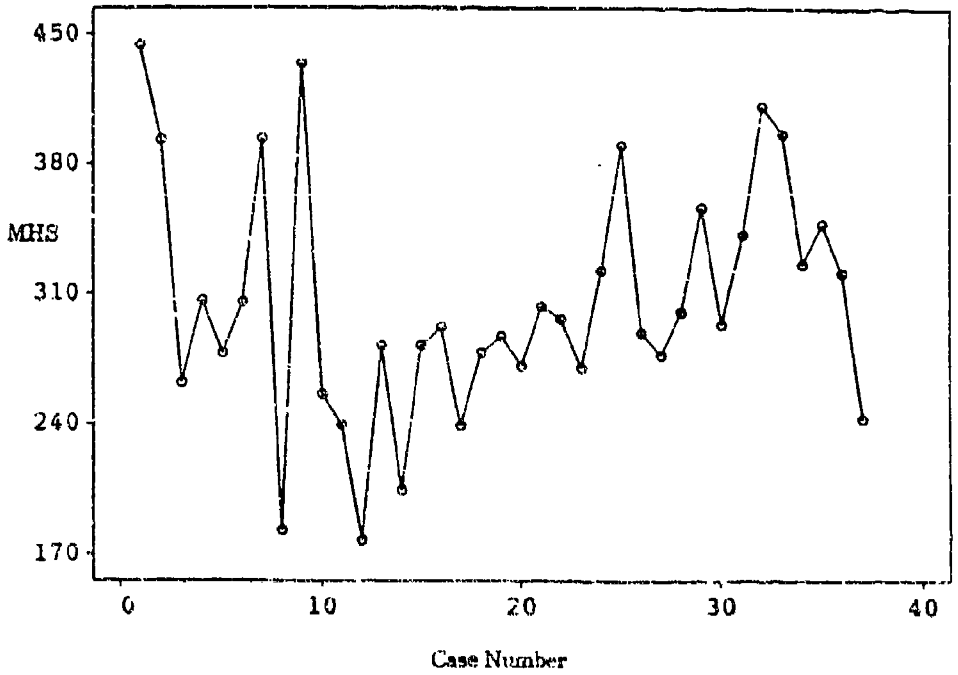

Time Series Plot of LTO
26
18
LTO
10
2
0
10
20
30
40
Case Number

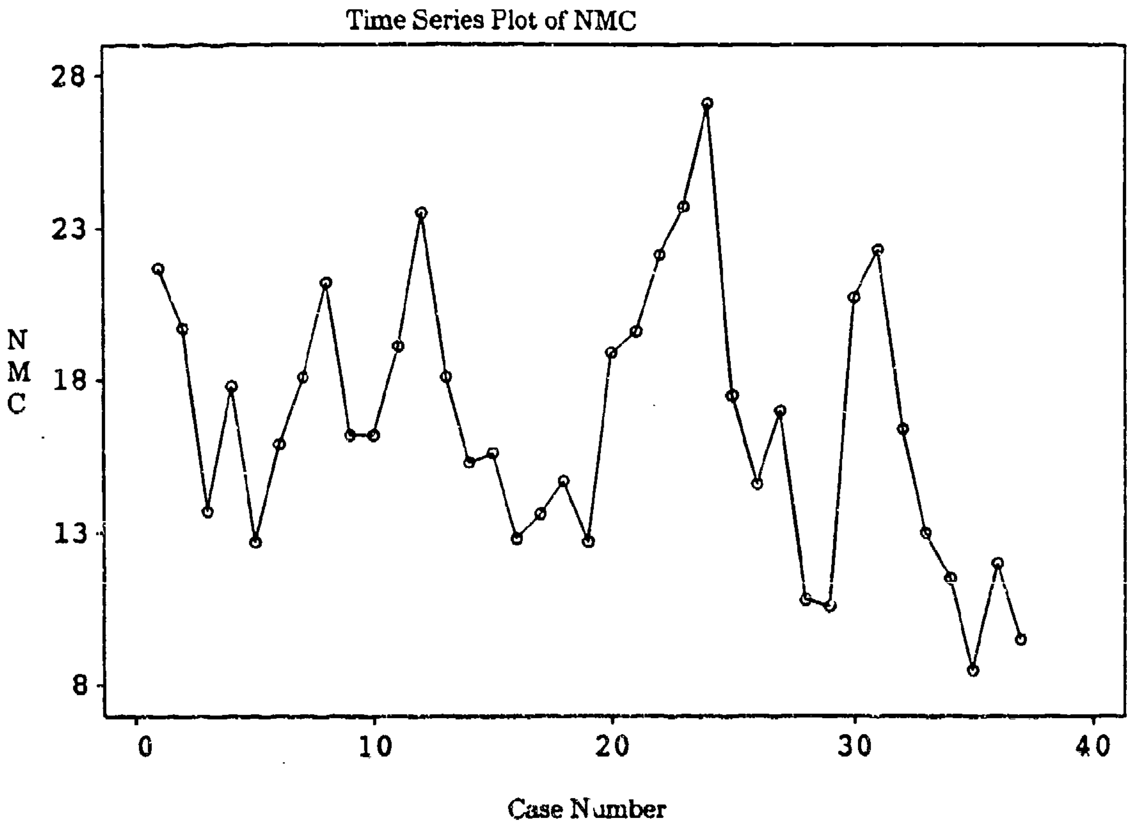

Time Series Plot of MC
89
80
MC
71
62
0
10
20
30
40
Case Number

Time Series Plot of MHFH



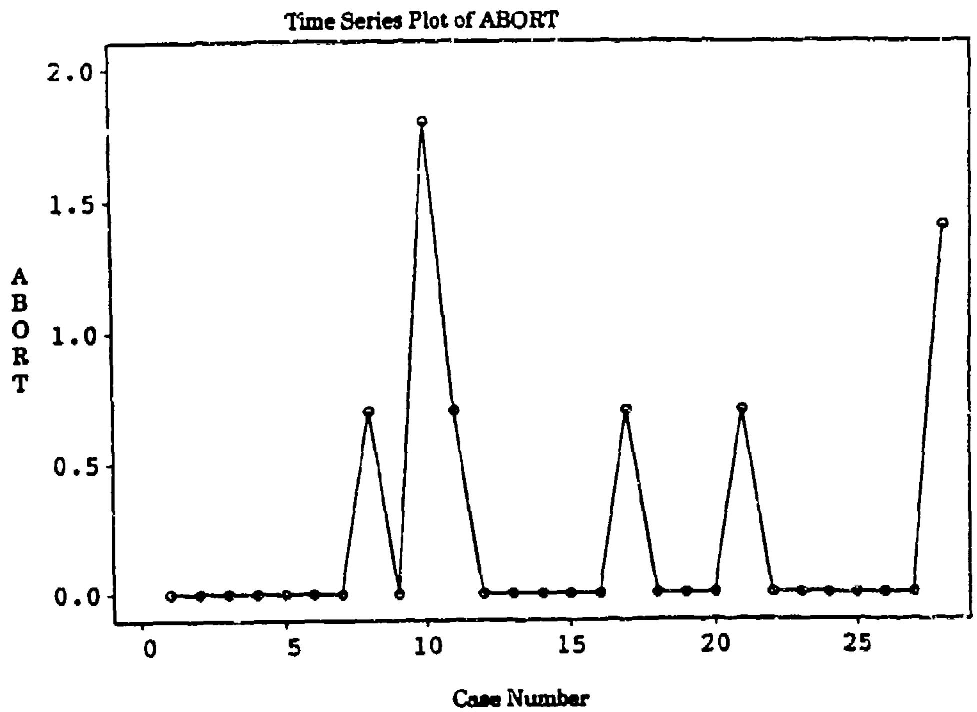
Time Series Plot of MHS

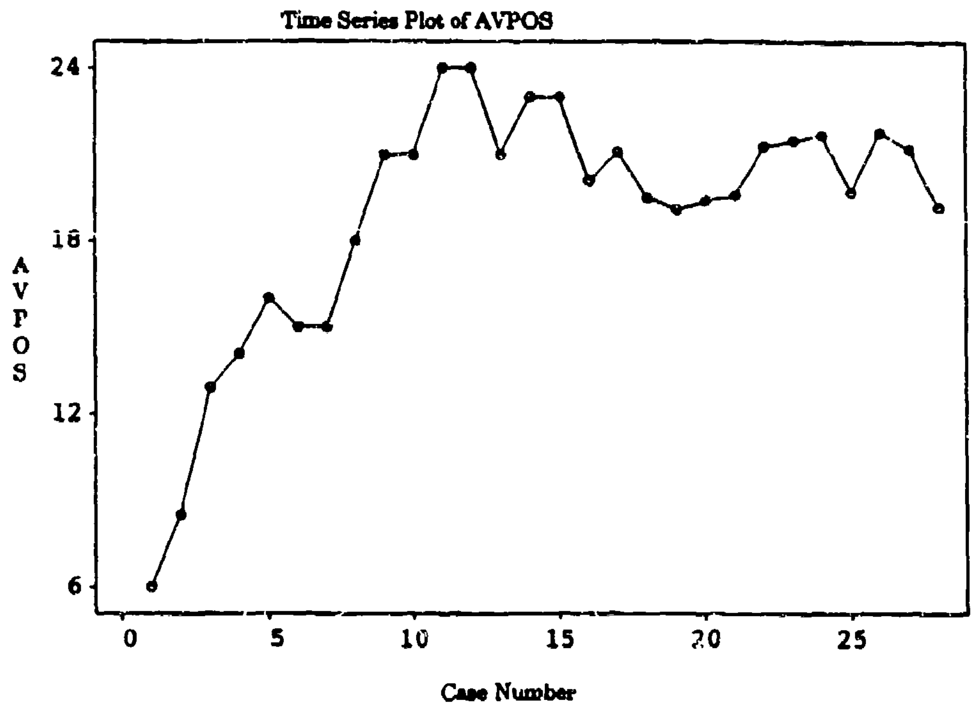


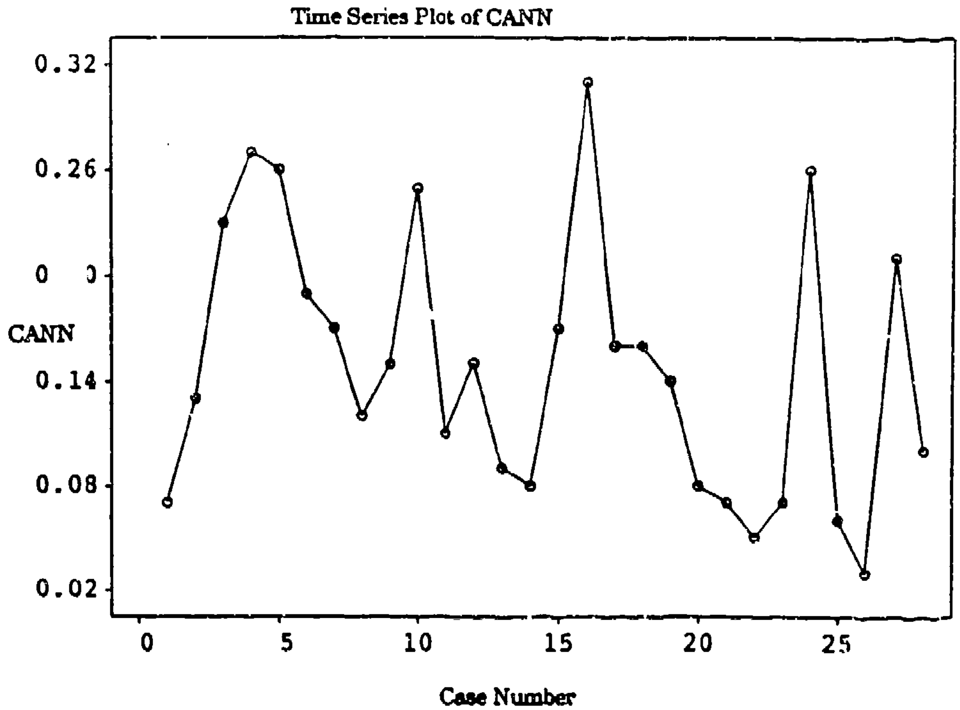

Time Series Plot of NMC
NMC
28
23
18
13
8
0
10
20
30
40
Case Number

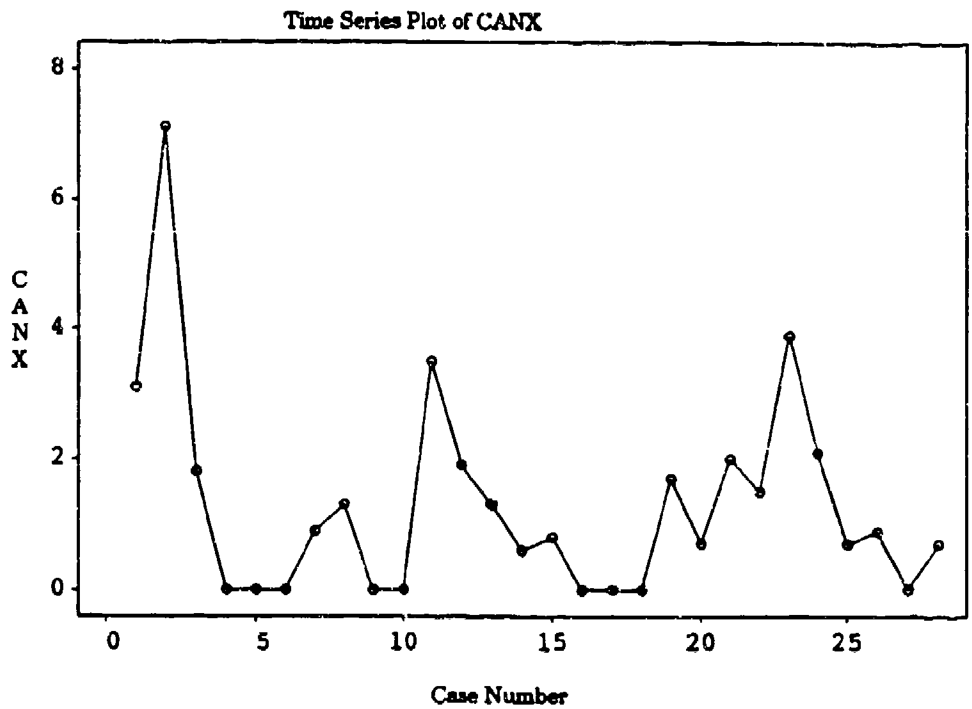
2. KC-135R

Month	MC	NMC	ABORT	MHS	MHFH	CANN	LTO	CANX	DD	AVPOS	EFFEC
Oct 90	89.0	7.2	0.0	97.9	23.9	.07	6.60	3.1	06.21	6.0	97.7
Nov 90	80.2	13.4	0.0	108.2	34.7	.13	4.20	7.1	10.24	8.5	95.9
Dec 90	83.3	12.1	0.0	63.50	18.9	.23	9.80	1.8	10.85	12.9	97.7
Jan 91	87.8	10.2	0.0	66.1	15.4	.27	1.50	0.0	11.91	14.1	100
Feb 91	87.3	05.5	0.0	72.50	13.9	.26	2.10	0.0	8.800	16.0	100
Mar 91	81.9	11.4	0.0	89.60	22.5	.19	4.30	0.0	9.500	15.0	100
Apr 91	87.8	6.79	0.0	126.0	35.8	.17	1.90	0.9	13.3	15.0	98.2
May 91	87.5	6.04	0.7	104.7	27.6	.12	0.00	1.3	10.5	18.0	98.7
Jun 91	87.5	05.6	0.0	110.4	34.3	.15	3.40	0.0	11.20	21.0	100
Jul 91	83.5	07.5	1.8	124.6	35.3	.25	5.40	0.0	11.00	21.0	100
Aug 91	83.6	12.3	0.7	127.2	31.1	.11	5.00	3.5	11.20	24.0	96.9
Sep 91	86.7	10.0	0.0	159.6	43.3	.15	10.3	1.9	13.30	24.0	98.3
Oct 91	88.5	06.6	0.0	150.6	39.4	.09	3.00	1.3	10.80	21.0	98.8
Nov 91	82.2	10.0	0.0	148.2	44.1	.08	3.00	0.6	10.40	23.0	99.4
Dec 91	89.0	08.2	0.0	142.1	42.8	.17	3.00	0.8	9.300	23.0	99.3
Jan 92	89.3	07.8	0.0	143.1	36.7	.31	4.10	0.0	6.400	20.1	95.9
Feb 92	91.9	07.1	0.7	124.3	30.9	.16	3.70	0.0	7.000	21.1	96.4
Mar 92	92.9	05.8	0.0	124.3	28.1	.16	3.50	0.0	5.500	19.5	96.6
Apr 92	87.8	10.7	0.0	135.1	26.3	.14	2.50	1.7	5.500	19.1	96.0
May 92	87.2	10.8	0.0	108.3	30.1	.08	4.10	0.7	5.800	19.4	95.3
Jun 92	93.3	04.1	0.7	76.50	20.1	.07	3.00	2.0	7.500	19.6	96.1
Jul 92	94.2	04.8	0.0	142.6	38.9	.05	0.70	1.5	4.600	21.3	98.1
Aug 92	92.8	06.2	0.0	112.4	25.6	.07	2.00	3.9	4.500	21.5	94.6
Sep 92	90.9	04.2	0.0	180.4	40.0	.26	0.90	2.1	3.700	21.7	97.4
Oct 92	88.4	07.4	0.0	115.8	30.3	.06	5.40	0.7	5.900	19.7	93.9
Nov 92	93.9	05.4	0.0	134.1	34.6	.03	4.30	0.9	6.400	21.8	94.3
Dec 92	89.7	09.0	0.0	144.1	32.4	.21	4.00	0.0	6.500	21.2	96.1
Jan 93	87.5	10.1	1.4	91.30	20.5	.10	3.40	0.7	7.100	19.2	95.2

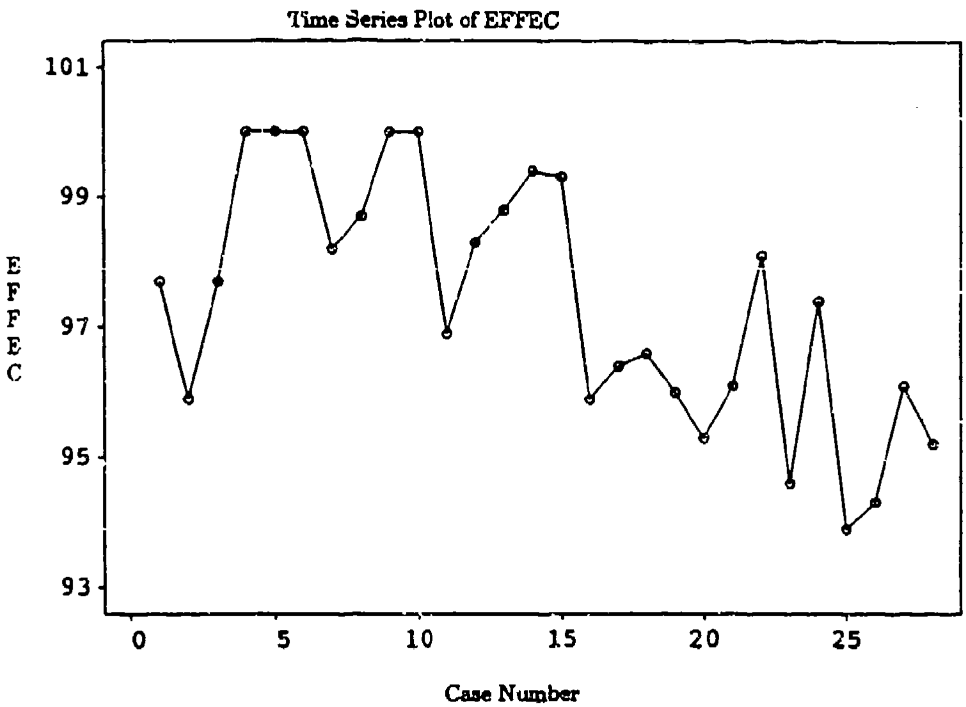

Time Series Plot of ABORT
2.0
1.5
1.0
0.5
0.0
ABORT
0
5
10
15
20
25
Case Number


Time Series Plot of AVPOS
24
18
12
6
AVPOS
0
5
10
15
20
25
Case Number

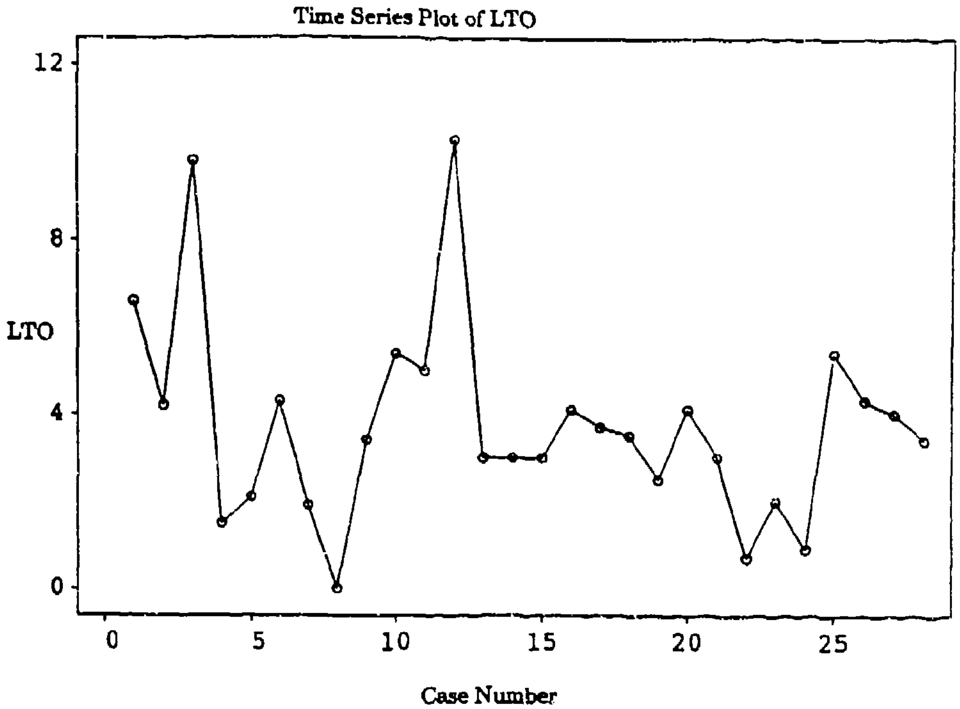

Time Series Plot of CANN
0.32
0.26
0
CANN
0.14
0.08
0.02
0
5
10
15
20
25
Case Number

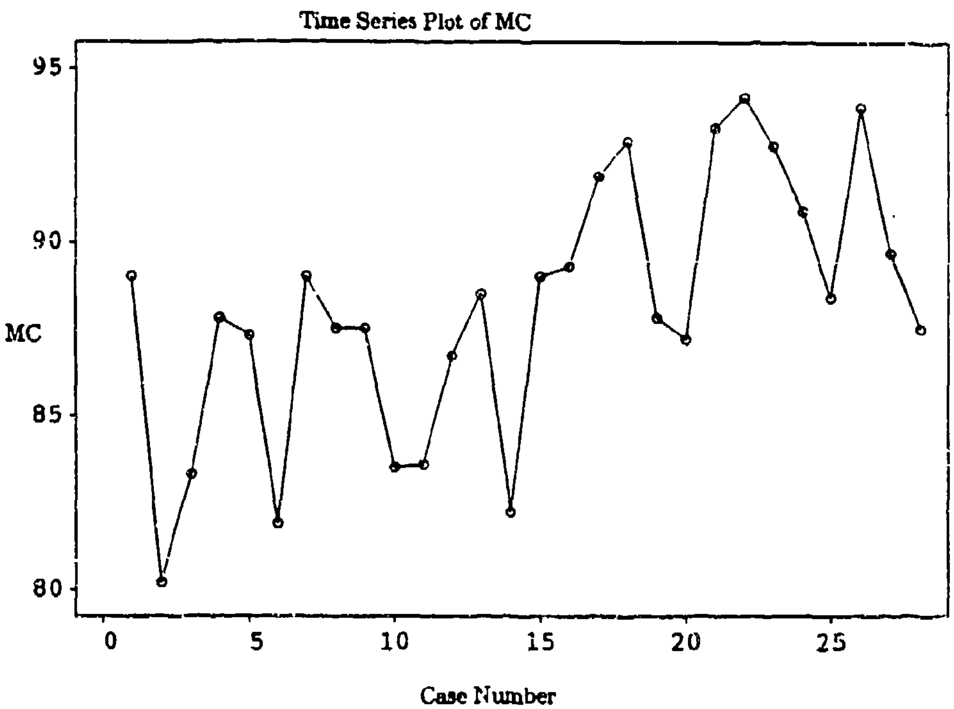

Time Series Plot of CANX
8
6
CANX
4
2
0
0
5
10
15
20
25
Case Number

Time Series Plot of DD
15
11
DD
7
3
0
5
10
15
20
25
Case Number

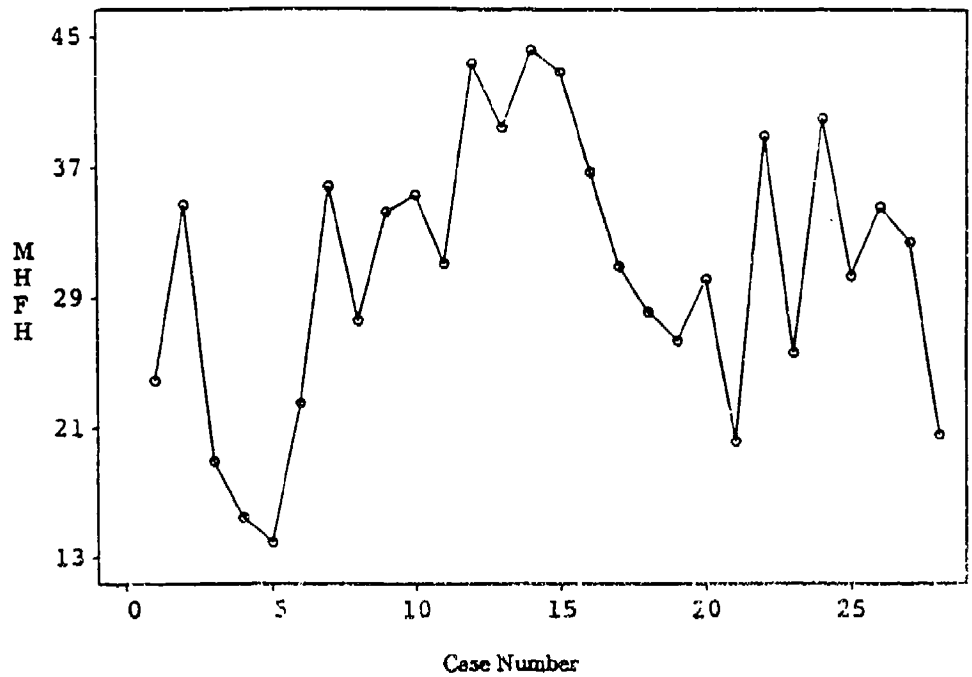


Time Series Plot of EFFEC
101
99
EFFEC
97
95
93
0
5
10
15
20
25
Case Number

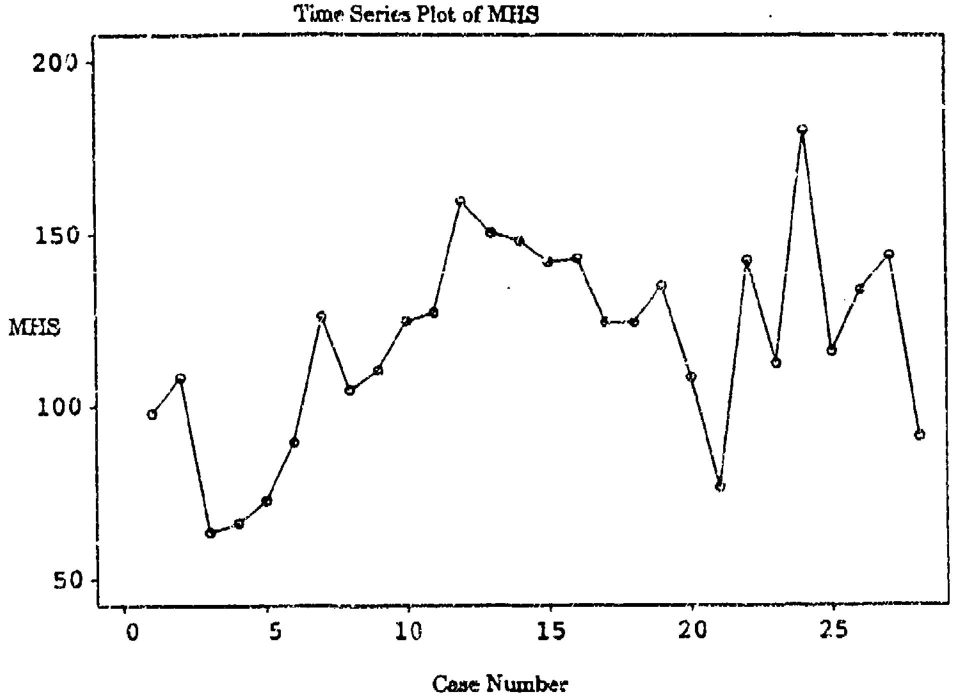

Time Series Plot of LTO
12
8
LTO
4
0
0
5
10
15
20
25
Case Number

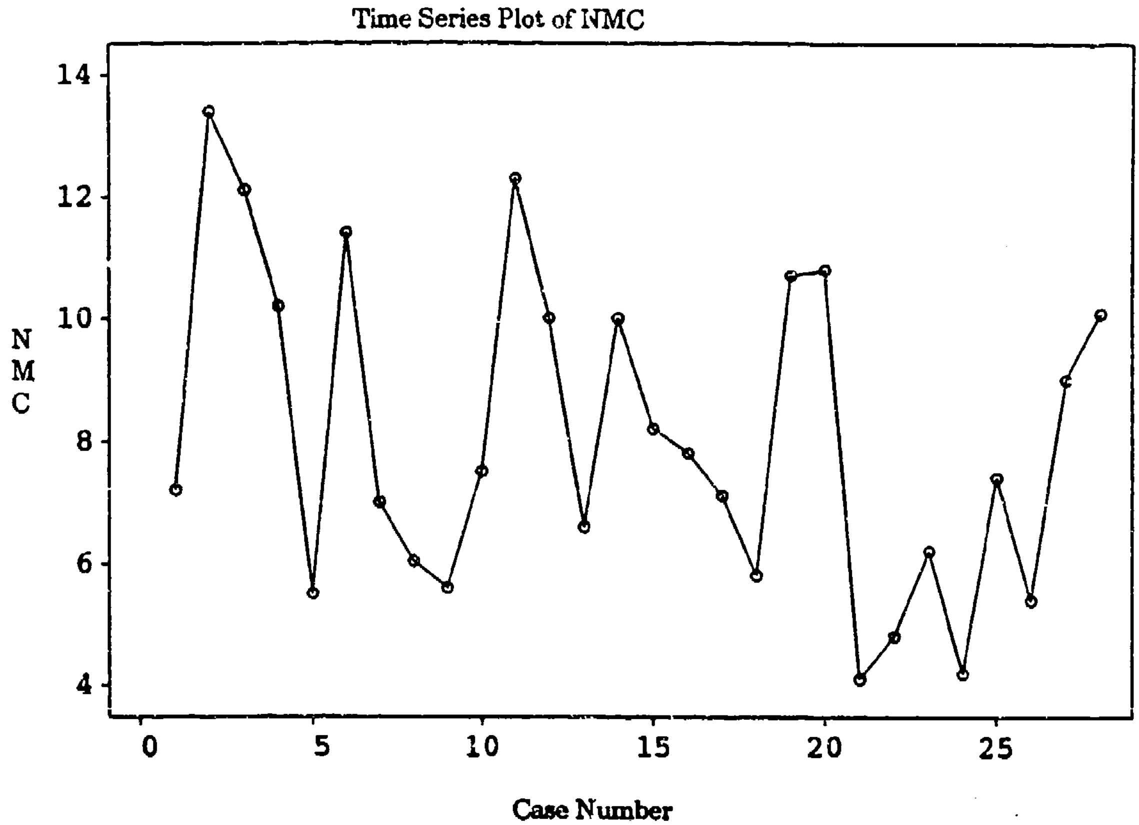

Time Series Plot of MC
95
90
MC
85
80
0
5
10
15
20
25
Case Number

Time Series Plot of MHFH



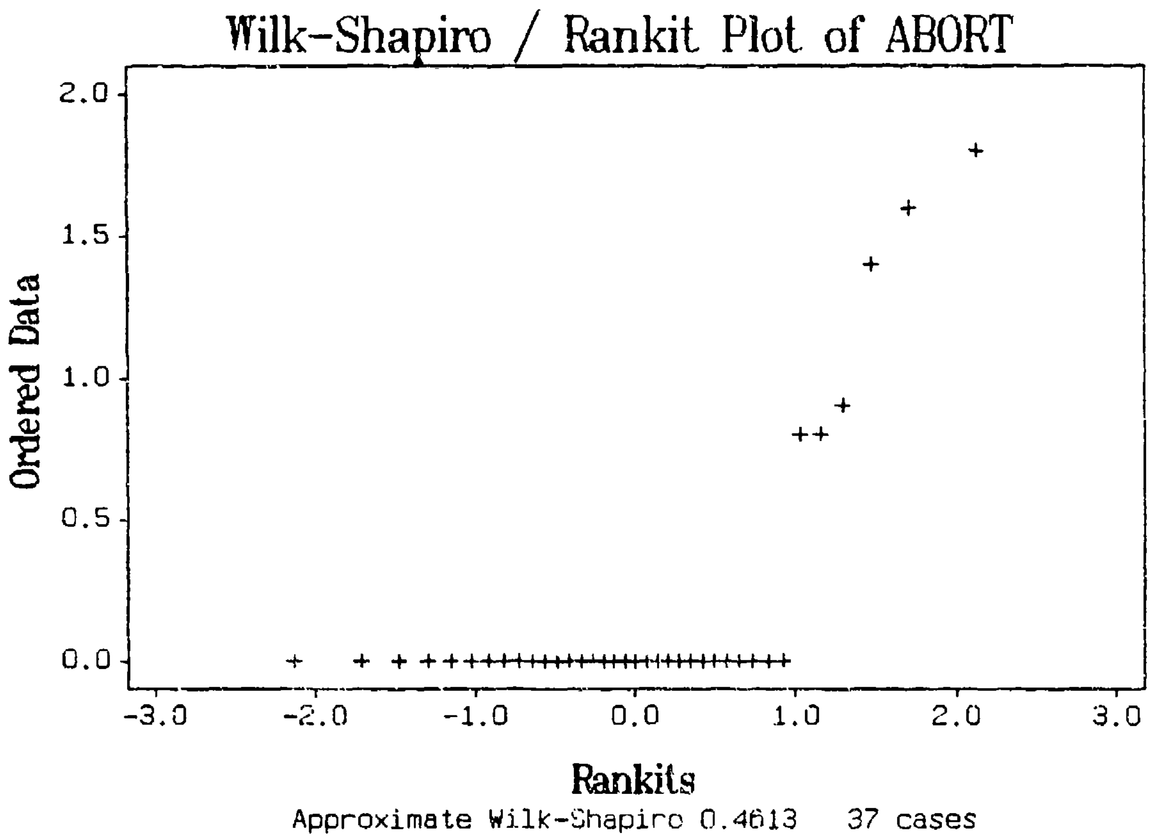
Time Series Plot of MHS

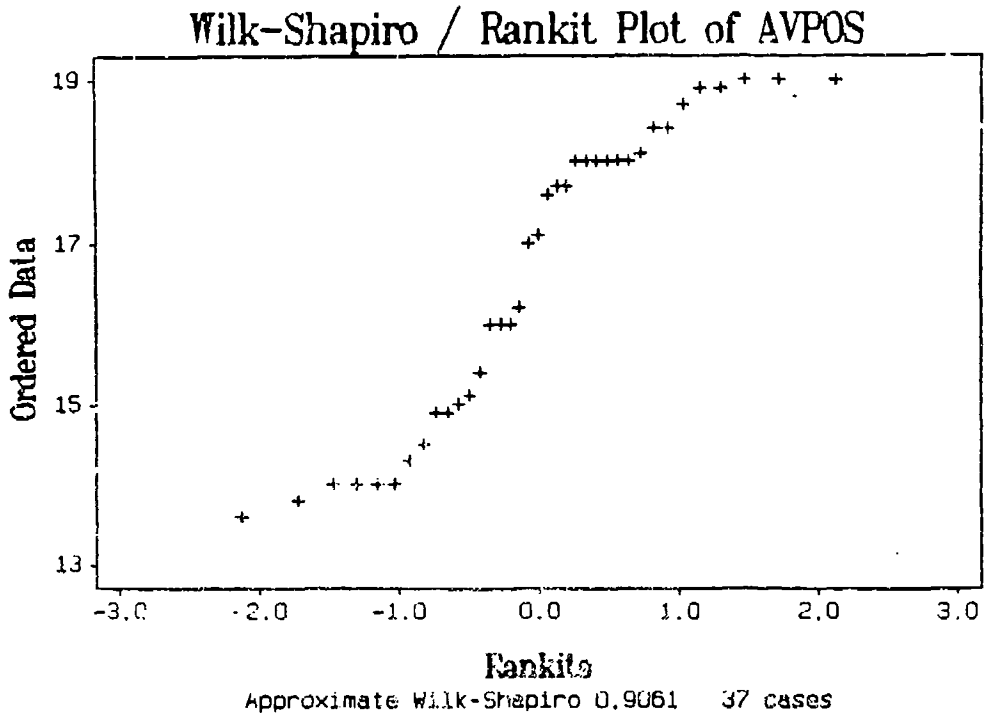


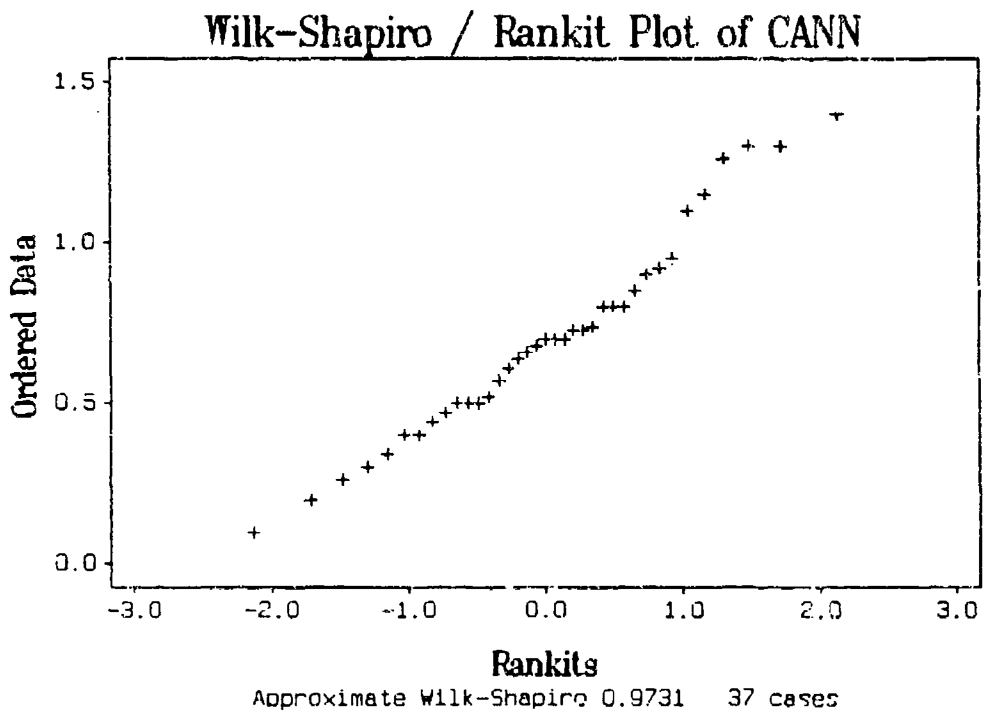

Time Series Plot of NMC
14
12
10
8
6
4
N
M
C
0
5
10
15
20
25
Case Number

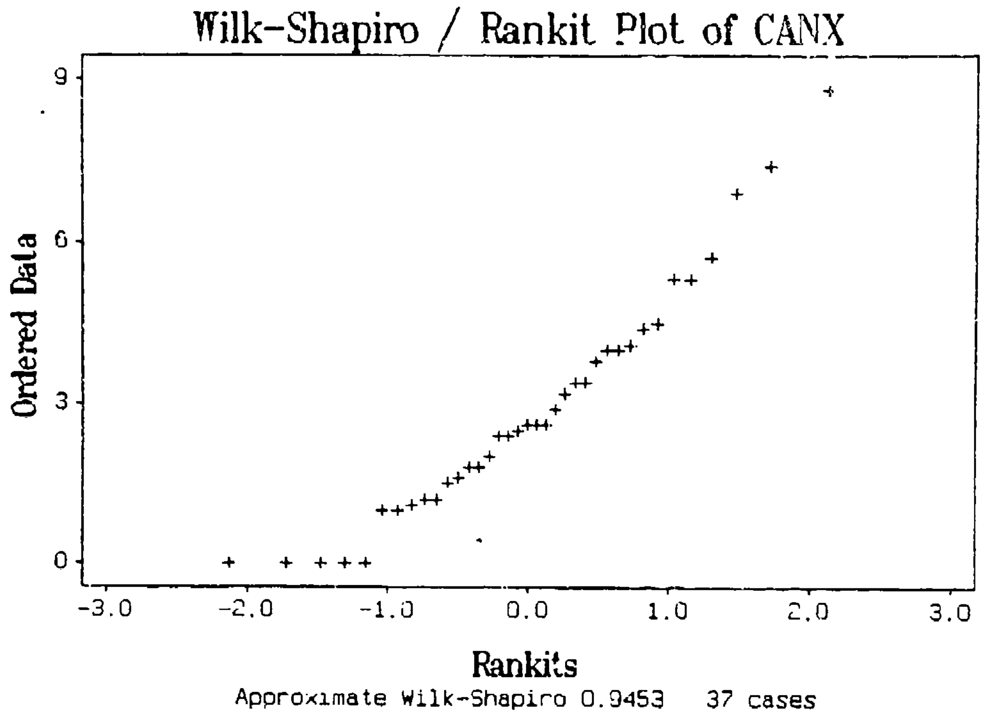
Appendix C: Rankit Plots

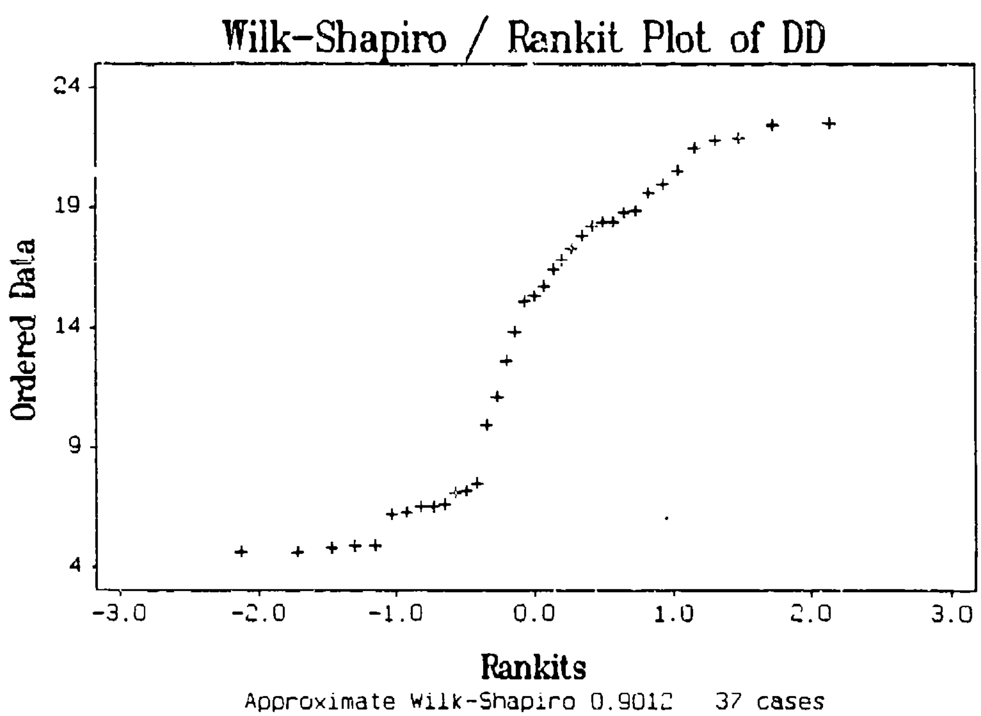
1. B-52H

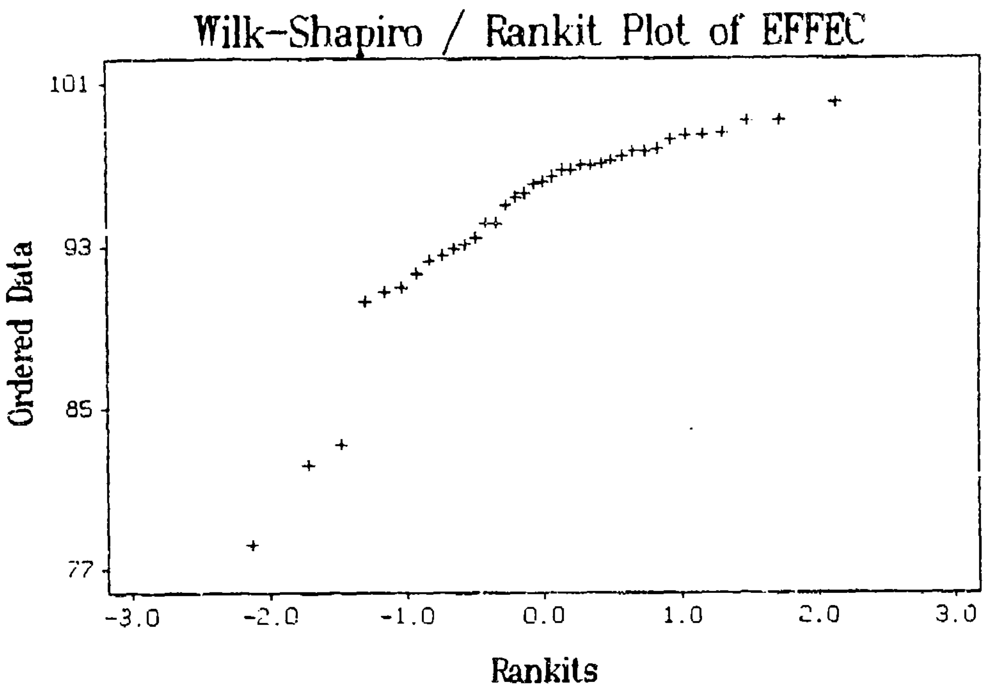



Wilk-Shapiro / Rankit Plot of AVPOS
Ordered Data
19
17
15
13
-3.0
-2.0
-1.0
0.0
1.0
2.0
3.0
Rankits
Approximate Wilk-Shapiro 0.9061 37 cases

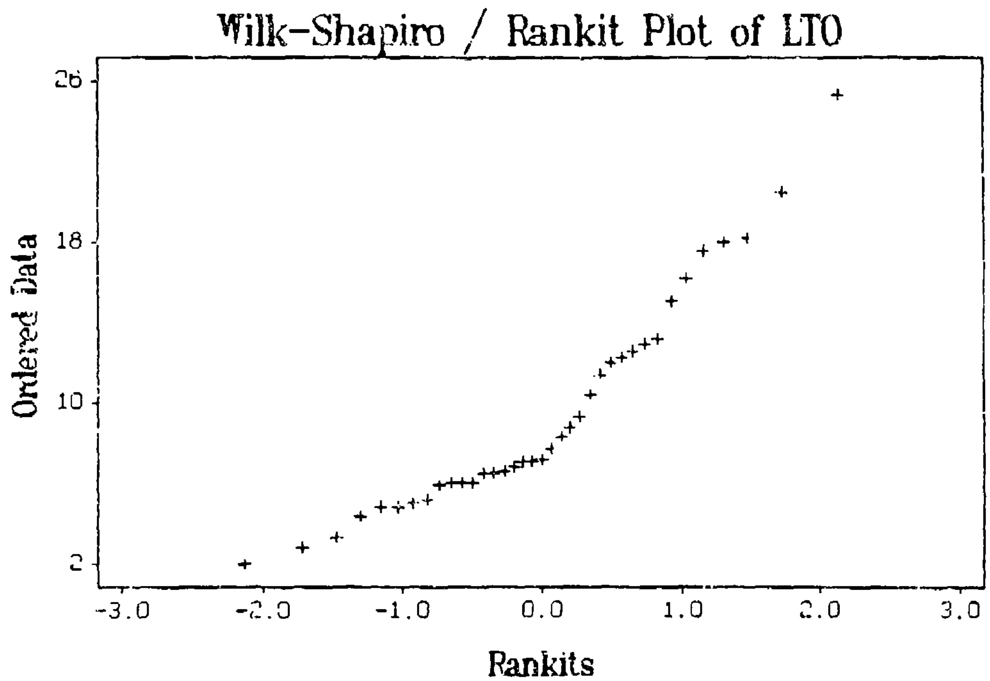

Wilk-Shapiro / Rankit Plot of CANN
Ordered Data
1.5
1.0
0.5
0.0
-3.0
-2.0
-1.0
0.0
1.0
2.0
3.0
Rankits
Approximate Wilk-Shapiro 0.9731 37 cases


Wilk-Shapiro / Rankit Plot of CANX
Ordered Data
9
6
3
0
-3.0
-2.0
-1.0
0.0
1.0
2.0
3.0
Rankits
Approximate Wilk-Shapiro 0.9453 37 cases


Wilk-Shapiro / Rankit Plot of DD
Ordered Data
24
19
14
9
4
-3.0
-2.0
-1.0
0.0
1.0
2.0
3.0
Rankits
Approximate Wilk-Shapiro 0.9012 37 cases

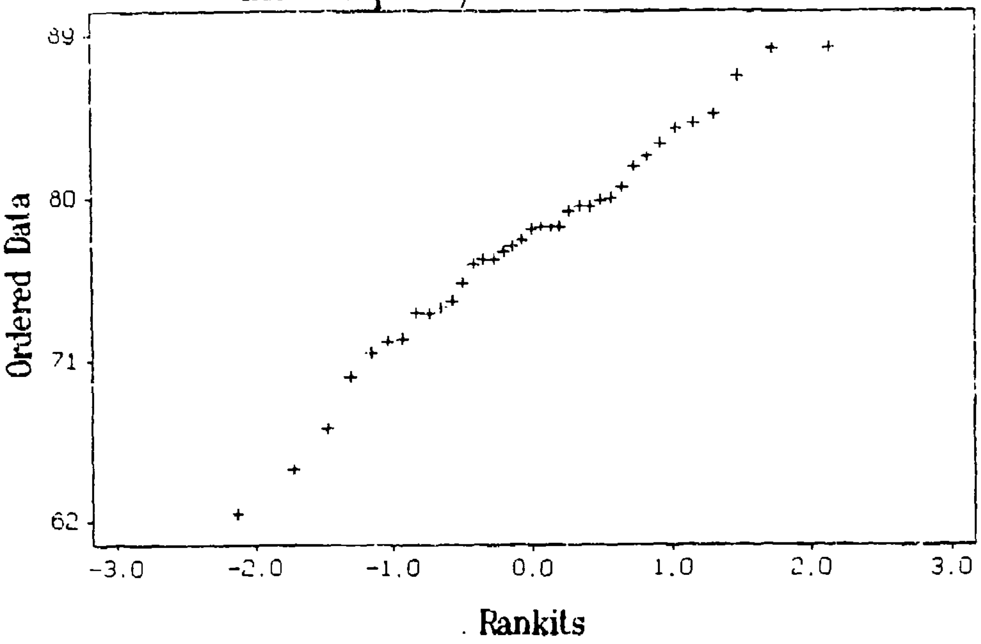


Approximate Wilk-Shapiro 0.7958 37 cases



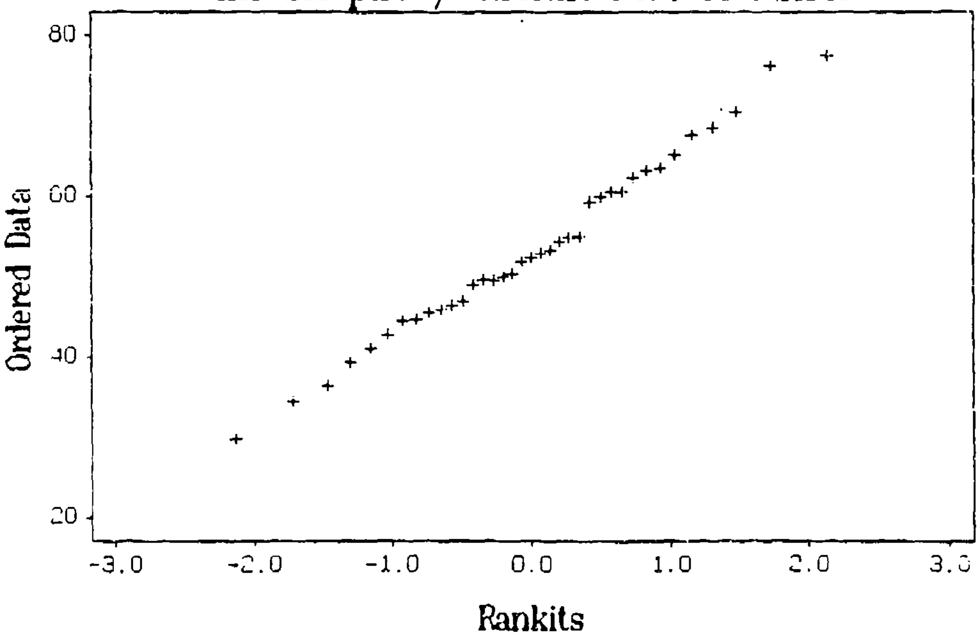
Approximate Wilk-Shapiro 0.9082 37 cases

Wilk-Shapiro / Rankit Plot of MC



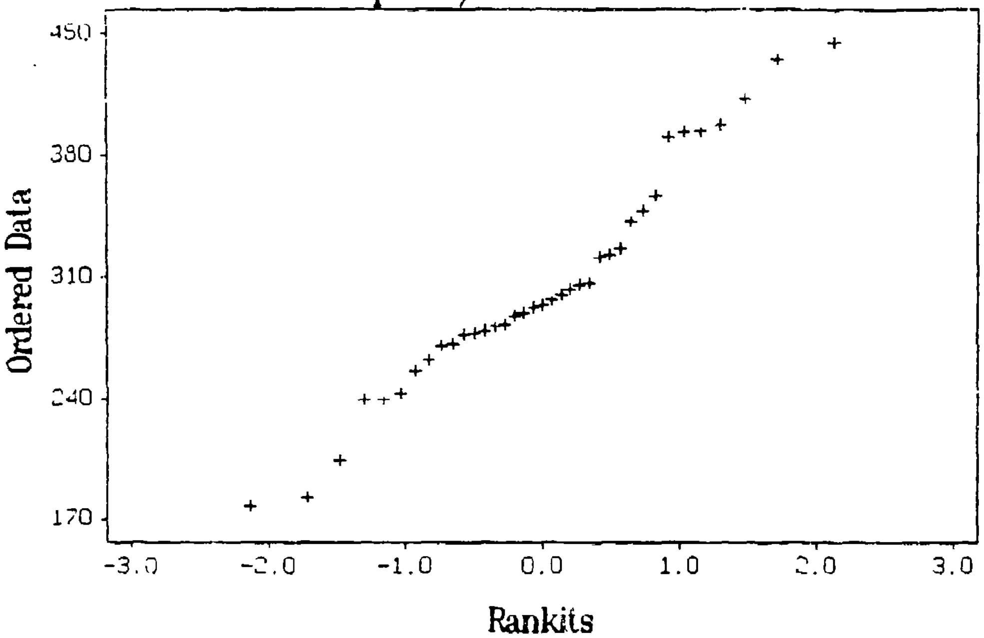
Approximate Wilk-Shapiro 0.9769 37 cases

Wilk-Shapiro / Rankit Plot of MHFH



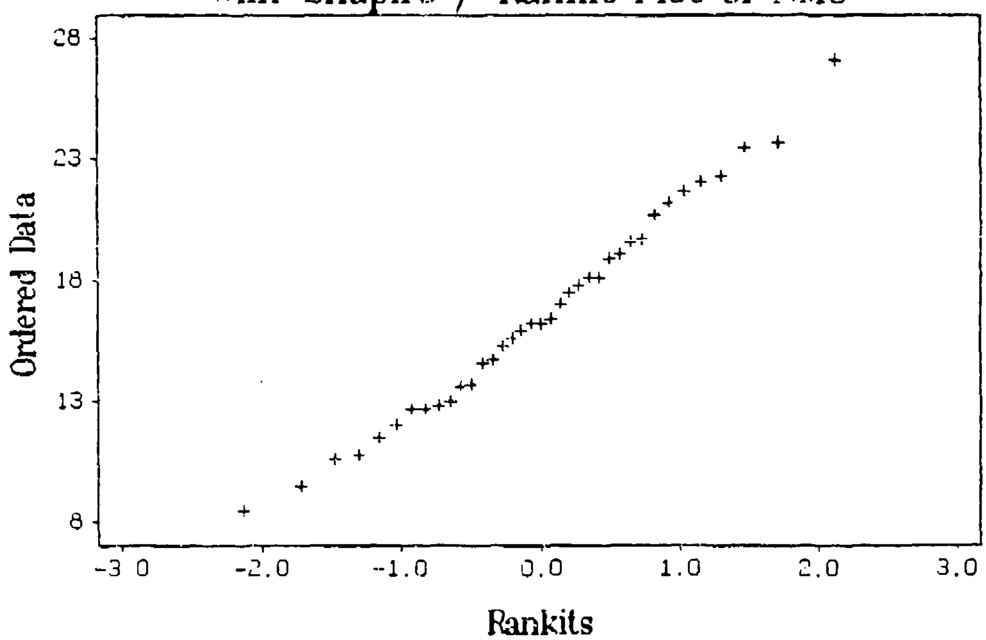
Approximate Wilk-Shapiro 0.9903 37 cases

Wilk-Shapiro / Rankit Plot of MHS



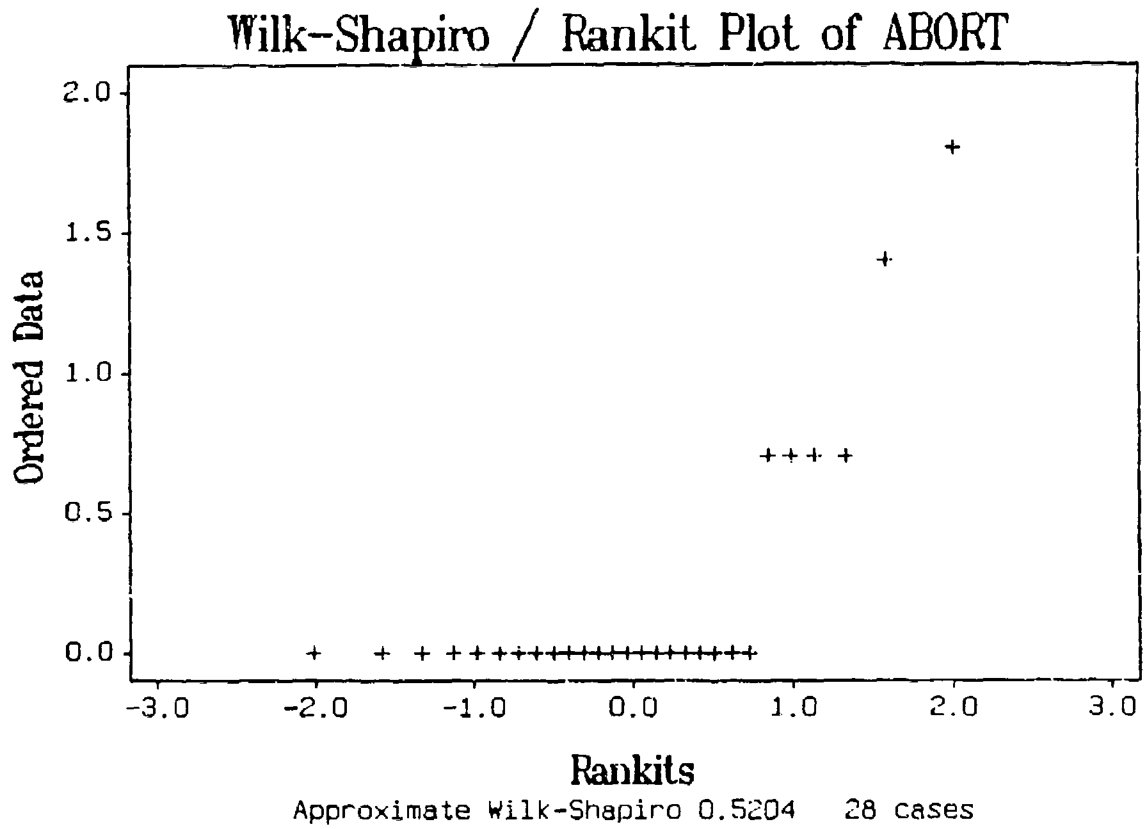
Approximate Wilk-Shapiro 0.9649 37 cases

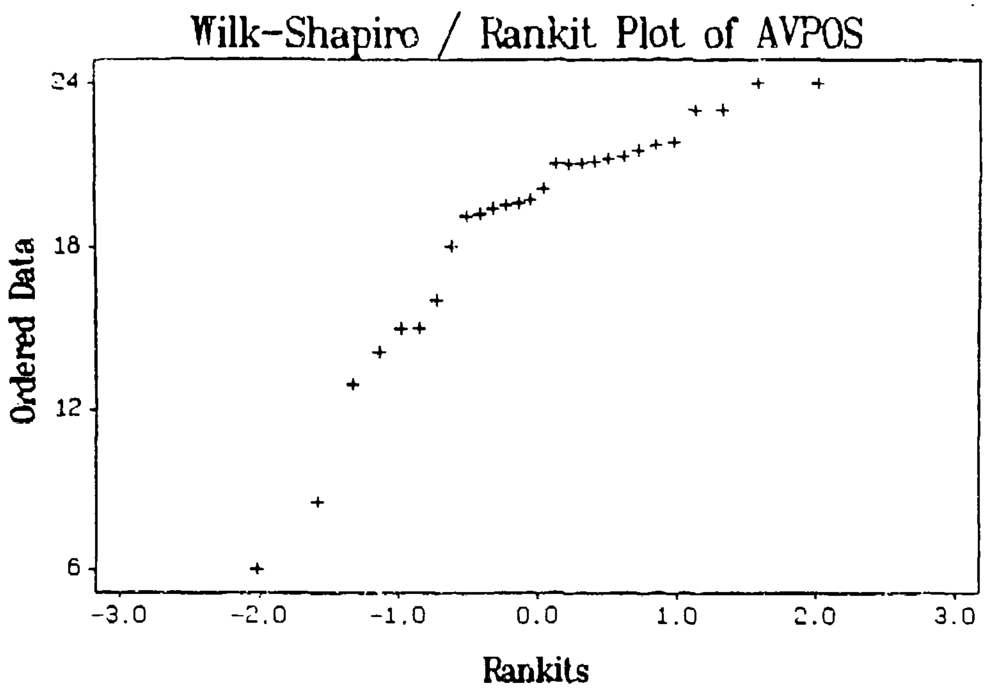
Wilk-Shapiro / Rankit Plot of NMC



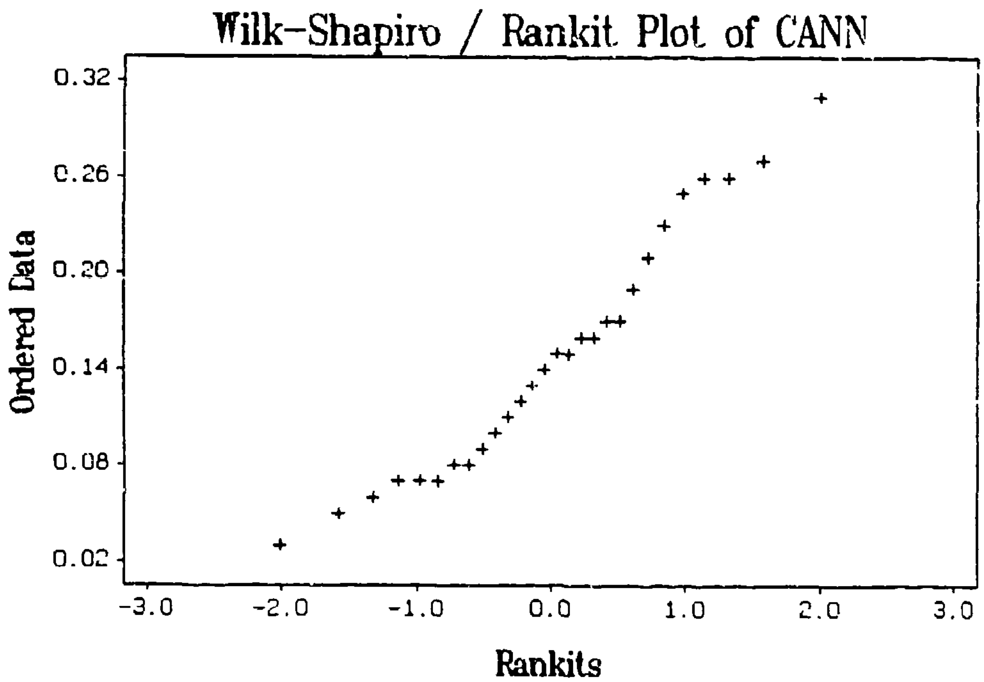
Approximate Wilk-Shapiro 0.9896 37 cases

2. KC-135R


Wilk-Shapiro / Rankit Plot of ABORT
Ordered Data
2.0
1.5
1.0
0.5
0.0
-3.0
-2.0
-1.0
0.0
1.0
2.0
3.0
Rankits
Approximate Wilk-Shapiro 0.5204 28 cases

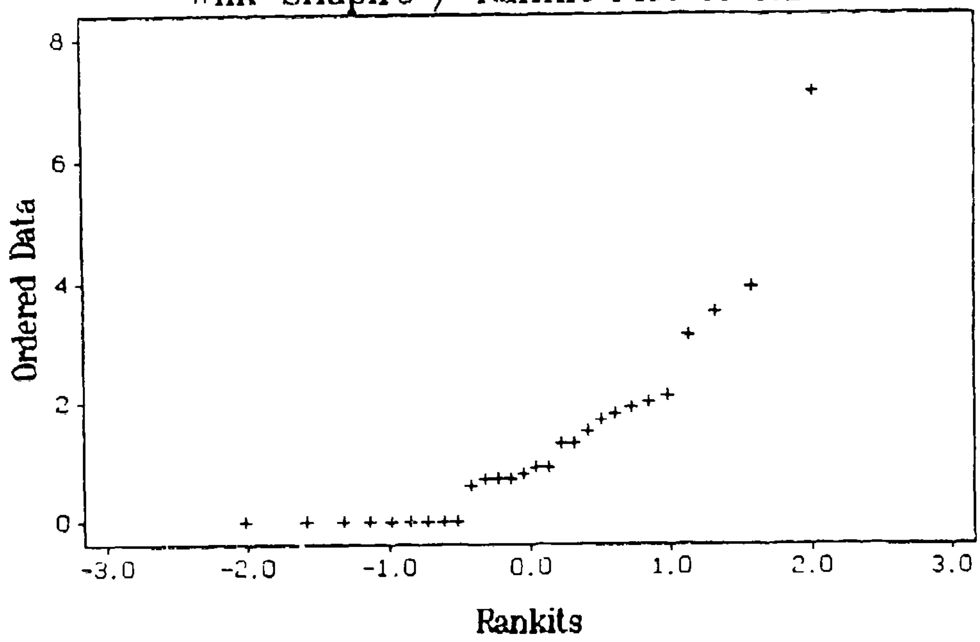


Approximate Wilk-Shapiro 0.8467 28 cases



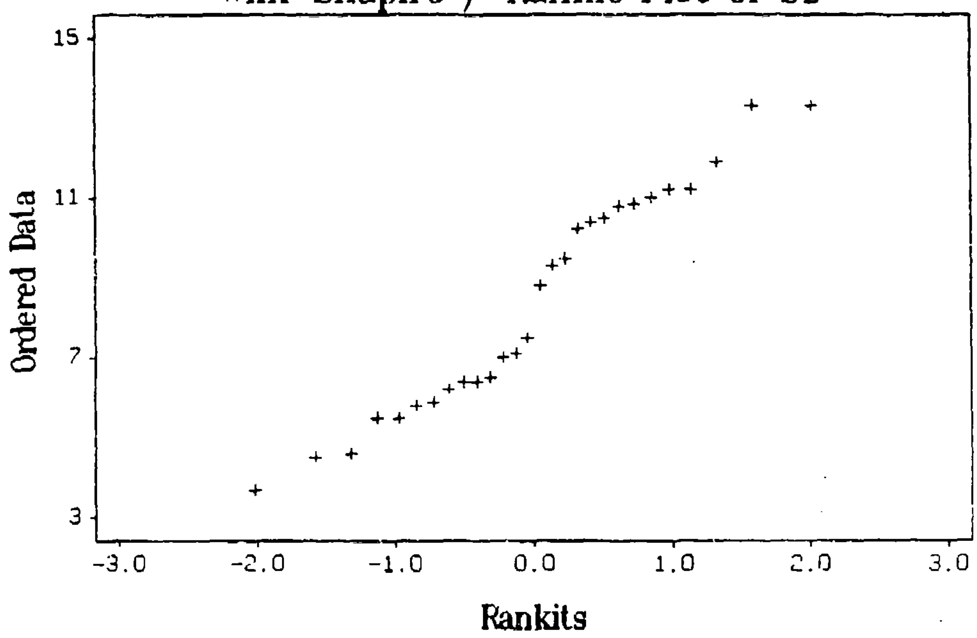
Approximate Wilk-Shapiro 0.9592 28 cases

Wilk-Shapiro / Rankit Plot of CANX

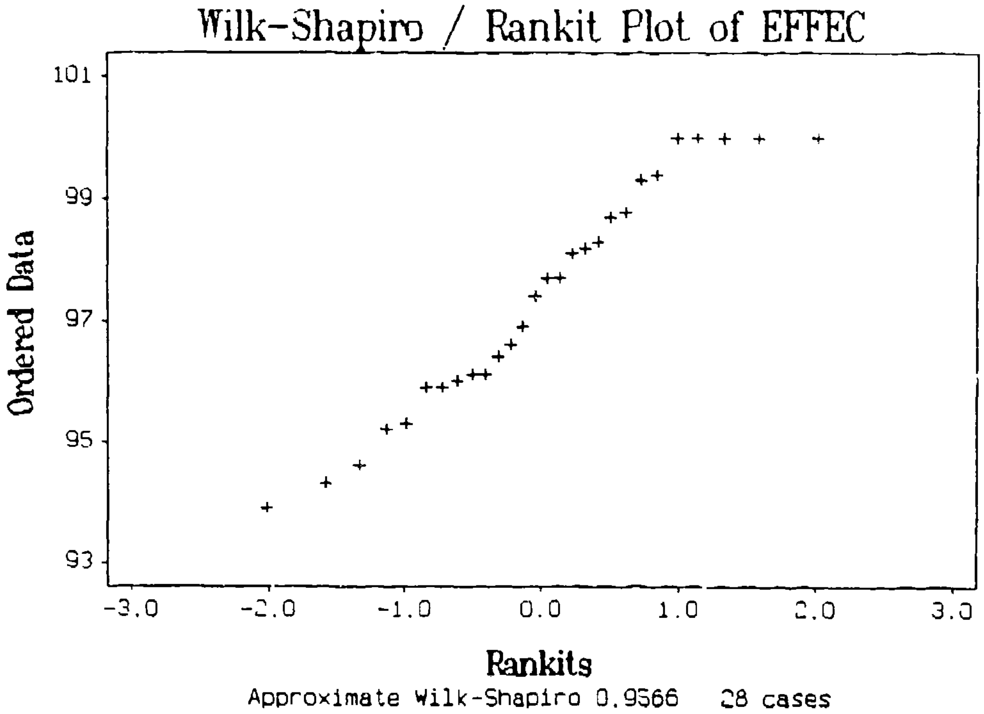


Approximate Wilk-Shapiro 0.7669   28 cases

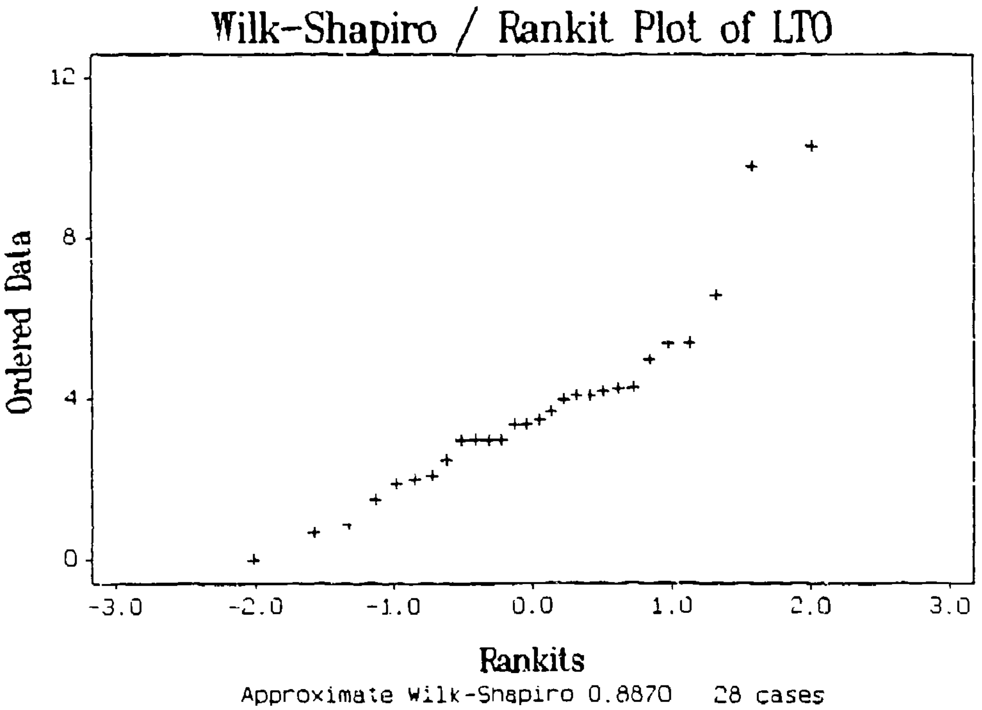
Wilk-Shapiro / Rankit Plot of DD



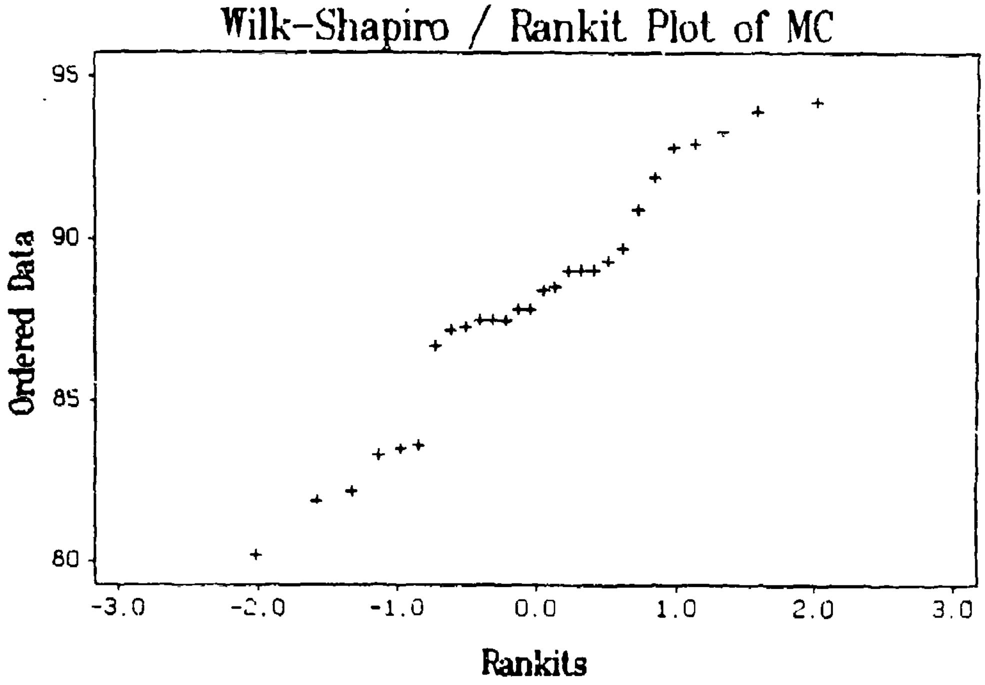
Approximate Wilk-Shapiro 0.9516   28 cases



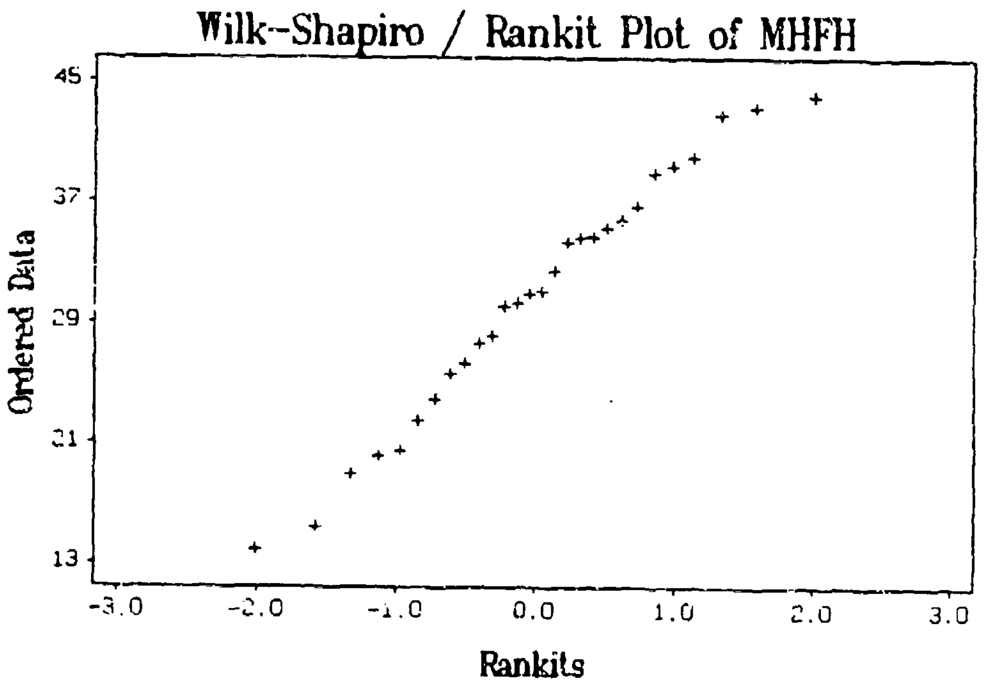
Wilk-Shapiro / Rankit Plot of EFFEC
101
99
97
95
93
Ordered Data
-3.0
-2.0
-1.0
0.0
1.0
2.0
3.0
Rankits
Approximate Wilk-Shapiro 0.9566 28 cases



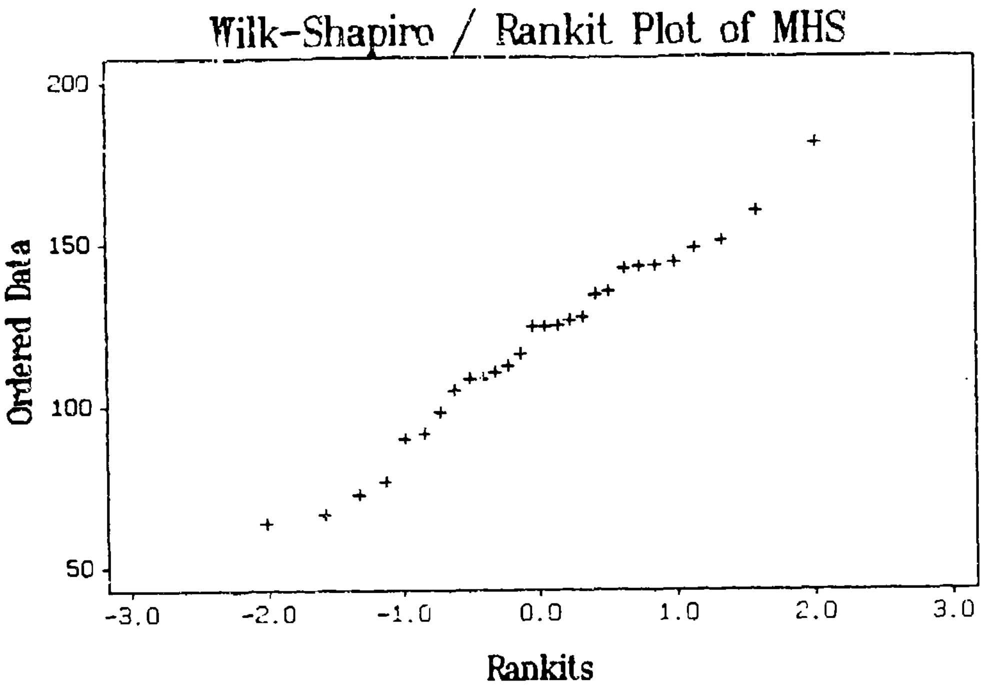
Wilk-Shapiro / Rankit Plot of LTO
12
8
4
0
Ordered Data
-3.0
-2.0
-1.0
0.0
1.0
2.0
3.0
Rankits
Approximate Wilk-Shapiro 0.8870 28 cases



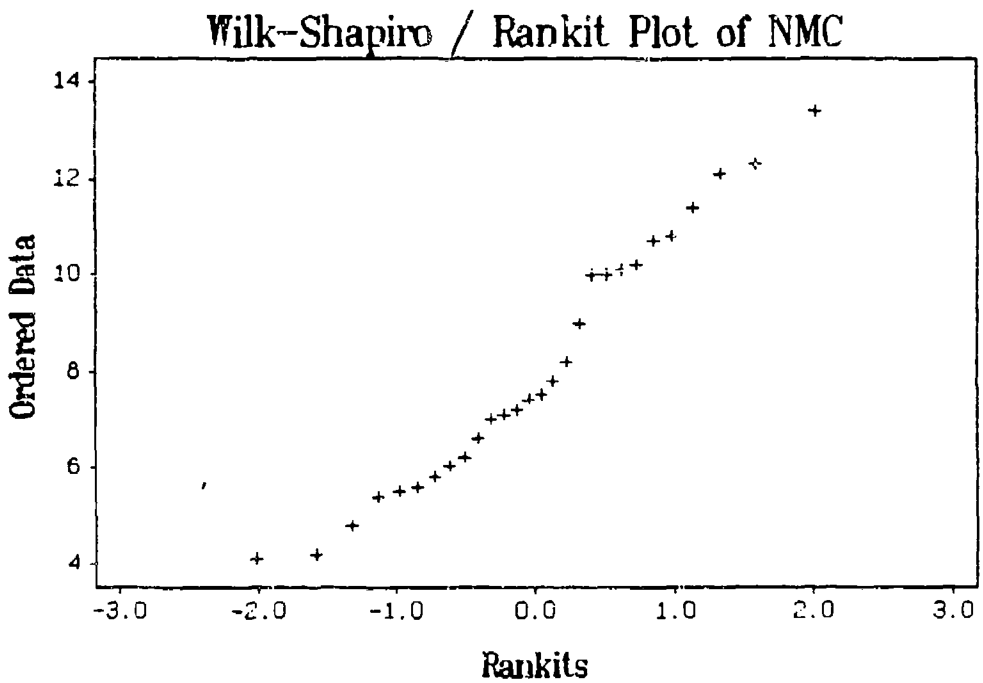
Approximate Wilk-Shapiro 0.9585 28 cases



Approximate Wilk-Shapiro 0.9822 28 cases



Approximate Wilk-Shapiro 0.9796 28 cases

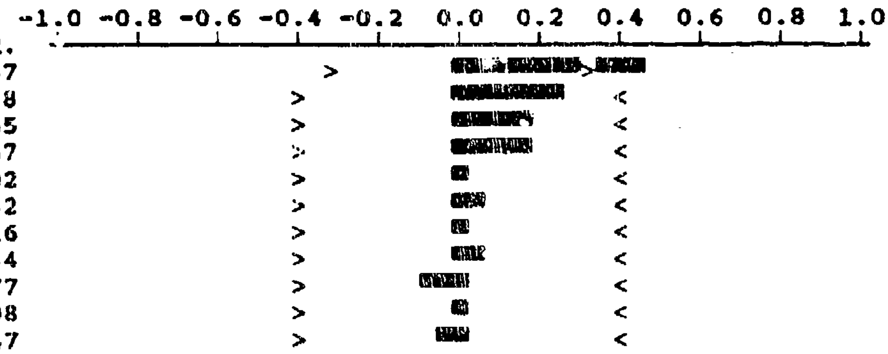


Approximate Wilk-Shapiro 0.9647 28 cases

Appendix D: Autocorrelation Plots of Dependent Variables

1. B-52H

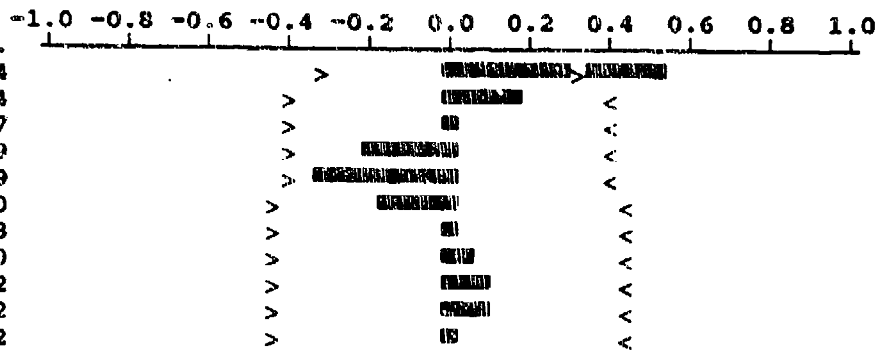
AUTOCORRELATION PLOT FOR MC



LAG	CORR.
1	0.447
2	0.238
3	0.155
4	0.167
5	-0.002
6	0.042
7	0.016
8	0.044
9	-0.077
10	0.008
11	-0.047

MEAN OF THE SERIES	77.5000
STD. DEV. OF SERIES	5.83609
NUMBER OF CASES	37

AUTOCORRELATION PLOT FOR NMC

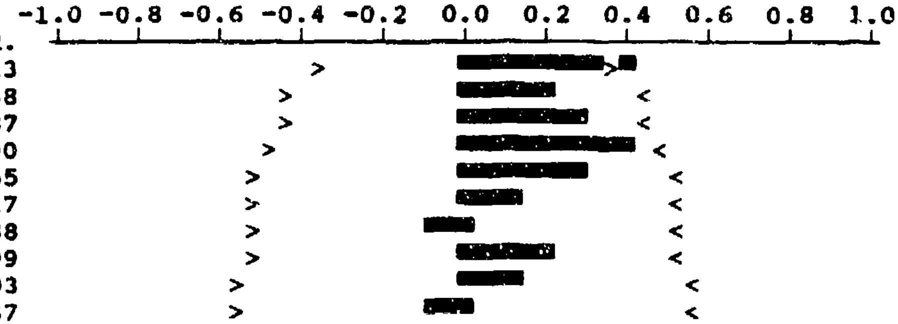


LAG	CORR.
1	0.514
2	0.154
3	-0.017
4	-0.199
5	-0.329
6	-0.150
7	-0.008
8	0.050
9	0.082
10	0.072
11	0.012

MEAN OF THE SERIES	16.6054
STD. DEV. OF SERIES	4.32234
NUMBER OF CASES	37

2. KC-135R

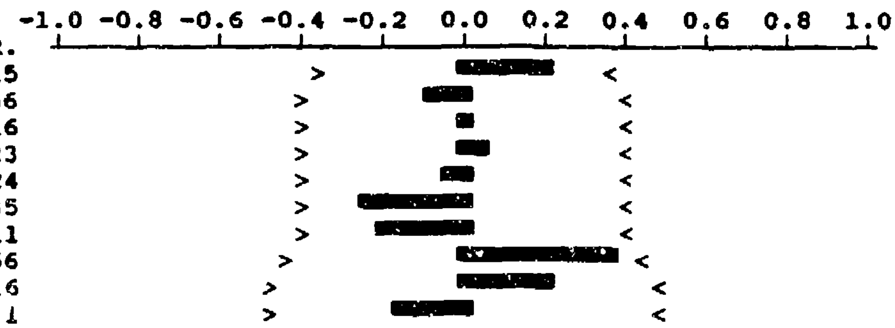
AUTOCORRELATION PLOT FOR MC



LAG	CORR.
1	0.413
2	0.188
3	0.287
4	0.400
5	0.265
6	0.117
7	-0.088
8	0.199
9	0.103
10	-0.087

MEAN OF THE SERIES	88.1000
STD. DEV. OF SERIES	3.66820
NUMBER OF CASES	28

AUTOCORRELATION PLOT FOR NMC



LAG	CORR.
1	0.215
2	-0.066
3	-0.016
4	0.023
5	-0.024
6	-0.235
7	-0.211
8	0.356
9	0.216
10	-0.171

MEAN OF THE SERIES	8.08714
STD. DEV. OF SERIES	2.56952
NUMBER OF CASES	28

Appendix E: Results of Stepwise Regression

1. B-52H

The SAS System

Stepwise Procedure for Dependent Variable MC

Step 1 Variable DD Entered R-square = 0.34133540 C(p)=4.08904153

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	1	360.68757348	360.68757348	15.03	0.0006
Error	29	696.00791039	24.00027277		
Total	30	1056.69548387			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	85.31408537	2.07198756	40689.59510732	1695.38	0.0001
DD	-0.54427003	0.14039671	360.68757348	15.03	0.0006

Bounds on condition number: 1, 1

Step 2 Variable ABORT Entered R-square = 0.43518950 C(p) = 1.65911777

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	2	459.86277572	229.93138786	10.79	0.0003
Error	28	596.83270815	21.31545386		
Total	30	1056.69548387			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	84.61785542	1.97915616	38963.54706389	1827.95	0.0001
ABORT	3.49437726	1.62000194	99.17520224	4.65	0.0397
DD	-0.55374812	0.13238400	372.94788218	17.50	0.0003

Bounds on condition number: 1.001103, 4.004412

Step 3 Variable MRFH Entered R-square = 0.51397838 C(p) = -0.05972614

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	3	543.11863221	181.03954407	9.52	0.0002
Error	27	513.57685166	19.02136438		
Total	30	1056.69548387			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	73.19451974	5.77139232	3059.40951960	160.84	0.0001
ABORT	4.46461155	1.59906944	148.27720337	7.80	0.0095
DD	-0.42369804	0.13965466	175.08288273	9.20	0.0053
MHFH	0.18157683	0.08679084	83.25585649	4.38	0.0460

Bounds on condition number: 1.349294, 11.07235

All variables left in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

The SAS System

Summary of Stepwise Procedure for Dependent Variable MC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	DD		1	0.3413	0.3413	4.0890	15.0285	0.0006
2	ABORT		2	0.0939	0.4352	1.6591	4.6527	0.0397
3	MHFH		3	0.0788	0.5140	-0.0597	4.3770	0.0460

The SAS System

Stepwise Procedure for Dependent Variable NMC

Step 1 Variable CANN Entered R-square = 0.11877842 C(p) = 1.55849672

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	1	60.67876005	60.67876005	3.91	0.0576
Error	29	450.17801415	15.52337980		
Total	30	510.85677419			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	13.20454178	1.69737027	939.46319769	60.52	0.0001
CANN	4.60814838	2.33077981	60.67876005	3.91	0.0576

Bounds on condition number: 1, 1

All variables left in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable NMC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	CANN		1	0.1188	0.1188	1.5585	3.9089	0.0576

2. KC-135R

The SAS System

Stepwise Procedure for Dependent Variable MC

Step 1 Variable DD Entered R-square = 0.40800640 C(p) = -2.99600845

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	1	116.24695864	116.24695864	13.78	0.0014
Error	20	168.66758681	8.43337934		
Total	21	284.91454545			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	95.19840377	1.89588915	21263.51638191	2521.35	0.0001
DD	-0.83365542	0.22454149	116.24695864	13.78	0.0014

Bounds on condition number: 1, 1

All variables left in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable MC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	DD		1	0.4080	0.4080	-2.9960	13.7841	0.0014

The SAS System

Stepwise Procedure for Dependent Variable NMC

Step 1 Variable LTO Entered R-square = 0.21690024 C(p) = -0.95171503

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	1	27.76829449	27.76829449	5.54	0.0289
Error	20	100.25505097	5.01275255		
Total	21	128.02334545			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	6.03608867	0.87944749	236.13896749	47.11	0.0001
LTO	0.45048350	0.19140021	27.76829449	5.54	0.0289

Bounds on condition number: 1, 1

Step 2 Variable MHFH Entered R-square = 0.30198917 C(p) = -0.80412307

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	2	38.66166370	19.33083185	4.11	0.0329
Error	19	89.36168175	4.70324641		
Total	21	128.02334545			

Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	8.68924331	1.94033065	94.32138308	20.05	0.0003
LTO	0.45204683	0.18540004	27.96050130	5.94	0.0248
MHFH	-0.08773565	0.05764927	10.89336922	2.32	0.1445

Bounds on condition number: 1.000031, 4.000123

All variables left in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable NMC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	LTO		1	0.2169	0.2169	-0.9517	5.5395	0.0289
2	MHFH		2	0.0851	0.3020	-0.8041	2.3161	0.1445

Appendix F: Principal Component Information

1. B-52H

Correlation Matrix

	ABORT	AVPOS	CANN	CANX	DD	EFFEC	LTO	MHFH	MHS
ABORT	1.0000	0.2085	-.3535	-.0750	0.0332	0.1818	-.1505	-.2752	-.2263
AVPOS	0.2085	1.0000	0.4597	0.1660	0.8560	0.4370	0.3472	-.2630	-.3453
CANN	-.3535	0.4597	1.0000	0.3223	0.5322	0.2616	0.3262	0.0744	0.0210
CANX	-.0750	0.1660	0.3223	1.0000	0.2148	-.3304	0.4517	-.1206	-.1379
DD	0.0332	0.8560	0.5322	0.2148	1.0000	0.6022	0.3571	-.4368	-.4332
EFFEC	0.1818	0.4370	0.2616	-.3304	0.6022	1.0000	-.2556	-.2325	-.1836
LTO	-.1505	0.3472	0.3262	0.4517	0.3571	-.2556	1.0000	-.3483	-.4115
MHFH	-.2752	-.2630	0.0744	-.1206	-.4368	-.2325	-.3483	1.0000	0.9102
MHS	-.2263	-.3453	0.0210	-.1379	-.4332	-.1836	-.4115	0.9102	1.0000

Eigenvectors

	PRIN1	PRIN2	PRIN3	PRIN4	PRIN5
ABORT	0.082886	-.485319	-.100186	0.725669	0.053628
AVPOS	0.444383	0.030070	0.242909	0.318926	0.365222
CANN	0.266110	0.450994	0.330477	-.066414	-.178379
CANX	0.175191	0.429578	-.308294	0.426166	-.627153
DD	0.493767	0.038847	0.250791	0.022874	0.006107
EFFEC	0.255842	-.314219	0.516046	-.157039	-.254802
LTO	0.302864	0.346246	-.357526	-.048613	0.563253
MHFH	-.374377	0.303889	0.363619	0.280571	0.219112
MHS	-.391154	0.251297	0.370749	0.281770	0.091495

	PRIN6	PRIN7	PRIN8	PRIN9
ABORT	0.430452	0.036211	-.080011	0.158380
AVPOS	-.342670	-.377592	0.174361	-.465954
CANN	0.673116	-.342362	-.099076	0.015247
CANX	-.210188	0.182691	0.166916	-.096804
DD	-.347159	0.136281	-.422137	0.611504
EFFEC	0.108498	0.547771	0.354860	-.205357
LTO	0.247080	0.519588	0.093341	-.034816
MHFH	-.068419	0.019691	0.545102	0.454246
MHS	-.044763	0.341380	-.561734	-.352900

Principal Components:

Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7	Prin8	Prin9
-0.8420	1.4520	3.3530	0.8650	0.5380	-0.1060	-0.2120	-0.3030	0.1940
-0.0518	0.7470	1.8030	0.3590	0.2730	-0.4040	0.4500	-0.3180	-0.3000
1.0560	-0.8770	0.1970	0.8090	0.1970	0.1180	-0.5950	0.1990	-0.1270
0.5950	-1.4230	0.3260	0.7920	0.5460	-0.1600	0.6620	-0.1180	0.0038
0.9040	-2.6900	-0.3290	1.4330	1.0280	0.1860	0.7880	-0.0778	-0.0118
0.2110	-0.6760	1.2120	-0.4450	-0.1950	-0.9620	0.2970	-0.0307	0.3620
1.9090	-1.4580	-1.1270	-0.9660	-1.0770	-1.5530	-0.3520	-0.1820	-0.0361
3.1730	1.3500	0.1090	-0.9200	0.2470	1.3240	0.1130	-0.3230	0.0353
3.2170	0.3800	-1.5440	-1.1810	1.5020	0.3250	0.2080	0.2380	-0.2610
2.7850	2.6610	0.2370	0.8820	-0.9600	0.1920	0.4230	0.4860	-0.0990
2.7930	-0.7980	0.0475	-1.2690	0.7690	-0.4070	0.0380	-0.0069	-0.0830
1.8790	1.1410	1.0730	0.1790	-0.3980	-0.1420	-0.6960	-0.0784	0.1540
1.0490	0.3140	0.9670	-0.1720	0.1950	-0.3600	-1.2130	-0.4510	-0.0818
0.7610	-1.9150	0.2960	0.2860	-0.1380	-0.0193	-0.4530	0.4250	-0.1270
1.0280	-1.9600	0.2080	2.1980	-0.5950	0.9480	-0.4890	-0.2810	0.0835
1.0920	0.8320	0.4930	0.0235	0.0145	-0.2250	0.0948	0.3270	0.0785
1.2030	0.8680	-0.8230	-0.3640	-0.4530	-0.0404	0.9100	-0.0980	0.3290
0.8470	1.8840	-0.3830	0.6380	-0.9140	-0.1650	0.3000	0.2100	0.1030
-0.6040	-1.5810	0.4310	-1.9250	-0.9840	0.6630	0.1590	-0.2920	0.0526
-2.5840	1.0070	0.2270	0.0597	-0.2760	0.5700	0.1580	-0.0476	-0.0635
-1.4200	1.4120	-2.3840	-0.1760	-0.5120	0.5640	-0.4260	-0.2150	0.1410
-1.6580	-0.2720	-0.0216	-1.0790	0.3870	0.8250	-0.5620	0.6440	0.1750
-2.3780	-0.7750	-0.0610	-1.1130	0.0259	0.2720	0.4500	-0.5730	-0.0671
-1.7490	-1.3840	0.4240	-1.2840	-0.4610	0.0862	-0.0857	0.2540	0.0406
-1.6250	1.6800	-2.5550	0.5960	-0.4940	-0.3000	-0.0299	-0.4750	-0.4530
-2.7630	0.0591	1.6650	-0.0528	-0.0950	0.0087	0.4480	0.1300	0.0379
-2.4220	0.4520	0.7870	0.2210	0.7610	-0.2370	0.0438	0.1530	-0.2630
-1.8880	0.3270	-0.7260	0.1780	-0.5940	-0.6290	0.2150	0.4540	-0.0518
-1.8680	-0.0522	0.7680	-0.2730	0.1060	0.0716	-0.2620	0.3400	-0.2980
-1.9830	1.4430	-2.3780	0.3570	2.0390	-0.5860	-0.3750	-0.0756	0.4150
-0.6840	-2.1500	-2.2930	1.3420	-0.4830	0.1410	-0.0090	0.0844	0.1170

2. KC-135R

Correlation Matrix

	ABORT	AVPOS	CANN	CANX	DD	EFFEC	LTO	MHFH	MHS
ABORT	1.0000	0.1082	0.1054	-.2204	0.1646	0.0701	-.0472	-.1531	-.1904
AVPOS	0.1082	1.0000	-.1130	-.1833	-.0359	-.1636	-.2223	0.6708	0.6453
CANN	0.1054	-.1130	1.0000	-.3786	0.2688	0.4014	0.1020	-.0714	-.0124
CANX	-.2204	-.1833	-.3786	1.0000	-.3063	-.2791	0.0667	-.0786	0.0485
DD	0.1646	-.0359	0.2688	-.3063	1.0000	0.7076	0.3771	0.0312	-.2292
EFFEC	0.0701	-.1636	0.4014	-.2791	0.7076	1.0000	-.0176	0.1342	-.0445
LTO	-.0472	-.2223	0.1020	0.0667	0.3771	-.0176	1.0000	0.0055	-.1315
MHFH	-.1531	0.6708	-.0714	-.0786	0.0312	0.1342	0.0055	1.0000	0.9057
MHS	-.1904	0.6453	-.0124	0.0485	-.2292	-.0445	-.1315	0.9057	1.0000

Principal Component Analysis

Eigenvectors

	PRIN1	PRIN2	PRIN3	PRIN4	PRIN5
ABORT	-.137553	0.143605	-.552969	0.585655	0.103354
AVPOS	0.476044	0.225558	-.217604	0.266823	0.011033
CANN	-.198304	0.370162	-.079252	-.355871	-.605278
CANX	0.085012	-.412609	0.395160	0.038526	0.329843
DD	-.276105	0.476881	0.240389	0.231151	0.320406
EFFEC	-.210907	0.493978	0.131611	-.304307	0.462722
LTO	-.176048	0.081486	0.590585	0.548279	-.430774
MHFH	0.501785	0.322370	0.209507	0.052176	0.048658
MHS	0.551736	0.198097	0.129030	-.091209	-.096607

	PRIN6	PRIN7	PRIN8	PRIN9
ABORT	0.487712	-.248397	-.036329	-.011164
AVPOS	-.144802	0.636019	0.408271	0.108005
CANN	0.450192	0.306650	-.042057	-.160915
CANX	0.653569	0.347095	0.020190	-.089774
DD	-.154222	0.353619	-.577603	-.004162
EFFEC	0.157227	-.193989	0.536189	0.193950
LTO	-.015034	-.136073	0.297364	0.142243
MHFH	0.043202	-.294152	-.025136	-.711535
MHS	0.246470	-.227046	-.345888	0.624587

Principal Components

Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7	Prin8	Prin9
-1.9922	-2.3895	2.0363	-0.3712	0.5114	0.9708	-1.6221	-0.2037	-0.0463
-3.2715	-0.3057	1.8893	0.4786	-0.9979	0.2483	0.5183	0.2276	-0.1765
-3.3103	0.9988	-0.6279	-1.7608	0.1865	-0.4825	0.7406	-0.2842	0.0438
-2.1007	0.7980	0.1256	-0.9697	0.0095	-0.6170	-0.3019	0.3784	0.2575
-0.7339	0.3565	-1.0603	-0.2603	1.5989	0.3596	0.1703	-0.5497	-0.1433
-0.2891	1.8124	0.1638	-0.4336	0.6744	-0.9139	0.1855	0.2869	-0.1458
-0.8213	2.9433	-1.3666	1.5825	-0.1079	1.4962	-0.5911	0.2141	-0.0662
1.1664	2.0852	2.7955	1.6588	-0.1656	0.2823	0.6430	-0.0472	0.2296
1.2004	1.1260	0.7926	-0.1461	1.1637	-0.1801	-0.0217	-0.4229	0.1156
1.6276	1.7110	0.5532	-0.0809	1.1612	-0.6564	-0.2241	0.0315	-0.1499
0.8120	0.9924	-0.2626	-0.8954	-2.2387	0.2230	0.0807	-0.3162	-0.3766
0.3277	0.4219	-1.1702	0.5479	-0.6906	-0.1506	-0.2759	0.0131	0.0740
0.2947	-0.1869	-0.5513	-0.5825	-0.9442	-0.6819	-0.2847	0.2458	0.2994
0.6495	-1.1305	-0.1604	-0.6273	-0.2941	0.2842	0.2159	-0.1501	0.4522
0.4321	-1.1067	-0.1511	0.2025	-0.4394	-0.9449	-0.1986	0.1239	-0.2003
-0.9748	-1.5878	-0.8891	0.9276	0.7828	0.1156	0.6595	0.2587	-0.0740
2.0133	-0.4843	-0.2652	-0.8159	1.0687	-0.0544	-0.5693	0.5370	-0.1227
1.1050	-2.8643	0.1715	0.0100	0.6198	0.8922	1.2724	0.2026	-0.0976
2.4985	0.2432	-0.1616	-1.7237	-0.7355	1.7607	0.1062	0.0618	0.0496
0.7158	-1.4152	0.1056	0.7919	-0.8465	-1.1293	-0.2099	-0.1694	-0.0794
1.6373	-1.0722	0.0959	0.7871	-0.2520	-1.0694	-0.1341	-0.2798	0.0034
-0.9864	-0.9457	-2.0629	1.6806	-0.0645	0.2573	-0.1591	-0.1581	0.1537

Appendix G: Model Information and Residual Plots

1. B-52H MC Reduced Regression Model

The SAS System

Model: MODEL1
Dependent Variable: MC

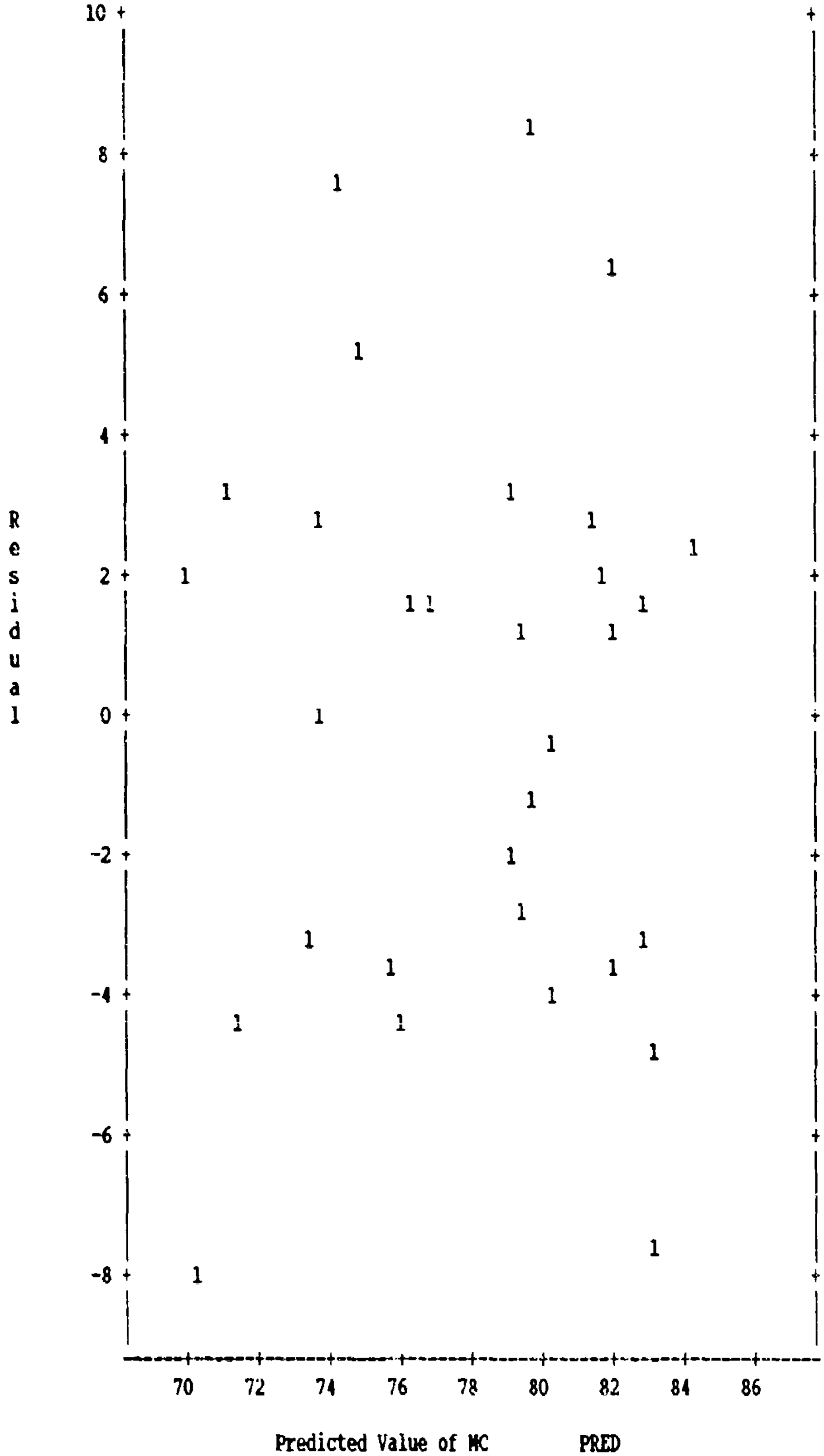
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	543.11863	181.03954	9.518	0.0002
Error	27	513.57685	19.02136		
C Total	30	1056.69548			

Root MSE	4.36135	R-square	0.5140
Dep Mean	78.04194	Adj R-sq	0.4600
C.V.	5.58847		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	73.194520	5.77139232	12.682	0.0001
ABORT	1	4.464612	1.59906944	2.792	0.0095
[illegible]	1	-0.423698	0.13965466	-3.034	0.0053
MHPH	1	0.181577	0.08679084	2.092	0.0460


Residual
10
8
6
4
2
0
-2
-4
-6
-8
70
72
74
76
78
80
82
84
86
Predicted Value of MC PRED

2. B-52H NMC Reduced Regression Model

The SAS System

Model: MODEL1
Dependent Variable: NMC

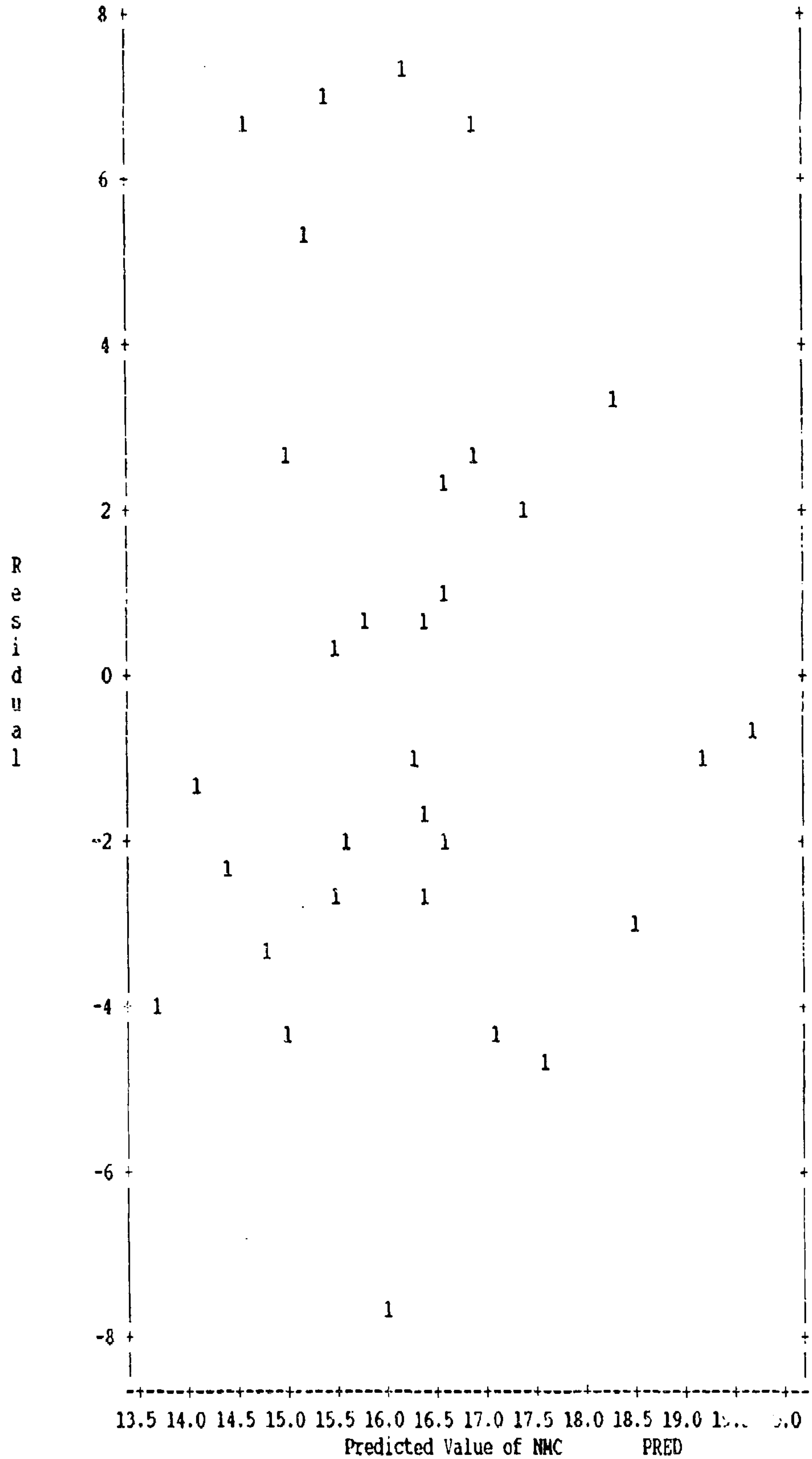
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	60.67876	60.67876	3.909	0.0576
Error	29	450.17801	15.52338		
C Total	30	510.85677			

Root MSE	3.93997	R-square	0.1188
Dep Mean	16.25484	Adj R-sq	0.0884
C.V.	24.23876		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	13.204542	1.69737027	7.779	0.0001
CANN	1	4.608148	2.33077981	1.977	0.0576



Residual
8
6
4
2
0
-2
-4
-6
-8
13.5 14.0 14.5 15.0 15.5 16.0 16.5 17.0 17.5 18.0 18.5 19.0
Predicted Value of NHC PRED

3. B-52H MC Reduced Principal Components Regression Model

The SAS System

Model: MODEL1
Dependent Variable: MC

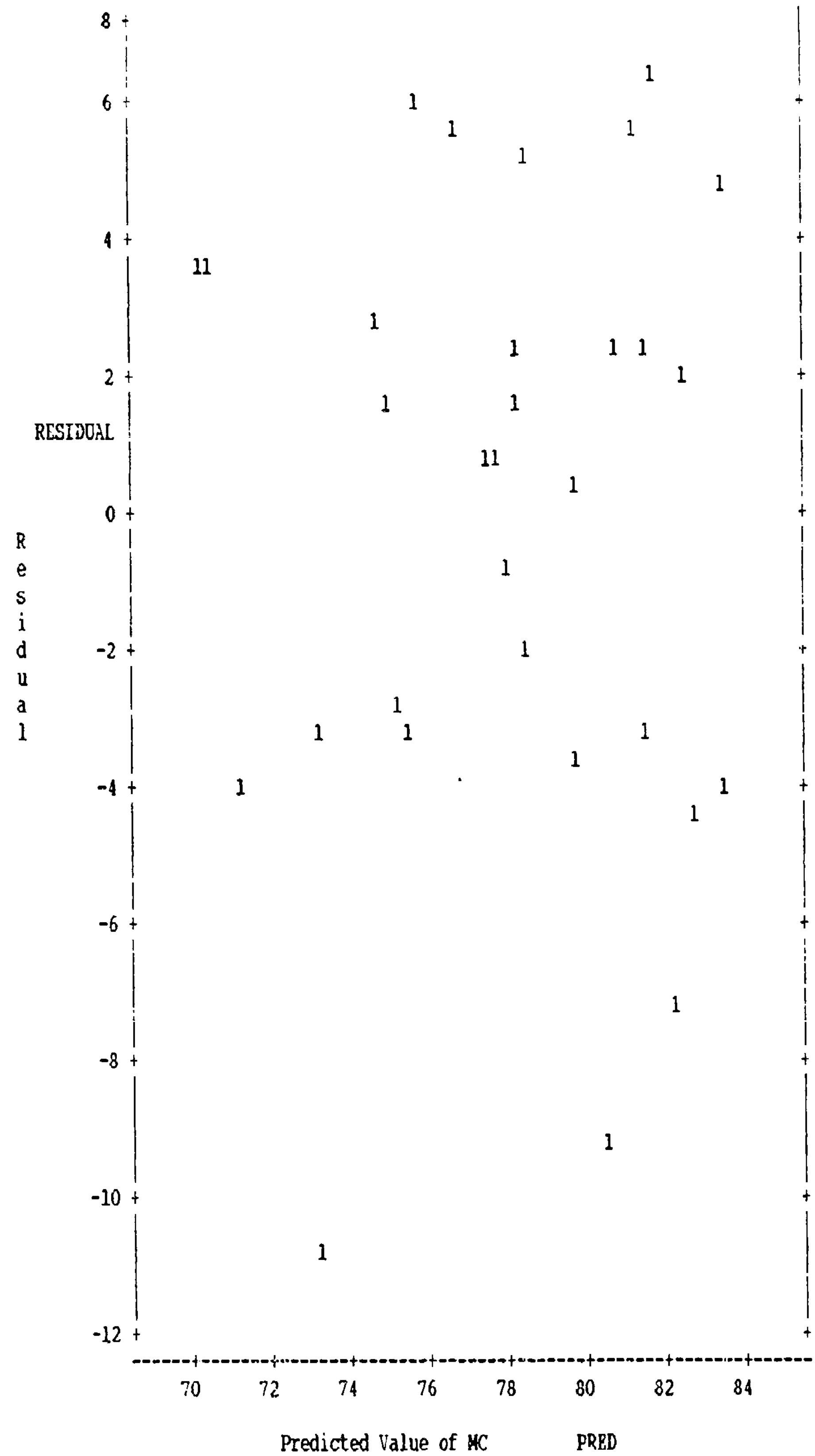
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	445.55836	222.77918	10.207	0.0005
Error	28	611.13712	21.82633		
C Total	30	1056.69548			

Root MSE	4.67187	R-square	0.4217
Dep Mean	78.04194	Adj R-sq	0.3803
C.V.	5.98635		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	78.042019	0.83909179	93.008	0.0001
P1	1	-2.004460	0.46640564	-4.298	0.0002
P2	1	-0.864031	0.61983619	-1.394	0.1743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Residual
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6
4
2
0
-2
-4
-6
-8
-10
-12
70
72
74
76
78
80
82
84
Predicted Value of MC PRED

4. B-52H NMC Reduced Principal Components Regression Model

The SAS System

Model: MODEL1
Dependent Variable: NMC

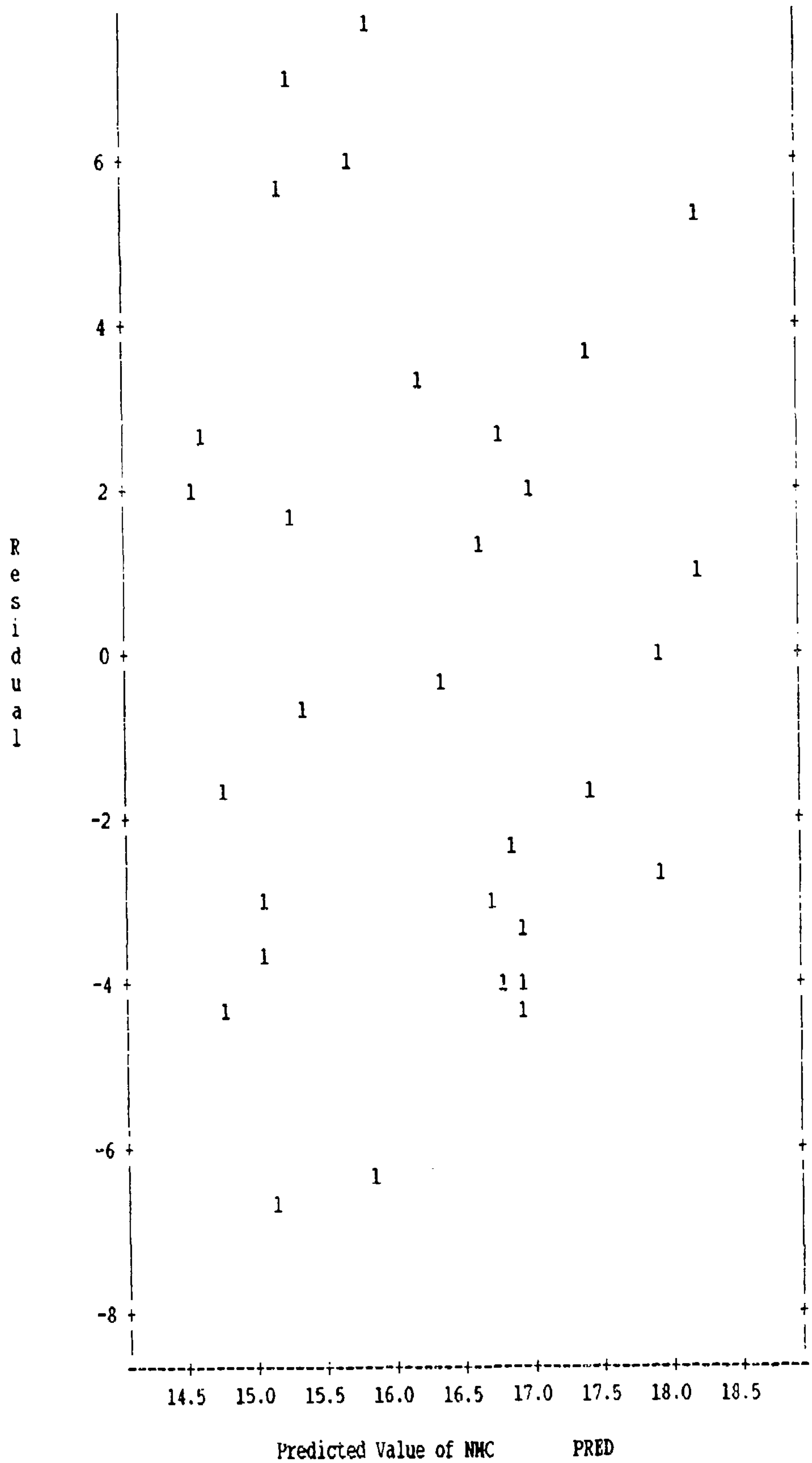
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	37.50612	37.50612	2.298	0.1404
Error	29	473.35065	16.32244		
C Total	30	510.85677			

Root MSE	4.04010	R-square	0.0734
Dep Mean	16.25484	Adj R-sq	0.0415
C.V.	24.85477		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	16.254795	0.72562401	22.401	0.0001
P1	1	0.611399	0.40333505	1.516	0.1404


6
4
2
0
-2
-4
-6
-8
Residual
14.5 15.0 15.5 16.0 16.5 17.0 17.5 18.0 18.5
Predicted Value of NHC PRED

5. KC-135R MC Reduced Regression Model

The SAS System

Model: MODEL1
Dependent Variable: MC

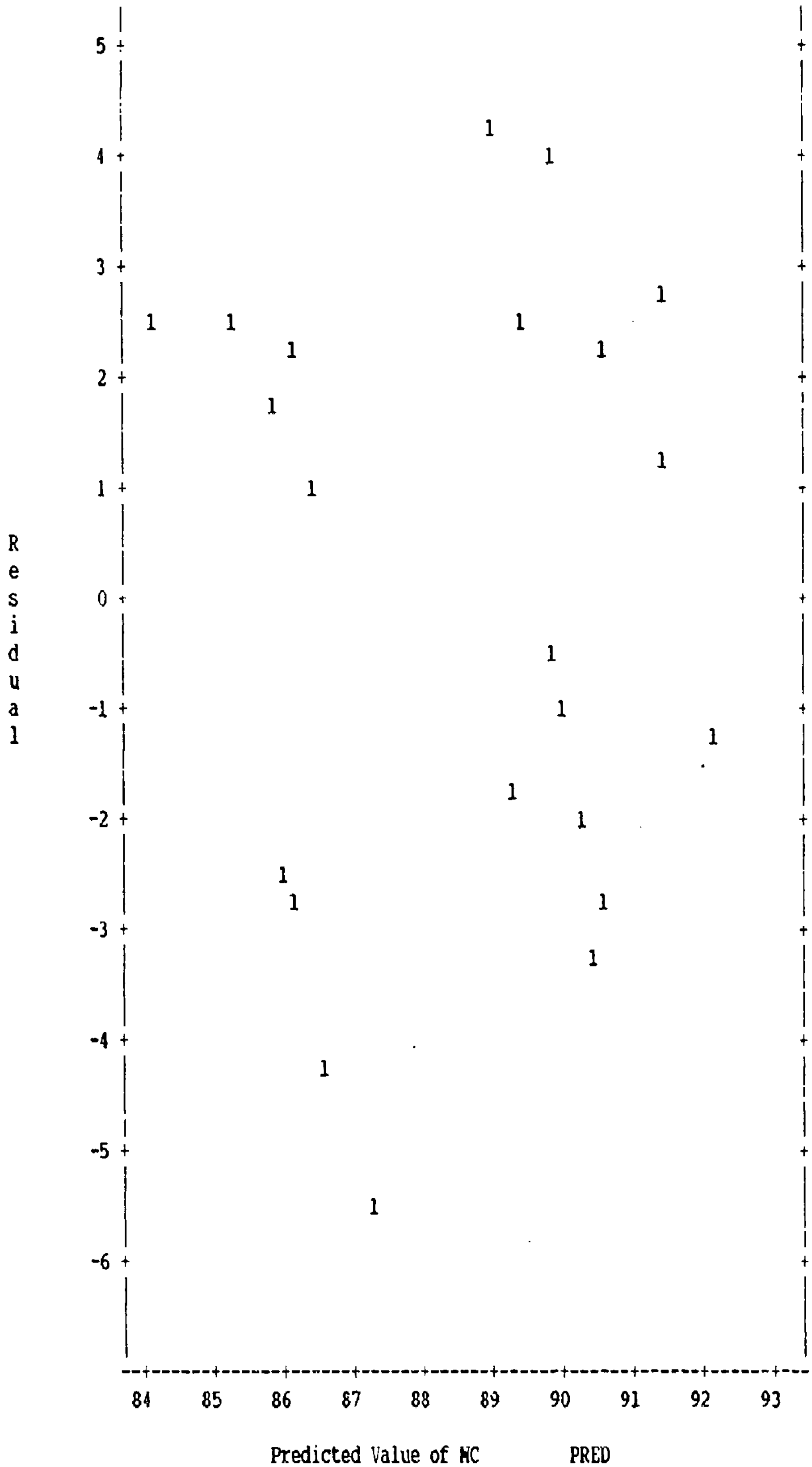
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	116.24696	116.24696	13.784	0.0014
Error	20	168.66759	8.43338		
C Total	21	284.91455			

Root MSE	2.90403	R-square	0.4080
Dep Mean	88.54545	Adj R-sq	0.3784
C.V.	3.27970		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	95.198404	1.89588915	50.213	0.0001
DD	1	-0.833655	0.22454149	-3.713	0.0014


Residual
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3
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1
0
-1
-2
-3
-4
-5
-6
84
85
86
87
88
89
90
91
92
93
Predicted Value of MC PRED

6. KC-135R NMC Reduced Regression Model

The SAS System

Model: MODEL1
Dependent Variable: NMC

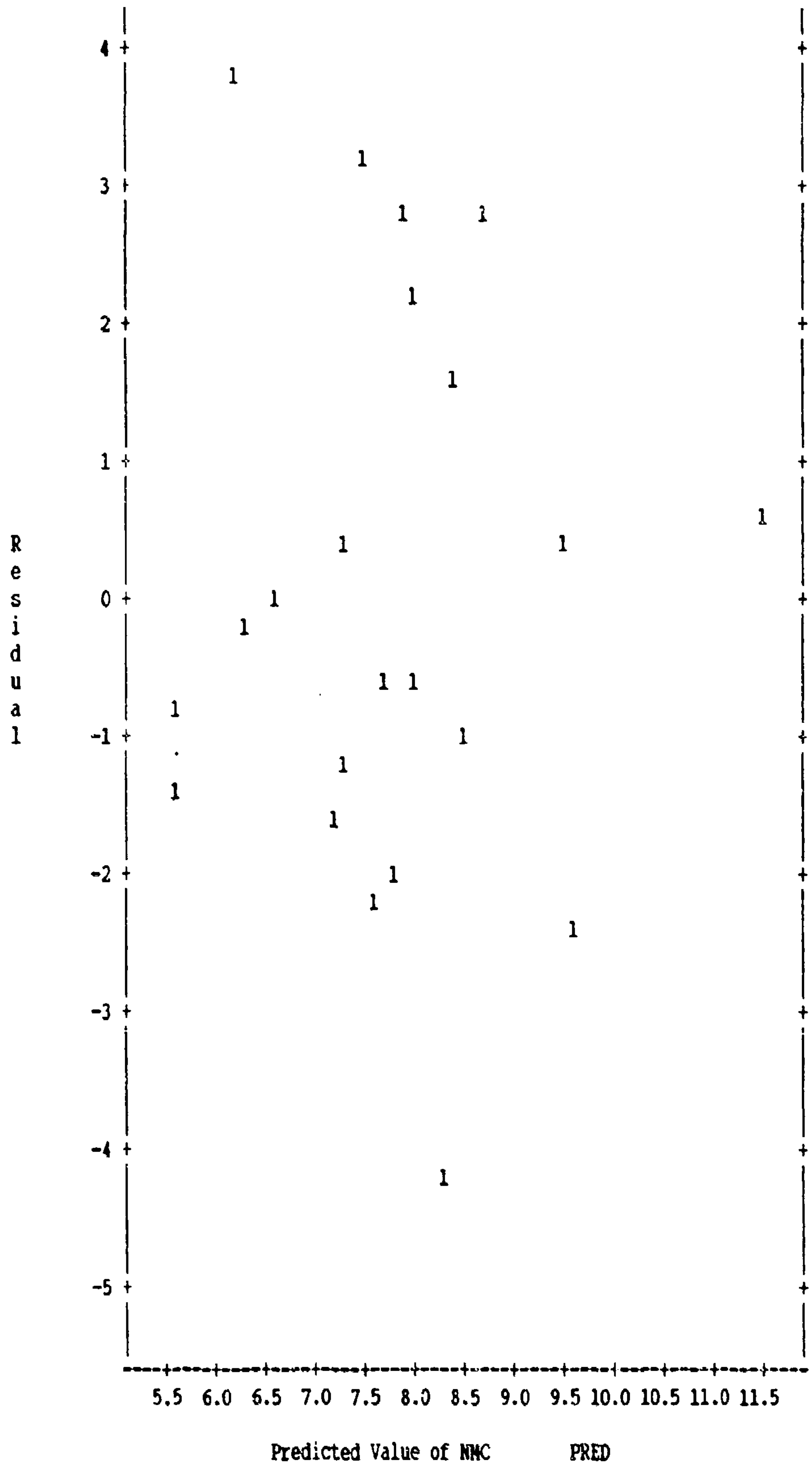
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	38.66166	19.33083	4.110	0.0329
Error	19	89.36168	4.70325		
C Total	21	128.02335			

Root MSE	2.16870	R-square	0.3020
Dep Mean	7.77455	Adj R-sq	0.2285
C.V.	27.89484		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: arameter=0	Prob > |T|
INTERCEP	1	8.689243	1.94033065	4.478	0.0003
LTO	1	0.452047	0.18540004	2.438	0.0248
MHFH	1	-0.087736	0.05764927	-1.522	0.1445


R
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-1
-2
-3
-4
-5
5.5 6.0 6.5 7.0 7.5 8.0 8.5 9.0 9.5 10.0 10.5 11.0 11.5
Predicted Value of NMC PRED

7. KC-135R Reduced Principal Components Regression Model

The SAS System

Model: MODEL1
Dependent Variable: MC

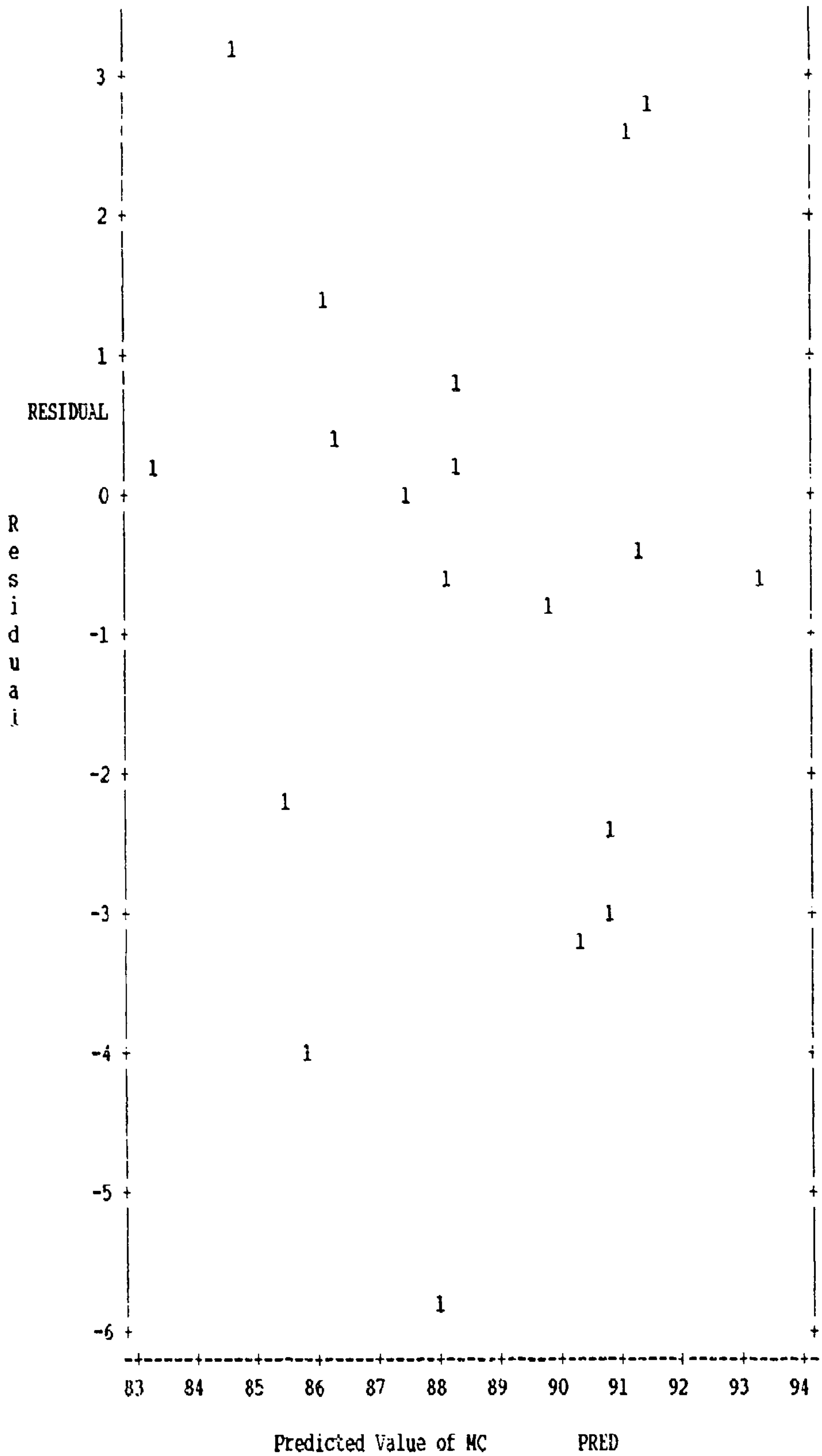
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	134.04821	44.68274	5.331	0.0083
Error	18	150.86634	8.38146		
C Total	21	284.91455			

Root MSE	2.89508	R-square	0.4705
Dep Mean	88.54545	Adj R-sq	0.3822
C.V.	3.26959		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	88.545446	0.61723221	143.456	0.0001
P1	1	0.989671	0.39077984	2.533	0.0208
P2	1	-1.285073	0.42309078	-3.037	0.0071
P4	1	-0.381462	0.64111664	-0.595	0.5593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Residual
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0
-1
-2
-3
-4
-5
-6
83
84
85
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89
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92
93
94
Predicted Value of MC
PRED

8. KC-135R NMC Reduced Principal Component Model

The SAS System

Model: MODEL1
Dependent Variable: NMC

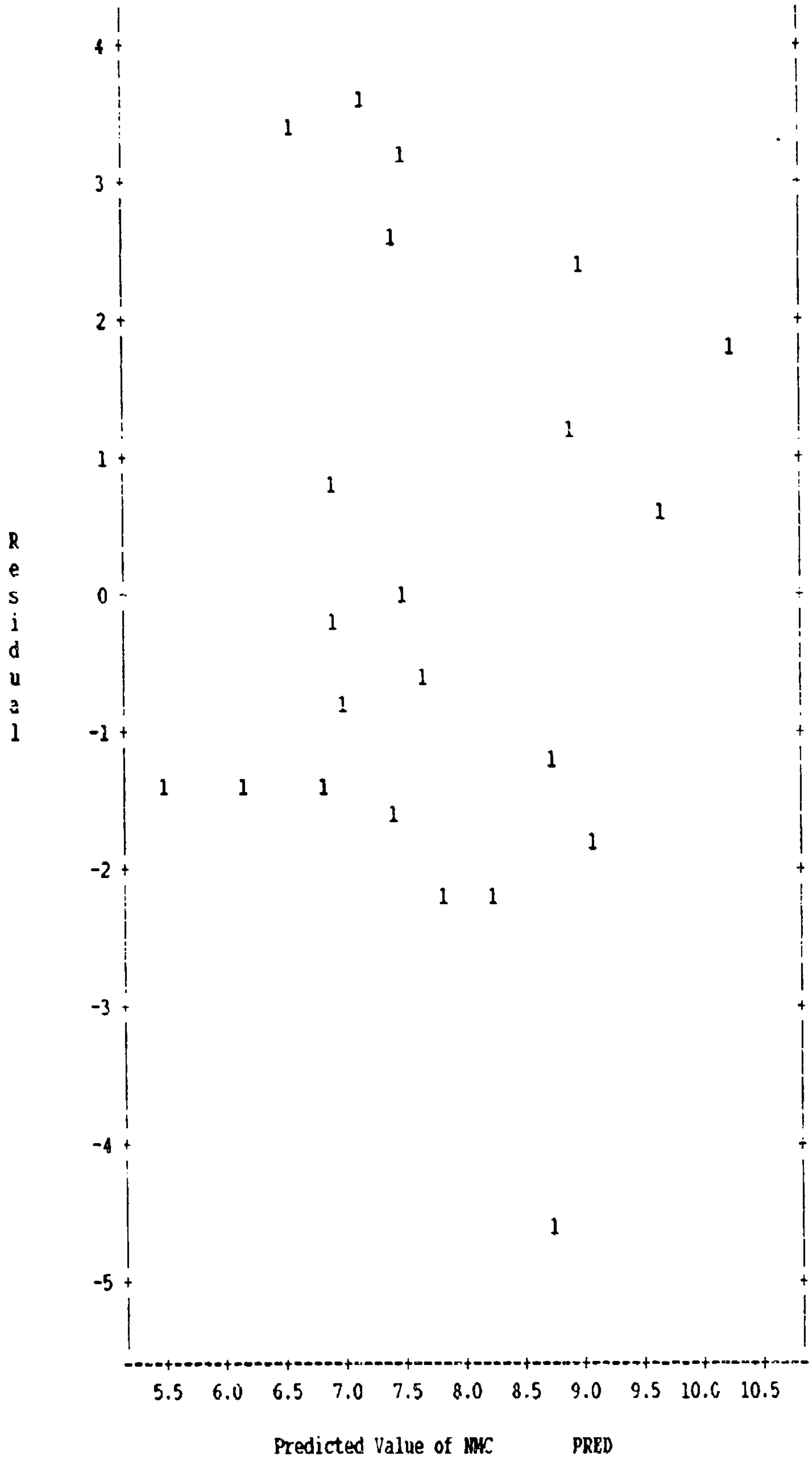
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	28.98284	14.49142	2.780	0.0873
Error	19	99.04050	5.21266		
C Total	21	128.02335			

Root MSE	2.28312	R-square	0.2264
Dep Mean	7.77455	Adj R-sq	0.1450
C.V.	29.36666		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	7.774547	0.48676381	15.972	0.0001
P1	1	-0.707263	0.30817815	-2.295	0.0333
P4	1	0.273760	0.50559963	0.541	0.5945



Residual
4
3
2
1
0
-1
-2
-3
-4
-5
5.5 6.0 6.5 7.0 7.5 8.0 8.5 9.0 9.5 10.0 10.5
Predicted Value of NWC PRED

Appendix H: Autoregression Model Results

1. B-52H Reduced Autoregression Model

The SAS System

Autoreg Procedure

Dependent Variable = MMC

Ordinary Least Squares Estimates

SSE	436.8531	DFE	27
MSE	16.17974	Root MSE	4.022405
SBC	183.724	AIC	177.9881
Reg Rsq	0.1316	Total Rsq	0.1316
Durbin-Watson	1.2057		

Variable	DF	B Value	Std Error	t Ratio	Approx Prob
Intercept	1	23.0147738	4.9642	4.636	0.0001
ABORT	1	-2.6058452	1.6237	-1.605	0.1202
DD	1	-0.000143304	0.1233	-0.001	0.9991
MHFH	1	-0.1053709	0.0748	-1.409	0.1702

Estimates of Autocorrelations

Lag	Covariance	Correlation	-1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
0	14.09204	1.000000	| |******************** |
1	5.070496	0.359813	| |******* |

Preliminary MSE = 12.26761

Estimates of the Autoregressive Parameters

Lag	Coefficient	Std Error	t Ratio
1	-0.35981287	0.18298116	-1.966393

Yule-Walker Estimates

SSE	366.8579	DFE	26
MSE	14.10992	Root MSE	3.756317
SBC	181.8834	AIC	174.7134
Reg Rsq	0.0769	Total Rsq	0.2708
Durbin-Watson	1.5872		

Variable	DF	B Value	Std Error	t Ratio	Approx Prob
Intercept	1	20.6903653	4.4975	4.600	0.0001
ABORT	1	-1.4847696	1.6158	-0.919	0.3666
DD	1	0.0265431	0.1599	0.166	0.8694
MHFH	1	-0.0727348	0.0609	-1.194	0.2434

2. B-52H Reduced Principal Components Autoregression Model

Autoreg Procedure

Dependent Variable = NMC

Ordinary Least Squares Estimates

SSE	491.523	DFE	29
MSE	16.94907	Root MSE	4.116925
SBC	180.5113	AIC	177.6434
Reg Rsq	0.0230	Total Rsq	0.0230
Durbin-Watson	0.9939		

Variable	DF	B Value	Std Error	t Ratio	Approx Prob
Intercept	1	17.0432610	0.74037	23.020	0.0001
P1	1	0.3448568	0.41764	0.826	0.4157

Estimates of Autocorrelations

```
Lag  Covariance  Correlation -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 0    15.85558     1.000000  |                    |********************|
 1    7.584936     0.478376  |                    |**********          |
```

Preliminary MSE = 12.22712

Estimates of the Autoregressive Parameters

Lag	Coefficient	Std Error	t Ratio
1	-0.47837647	0.16595567	-2.882556

Yule-Walker Estimates

SSE	366.2385	DFE	28
MSE	13.07995	Root MSE	3.616621
SBC	175.0842	AIC	170.7823
Reg Rsq	0.0593	Total Rsq	0.2720
Durbin-Watson	1.5865		

Variable	DF	B Value	Std Error	t Ratio	Approx Prob
Intercept	1	16.9010817	1.2103	13.964	0.0001
P1	1	0.7760043	0.5842	1.328	0.1948

Appendix I: Validation Interval Results

1. B-52H MC Reduced Regression Model

Actual MC Rate	Predict Value	Lower95% Predict	Upper95% Predict	Lower99% Predict	Upper99% Predict
79.9	79.4707	69.0115	89.9299	65.3471	90.3132
79.3	76.9770	67.1008	86.8532	63.6407	84.9375
79.5	72.2196	62.8014	81.6379	59.5017	84.9375
73.6	75.9361	66.6607	85.2115	63.4111	88.4611
64.9	80.5119	71.2503	89.7735	68.0055	93.0182
73.9	82.1038	72.7307	91.4769	69.4468	94.7607

2. B-52H MC Reduced Principal Components Regression Model

Actual MC Rate	Predict Value	Lower95% Predict	Upper95% Predict	Lower99% Predict	Upper99% Predict
79.9	74.4917	64.0902	84.8932	60.4602	88.5231
79.3	75.9737	65.5752	86.3721	61.9463	90.0000
79.5	75.5131	65.6885	85.3376	62.2599	88.7661
73.6	79.1906	69.4471	88.9341	66.0468	92.3343
64.9	80.2161	70.4152	90.0169	66.9949	93.4371
73.9	80.8576	70.9665	90.7486	67.5147	94.2004

3. B-52H NMC Autoregression Model

Actual NMC Rate	Predict Value	Lower95% Predict	Upper95% Predict
21.7	15.6311	6.3751	24.8870
19.7	16.7491	8.0350	25.4632
13.7	16.3393	7.5436	25.1351
8.5	14.5296	6.1224	22.9368
12.0	15.6206	6.7904	24.4508
9.5	15.4539	5.7547	25.1531

4. B-52H NMC Principal Component Autoregression Model

Actual NMC Rate	Predict Value	Lower95% Predict	Upper95% Predict
21.7	16.2477	7.3905	25.1048
19.7	16.8609	8.0673	25.6545
13.7	17.7205	8.8455	26.5956
8.5	13.5686	5.4270	21.7103
12.0	14.4615	5.5455	23.3776
9.5	15.9394	7.1514	24.7274

5. KC-135R MC Regression Model

Actual MC Rate	Predict Value	Lower95% Predict	Upper95% Predict	Lower99% Predict	Upper99% Predict
80.2	86.6618	80.3782	92.9454	78.0987	95.2329
87.3	87.8622	81.6565	94.0680	79.3974	96.3270
87.8	84.1108	77.4346	90.7870	75.0041	93.2174
83.6	85.8615	79.4867	92.2362	77.1660	94.5569
89.0	87.4454	81.2208	93.6700	78.9548	95.9360
89.7	89.7796	83.5471	96.0122	81.2782	98.2811

6. KC-135R MC Principal Component Regression Model

Actual MC Rate	Predict Value	Lower95% Predict	Upper95% Predict	Lower99% Predict	Upper99% Predict
80.2	90.7324	84.0920	97.3728	81.6345	99.8303
87.3	85.0644	78.1872	91.9416	75.6421	94.4867
87.8	86.9777	80.5819	93.3734	78.2149	95.7404
83.6	88.4647	81.8159	95.1135	79.1869	97.5741
89.0	88.1229	81.6007	94.6451	79.1869	97.0589
89.7	89.4033	83.1089	95.7378	80.7720	98.0747

7. KC-135R NMC Regression Model

Actual NMC Rate	Predict Value	Lower95% Predict	Upper95% Predict	Lower99% Predict	Upper99% Predict
13.4	7.5434	2.8703	12.2165	1.1558	13.9310
5.5	8.4190	3.3287	13.5093	1.4610	15.3769
6.79	6.4072	1.6572	11.1572	-.0855	12.8999
12.3	8.2209	3.5578	12.8840	1.8469	14.5949
8.2	6.2903	1.3986	11.1820	-.3961	12.9768
9.0	7.6548	3.0065	12.3030	1.3010	14.0085

8. KC-135R NMC Principal Component Regression Model

Actual NMC Rate	Predict Value	Lower95% Predict	Upper95% Predict	Lower99% Predict	Upper99% Predict
13.4	8.3107	3.3440	13.2775	1.5217	15.0997
5.5	9.4275	4.0617	14.7934	2.0930	16.7620
6.79	7.8254	2.8666	12.7841	1.0473	14.6034
12.3	7.8626	2.6389	13.0862	0.7224	15.0027
8.2	6.6230	1.6193	11.6267	-.2165	13.4626
9.0	6.9138	1.9559	11.8716	0.1369	13.6906

Appendix J: Results of Median Tests

1. B-52H DD

MEDIAN TEST FOR DD BY TYPE

	TYPE 1	TYPE 2	TOTAL
ABOVE MEDIAN	18	0	18
BELOW MEDIAN	9	9	18
TOTAL	27	9	36
TIES WITH MEDIAN	1	0	1

MEDIAN VALUE 15.300

CHI-SQUARE 12.00 DF 1 P-VALUE 0.0005

MAX. DIFF. ALLOWED BETWEEN A TIE 0.00001

CASES INCLUDED 37 MISSING CASES 0

2. KC-135R LTO

MEDIAN TEST FOR LTO BY TYPE

	TYPE 1	TYPE 2	TOTAL
ABOVE MEDIAN	10	4	14
BELOW MEDIAN	9	5	14
TOTAL	19	9	28
TIES WITH MEDIAN	0	0	0

MEDIAN VALUE 3.4500

CHI-SQUARE 0.16 DF 1 P-VALUE 0.6857

MAX. DIFF. ALLOWED BETWEEN A TIE 0.00001

CASES INCLUDED 28 MISSING CASES 0

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Vita

Captain Mark A. Gray was born 13 December 1963 in Honolulu, Hawaii at Army Tripler Hospital. He graduated from Alamogordo High School, New Mexico in 1982 and began college at Auburn University, Alabama. He graduated from Auburn in 1986 with a Bachelor's in Aerospace Engineering. After completing Aircraft Maintenance Officer's Course at Chanute AFB IL, he was assigned to Keesler AFB MS, where he served in numerous positions. His maintenance duties included Maintenance Support Branch OIC, Aerospace Systems Branch OIC, Mission Systems Branch OIC, TAC Flight Line Branch OIC, and Job Control OIC. Following the reorganization of the 3380th Maintenance Group into an Objective Wing structure, Captain Gray was assigned to the 3300th Technical Training Wing at Keesler where he served as Executive Officer for the Vice Wing Commander. He served in this capacity for one year before he entered the School of Logistics and Acquisition Management, AFIT, Wright-Patterson AFB OH in May 1992.

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Vita

Captain Margaret M. Ranalli was born on 13 November, 1964 at Wheelus AB. She graduated from Mount Mercy Academy, Buffalo, New York in 1982. She attended Syracuse University, Syracuse, NY, and graduated in May 1986 with a Bachelor's degree in Mathematics. She came on active duty in October 1986 and attended the Aircraft Maintenance Officer Course at Chanute Air Force Base, Illinois. Capt Ranalli was assigned to the 92nd Bomb Wing, Fairchild AFB, Washington in April 1987. Her duties included Assistant Officer in Charge, Tanker Branch, 92nd Organizational Maintenance Squadron; OIC Propulsion Branch and Assistant Maintenance Supervisor, 92nd Field Maintenance Squadron; Maintenance Supervisor, 92nd Avionics Maintenance Squadron; OIC Standardization and Training, 92nd Bomb Wing; OIC Tanker Branch and Maintenance Supervisor, 92 OMS. She completed Squadron Officer School in May 1992 as a distinguished graduate. She entered the School of Logistics and Acquisition Management in May 1992. She has been married to Captain Steven A. Ranalli since September 1987. Her next assignment is a Logistics Officer Professional Development assignment to the 92nd Transportation Squadron, Fairchild AFB, Washington.

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No 0704-0188

Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503.

1. AGENCY USE ONLY (*Leave blank*)	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	September 1993	Master's Thesis

4. TITLE AND SUBTITLE
AN EVALUATION OF AIRCRAFT MAINTENANCE PERFORMANCE FACTORS IN THE OBJECTIVE WING

5. FUNDING NUMBERS

6. AUTHOR(S)
Mark A. Gray, Capt, USAF
Margaret M. Ranalli, Capt, USAF

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Air Force Institute of Technology
WPAFB OH 45433-6583

8. PERFORMING ORGANIZATION REPORT NUMBER
AFIT/GLM/LA/93S-22

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
92 Bomb Wing/LG
Fairchild AFB, WA 99011

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

12b. DISTRIBUTION CODE

13. ABSTRACT (*Maximum 200 words*)

Prior to 1992, organizational maintenance was aligned under a separate maintenance organization. In 1992, the Air Force restructured into Objective Wings with organizational maintenance aligned under the flying squadrons. This study looks at the impact of this reorganization on maintenance performance factors.

The researchers developed maintenance performance models using regression and principal component analysis. Mission Capable Rate and Total Not Mission Capable Maintenance Rate are used as dependent variables. A comparison of key maintenance performance indicators and model predictions before and after the reorganization is accomplished.

Based on the results of this analysis, the researchers conclude that there is significant improvement in all dependent variables, model predictions of these dependent variables and improvement in some of the independent variables. Improvement occurred after organizational structure changed, however, other factors not included in the models such as the stand-down of the Alert Force may also contribute to this improvement.

14. SUBJECT TERMS
Maintenance Management, Aircraft Maintenance, Regression Analysis
Air Force Organizations, Principal Component Analysis

15. NUMBER OF PAGES 152

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	UL

AFIT Control Number AFIT/GLM/LA/93S-22

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